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Uncovering Online Communities Inducing Social Unrest via Non-negative Matrix Factorization

Shafia Bashir and Manzoor Ahmad Chachoo

***Abstract*—People are forming social interactions and expressing their thoughts in cyberspace as social networking services like Web 2.0 have become more popular. Natural language processing and machine learning techniques, along with other approaches, can extract attitudes from vast amounts of text on social platforms. Non-negative Matrix Factorization (NMF), being a powerful text analysis technique, was used to determine the sentiment polarity of tweets. This paper presents a novel knowledge-based NMF strategy for detecting online communities that are producing social unrest. The primary motivation for our goal was to find online user communities that are socially connected and share similar social sentiments. Further, faced with the threat of social unrest fuelled by social media, our proposed strategy can help the government organizations to ensure the tracking of information flow patterns across social media platforms and the influence of social network data that are fuelling ethnic tensions.**

***Index Terms*—Non-negative Matrix Factorization, Natural Language Processing, Social Context, Social Network Analysis, Sentiment Analysis, Application Programming Interface.**

I. INTRODUCTION

An online social media platform facilitates information sharing, allowing discussions on distinct problems and encourages users to either post the information or access it. Consequently, it serves as a factor that increases knowledge profiles for every member within social network dynamics. Users of the internet have grown rapidly in tandem with new technologies, frequently voicing their ideas on social media platforms and personal blogs.

They have both favorable and negative feelings regarding individuals, organizations, locations, and events. A dynamic community provides traditional communities with openness, scalability, extensibility, and interoperability. When people live in a society, they make decisions about the universe all around them. They show positive or negative attitudes towards the people, products, places, and events.

Shafia Bashir
Department of Computer Science, University of Kashmir, Srinagar, J&K, India
imshafia@gmail.com

Manzoor Ahmad Chachoo
Department of Computer Science, University of Kashmir, Srinagar, J&K, India
manzoor@kashmiruniversity.ac.in

Such attitudes are called sentiments. Individual extremists do utilize private channels, but they are also active on mainstream social networks. This characteristic of online propaganda is profoundly embedded in its nature.

Since social networks can be viewed as a theoretical construct important in the domain of social sciences, so as to study interactions among people, organizations, or in entire civilizations. Hence, a social media network provides a straightforward tool for examining the structure of social entities. An axiom of the social media network approach to understanding social interactions is that social phenomena must be initially visualized and analyzed in terms of the features of relations within elements, rather than the features of the elements themselves.

A social media platform user can share their ideas, fears, and day-to-day activities online. The data shared by users, when brought together, provides a rich, naturally occurring source. Facebook status updates, Twitter tweets, and Instagram photos reveal information about their users' social activities.

Many terrorist groups are active on social media, and they are expanding their network in order to cause social unrest by creating fear in the hearts of the people of any country they target around the globe. Why not? After all, it is the simplest form of communication and has a captive audience, particularly young minds who can be influenced by its content [1]. Faced with the threat of social unrest fueled by social media, the government has established a number of organizations to track information flows on social media platforms and the influence of content that is fueling ethnic tensions.

Social networks may be seen as a mirror of the real world, providing insights into real-world civilizations and events [2]. Community identification, as a basic aspect of social network research, has been extensively investigated over the last decade, yet remains an unresolved challenge due to the network's complexity.

In general, social networks are made up of interconnected communities of people who communicate with one another. The initial step in analyzing a network is to convert it into a graph G(V, E), where V is the set of nodes and E is the set of edges between nodes [2], [3]. As a result, social network community detection can be viewed as an optimization problem aimed at identifying node groupings with more intra-group connections and fewer inter-group connections.

In this paper, a novel NMF-based community detection technique is proposed that accounts for interactions among individuals in the network, along with their sentiments, to detect communities causing social unrest. NMF is a matrix factorization technique that reduces a large matrix into a product of matrices of smaller size that are manageable to work with or easy to interpret [4]. Moreover, NMF, being a powerful text analysis technique, has been used to determine the sentiment polarity of tweets/posts. Since NMF offers significant flexibility for semantic sentiment analysis and clustering, the development of a robust, adaptable NMF-based community detection approach is therefore promising.

Further, the following two observations provide the foundation for our approach: (i) the degree of interactions between each user pair can vary widely, which we refer to as "tie strength", and (ii) for each user pair, the degree of interactions with shared neighbors (like Facebook mutual friends), which we refer to as the group behavior, plays a significant role in determining whether or not they belong to the similar community. Based on these two observations, we propose an effective NMF-based approach for detecting communities in online social networks that account for interactions between each user pair and among mutual friends. Fig.1. shows the framework of the proposed research, wherein C0 represents the community at time 0, and Ct denotes the community at time t.

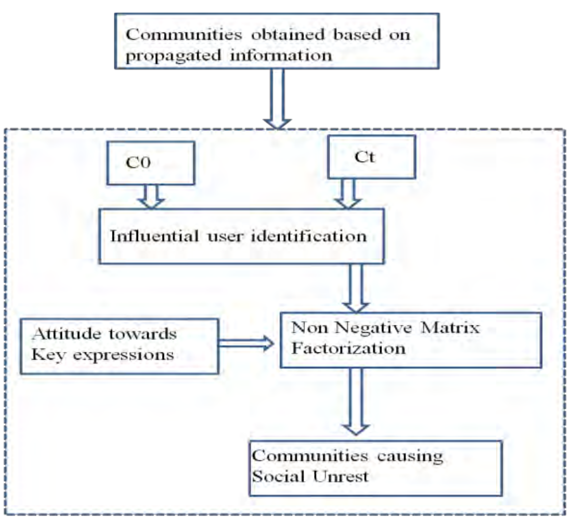

Fig.1. Framework of the Proposed Research.

This paper is organized as follows: After brief introduction in Section I, Section II provides a summary of related works in the area of identification of communities using data from social networking sites. Section III describes the proposed methodology. Section IV presents the results and discussion followed by some applications in Section V. Finally, we have concluded the paper with some future work guidelines in Section VI.

II. BACKGROUND AND MOTIVATION

The amount of data generated by social media platforms is enormous, and is rising at an exponential rate. Since the individuals on these social media platforms generate mountains of raw data every day [1], [2]. These platforms have had a significant impact on our lives, and their social impact cannot be underestimated.

The researchers' primary goal regarding the online community is to develop technology that serves the community's interests. The primary goal of an online community is to provide a meeting place for people who share common interests. Online communities provide an ideal medium of faster online utilities, because the information can be exchanged very quickly. Another benefit is that online community members can obtain membership and association services. Users can provide and receive support from one another through such membership services.

Everyone, even malicious individuals and organizations, uses online social media platforms in their daily lives [1]. We must examine network structures and user sentiment to properly understand the principal dynamics of online communities. Users who belong to a similar sentiment community are not only close friends but also share nearly the same sentiments. In the computer science domain, the last several years have seen significant advances in large-scale social network analysis. One of the prime challenging aspects in social network analysis is regarded as community detection; in multi-million user networks, analysts employ a range of methods to visualize the spontaneous group structures that emerge from interactions in addition to friendship links. Such visualization, together with influencer discovery and topic detection tools, enables the analysts to understand the majority of a social network's intricacy.

Thanks to advances in information networking, the community detection problem has been extensively explored in recent years. The utilization of user-generated content on social media allows individuals to express their feelings on a variety of issues. Extraction of such issues is of utmost importance for understanding individuals' opinions on them. Many attempts [6], [7] have been undertaken to extract these issues or related features in this regard. However, for these algorithms to work effectively, they need adequate training examples for a certain domain. Social interactions, such as retweets on Twitter and friendships on Facebook, are among the most effective sources for identifying communities [8]. However, these sources don't account for the many types of interactions and degrees of interaction among individuals, so they don't recognize active communities.

Tajfel [9] suggested focusing on unit-forming factors (such as similarities and shared risks), which function as cognitive criteria for categorizing the social world into discrete categories. As a result, contentious issues over which individuals hold differing viewpoints can be examined to uncover the motivations for social media segmentation and community formation. When attempting to understand the relationships between users of social networks who share thoughts about marketing and services, the sentiments conveyed in their conversations are significant in gaining a comprehensive knowledge of social communities. To our best knowledge, existing approaches to community detection have not taken user sentiment into account [8], [9]. By solely assessing network connectivity without accounting for user sentiment, these approaches are unable to distinguish users who are actively communicating with one another but have opposing sentiments. On the contrary, identifying groups of people who are strongly connected via both sentiments and social relationships will be more valuable to businesses for consumer segmentation and viral marketing on social media platforms. It is pertinent to note the two types of sentiment classification: binary and multi-class. However, our approach mainly focused on binary sentiments.

Sentiment classification [10] is described as recognizing the polarity of subjective sentences' sentiments. Machine learning algorithms have also been used to resolve the task of tweet sentiment analysis [11], [12]. To determine the sentiment polarity of movie reviews, Pang et al. [13] conducted a comparison analysis using methods such as maximum entropy, Naive Bayes, and Support Vector Machine. These investigations were successful, but they failed to account for semantics in capturing the tweet meanings. To model crime risk for mobile groups using tweets, Malleson et al. [14] employed a variety of geographic analytical techniques. The primary limitation of these investigations was their exclusive focus on geolocation data, with no consideration given to tweet text.. As monitoring the social behavior data of a vast society is a difficult and challenging task, the main drawback of these models is that they reduce the social context to a verifiable criminal record while ignoring information on the social behavior available on the social networking platforms, including the victim and the criminal behavior [15]. Based on the research review discussed so far in this study, it is clear that more research is required to advance this field of study. Therefore, our research is intended to address this gap in existing community identification algorithms and provides an innovative approach for detecting sentimental communities causing social unrest over social media platforms.

III. METHODOLOGY

The goal of this research was to determine whether there was useful information across social media platforms that could help analyze sentiments in specific contexts. To determine whether two users of the social network belong to the same community, the proposed approach considers both the impact of their interactions and the influence of group behavior, as users exhibit it through their social interactions with mutual friends.

Our framework that uses social networks to recognize active communities causing social unrest has three main phases (fig. 1), wherein the initial phase, our approach assesses the level of interaction between each connected user pair in the online social network, and depending on such interactions, the approach assesses the propagation of information for each user pair that is connected through common neighbors. In the next phase, we identify K influential users within those communities that were created in the first phase, and in the final phase, based up on the influential nodes' attitude towards the key expressions, communities causing social unrest are unfolded naturally as is described below:

A. Information Interaction and Information Propagation

To better simulate information propagation, Bashir et al. [4] have suggested using node similarity in addition to connection strength to model information. For clarity, consider a sample network of 15 nodes (fig. 2) ranging from 1 to 15. Formally, suppose $I_{u->v}$ indicates that information which a node v receives from its neighbor node u, as is described below:

$$I_{u->v} = JS_{uv} CS_{uv} \quad (1)$$

Where $JS_{uv} = \frac{T(v) \cap T(u)}{T(v) \cup T(u)}$ wherein JS_{uv} describes the jaccard similarity coefficient between the node u and the node v, T_u represents the no. of triangles of vertex u.

$CS_{uv} = \frac{N(u) \cap N(v)}{Tu}$ wherein CS_{uv} describes the contact strength of node v over node u and the intersection between N(u) and N(v) denotes the no. of triangles common to node u and node v.

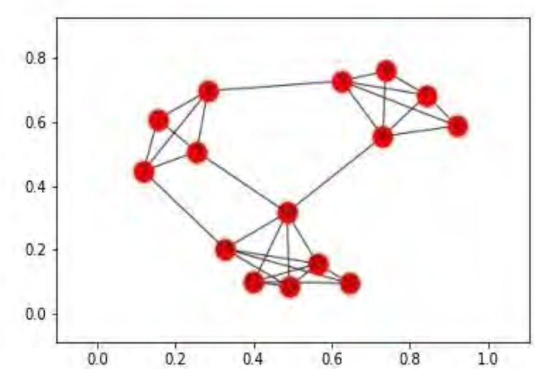

Fig.2. Sample network.

The following provides information about a v node over t time:

$$I_{v(t+1)} = I_{v(t)} + \Sigma_{u \in N(v)} (I_{u->v}) \quad (2)$$

Wherein $I_{v(t)}$ describes the information of a v node at t time, and the second part of the expression represents the information that is gained from its neighbors. As can be seen, information about the v node at time t+1 involves information from time t plus information gained from its neighbors at time t+1. With the time evolution, the propagation of information tends to zero. Ultimately, the network's information will achieve a state of equilibrium, allowing communities to uncover naturally, as is shown clearly in fig. below:

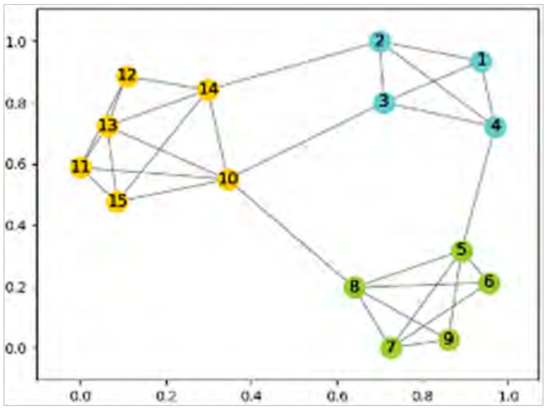

Fig. 3. Community formation with each community represented by distinct colors.

B. Influential users identification

As the different community formations are done, degree centrality is applied to these communities to identify the influential nodes. The influence of nodes in a network is determined by two main factors. (i) When a node is at the network's center, it has a lot of influence. Otherwise, when the node is at the network's edge, its influence will be minimal. (ii) The number of node neighbors: the more neighbors a node has, the more influence it has. Due to these factors, we have employed the degree centrality measure as a measurement based on centrality, attempting to get the relative node importance inside a network, such as:

$$C_d(i) = \sum_{i=1}^{N} A_{ij} \quad (3)$$

Where N is no. of nodes, A is the adjacency matrix having $A_{ij}=1$ if and only if there is a link between node i and node j. The degree centrality measure is applied to each node of each community. Hence, the actor with the highest degree centrality within the community represents the influential node within that community, as illustrated in fig. 4.

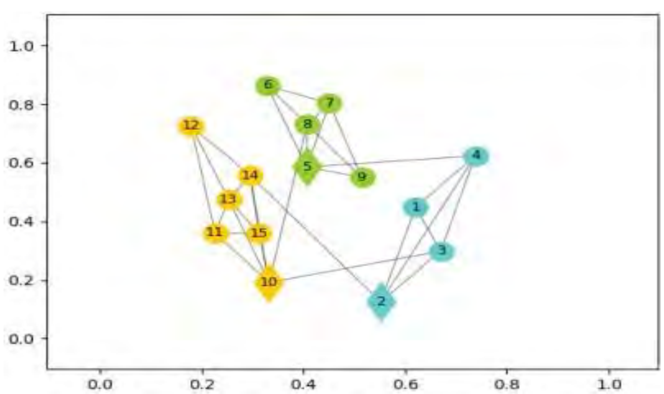

Fig. 4. Influential node formation denoted by diamond shapes.

C. Sentiment-driven community extraction via nonnegative matrix factorization(NMF)

Since Non negative matrix factorization has grown to be a popular approach towards community detection network complexity, the development of such an adaptable NMF-based community detection framework is therefore promising. While streaming Tweets, 20 distinct keywords were used and an English language filter was employed. The JSON-extracted tweets were then imported into a Python pandas data frame and downloaded as a CSV file. We were able to extract the tweets by using Twitter's API(application programming interface) . After that, tweets were grouped by similarity to create Twitter's API collection. Assume a set of influential users n as $U = \{u_1, u_2, ..., u_n\}$ and a set of communities k as $C = \{c_1, c_2, ..., c_k\}$to which the influential users belong, and a set of key expressions m as $S = \{s_1, s_2, ..., s_k\}$. NMF, the matrix factorization method, reduces a complex matrix to the product of two matrices of much smaller size, which are manageable and easily interpretable. Here NMF reduces the matrix $X \in R^{m\times n}$ into two nonnegative matrices like $V \in R^{m\times k}$ and $U \in R^{k\times n}$, such that $X \cong VU$ [15]. $X \in R^{m\times n}$ represents the matrix comprised of the attitudes of influential users towards the key expressions, whereas Xli represents the attitude of Ui, an influential user, towards the s_l key issue. Furthermore $U \in R^{k\times n}$ represents the influential user community membership matrix, wherein U_{ik} represents the membership strength of the U_i influential user in c_k community. Since our framework provides the soft community membership, we select the community having the highest membership value for each influential user as the community to which he/she belongs.

Given an influential user attitude X matrix, we intend to acquire 'U', the matrix of influential user membership. Thus to detect the communities causing social unrest, we exploit NMF as follows:

$$\min_{U,V} \|X - VU\|_F \quad S.t\ U \geq 0 \quad (4)$$

Normally, NMF requires two input parameters: A (adjacency matrix) and K (number of communities). Since we have two types of key issues here, positive and negative, we put K=2.

In order to quantify the approximation error, the Frobenius norm [5] is utilized most often, which is the square root of the summation of the absolute squares of the elements of the matrix X:

$$\|X\|_F = \sqrt[2]{\sum_{i=1}^{m} \sum_{j=1}^{n} |x_{ij}|^2} \quad (5)$$

The output U is normalized by using:

$$u_{ij} = \frac{u_{ij}}{\sum_{x=1}^{k} u_{xj}} \quad (6)$$

so that each and every node is linked with k values that sum to 1, such values indicate the probabilities of belonging to the different communities (*U's rows*). Only those nodes with values not less than the threshold α (values shown in equation 7) are retained as the initial members of the community. Their neighbors (adjacent nodes) are also appended as members of the target community.

$$U[U \geq \alpha] = 1,\ \alpha \in [0.70, ..., 1.0] \quad (7)$$

Apart from the nodes with the highest probability value of 1, which should be the parts of the community, different probabilities have been used to predict additional nodes to apply to the target community. Since the probability value ‘1’ is very restrictive, we set the minimum probability to ‘0.70’, which provides full confidence in admitting a node into the target community. In order to visualize more clearly, only the influential nodes with positive or negative behavior are considered first, thereby getting the corresponding communities as shown below:

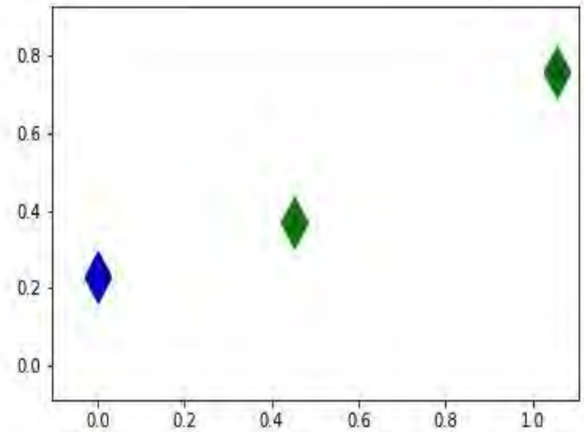

Fig.5. Blue colored diamond shapes represent the community pertaining to that influential node contributing to social unrest.

The steps of our framework are summarized algorithmically as follows:

Algorithm Sentiment Driven Social Unrest Community Detection

INPUT: Graph *G* built from a dataset

A. Phase I: Finding initial communities
   1. Calculate information interaction, using Eq. (1) and Eq. (2)
   2. Return initial communities G_s

B. Phase II: Identifying influential users
   1. Identify influential users using Adjacency matrix *A* of G_s, Solving Eq. (3)

C. Phase III: Sentiment-driven community identification
   1. Estimate *k* according to classes of sentiment terms
   2. *V*, *U*←NMF (*A*, *k*), solving Eq. (4) & Eq. (5)
   3. *U*←Normalize(*U*) using Eq. (6) and Eq. (7)
   4. **for** *i* in range [0, ..., *k*] **do**
   5. Community$_i$ ←nodes in row u_i whose entries are 1and their neighbor nodes.
   6. **end for**

OUTPUT: Community1,…,Community*k*

IV. EMPIRICAL RESULTS AND DISCUSSION

In this section, our framework was evaluated using experiments on a real-world network like Facebook and Twitter. Facebook is a network of friendships among Facebook users, wherein the vertex denotes a user and the edge depicts that the users represented with the end points are friends. This is a friendship network (available in SNAP library also) with 347 vertices and 5038 edges [3] as is shown in fig.6.

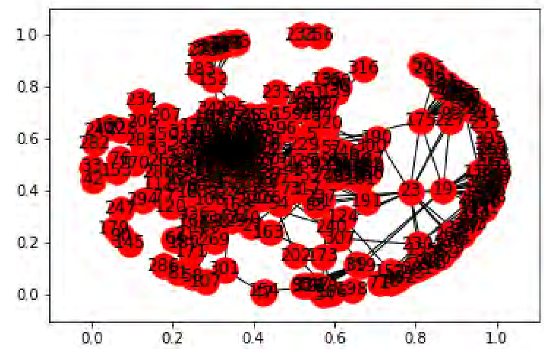

Fig.6. Facebook frienship network.

The first major objective was to identify the communities based on the information interaction and propagated information as was discussed in section A (fig.7).

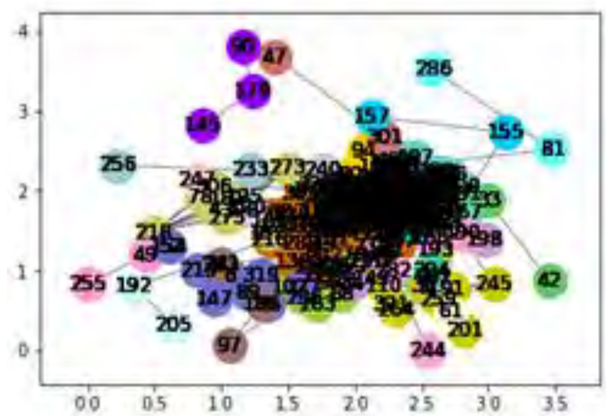

Fig.7. Phase I: 27 Communities in the facebook data set. Different communities are shown with different colors.

After obtaining information-dynamics-driven communities, our goal was to identify the influential users in each community so that sentiment-driven non-negative matrix factorization could be applied only to key players, rather than to each member of the corresponding community. Since the whole community can be represented by the most influential node, which serves the community's sole purpose, the complexity decreases to only the influential nodes within the corresponding community. This property distinguishes our model from other existing community approaches, where complexity increases with larger networks. The influential users within each community have been differentiated from the rest of the members of the corresponding communities by diamond shapes, as is clearly seen in the figure below:

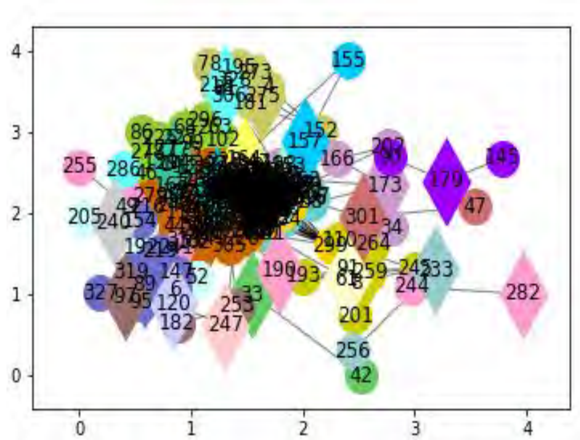

Fig.8. Phase II: One influential user in each community.

The final major objective, the sentiment-driven communities detection causing social unrest, was accomplished by non-negative matrix factorization as discussed in section C. We detect categories of the influential nodes (u1,u2,u3, etc.) with their topics of interest. Sentiment classification was applied to the topics of influential nodes and the sentiment learning of these influential nodes towards the sentiment terms(keywords), as shown in fig. 9, was analyzed, thus giving rise to different communities like c1,c2,c3, etc. Here, the blue colored diamond nodes indicate the communities causing social unrest. These diamond-shaped blue color nodes are further represented as negative communities, as shown in the figure below:

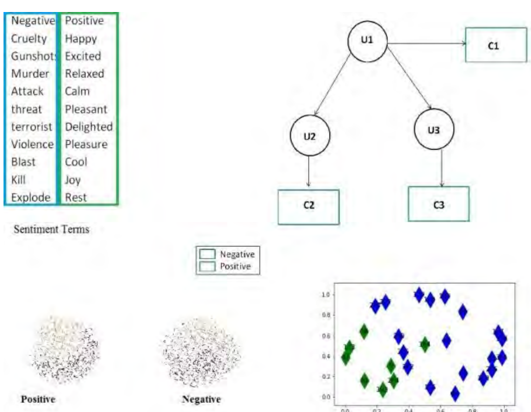

Fig.9. Phase III: Facebook communities causing social unrest. Blue colored diamond shapes represent communities creating social unrest.

Further, we used the Twitter API and selected tweets related to COVID-19. We explore which Twitter users share similar content on COVID-19 issues. The collected tweets were used to construct a social network to identify communities and their influential users, and to capture only those users' interests. This process of recognizing influential users' interests and leanings primarily consists of 3 steps. At first the users of the network retweeting one another was constructed (Fig. 10) so that the connected components (communities) were detected (Fig. 11). In the second step, influential users pertinent to each community were identified (Fig.12) and finally the content tweeted by these influential users were analyzed so as to reveal interest of influential users and hence the community leanings towards different issues is uncovered naturally (Fig.13).

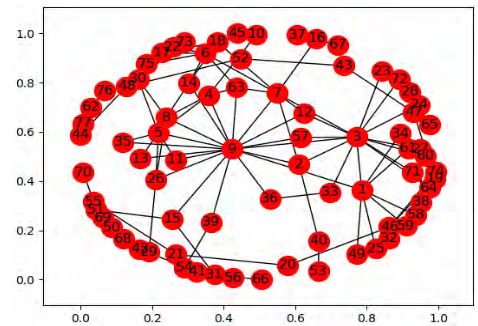

Fig.10. Twitter network.

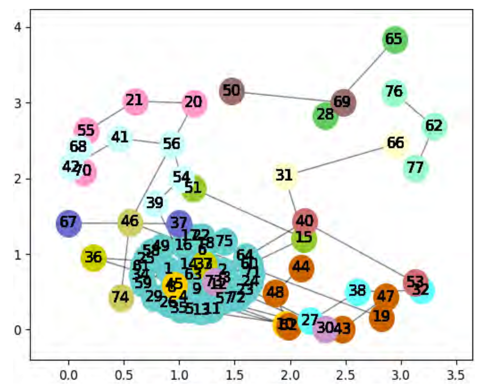

Fig.11. Phase I: Communities in the twitter data set. Different communities are shown with different colors.

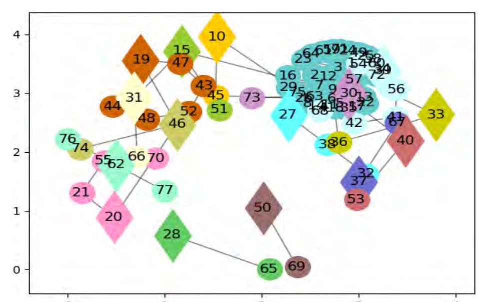

Fig.12. Phase II: One influential user in each twitter community.

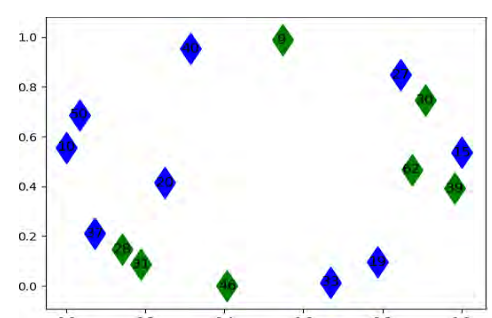

Fig.13. Phase III: Twitter communities causing social unrest. Blue colored diamond shapes represent communities creating social unrest.

Moreover the communities inducing social unrest have been denoted by Negative label as shown clearly below:

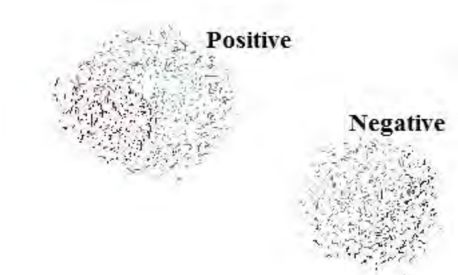

Fig.14. Sentiment-based tweet clustering.

We have evaluated our model using various metrics, such as precision and recall. The model's performance, as shown in Table I, was determined by averaging the three metrics across each sentiment class.

Precision =True Positive/ (True Positive + False Positive)

Recall = True Positive / (True Positive + False Negative)

$$F1 = 2 * \frac{precision * recall}{precision + recall}$$

TABLE I
MODEL PERFORMANCE

Positive Sentiment			
Precision	**Recall**	**F1 Measure**	**Performance**
93.37	94.71	94.04	94.04
Negative Sentiment			
Precision	**Recall**	**F1 Measure**	**Performance**
80.21	83.43	81.79	81.81

V. APPLICATIONS

Our framework, we believe, can lead in a new era of study in which peoples' specific tweets or posts over social media can serve as an effective means of spotting possible social unrest. By exploiting such findings, companies can identify positive sentiment communities as loyal customers for target marketing in the form of new product recommendations and promotions. Moreover, the real-time application of this framework can benefit society by serving as a monitoring mechanism for people who participate in dubious activities. Since social unrest undoubtedly affects a person's emotions and cognition. Therefore, it is very important to assess the people's behavioural issues and mental health concerns over social media using advanced technology. The study[17] advances knowledge on the potential applications of machine learning in healthcare environments.

VI. CONCLUSION AND FUTURE SCOPE

In this study, an attempt has been made to detect sentiment based communities causing social unrest grounded over user interaction dynamics in online social networks. To identify the active communities, both the impact of the interaction between users as well as the impact of the group behaviour which the users' exhibit based on their interactions with their mutual friends has been taken into account. To our knowledge, this is the first method for detecting communities leading to social unrest that considers both pair and group interaction dynamics, in addition to sentiment analysis.

By leveraging these findings, companies can identify positive-sentiment communities as loyal customers for targeted marketing through new product recommendations and promotions.

This research proposed a novel knowledge-based methodology for detecting communities that cause social unrest on social media. Our theoretical contribution is to include sentiment within the community detection in social networking analytics, and towards our technical contribution, we present the computational method for identifying sentiment-based communities that lead to unrest over social networks.

We intend to expand this research in the future by examining the dynamics of community sentiment. Since it is an ongoing study, we're working to improve our approach by examining how sentiment communities have evolved and how they might help businesses discover dynamic customer attitudes on social media.

CONFLICT OF INTEREST

We hereby declare that we have no conflict of interest.

DATA AVAILABILITY

The facebook data set is a friendship network (available in SNAP library) and twitter data was collected online at COVID-19_ Sentiment Analysis & Social Networks_ Kaggle.html.

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Shafia Bashir received the BCA and MCA from University of Kashmir and Jamia Hamdard New-Delhi respectively. Further she received the PhD from University of Kashmir. She is currently working as a Woman Scientist at University of Kashmir under Department of Science and Technology New-Delhi. Her research interests include machine learning, social computing. She has published several conference and journal papers.

Manzoor Ahmad Chachoo received the BE degree from Karnatak University, MS in software systems from BITS pilani, MBA & the PhD from University of Kashmir Srinagar. He is currently working as a Scientist D at Department of Computer Science, University of Kashmir. His research interests include artificial intelligence, data science, machine learning and social computing. He has published over 30 papers on international journals and conferences. Further he has worked on several national and regional projects as PI &Co PI.