# Discovering *Flow of Sentiment* and *Transient Behavior* of Online *Social Crowd*: An Analysis Through Social Insects

**Goldina Ghosh, Soumya Banerjee, and Vasile Palade**

**Abstract** Social media is growing at substantially faster rates, with millions of people across the globe generating, sharing and referring content on a scale apparently impossible a few years back. This has cumulated in huge participation with plenty of updates, opinions, news, blogs, comments and product reviews being constantly posted and churned in social Websites such as *Facebook, Digg and Twitter* to name a few. Even the events that are offline fetch the attention of social crowds, and considerably, their rapid sharing of views could signify the sentiment and emotional state of crowds at that particular instance. In the recent past, social media during *terrorist strikes* or natural disasters or in panic situations exhibits a tremendous impact in propagating messages among different communities and people. But the crowd participation in these interactions is grouped *on the fly,* and once the events fade out, they slowly disappear from the social media. We continuously iterate the challenges of identifying the behavioral pattern of the so-called *transient crowd* and their dispersion or convergence of sentiment and broadly answer how that could tell upon the offline events as well. While modeling the dynamics of such crowds, relevant clustering techniques have been consulted, although any method alone was not found compatible with the social media setup. The continuous cognitive pattern like a homophilic or curious and intuitive crowd with vector attributes on such social interaction motivates to incorporate an ant's or swarm's colonial behavior. Ants and swarms demonstrate well-defined chemical communication signals known as *pheromones* to segregate and distinguish specific communication patterns from cells of high concentration to those of low concentration. Hence, the *positive and negative sentiment* of transient *crowds* could be modeled, and the local influence can be measured on their posts through pheromone modeling and reinforcement of the shortest path of an ant or swarm's

G. Ghosh • S. Banerjee (✉)
Department of Computer Sciences, Birla Institute of Technology, Mesra, India
e-mail: dr.soumya@ieee.org

V. Palade
Department of Computer Science, Oxford University, Oxford OX1 3QD, UK

N. Agarwal et al. (eds.), *Online Collective Action*, Lecture Notes in Social Networks,
DOI 10.1007/978-3-7091-1340-0_3, 

life cycle. The primary objective of the chapter is to introduce a comparative smart methodology of ants and swarms as agent-based paradigms for investigating the community identification, namely, for *Facebook and Twitter.* The social media platforms are large enough to accommodate the ant and swarm graph for a pheromone model, tuning the time complexity of pheromone deposition and evaporation. Subsequently, the strength of association between transient users also could vary in terms of edge distribution and decay over stochastic measures of social events. We inculcate a couple of test cases fetched from *Facebook* on recent terror strikes of Mumbai, India, modeled using ants' and swarms' behavior. The results are encouraging and still in process. Empirically, the flow of sentiment and the corresponding dispersion of the crowd effect should infer or ignore a particular event, will leave a socio-computational benchmark for the mentioned proposition and will assist the ant alive in the system to reciprocate.

## 1 Background and Introduction

Communicating or interacting is a means of sharing ideas and placing opinion on some topic or field and also expressing different emotional feelings like being happy or expressing sadness on some events by putting some comments. In the present world of social media and networking, the means of such interaction has taken a wide range irrespective of geographical boundary, language or age. This has cumulated in huge participation, with plenty of updates, opinions, news, blogs, comments and product reviews being constantly posted and churned in social Websites such as *Facebook, Digg and Twitter* (Galuba et al. 2010) to name a few. Even the events that are offline fetch the attention of social crowds, and considerably, their rapid sharing of views could signify the sentiment and emotional state of crowds at that particular instance.

In the recent past, social media, during *terrorist strikes* or natural disasters or in panic situations exhibited a tremendous impact in propagating messages among different communities and people. But the crowds participating in these interactions are grouped *on fly,* and once the events fade out, they slowly disappear from the social media. We continuously iterate the challenge of identifying the behavioral pattern of the so-called *transient crowd* and their dispersion or convergence of sentiment (Cha et al. 2010; Kamath and Caverlee 2010) and broadly how that could tell upon the offline events as well. While modeling the dynamics of such crowd, relevant clustering techniques have been consulted, although any single method alone was not found compatible with the social media setup. The continuous cognitive pattern like a homophilic or curious and intuitive crowd with vector attributes on such social interaction motivates to incorporate an ant's or swarm's colonial behavior (Parunak 2011). Ants and swarms demonstrate well-defined chemical communication signals known as *pheromones* to segregate and distinguish specific communication patterns from cells of high concentration to those of low concentration. Hence, the *positive and negative sentiment* of transient *crowds* (Kamath and Caverlee 2011) could be modeled, and the local influence can be measured on their posts through pheromone modeling and reinforcement of the shortest path of an ant or swarm's life cycle. The primary objective of the chapter is to introduce a comparative smart methodology of ants and swarms as agent-based paradigms for investigating the community identification, namely, for *Facebook*. The social media platforms are large enough to accommodate the ant and swarm graph for pheromone models, tuning the time complexity of pheromone deposition and evaporation. We inculcate a couple of test cases fetched from *Facebook* on recent terror strikes of Mumbai, India, modeled using an ant's and swarm's behavior. The results are encouraging and still in process. Empirically, the flow of sentiment and the corresponding dispersion of the crowd effect should infer or ignore a particular event, will leave a socio-computational benchmark for the mentioned proposition and will assist the ant alive in the system to reciprocate.

If this could be the foundation of this research investigation, then the sustained implications were also envisaged with the behavior of natural ants and swarms during the conceptual layout of the proposal. Inspired by Dorigo, Ramos and others (Dorigo and Stützle 2001; Dorigo et al. 1996; Fernandes et al. 2008), the complex pattern of communication of ants with a chemical known as pheromone pointed a substantial clue to explore the temporal behavior exchange of their opinion and sentiment of crowds across a Web graph. Even such a social media and event graph also leads towards certain learning artifacts in the form of incremental learning as described by Dorigo et al. (Montes de Oca et al. 2011).

The role and reference of social media has been evenly poised from the occurrence of revolutionary social events. Considering the tune of stochastic measures of social crowd, the concept of temporal crowd and, subsequently, the strength of association between transient users also could vary in terms of edge distribution and decay over stochastic measures of social events.

The remaining part of the chapter has been organized as follows: Associated definitions and terminologies used in the context of social crowds have been elaborated in Sect. 2. Section 3 describes the prologue to understand the use of the pheromone communication model and its social modeling counterparts. Section 4 mentions certain real-life cases and proposes algorithms to address the problem. Section 4.1 discusses the results and observations from the proposal. Finally, Sect. 5 summarizes the content and mentions the scope for further research towards this direction.

## 2 Definitions, Terminologies and Mathematical Interpretations

Considering the structure of Facebook, it will be convenient to keep track of the post and broadcast tendency of the events through an ideal connected graph paradigm. We also consider m number of participants across social media site $U$, where each participant may post the messages with timestamps and will lead to a coherent campaign. Mathematically, it could be expressed as

$$M^{u}{}_{i} = \{m_{it_1}u_i | u_i \in U \cap m_{it_1}\} \tag{1}$$

This expression also yields concepts of forming message graphs either for strong campaigns or weak campaigns for the dispersed messages. Analytically, the content-driven campaign could be appealing when it becomes cohesive. This again can be validated if the number of edges of a subgraph for the original message graph is close to the maximal number of edges with the same number of vertices of that subgraph (Kamath and Caverlee 2011; Lee et al. 2011). There are different related definitions to conceptualize the present target model (Kamath and Caverlee 2011):

- ***Transient crowd***: *"A transient crowd $C \in K_t$ is a time-sensitive collection of users who form a cluster in $G_t$, where $K_t$ is the set of all transient crowds in $G_t$. A transient crowd represents a collection of users who are actively communicating with each other at time t."*
- ***Time-Evolving Communication Network:*** *"A time-evolving communication network is an undirected graph $G_t$ (V, E) graph with $|V| = n$ vertices and $|E| = m$ edges, where each vertex corresponds to a user in the social messaging system and an edge corresponds to a communication between two users. The weight of an edge between vertices u and v at time t is represented by $w_t(u, v)$."*

## 3 Pheromone Communication and Social Network: Functional Analogy

Since the inception of Web 2.0, the complexity in the pattern of social interaction has been a point of investigation and emergence of the interaction pattern of social networks. The pattern of several interactions emerges from the structure of a positional reference of the person under the particular social network and the latest opinion shared by the person. Therefore, the evolution of a person-centric interest of the person for a group may be temporal and could devise the shape of the environment, resulting in a complex feedback process. Eventually, as a result of such dynamics, collective cognitive effects may emerge at the system level (across groups of people under social networks) that can influence the individuals' opinion without informing the person's. This alignment of opinions is called *consensus formation* (Parunak et al. 2011a). The coordination of exchange of opinion under social networks for a temporal event is quite similar to the feedback propagation through a shared environment known as *stigmergy,* and it can emerge a global pattern. In this chapter, we investigate such a possibility of pheromone communication envisaging social media as a container of events, and also we further analyze the temporal behavior and influence of stigmergic coordination of such events. Considering the social insect agents like ants could assign several types of pheromone in the same environment. The type of pheromone is identified by the subscripts and those assignments of pheromone that did not interact with each other. Each ant agent can drop pheromone on the ground by dropping action. Dropped pheromone gradually evaporates and diffuses in the air. Ant agents can detect diffusing pheromone only. Dropped pheromone and diffusing pheromone at position $(x, y)$ are represented by $T_v(x, y)$ and $P_v(x, y)$ respectively (Dorigo and Stützle 2001; Fernandes et al. 2008).

$$
\begin{aligned}
&T_v^*(x,y) = (1-\gamma_{\mathrm{eva}})T_v(x,y) + \sum_{k=1}^{N_a}\Delta T_v^k(x,y) \\
&\Delta T_y^k(x,y) = \begin{cases} Q_p & \text{if } k\text{-th ant agent on the grid } (x,y) \text{ put the pheromone } v \\ 0 & \text{otherwise} \end{cases}
\end{aligned}
\tag{2}
$$

The occurrence of temporal events and pheromone evaporation initiates a stochastic probability of communication, and there is a significant convergence of opinion on social media irrespective of number of participants and group theme (Parunak et al. 2011b). It is also phenomenal that under similar theme spaces, a homogenous sample distribution under social media exhibits a reconfigurable mean and variance of space discarding the group theme at a particular instance of timestamps of the events. The proposed model also argues that in a high-dimensional social media, the attractive force between two or more participants decreases with distance and offer lower pheromone deposition and faster evaporation. The pheromone communication acts on elements that are already close to each other and defines the characteristic behavior on opinion and oral anxiety over the temporal events.

All ant agents in each case of colony are homogeneous and demonstrate the reinforcement strategy for case-specific inference on social message propagation. Each agent performs steps in the following logical chronology:

- The ant agent senses whether a food resource exists on the message graph, senses whether the message graph is a part of a nest and recognizes whether it is carrying a relevant message post under emergency.
- The ant agent might drop a certain type of pheromone depending on the output of the final termination of message. Each ant agent can use a value or type of pheromone.

- When there is positive response against the root message under emergency, if the ant agent carries no message in reply, it picks it up, and if the ant agent has a relevant support message and is on the nest part of a message graph, it drops it.
- Even the sense of direction can also be an indication for the implication of the final transient mood of the crowd.

The relevant application also supports the present study to identify the potential link of Facebook group participation with viral advertising responses. The results suggest that college-aged Facebook group members are generally involved in higher levels of self-disclosure and maintain more favorable attitudes toward social media and advertising compared to non-group members (Chu 2011). Similarly, fundraising events for a cause also deployed a Facebook campaign and received a substantial impact of opinion diffusion and similarity toward a specific social call (Kamath and Caverlee 2010).

The inclusion of pheromone communication creates deliberate space with the concept of transient crowd in social media (Kamath and Caverlee 2011). Transient crowds are dynamically formed and have a short span of life. We interpret and explore the stochastic relationship of time-evolving graphs for transient and temporal crowd formation on Web media. The participants of these social networks may be clustered along a number of dimensions including content-based or thematic interest or may be diversified geographic locations driven toward the same interest. This concept motivates us to incorporate the concept of dynamic clustering of the time-evolved graph. In this particular proposed model, the structure of edges is changing. The interesting relationship between transient crowds for a particular time instant and the swarm's behavior has already been identified. The dense coverage of edges is prone to demonstrate the distinguished clusters shown in several contemporary literatures (Saha and Mitra 2006). The proposed model inculcates a flow of sentiment and opinion over a post analytically, and we also solicit certain contextual definitions to point out the foundation of the proposal elaborated in Sect. 2 (Kamath and Caverlee 2011).

## 4 Presentation of Data Snippets and Analysis with Proposed Model

The social network sites could be contemplated as a temporal media for transferring crucial events and drawing the attention of different people. This is usually done (Burke et al. 2010; Leskovec et al. 2008) when there is a requirement of sudden critical social causes. The evidence is obtained from Facebook. The recent *Mumbai blast* had experienced casualties in large scale, and many of them required blood. This issue became a crisis, and one of the common citizens posted some photographs on his Facebook wall of the blood donation camp in order to seek help for the sake of those affected in the blast. Seeing this post, as many as 14 people started communicating with him immediately on Facebook either through the comment

**Table 1** Temporal event propagation under Facebook

| Name of the FaceBook participants | Date | Time stamp | Information shared |
|---|---|---|---|
| Mohit Sharma | July 14, 2011 | 7:37 p.m. | i have also denated blood on this camp |
| Rajendra Suryawanshi | July 14, 2011 | 11:21 a.m. | Go to Mumbai |
| Shreekant Jagtap | July 14, 2011 | 11:59 a.m. | Blood group B+ |
| Vaishnavi-piyali Suratwala | July 14, 2011 | 12:58 p.m. | AB+ |
| Prashant Suratwala | July 14, 2011 | 1:21 p.m. | B+ |
| Pinkesh Suratwala | July 14, 2011 | 4:29 p.m. | B+ |
| Manish Suratwala | July 14, 2011 | 5:15 p.m. | my blood group is b+ve and i am willing to go to Mumbai |
| Milind Joshi | July 14, 2011 | 6:24 p.m. | O+ |
| Ranjit Bansode | July 14, 2011 | 8:19 p.m. | I m also with u.My bld grp is A+ n my wife's O+ |
| Dhawal Manojkumar Suratwala | July 14, 2011 | 11:02 p.m. | if u need i will surely cum to help u out |
| Milind Joshi | July 15, 2011 | 6:03 p.m. | good job man |
| Chandan Shantilal Suratwala | July 15, 2011 | 9:32 p.m. | thanks to u all to support my appeal. . .we will surely do our best to make our pune best |
| Viraj Gelada | July 16, 2011 | 7:12 p.m. | my blood group b+. . . |
| Dhawal Manojkumar Suratwala | July 16, 2011 | 10:43 p.m. | will always support u and even pune 4 ne kind of work. |

box or through short messages in their phones on the same date and on the following dates. The information obtained from the wall post has been described in Table 1 (retrieved from http://www.facebook.com):

It is also noticed in Cho et al. (2011) that the information was transferred to different parts of the country at different time instants to different individuals through other groups or people via an obvious interconnected fashion. The formations of connected networks and cascaded events are deliberate, and they also exhibit a structure of graph in their representation. Table 2 demonstrates the evidence of the said event.

## *4.1 Proposed Algorithm and Analysis*

As Table 2 extracts the snippet that how diversified people, irrespective of regions, could have been accumulated in shared environments for sharing their opinions (Cho et al. 2011; De Choudhury et al. 2010). Considering these two attributes of

**Table 2** Dataset of Facebook based on the Mumbai blast

| Name of the event | Personal id number | Location | Start time | End time |
|---|---|---|---|---|
| Support the people of Mumbai in blast | 246599782018044 | Zaveri Bazar OPERA HOUSE | 2012-07-13T13:30:00 | 2012-08-15T15:30:00 |
| Need 10,00,000 Supporter to protest Against Blast in Mumbai-Invite 100+ | 240232295996771 | http://www.facebook.com/imanojsingh | 2012-01-26T01:00:00 | 2012-01-26T01:00:00 |
| Again blast in Mumbai | 161485890589611 | Jaipur, Rajasthan | 2012-07-14T00:30:00 | 2012-07-14T03:30:00 |
| Again blast in Mumbai | 247294775280525 | Jaipur, Rajasthan | 2012-07-14T00:30:00 | 2012-07-14T03:30:00 |
| Again blast in Mumbai | 219309511444604 | Jaipur, Rajasthan | 2012-07-14T00:30:00 | 2012-07-14T03:30:00 |
| To see bomb blast in Mumbai | 264469923566556 | Mumbai | 2013-07-13T07:00:00 | 2013-07-13T09:00:00 |

record sets, a schema can be conceptualized as shown to present the distribution of data for different perspectives (Scheme 1).

Computationally, we can generate the rate of flow of information among different individuals denoted as nodes, and the links between these nodes are known as edges. This is analogous to the proposed pheromone communication to indicate reinforcement of a particular edge as per the pheromone deposition and evaporation rule followed by natural insects (Dorigo and Stützle 2001).

A node takes the initiative to send a message to its connected links. These linked nodes can again spread this message to all other connected nodes. In Fig. 1, it is seen that Node 1 is the original sender of information. Node 2 and Node 4 are the receivers. Node 3 and Node 5 receive the message from Node 2 and Node 4 respectively. Thus, if there are other links between Node 2, 3, 4, or 5, then they will also get the message through them. As preprocessing steps, we incorporate MATLAB to simulate the interaction diagram for the transfer of messages and find the difference in characteristics of path that in turn provide a substantial insight to further analyze its semantics.

The rate of message transformation will depend on the number of connectivity each node has of itself, that is, the rate of flow of messages is

$$R_i = n^m \tag{3}$$

where $R_i$ is the rate of information flow $R_i = \{r_1, r_2, \ldots r_t\}$, n is the number of nodes that received the message first $n_i = \{n_1, n_2, \ldots n_t\}$, m is the number of links in the node $= \{1,2, \ldots t\}$.

Figure 2 shows the rate of flow of information among the other nodes with the direction of the flow of messages.

**Scheme 1** Distribution of sharing

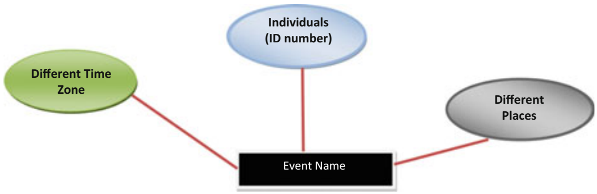
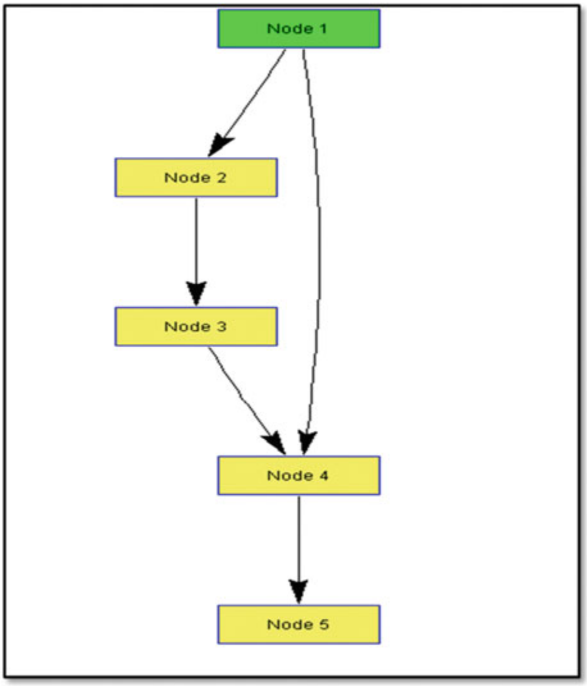



**Fig. 1** Propagation of message from the main sender




Here, Node 1 is left isolated since it has already sent the message to its connected links. It is the responsibility of other connected nodes to transfer the message. In the figure, Node 2 is sending the message to Node 6, and Node 3 is sending it to Node 7. Similarly, Node 4 is sending it to Node 9, and Node 9 delivers it to Node 5 and Node 8. With the help of this propagation style, the message or some events are spread through a social network through connected links. Node 1, being the original sender, will always wait for either some response or some positive effect from the receivers. In Fig. 3, it is shown how all the nodes ultimately got connected to the information given by Node 1 and even shared opinion or transferred the message between themselves and Node 1.

Immediately before the event of the Mumbai bomb blast, the particular participant had general discussions among his community in Facebook. This information that is shared in the communication was very conventional and of lesser social message value, thus as likely as blood donating camp. A survey report on this issue

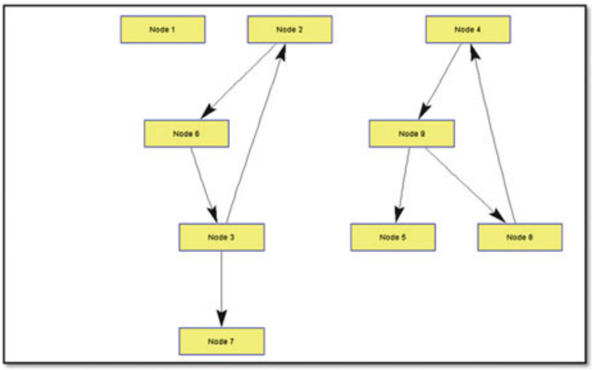



**Fig. 2** Transmission of the message via other connected links in a social network

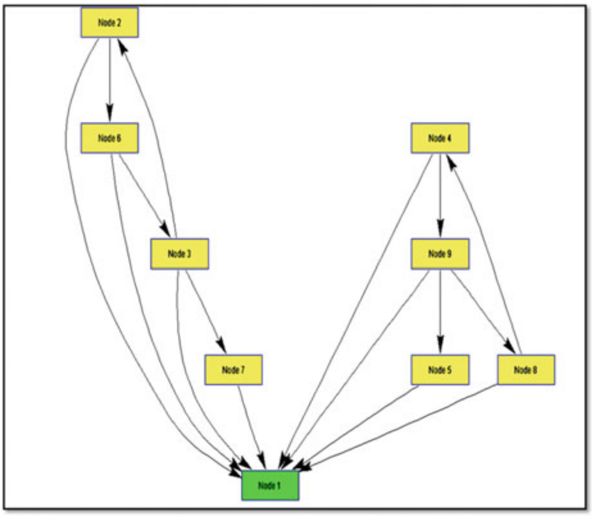



**Fig. 3** Flow of message to all connected link leading to communicate with the primary sender of the message

is given in Table 3. As seen, there are no crucial messages; hence, there will be no option of spreading them in a wide range. Thus, the rate of flow of the information will also depend on two factors: Firstly, it will depend on the weightage of the message, that is, how important the message is. If it is a vital issue, then it will be propagated to all the different connective nodes. If not, then the flow will be restricted. Secondly, if the information is forwarded, then also the response rate will be much lower.

In Fig. 4, the description of the message flow exists where only Node 2 transfers the information to Node 7 and Node 5 transfers it to Node 8, Nodes 3, 4, 6, and 9 are isolated in the graph since they did not transfer the message, whereas it is seen that Node 3 had transferred the message to Node 7 in Fig. 2. With respect to Fig. 1, it is also seen that there is an initial connectivity between Node 1 and Node 2 and Node 1 and Node 4, which means that the information is passed to Node 2 and Node 4. Node 2 transfers the message to Node 3 and Node 4 to Node 5. Still, in Fig. 3, we

**Table 3** Data snap from Facebook of the root initiator immediate before *Mumbai Blast* [https://www.facebook.com/chandan.suratwala (Refer Mr. Chandan Shantilal Suratwal)]

| Types of post | Date | Time | Responses |
|---|---|---|---|
| Shared information of donating eye in H.V.DESAI EYE HOSPITAL | July 13, 2011 | 11:35 a.m. | 3 people like this |
| A general broad cast of a poetry on life | July 12, 2011 | 12:28 a.m. | 2 people like this. |
| Uploaded 5 photos and using the tag line “MY PUNE’S WORST BLACK DAY 12TH JULY 1961” | July 11, 2011 | 10:35 p.m. | No comments made |
| Share an opinion on a simple matter | July 11, 2011 | 12:33 p.m. | 6 people like this. |
| Made a comment on a tourist travel | July 11, 2011 | 10:21 p.m. | No moments made |

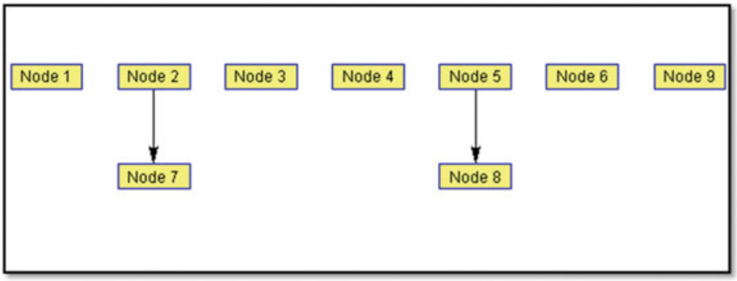



**Fig. 4** Selected nodes as recipients

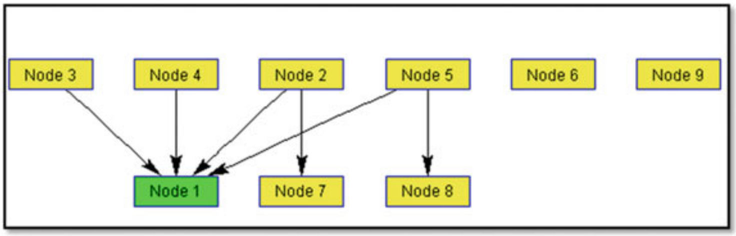



**Fig. 5** Node 1 being the originator of message obtains response from different nodes

observe that Nodes 3 and 4 do not take the initiative to transfer the information further to the other nodes.

As Node 1 was the original sender of the information, it will again wait for some response or reaction from other nodes. But since the message or event is not very important, so the propagation of information will be less compared to the previous case, and also the response might or might not occur. In Fig. 5, we observe that Nodes 2, 3, 4, and 5 only respond to the message that Node 1 sent, whereas Node 7 and Node 8, although receiving the message, did not respond. Compared to Figs. 3 and 5, it has much less connectivity or interactions among the nodes.

## 4.2 Validating the Flow of Information

The information that is obtained from Table 1 gives a detailed explanation about the date, time, and some vital information related to the event of the Mumbai blast and where a blood donation camp required blood. Similarly, from Table 3, we obtain the information in respect to some basic common discussions before the event of the Mumbai blast. These messages are obtained from "Mr. Chandan Shantilal Suratwal's" Facebook account. Now, we can create a survey report based on reference (Backstrom and Leskovec 2011) that will help in testing the *"Rate of Sentiment Flow."* Firstly, let "$u$" be the number of his friends who receive the message. Then, if those friends find the information to be important and feel that it needs to be shared, then they will be transferring it to more of his friends. In this way, the flow of messages will take place. Gradual transfer of the messages can take place in "$n$" levels of propagation. The initial set of friends who had obtained the message first from the sender always remains fixed, say, $x_p$. Therefore, the increase in members for the flow of information at each level is given by $(1+X_p/n)^n$. We consider two parameters, that is, "the date of propagation" and "time in Hours," which is denoted as $D_{\mathrm{T}}(H)$.

The rate of sentiment flow is inversely proportional to time $D_{\mathrm{T}}(H)$.

The rate of sentiment flow is proportional to the number of people who received the message. Therefore, we can frame that

$$\text{Rate of sentiment flow} = k \times \frac{\text{Number of People}}{D_{\mathrm{T}}(H)}$$

$$\text{The final Flow Rate of Sentiment } F(S)_{\mathrm{r}} = \frac{1}{\exp(D_{\mathrm{T}}(H))}\left[X_p \times \sum_{n=1}^{\infty}\left(1+\frac{X_p}{n}\right)^n\right]. \quad (4)$$

Now, by considering the status of Table 1, we design the "Rate of Flow of Sentiment" among different friends and their friends of friends in a different date and time. Since an event like the Mumbai blast is a very vital and a sensitive issue, hence this information needs to flow at a very fast rate to many people within a short period of time.

The event was uploaded on June 14 at 11 a.m.; soon after that, the propagation of messages starts taking place. Initially, only four of the friends receive the message. They forward it to their friends, and then further those friends send it to their friends of friends. Here, totally 11 propagations take place. At each level, there is an increase of receivers. Table 4 gives the complete picture of this scenario, which is actually based on Eq. (2). The rate of flow of information increases exponentially as time increases soon after the uploading of events takes place, but the flow rate will decrease as the number of days increases. This is so since the event is important and sensitive, so the delay in propagation is not appreciated. This is proved in Figs. 6 and 7.

Here, in Fig. 6 we see that there is a gradual increase in the flow of information on June 14 as time duration increased. There is an exponential curve that denotes the increase in the flow of sentiment. As time passes, the value of the message

**Table 4** Evaluation table for detecting the flow rate of sentiment

| Date of propagation | Propagation time (Hrs) $D_T(H)$ | 1/exp $(D_T(H))$ | First level receivers $(X_p)$ | Number of propagation $(n)$ | $1+(X_p/n)^n$ | Flow rate of sentiment $(F(S)_r)$ |
|---|---|---|---|---|---|---|
| July 14, 2011 | 11:21 a.m. | 0.06 | 4 | 2 | 9 | 2.16 |
| July 14, 2011 | 11:59 a.m. | 0.31 | 4 | 3 | 12.7 | 3.93 |
| July 14, 2011 | 12:58 p.m. | 3.21 | 4 | 4 | 16 | 205.4 |
| July 14, 2011 | 4:29 p.m. | 41.3 | 4 | 5 | 18.8 | 3121.5 |
| July 14, 2011 | 6:24 p.m. | 7.4 | 4 | 7 | 23.6 | 22750.4 |
| July 14, 2011 | 7:37 p.m. | 8.61 | 4 | 1 | 5 | 172.3 |
| July 14, 2011 | 8:19 p.m. | 9.31 | 4 | 8 | 25.62 | 143403.33 |
| July 15, 2011 | 6:03 p.m. | 27.77 | 4 | 9 | 27.57 | 3040.25 |
| July 16, 2011 | 7:12 p.m. | 3895.5 | 4 | 10 | 28.92 | 45057.36 |
| July 16, 2011 | 10:43 p.m. | 3.61 | 4 | 11 | 30.31 | 1.14 |

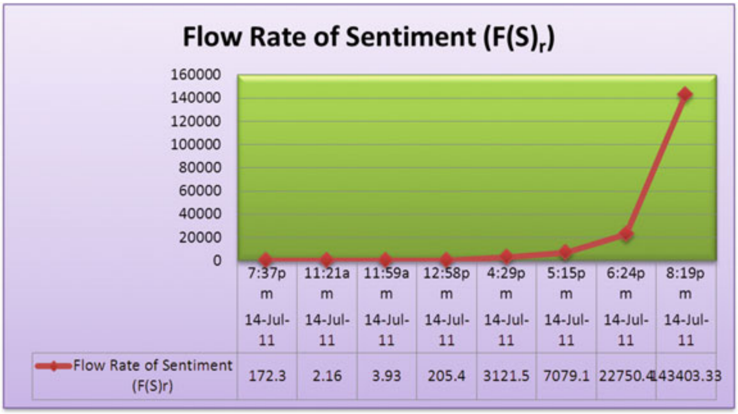



**Fig. 6** Flow rate of sentiment on 14 June

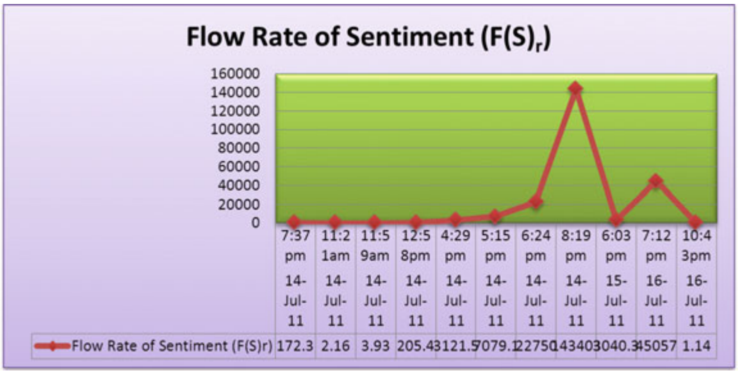



**Fig. 7** Flow rate of sentiment from 14 June to 16 June

gradually decreases since the requirement gets fulfilled within a particular time limit. Thus, the curve gradually decreases from June 15 and 16. This phenomenon is shown in Fig. 7.

**High Level Description of the *Pheromone Crowd* Algorithm**

*/* Parameter list: Message graph of FaceBook,, Social crowd Set ($P_{si}$ ), Message with time instant ($m_{it_1}$) Pheromone evaporation and dropping as per equation (1), , set of colour paths red, green and blue on message graph */*

Let $P_{si}$ is the social crowd set for immediate time instant and $P_{si-1}$ is the immediate predecessor node

for every crowd $P_{si}$ and for every message m, $P_{si} \in P_s m_{it_1} u_i$ do

if $m_{it_1}$ is a recent message under t time instant

Then create a green edge on message graph and call:

$$T_v^*(x, y) = (1 - \gamma_{eva}) T_v(x, y) + \sum_{k=1}^{N_a} \Delta T_v^k(x, y)$$

else

Get the parent current set of recipient message as M $\in$ u with maximum similar messages. If there is more than one participants with same number of common nodes connected or shared then select $P_{si}$

Create a new blue continuous edge and insert a directed edge with the immediate previous node from the root initiator to $P_{si}$

else

Insert red edge for indirect connection with other nodes of same message graph

end if

end for

Traverse entire block of message graph, that does not have any child node

do

Mark the pheromone with green, red or blue

end for

### 4.3 Post-Simulation Experience and Visualization

After initial modeling on data sets acquired from Facebook snaps, the temporal rating of event deceleration (e.g., blood donation request for casualties) for a given time instant has been visualized through the *Python library standard* with a standard hardware setup. As shown in Fig. 8, the blocks of the posts are shown; the red indication implies the connectivity with other nodes that are indirectly connected with the root request. Absent pheromones signify if and only if there is no substantial response of the request within the intra and inter nodes as well. Presence of pheromone describes the reinforcement of message requests, and hence the entropy seems more explicit with oral anxiety enhancements in the social group. The timestamp rating has been simulated from 5 units to 20 units, and anxiety on opinion also becomes slightly enlarged. It cannot be inferred that oral anxiety is a function of the duration of temporal events and the size of transient crowds, but the pheromone map shown in red and green polygons could be able to define it. The bubbles shown are the nodes of the social group where the temporal events take place with the participants of crowds. There may be certain participants who are transient in nature in this event.

Continuing the analysis of the pheromone-based model for sentiment flow, the model incorporates a $Z$ score. The most general way to obtain a $Z$ score is to accomplish a $Z$ test. This is to define numerical test statistics that can be calculated from a collection of data, such that the sampling distribution of the statistic is approximately normal under the null hypothesis. Statistics that are averages (or approximate averages) of approximately independent data values are generally well approximated by a normal distribution. An example of a statistic that would not be well approximated by a normal distribution would be an extreme value such as the sample maximum.

The standard score is

$$z = \frac{x - \mu}{\sigma} \tag{5}$$

where $x$ is a raw score to be standardized, $\mu$ is the mean of the population, and $\sigma$ is the standard deviation of the population.

The quantity $z$ represents the distance between the raw score for the responses made against the social post and the population, meaning the total number of Facebook participants in units of the standard deviation. $Z$ is negative when the raw score is below the mean, positive when it is placed above. The red line indicates $Z$ scores against the normal Facebook posts as shown in Figs. 4 and 5, whereas the blue line indicates the presence of pheromone-based reinforcement under the message posts in emergency. Figure 9 puts an analysis for the absence ratings of responses from 6 units' time instants to 14 units since this span of time is given for recording the responses. We concentrate on the $Z$ score due to its population mean and population deviation for messages and participants respectively of the social network (Fig. 10).

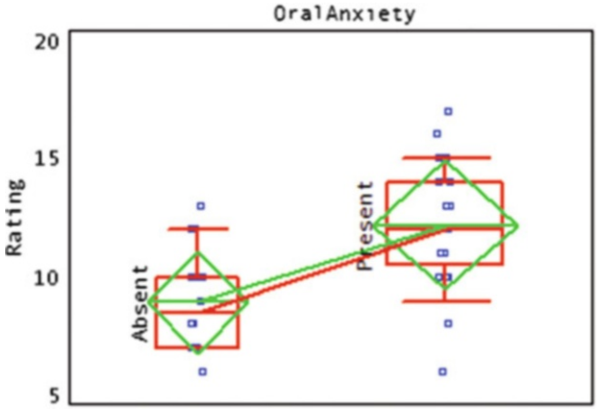



**Fig. 8** Temporal rating of events: simulation of pheromone presence and absence tag

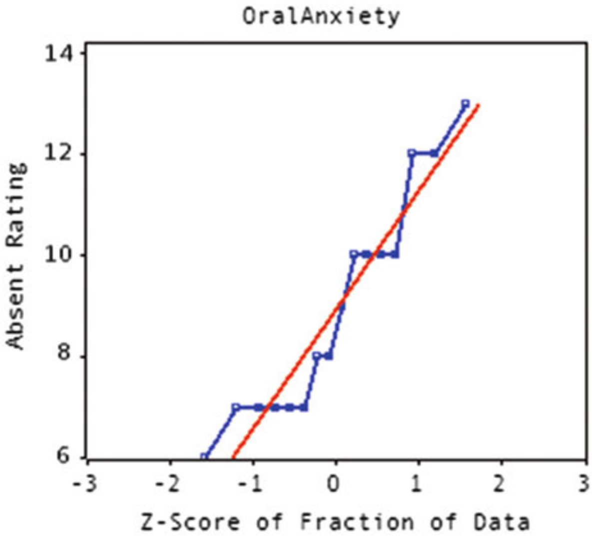



**Fig. 9** Anxiety and opinion plot on pheromone

The probability distribution for each set of different opinions against the message post comparing two probability distributions can be obtained by plotting their quantiles against each other. First, the set of intervals for the quantiles are chosen. A point ($x$,$y$) on the plot corresponds to one of the quantiles of the second distribution ($y$-coordinate) plotted against the same quantile of the first distribution ($x$-coordinate). Thus, the line is a parametric curve with the parameter, which is the (number of the) interval for the quantile. As the difference of opinion is explicit in responses, therefore a typical cumulative distribution of opinion and flow could be plotted. Here also, the blue line indicates the quantile plot of responses under emergency.

Finally, a box plot of normalized data has been presented demonstrating the message continuity over the Facebook message graph. There are instances of pheromone dispersion and discontinuity in post simulation, and the *reliability* of

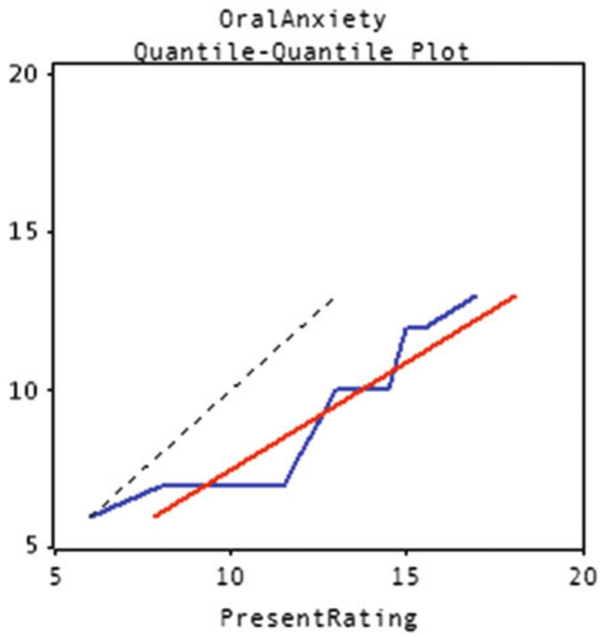



**Fig. 10** Dispersion of opinion on different nodes

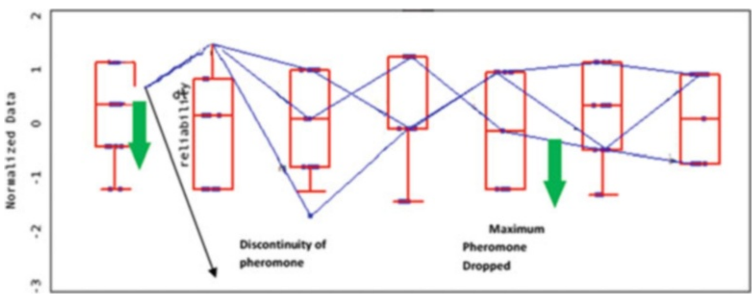



**Fig. 11** Community response and pheromone plot

the communication was visible during emergency by certain groups. The base line of the plot in Fig. 11 follows the univariate range from 5 to 25 units sessions on which the transient crowd accumulated and dispersed, although the pheromone threshold value has been threshold as random and as per the dataset collected it assigns approximate maximum pheromone dropped became maximum with a few box plot only on the message graph. The plot is still an estimation with one case study, and more accuracy could be devised if a few similar instances of crisis responses of Facebook could be collected.

From all these observations, we emphasize on statistical simulation derived from pheromone assignment. XML extraction of the semantic relation of each post may reveal extended versions of transient behavior. As also shown, the immediate previous simulation (Figs. 4 and 5) of the same message graph before the crisis also concentrates on nodal analysis without pheromone population, but nontransmission of information and isolation of nodes were also clearly evident leading toward expected temporal tendency of social crowds.

## 5 Conclusion and Further Scope of Research

In this chapter, we have investigated the metaphorical relationship of a swarm's pheromone map with the sentiment and opinion flow of transient crowds of social media under particular situations of crisis. We present a case study of such crowds and message boards with opinion flows from Facebook, and the same message graph is referred to distinguish the crisis and precrisis paradigm. Analytically, we present a novel pheromone-driven algorithm to trace such events and flows of sentiment of the crowd accumulated for a particular theme on social media. The preprocessing and post-simulation experiments depict interesting observations of transient crowds and their opinion propagation. Pheromone tracing has been proposed as a compatible and justified tool for such stochastic and time-bound social graph analysis scenarios. The model can be well placed under the analysis of tweets, although certain other hybrid optimization algorithms, e.g., clustering, could also be incorporated. From a technical implementation point of view, XML semantics and nodal analysis could reveal empirical validation as more realistic. Interfacing the semantic analysis of XML and MATLAB simulation would be a good challenge if more Facebook instances could have been collected.

As part of our future work, we plan to develop a hybrid algorithm from these experiments to further explore social graph mining perspectives. We also plan to investigate hybrid social graph clustering approaches for implementation.

## References

Backstrom L, Leskovec J (2011) Supervised random walks: predicting and recommending links in social networks. In: WSDM'11, 9–12 Feb 2011, Hong Kong, China

Burke M, Marlow C, Lento T (2010) Social network activity and social well-being. In: CHI 2010, Atlanta, GA, 10–15 Apr 2010

Cha M, Haddadi H, Benevenuto F, Gummadi KP (2010) Measuring user influence in Twitter: The million follower fallacy. In: Fourth international AAAI conference on weblogs and social media, Washington, DC, 23–26 May 2010

Cho E, Myers SA, Leskovec J (2011) Friendship and mobility: user movement in location-based social networks. In: KDD'11, San Diego, CA, 21–24 Aug 2011

Chu S-C (2011) Viral advertising in social media: participation in Facebook groups and responses among college-aged users. J Interact Advert 12(1, Fall):30–43

De Choudhury M, Mason WA, Hofman JM, Watts DJ (2010) Inferring relevant social networks from interpersonal communication. In: WWW 2010, Raleigh, NC, 26–30 Apr 2010. ACM, 978-1-60558-799-8/10/04

Dorigo M, Stützle T (2001) An experimental study of the simple ant colony optimization algorithm. In: Mastorakis N (ed) Advances in fuzzy systems and evolutionary computation, Artificial intelligence series. World Scientific and Engineering Society Press, Dallas, TX, pp 253–258

Dorigo M, Maniezzo V, Colorni A (1996) Ant system: optimization by a colony of cooperating agents. IEEE Trans Syst Man Cybern B 26(1):29–41

Fernandes C, Merelo JJ, Ramos V, Rosa A (2008) A self-organized criticality mutation operator for dynamic optimization problems. In: Keijzer M (ed) Proceedings of GECCO'08 - 10th annual conference on genetic and evolutionary computation. ACM Press, Atlanta, GA, pp 937–944

Galuba W, Chakraborty D, Aberer K, Despotovic Z, Kellerer W (2010) Outtweeting the Twitterers – predicting information cascades in microblogs. In: 3rd Workshop on online social networks (WOSN 2010), Boston, MA, 22 June 2010

Kamath KY, Caverlee J (2010) Identifying hotspots on the real-time web (Short paper). In: Proceedings of 19th ACM international conference on information and knowledge management (CIKM 2010), Toronto, ON

Kamath KY, Caverlee J (2011) Transient crowd discovery on the real-time social web. In: Proceedings of 4th ACM international conference on web search and data mining (WSDM 2011), Hong Kong, China

Lee K, Caverlee J, Cheng Z, Sui DZ (2011) Content-driven detection of campaigns in social media (short paper). In: 20th ACM international conference on information and knowledge management (CIKM), Glasgow

Leskovec J, Backstrom L, Ravi Kumar, Tomkins A (2008) Microscopic evolution of social networks. In: KDD'08, 24–27 Aug 2008, Las Vegas, NV

Montes de Oca M, Stützle T, Van den Enden K, Dorigo M (2011) Incremental social learning in particle swarms. IEEE Trans Syst Man Cybern B 41(2):368–384

Parunak HVD (2011) Swarming on symbolic structures: guiding self-organizing search with domain knowledge. In: Proceedings of the eighth international conference on information technology: new generations (ITNG 2011), Las Vegas, NV. IEEE, Piscataway, NJ

Parunak HVD, Brueckner SA, Downs E, Yinger A (2011) Opinion dynamics with social constraints and exogenous drivers. In: Cultural and opinion dynamics workshop at ECCS 2011 (CODYM 2011), Vienna

Parunak HVD, Downs E, Yinger A (2011) Socially-constrained exogenously-driven opinion dynamics. In: Fifth international IEEE conference self-adaptive and self-organizing systems (SASO 2011), Ann Arbor, MI

Saha B, Mitra P (2006) Dynamic algorithm for graph clustering using minimum cut tree. In: ICDMW '06, Washington, DC, USA. IEEE Computer Society, Piscataway, NJ, pp 667–671