Emotion Dynamics of Public Opinions on Twitter

DEBASHIS NASKAR, Universitat Politécnica de Valéncia, Spain
SANASAM RANBIR SINGH, DURGESH KUMAR, and SUKUMAR NANDI,
Indian Institute of Technology Guwahati, Assam
EVA ONAINDIA DE LA RIVAHERRERA, Universitat Politécnica de Valéncia, Spain

Recently, social media has been considered the fastest medium for information broadcasting and sharing. Considering the wide range of applications such as viral marketing, political campaigns, social advertisement, and so on, influencing characteristics of users or tweets have attracted several researchers. It is observed from various studies that influential messages or users create a high impact on a social ecosystem. In this study, we assume that public opinion on a social issue on Twitter carries a certain degree of emotion, and there is an emotion flow underneath the Twitter network. In this article, we investigate social dynamics of emotion present in users' opinions and attempt to understand (i) changing characteristics of users' emotions toward a social issue over time, (ii) influence of public emotions on individuals' emotions, (iii) cause of changing opinion by social factors, and so on. We study users' emotion dynamics over a collection of 17.65M tweets with 69.36K users and observe 63% of the users are likely to change their emotional state against the topic into their subsequent tweets. Tweets were coming from the member community shows higher influencing capability than the other community sources. It is also observed that retweets influence users more than hashtags, mentions, and replies.

CCS Concepts: • **Information systems → Sentiment analysis**; • **Networks → Social media networks**; **Network dynamics**;

Additional Key Words and Phrases: Emotion transition, influence measure, opinion discussion, social agreement, social dynamics

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1 INTRODUCTION

With the explosive growth in its popularity, social networking sites such as Facebook, Twitter, and so on have become an important medium for people to acquire and share information. People often tend to rely on these platforms for retrieving information about topics of their interest, and often make their decisions/opinions based on the acquired information. Social network sites are used

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Authors' addresses: D. Naskar and E. O. de la Rivaherrera, Universitat Politécnica de Valéncia, Spain; emails: debashis @drtc.isibang.ac.in, onaindia@dsic.upv.es; S. R. Singh, D. Kumar, and S. Nandi, Indian Institute of Technology Guwahati, Assam; emails: ranbir@iitg.ernet.in; k.durgesh@iitg.ac.in; sukumar@iitg.ernet.in.

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in various tasks such as political campaigns [Gu et al. 2013; Stieglitz and Dang-Xuan 2013], social advertisement [Li and Shiu 2012], social aspects of emotions [Kim et al. 2012], expert finding [Pal and Counts 2011], viral marketing, and so on, [Bi et al. 2014; Chen et al. 2010; Ding et al. 2013; Shi et al. 2018; Sun and Ng 2013] for influencing people. Different studies credit the success of the Arab spring [Wolfsfeld et al. 2013], Brazilian protests [Costa et al. 2015], Nirbhaya justice [Ahmed et al. 2017], and so on, to social networking platforms. Social movements are believed to be highly influenced by social media sites, particularly in their organization and communication. *Do social media posts about current events, news, and sociopolitical debates influence people's opinions*? This is one of the core questions that many of the studies on social media data analysis are attempting to understand. Several studies [Kwak et al. 2010; Weeks et al. 2017] observe that social activities and interactions greatly affect people's day-to-day activities, lifestyle, reading habits, and so on. In regards to political and social issues and public policies, studies show different observations. Based on the finding in the Karakiza [2015] study, what people say or post on social media highly influences one's support on public policies. The same is also found to be true for political leaders while supporting or opposing a public policy. Cha et al. [2010] also noted that the influence pattern is different for different countries and leaderships. However, *has social media activities on a topic or news story ever changed one's opinion on a political issue*? Ziegler and Lausen [2005] analyzed propagation of trust and distrust on social networks, what can be considered the first paper in which sentiment propagation was studied. Interesting conclusions, like that positive and negative sentiments follow a different propagation pattern [Hillmann and Trier 2012], have been drawn from the various investigations on sentiments in social networks. Other works studied the correlation between emotions and information diffusion, finding that emotionally charged messages were re-tweeted more often [Stieglitz and Dang-Xuan 2013], or investigated if the topic and the opinion of the user's contacts affect the own user's opinion [Tang and Fong 2013]. Motivated by the above studies, this article investigates changing characteristics of people's opinions against an event on Twitter, and how mass discussions/interactions influence changing one's opinion against an event. We use the emotion of a user reflected in the post as the matrix to indicate his/her opinion in support/opposition of a social event.

This study focuses on emotion dynamics of a user while posting comments against an event/topic from three different social characteristics: (i) emotional (excitement, contentment, depression, and distress), (ii) community (follower followee, membership relationship), and (iii) conversational (tweet, retweet, mention, reply). Identifying influential features can help us to understand factors causing people to change their opinions and in turn help agencies such as advertisers and marketers to design more effective campaigns. This article systematically explores users' changing characteristics of emotion over time, and attempts to find answers to the following three questions.

- Do people change their opinion against an event/issue over time?
- What types of opinions against what type of events are more prone to change?
- If people change their opinion, which of the social factors cause them to change their opinion?

To investigate the above questions, we collect posts related to 12 different events from Twitter using *Search-API*. It consists of 12.91K users over a total of 17.65M tweets. Emotional states of the users reflected in the posts are determined for each tweet using Russell's model of affect, which correctly classifies the emotions expressed in over 90% of text messages [Hasan et al. 2014]. For each user against a topic/event, *Temporal Emotional State Chain* (TESC) is prepared. Details of the data preparation are given in Section 3. All the experimental analyses are conducted over the collection of TESCs across different users and different events. From various experimental setups, this article makes the following contributory observations:

- We show that 63% of users change their opinions, and if an individual shares positive emotion against a topic, s/he is likely to stay in the same emotion state in his/her subsequent tweets.
- Tweets coming from a member community have higher influential ability to an individual than other sources like followers.
- Retweets can also influence a user more than the tweets received through hashtag, reply, and mention.

The rest of this article is organized as follows: Section 2 reviews the related works. Section 3 describes how we collected the dataset and labeled sentiments as well as a brief note on Russell's model. Section 4 shows the emotion transition on Twitter. Section 5 explains the process of understanding influence of incoming tweets. Section 6 explains about different characteristics during emotion state transition. The last section concludes our work.

2 RELATED WORK

This section briefly reviews the earlier literature that exploits different characteristics of opinion dynamics and measuring user influence in social media. In Twitter, a number of studies has been conducted on changing opinion and discussion on user influence. A number of researchers have examined how message content affects individual retweeting decisions. They show users can influence brand content diffusion via retweets [Araujo et al. 2017] and the role of content influence on social media via retweet behavior [Zhang et al. 2017]. Authors in the O'Connor et al. [2010] study measure public opinion derived from polls with sentiment measured from analysis of text from the popular microblogging site Twitter.

2.1 Social Behavioral Aspect

Emotional contagion has an influence on individual and group-level communication behavior in terms of information coordination and sharing [Suh et al. 2010]. In the same direction, Ferrara and Yang [2015] conducted a study on the dynamics of emotional contagion using a random sample of Twitter users and measured the emotional valence of content the users are exposed to before posting their own tweets. A high level of cognitive involvement such as anger, anxiety, awe, or amusement might also trigger a high level of physiological arousal, whereby low arousal or deactivation is characterized by relaxation and high arousal or activation is characterized by activity [Berger 2011]. Social networking is a multidimensional concept where users share different types of behavioral aspects [Stieglitz and Dang-Xuan 2013] over a topic. An individual emotion on behavioral concepts possible to utilize through social networks in viral marketing. In this part, we study different emotion transitions of a user in social networks and also a different type of emotion detection [Colneriĉ and Demsar 2018]. Myers et al. [2012] present a model in which information can reach a node via the links of the social network or through the influence of external sources. The model used to infer the quantify the external influences over time and describe how these influences affect information adoption. Compared with others' studies, we consider four regions that are based on 16 emotions of Russell's model of affect. This emotion model is combined with two main dimensions (i.e., valence and arousal) in a 2D circular space.

The emotion transition leads to find out how likely a user expresses their emotion after receiving a tweet response. A study conducted by authors in Kim et al. [2012] shows social aspects of the user's emotion by using Plutchik's wheel model and also examines that the conversational partners can influence each others' emotions and topics. Bollen et al. [2011] investigate collective public mood states derived from large-scale collections of daily Twitter posts over time. They analyze tweets by using two mood tracking tools: namely, OpinionFinder and also six dimensions of mood measures Google-Profile of Mood States (GPOMS). Similarly, Amalanathan and Anouncia [2017] attempt to study the nine basic human emotions and their significance in various social network activities to determine the right strategies of marketing in e-business.

2.2 Social Influential Characteristics

Understanding influential factors is an important task to understand dynamics in users' opinions on social networks. A comprehensive comparison of different influential factors (indegree, retweets, and mentions) on users' social dynamics is studied in Cha et al. [2010]. A similar study is conducted by Ye and Wu [2010] where they measure propagation patterns of tweet messages and social influence by following three metrics, i.e., follower, reply, and retweet. Peng et al. [2017] examined a set of different characteristics (Dynamic, Propagative, Composable, Measurable, Subjective, Asymmetric, and Event-sensitive) to understand users' dynamics and identify influential users on Twitter. Kwak et al. [2010] study information diffusion pattern of topological features: namely, singleton, reply, mention, and retweet. They also study the temporal behavior of trending topics. Unlike above studies, Kim et al. [2012] explore the effect of social and conversational characteristics of users on emotional dynamics. Specifically, they look into the social conversational features that lead to transition of emotion states within a discussion chain. Shi et al. [2018] propose a theoretical framework to systematically investigate the determinants of individual dissemination behavior in a Twitter network. They found information related to topical preference and homophily value are most influential on individual dissemination behavior.

From the above discussion, we observe that while a large number of studies has been conducted to study the community channel, not many of them study the relationship between the community channel with the emotional aspect of the tweets. Few studies [Cha et al. 2010; Kim et al. 2012] that have been conducted in this direction do not consider a very wide ranges of characteristics. This study in particular considers the effect of a wide range of community and conversational characteristics on the emotion dynamics of a user while posting their opinion. Our experiment is completely based on Twitter datasets, and all the possible sources are accommodated into this analysis. The popular Cha et al. [2010] study defined that the majority of the people are influenced by three important activities: followers influence, retweets influence, and mentions influence. Including these three sources of influence, our study also covers some more extra parameters of influences, such as hashtag tweets, replies, member lists, and so on. Our finding shows that the member-list is one of the important community channels that shows more influential to the user and retweets is more influential characteristics among others.

2.3 Social Influence Evaluation Measure

Identifying influential users is an important aspect in social media–related studies. Identifying influential users can aid in tasks such as social or political campaigns, viral marketing, and so on. In this direction, Zhang et al. [2017] study the influence of content as well as users on the rebroadcasting pattern of a message. They observe that along with the content of a message, the rebroadcasting of a message by a user is also dependent on other users and the relevance of the message to the user. A similar study was conducted by authors in Araujo et al. [2017] where they study the influence of users in the diffusion of information in a Twitter network. Weng et al. [2010] proposed TwitterRank algorithm, an extension of PageRank algorithm, to find the influential users in a Twitter network for a given topic. Kwak et al. [2010] propose different measures for ranking influential users and report a comparison among them. Ding et al. [2015] proposed a novel random walk model to measure the users' influence. For measuring a user's influence, they take into account not only the follower network of the user but also the popularity of the tweets. A method for measuring user influence is also proposed in Zhang et al. [2016]. This article presents TrueTop, the first sybil-resilient system to measure the influence of Twitter users. ProfileRank, a random walk–based method inspired by PageRank, is proposed in Silva et al. [2013] to find influential users and relevant content.

Rather than finding influential users, Saez-Trumper et al. [2012] propose a method to find trend-setters in information networks. Trendsetters are different from other influential users in that they need not necessarily be famous but are able to spread a new idea over a social network successfully. While all of the above studies have considered Twitter as the experimental framework, Liakos et al. [2016] investigate the influence mechanisms on the Pinterest social media platform. Another influence study was conducted by Nguyen et al. [2017], where authors propose the computation of Influence Spectrum algorithm for seeking a set of influential people on several social networks such as NetHEPT, NetPHY, Epinions, DBLP, and Twitter. Similarly, Wang et al. [2018] define two influence maximization queries to track influential users over Twitter and Reddit datasets. Other than the community structure of a network, Vardasbi et al. [2017] propose a linear-time shell decomposition method based on the layer structure to maximize the influence in large-scale networks. Their method can explain the different behaviors of real networks and predict the saturation dynamics in the networks.

3 DATA PREPARATION AND EMOTIONAL MODELING

This section describes the experimental dataset used in this study. For our purpose of analyzing real-time events, we chronologically retrieved tweets through Twitter *Search-API*[1] and created our own datasets. We collected tweets related to different events that contain a specific hashtag. Our objective is to analyze the sentiments derived within a conversation that occurs in Twitter and investigate how the emotions are changed dynamically across the users who take part in the conversation. Datasets are categorized based on different events happening in the world related to policy, movie, accident, terrorism, and sport. We tried to address different types of topics to check whether the emotion of the user act differently or not. All the tweets collected were in the English language. This study considers 12 events/topics belonging to six different categories as shown in Table 1. Some of the hashtags representing the events/topics are manually identified. These hashtags are further used to collect the related post. The collected tweets mainly contain the following information (i) user information, i.e., the user who posted the tweet, (ii) tweet text, (iii) type of tweet, i.e., direct tweet, retweet, reply, quoted tweet, (iii) time of posting the tweet. To study opinion dynamics, one should post at least two tweets. We therefore first identify users who have posted at least two tweets against a topic. The dataset consists of about 17.65M tweets and 69.36K users. Out of the total number of tweets, 72.83K tweets sent by 12.91K users and the rest of the tweets (i.e., 10.36M) have been received by the same 12.91K users. Since our study focuses on the opinion dynamics of these users only, we therefore require users to have sent at least two tweets within a two-time frame. It means, out of total users, 12.91K users have posted at least two tweets. The descriptions of the datasets are given below:

- *#Blackmoneydebate* composed of the tweets of the user that are related to demonetization, which started in India from November 10 till December 30, 2016.
- *#Brexit* tweets are about the United Kingdom's referendum to withdraw from the European Union held on June 23, 2016.
- *#AlienCovenant* is an American science-fiction horror film directed by Ridley Scott. It was released in the United States on May 19, 2017.
- *#Baahubali2* is an Indian historical fiction film that was theatrically released over 9K screens worldwide on April 28, 2017.

[1] http://twitter4j.org.

Table 1. Sizes of all Datasets

Event/Topic	Categories	Starting Date	Ending Date	Total # of Tweets	Total # of Sent Tweets	# of Users	Avg # of Sent Tweets
#BlackMoneyDebate	Policy	14-11-2016 09:10:56	27-11-2016 16:51:03	616,343	15,936	1,260	12.6
#Brexit	Policy	18-07-2016 13:29:26	24-07-2016 14:58:39	686,434	17,053	2,688	6.3
#AlienCovenant	Movie	16-05-2017 14:20:16	20-05-2017 12:21:33	74,286	4,957	1,504	3.3
#Baahubali2	Movie	08-05-2017 21:44:17	10-05-2017 11:05:39	53,391	2,750	679	4.0
#BadmintonRio2016	Sport	13-08-2016 19:11:38	23-08-2016 12:24:54	66,679	7,413	784	9.4
#UCLFinal	Sport	04-06-2017 07:32:05	11-06-2017 15:21:09	100,547	7,481	1,996	3.7
#SyriaGasAttack	Terror Attack	06-04-2017 04:35:33	07-04-2017 04:19:38	10,823	1,477	557	2.6
#StockholmAttack	Terror Attack	07-04-2017 15:24:49	12-04-2017 18:13:00	2,092	375	128	2.9
#GrenfellTower	Accident	15-06-2017 10:59:25	17-06-2017 23:34:56	136,821	6,499	2,297	12.8
#UnitedAirlinesAssault	Accident	10-04-2017 16:17:14	13-04-2017 15:43:57	7,176	7,481	583	2.7
#MacronPresident	Politics	08-05-2017 06:38:01	10-05-2017 22:57:53	6,171	643	235	2.7
#Trumpregrets	Politics	13-03-2017 17:16:29	23-03-2017 12:11:11	4,884	768	201	3.8

- *#BadmintonRio2016* is composed of the tweets about the final championship of badminton in Rio2016.
- *#UCLfinal* is about the 2017 UEFA Champions League Final football tournament between the Italian side Juventus and Spanish side Real Madrid, which played at Millennium Stadium in Cardiff, Wales, on June 3, 2017.
- *#SyriaGasAttack* is about a gas attack in northwestern Syria where more than 80 people were killed on April 4, 2017. Survivors and aid workers shared their stories of horror and shock after a suspected chemical attack in Syria.
- *#StockholmAttacks* tweets are related to an attack that happened in Stockholm, the capital of Sweden, on April 7, 2017. A hijacked truck was deliberately driven into a crowd and killed four people, including many more injured.
- *#GrenfellTower* is a 220-foot high tower block of public housing flats in North Kensington, west London. Collected tweets are about the Grenfell Tower fire on June 14, 2017, which caused at least 80 deaths and over 70 injuries.
- *#UnitedAirlinesAssault* is about an Asian passenger, Dr. David Daoa, who was violently dragged off by security officers from an overbooked United Airlines flight on April 10, 2017.
- *#MacronPresident* is a French politician who won the second round of the presidential election on May 7, 2017.
- *#Trumpregrets* is a conversation about those American citizens who voted for Trump and now regret their decision.

3.1 Data Pre-processing

For each participating user, we extract and arrange the tweets posted by the user in the order of posting time. As mentioned above, we assign an emotional state to each of the selected tweets to

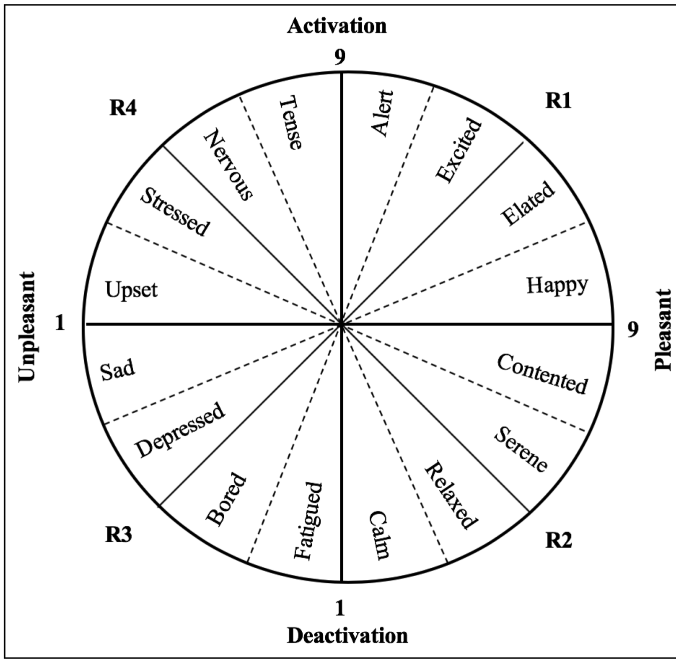


Fig. 1. Russell's Model of Affect [Feldman Barrett and Russell 1998].

enable us to investigate a user's emotion dynamics while participating in social discussions. The details of the data preparation are discussed below.

3.1.1 Russell's Model of Affect. We use the well-known 16-state Russell's circumflex model of affect [Feldman Barrett and Russell 1998] to estimate the state of emotion present in a given tweet.[2] According to this model, every affective experience is defined by *valence* and *arousal* coordinates in the 2D circumflex shown in Figure 1. A numerical value for valence ranges from 1 (*unpleasant*) to 9 (*pleasant*) and arousal ranges from 1 (*deactivation*) to 9 (*activation*). The emotional state or sentiment label of a given entity (message or user) has been formed according to its valence (x-axis) and arousal (y-axis) values. Figure 2 shows (on the right-hand side) the more pleasant states (+ve x); on the left-hand side, the more unpleasant ones (-ve x). The upper half shows the more activated states (+ve y); the lower half, the more deactivated ones (-ve y). To reduce the number of emotional states, we consider four quadrants defined in Russell [1980] and named them as *excitement* (R1), *contentment* (R2), *depression* (R3), and *distress* (R4). Excitement is a state with high positive affect ($x + y$), while contentment is a state with low negative affect ($x - y$). Similarly, distress is a state with high negative affect ($-x + y$) and depression is a state with low positive affect ($-x - y$) [Feldman Barrett and Russell 1998; Yik et al. 1999].

3.1.2 Finding Emotional State of a Tweet. To determine the emotional state of a tweet using Russell's circumflex model, we first need to estimate the valence and arousal score of the tweet. The aim of sentiment extraction is to compile sentiment words. One of the most efficient approaches for this purpose is the dictionary-based approach. Dictionary-based approaches use dictionaries of emotional words that are associated with a sentiment score. To estimate the valence and arousal score of a tweet, we use the ANEW dictionary of affect [Bradley and Lang 2010]. The new version

[2]This is the extension of the original eight-state Russell's model [Russell 1980].

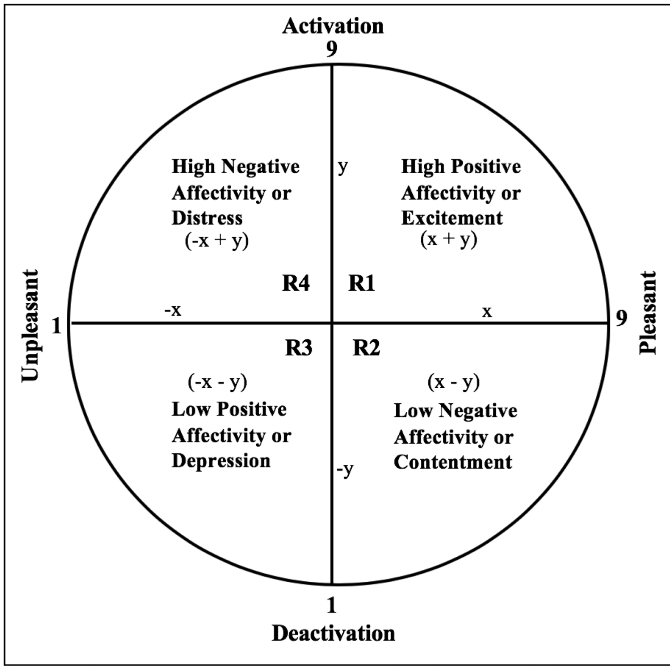


Fig. 2. A semantic structure of affect. The letters x and y represent semantic components: x = Pleasant; y = Activation [Feldman Barrett and Russell 1998; Yik et al. 1999].

of the Affective Norms for English Words (ANEW) dictionary [Nielsen 2011] is being developed to provide the mean and standard deviation of normative emotional ratings (valence v and arousal a) for 2,477 unique words in English. The word list of ANEW initiated from a set of obscene words as well as a few positive words. Later on, different slang words were included such as WTF, LOL, and ROFL. The entries of this dictionary match by applying Porter word stemming and WordNet lemmatization. It also contains another less strongly related dimension called dominance. However, for the purpose of our experiment, we only concentrate on two primary dimensions.

The performance of the dictionary-based approach can be evaluated according to two aspects: (1) the number of emotional words covered by the dictionary and (2) the nature of sentiment score provided by the dictionary. ANEW computes sentiment score with the valence and arousal values of the word, which range from 1 to 9. ANEW allows us to calculate a more accurate sentiment value, which better fits our aim of having a bi-dimensional representation of sentiments as well as measuring the intensity of expressed sentiments.

3.1.3 Sentiment Scores Calculation. We show an example of a tweet message composed of three emotional words that exist in the ANEW dictionary along with their valences and arousal values. **Hazirah Afifah** *@AzieFifa (Fri Aug 19 19:11:27 CEST 2016)*: "**Good job** guys!!!! We Malaysian re so **proud**!!!!! MalaysiaBoleh badmintonRio2016."

- **Good**, $v = [\mu : 7.47, \sigma : 1.45], a = [\mu : 5.43, \sigma : 2.85]$
- **job**, $v = [\mu : 5.83, \sigma : 2.15], a = [\mu : 5.20, \sigma : 2.23]$
- **proud**, $v = [\mu : 8.03, \sigma : 1.56], a = [\mu : 5.56, \sigma : 3.01]$

The aim of this phase is to associate each entity e with a tuple (v_e, a_e). The average sentiment score of a tweet message d is calculated with the valence and arousal of the stem words of d that appear in the ANEW dictionary (emotional words of d). Then, the sentiment score of a user u is calculated with the score of his/her tweet messages and we associate the corresponding sentiment label S_u.

The sentiment score of a user is calculated as the average emotional value of all the tweets sent by the user. For example, if we amalgamate the three words **Good**, **job**, and **proud** of the above message d, the result of the weighted average formula (1) for the valence and arousal is $X_d = 7.30$ and $Y_d = 5.41$, respectively. We then use the mean points to determine the emotional state in the Russell's circumflex model, i.e., the coordinate $(7.30, 5.41)$ falls in the excitement region ($R1$). In a given tweet, more than one emotional word may be present. Like in Naskar et al. [2016], we use the formula defined in Equation (1) to determine the overall emotional state of a tweet.

$$X = \frac{\sum_{i=1}^{N} \frac{\mu_i}{\sigma_i}}{\sum_{i=1}^{N} \frac{1}{\sigma_i}} \qquad (X, \mu, \sigma), \tag{1}$$

where X is the mean value of valence (similarly, mean value of arousal), N is the total number of emotional words within the message, μ is the word's mean value of valence (equivalently for arousal), and σ is the word's standard deviation of valence (equivalently for arousal).

3.2 Temporal Emotional State Chain

This section describes formation of a Temporal Emotional State Chain (TESC). Our presumption is that a person's emotion depends on his/her personal opinion and the past history s/he received from neighbors by following different emotions, popularity, and characteristics of messages. The Temporal Emotional State Chain is the sequence of *outgoing* and *incoming* tweets within two time frames. Every participating user's data is defined by the sequence of *outgoing* and *incoming* tweets arranged in the order of posting time. Outgoing tweets are those tweets posted by the target user about the topic under consideration; whereas the incoming tweets are those tweets posted by other users about target topic and are received by the user through one of the following: hashtag, mention, reply, retweet, following-list, member-list, other-list. We use the following terminologies to describe the chain formation:

- *User (u)*: User u is the current user for which we want to analyze the temporal emotional state chain.
- *Incoming mention (InM)*: If a tweet is posted by another user with @u, then this tweet is an *incoming mention* (InM) tweet to user u.
- *Incoming retweet (InRT)*: A quoted retweet with @u is referred to as *incoming retweet* (InRT) for user u.
- *Incoming reply (InR)*: An *incoming reply* (InR) to a user u is direct reply to u's post.
- *Incoming hashtag (InH)*: A tweet bearing the same hashtag as that of u's tweet is the *incoming hashtag* (InH) for u.
- *Incoming member-list (InML)*: Any user u of a group posts a tweet and correspondingly another user posts another tweet from the same group; we refer to this tweet as coming from *incoming member-list* ($InML$).
- *Incoming following-list (InFL)*: The user u who is following someone and list of tweets bearing the same hashtag seen by followee (u who is being followed); we refer to these tweets as coming from *incoming following-list* ($InFL$).
- *Incoming other-list (InOL)*: Any user u who is mentioned by someone but not associated with followee or member list, we refer to as a *incoming other-list* ($InOL$).

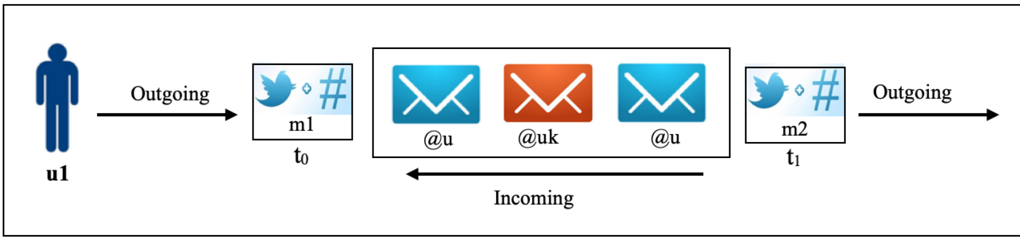


Fig. 3. Temporal emotional state chain.

In TESC, we wanted to register the message that causes the reaction of a user and, at the same time, whether the user reacts to this message or not. Consequently, we needed to know the message received by the user and the possible message sent by the user. More specifically, we consider the time at which tweets were posted. Given a user u, we estimate the incoming tweets that the user u has received between two consecutive tweets (i.e., m_0 and m_1) posted by u. The time of the two consecutive tweets sent by a user u is referred to as t_0 and t_1, and the received messages of the tweets that were posted at a time between t_0 and t_1.

Given a user u and a topic $\#h$, a typical *temporal tweet chain* is defined by the following tuple chain, where $\downarrow$ denotes incoming and $\uparrow$ denotes the outgoing tweets.

$$< u, \#h > \rightarrow < .., \downarrow m^{c}_{t_{0-1}} >, \uparrow \mathbf{m}_{\mathbf{t_0}}, <\downarrow m^{c}_{t_{0+1}}, .. >, \uparrow \mathbf{m}_{\mathbf{t_1}}, <\downarrow m^{c}_{t_{1+1}}, \ldots >, \uparrow \mathbf{m}_{\mathbf{t_2}}, \ldots,$$

where $c \in \{inH, inRT, inR, inM, inFL, inML, inOL\}$. When the user u posts his first tweet at t_0 on topic $\#h$, public discussion on the topic $\#h$ might have already taken place. It is denoted by the tuple $\downarrow m^{c}_{t_{0-i}}, i = 1, 2, ..$ and $c \in \{inH, inRT, inR, inM, inFL, inML, inOL\}$. Similarly, incoming tweets between the user's tweet $\uparrow m_{t_k}$ and $\uparrow m_{t_{k+1}}$ is denoted by the tuple $<\downarrow m^{c}_{t_{k+0}}, \downarrow m^{c}_{t_{k+1}}, .. >$. An example is also shown in Figure 3.

The emotional state of a tweet in a *temporal tweet chain* is determined using Russell's circumflex model of affect as described in Section 3.1.2. If $R_j, j \in 1, 2, 3, 4$ denotes one of the four emotional states for a given tweet, the above *temporal tweet chain* can be transformed into the following *temporal emotional state chain*.

$$< u, \#h > \rightarrow < .., \downarrow R^{InM}_{j, t_{0-1}} >, \uparrow \mathbf{R}_{\mathbf{j, t_0}}, <\downarrow R^{InH}_{j, t_{0+1}}, .. >, \uparrow \mathbf{R}_{\mathbf{j, t_1}}, <\downarrow R^{InH}_{j, t_{1+1}}, .. >, \uparrow \mathbf{R}_{\mathbf{j, t_2}}, ..$$

In the experimental analysis reported in the subsequent section, we use the above temporal emotional state chain for each user.

4 EMOTION TRANSITION ON TWITTER

This section analyzes the characteristics of the emotional state transition of a user in his/her subsequent tweets against a topic. We focus on analyzing the following characteristics: (i) transition probability of the user's emotional state change in subsequent tweets, (ii) likely initial state of the user's emotion while posting a tweet against a topic, (iii) relationship between the user's emotional state and nature of the topic, and (iv) participation of the user into the network conversation and their frequency while transiting from one state to another.

To perform the state transition of the user, a probabilistic sequence model, i.e., the Markov model, is adopted. The simplest Markov model is the Markov chain [Andrieu et al. 2003]. According to the Markov model, the next state is solely chosen based on the current state. The transition probabilities control the way the hidden state at time t is chosen given the hidden state at time $t - 1$. The set of transition probabilities for transitions from any given state must sum to 1. In this study, emotion states of users are likewise labeled with Russell's regions $S = R1, R2, R3$ and $R4$. The

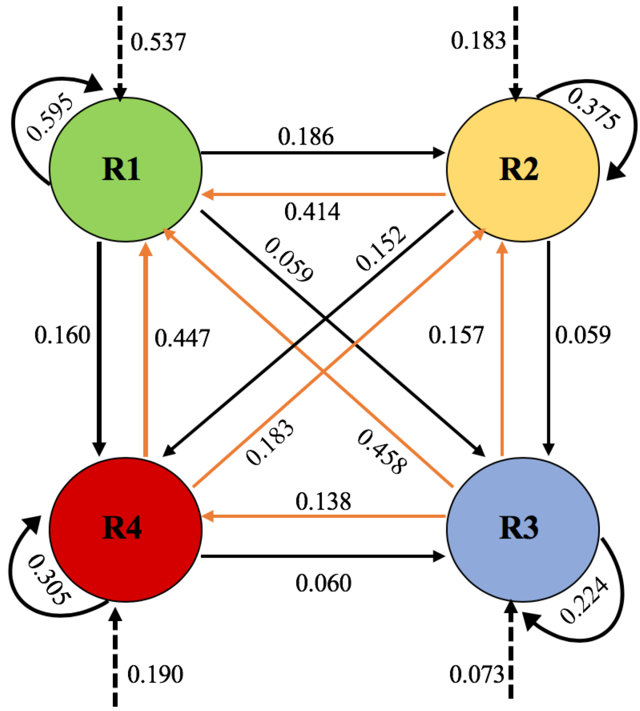
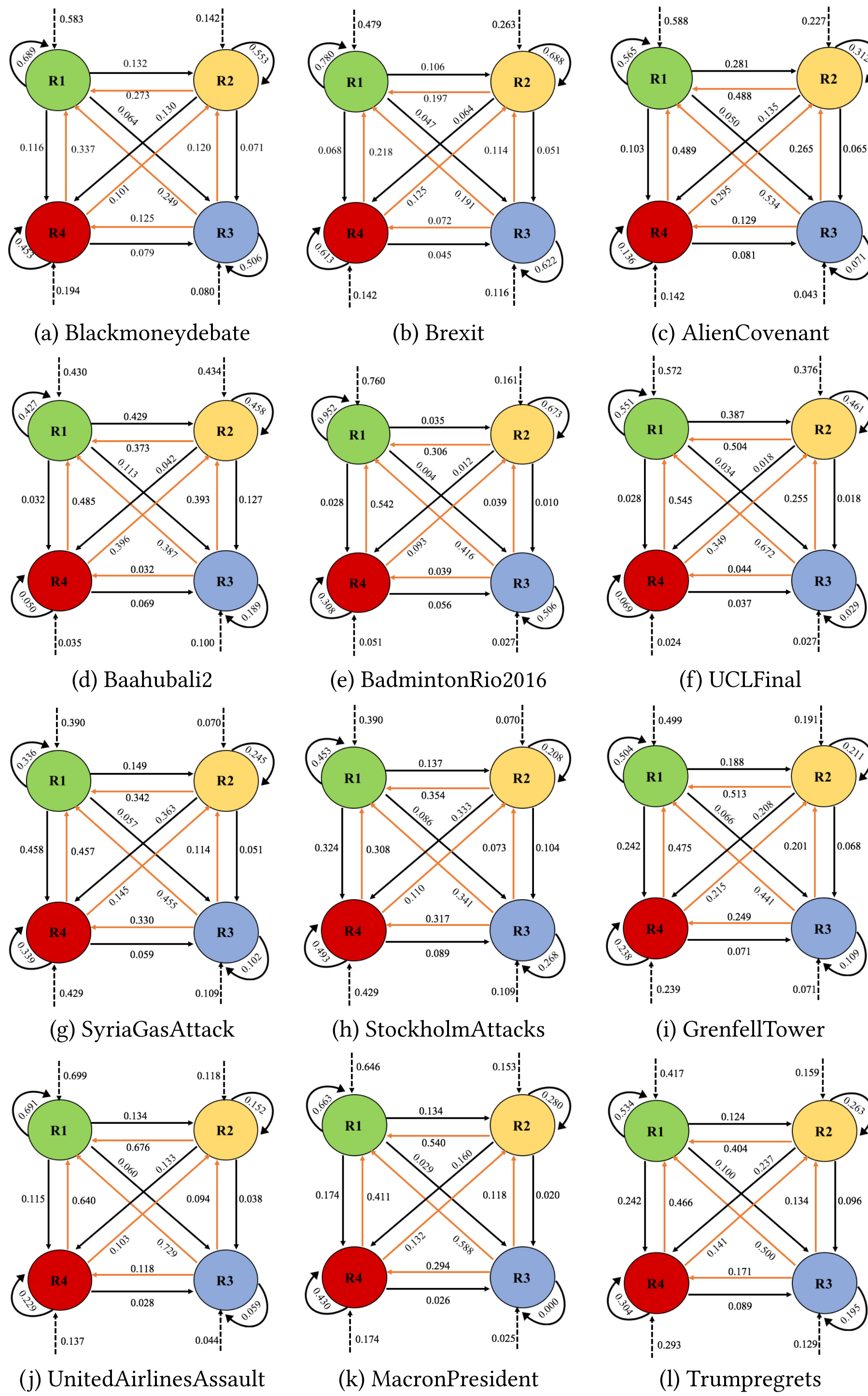


Fig. 4. Macro average transition probabilities over all topics. Initial state probability is represented by dot arrow.

process starts in one of these states and moves successively from one state to another. Each move is called a step. If the chain is currently in state s_i, then it moves to state s_j at the next step with a probability denoted by p_{ij}, and this probability does not depend upon which states the chain was in before the current state. The probabilities p_{ij} are called transition probabilities. The process can remain in the state it is in, and this occurs with probability p_{ii}. Let $\langle R1 \rangle$ be a current emotion state of the tweets sent by the user at t, then the next move can be towards $\langle R2 \rangle$, $\langle R3 \rangle$, or $\langle R4 \rangle$ or this transition can remain in the $\langle R1 \rangle$. However, the emotional state of the user can start with any of these four states.

Figure 4 shows average transition probability from one emotion state to another over the topics in different categories. First, Figure 4 shows the macro average transition probabilities over all topics. It is clearly evident that if a user is in a state with highly positive emotion $R1$, the probability of staying in the same state in the subsequent tweets from the same user is higher than that of the highly negative emotion state $R4$ (with probability 0.60 for staying in $R1$ and 0.31 for staying in $R4$). Further, it can be also seen that if a user makes a transition from one state to another, the user is more likely to move toward the state with highly positive emotion as compared to other states (on average probability 0.43, 0.17, 0.5, and 0.15 towards $R1$, $R2$, $R3$, and $R4$, respectively). Interestingly, $R1$ has got the highest initial transition probability. It means when a random user posts his/her opinion on a random topic, s/he is likely to start with highly positive emotion state. However, for the topics like *Terror Attack*, the observations deviate from the above average pattern.

The above observation may be biased by the nature of the topics/events that we consider in the experimental dataset. Users' emotional states may depend on the nature of the topic under consideration. To understand the topic-dependent characteristics, we further investigate topic-wise (Figure 5) transition probability as follows:



(a) Blackmoneydebate (b) Brexit (c) AlienCovenant

(d) Baahubali2 (e) BadmintonRio2016 (f) UCLFinal

(g) SyriaGasAttack (h) StockholmAttacks (i) GrenfellTower

(j) UnitedAirlinesAssault (k) MacronPresident (l) Trumpregrets

Fig. 5. Transition probability of a user over topics in different categories.

Table 2. Agreement and Disagreement by All Topics with Average Transition in Figure 4

Dataset	**Category**	P_{11}	P_{ij}	$P(\rightarrow i)$	π_i
#blackmoneydebate	Policy	√	×	√	√
#brexit	Policy	√	×	√	√
#AlienCovenant	Movie	√	√	√	√
#Baahubali2	Movie	×	×	√	×
#BadmintonRio2016	Sport	√	×	√	√
#UCLFinal	Sport	√	√	√	√
#SyriaGasAttack	TA	×	×	√	×
#StockholmAttack	TA	×	×	√	×
#GrenfellTower	Accident	√	√	√	√
#UnitedAirlinesAssault	Accident	√	√	√	√
#MacronPresident	Politics	√	×	√	√
#Trumpregrets	Politics	√	√	√	√

P_{11} considers self transition with high positive emotion (i.e., $R1$), P_{ij} considers transition from self state to other states, $P(\rightarrow i)$ considers from others state to $R1$, and π_i considers initial state.

- For the majority of the topics except in *Terror Attack* category, like in average case, a user in a highly positive emotional state ($R1$) is likely to continue in the same state with higher probability (with probability more than 0.5) as compared to that of the highly negative emotional state ($R4$).
- The topics in *Terror Attack* category show slightly different characteristics where probabilities of a user staying in the highly positive emotion state ($R1$) and highly negative emotion state ($R4$) are comparable. The probability of staying in $R4$ is even slightly higher than that of $R1$.
- Another interesting observation for the topics related to a terror attack is that when users make state transitions, the probabilities of moving towards both $R1$ and $R4$ are also comparable.
- For the topics related to *Policy*, in the majority of the cases, users continue to stay in the earlier state (with a probability higher than 0.5, users continue to take self-transition).
- In the majority of the cases, users in states $R2$ and $R3$ are more prone to take the transition to other states than that of $R1$ and $R4$. Further, users in $R3$ are more prone to change state than the users in other states.
- Unlike other topics, for the topics (*#StockholmAttack*, *#SyriaGasAttack*) *Terror Attack* category, the initial probability is quite high for region $R4$.

Table 2 summarizes agreement and disagreement of all the topics with that of the observation on average. It clearly shows that except for topics related to terror attacks, the majority of the cases agree with the average observations over all topics. Further, Figure 6 shows the number of times the users have changed their emotion state. We see that, for all the topics, the majority of the users change their emotion state against a topic only once. Comparatively, a very small number of users change their emotion state more than once for the same topic. Further, it is observed that 63% of users change his/her emotion state at least once against a topic. Users in emotion state $R3$ have the highest likelihood of changing state with a probability of 32%.

5 UNDERSTANDING INFLUENCE OF INCOMING TWEETS

On Twitter, a user receives messages from other users through various channels such as mention, reply, member-list, follower-list, and so on. From the Cha et al. [2010] study, it is noted that the

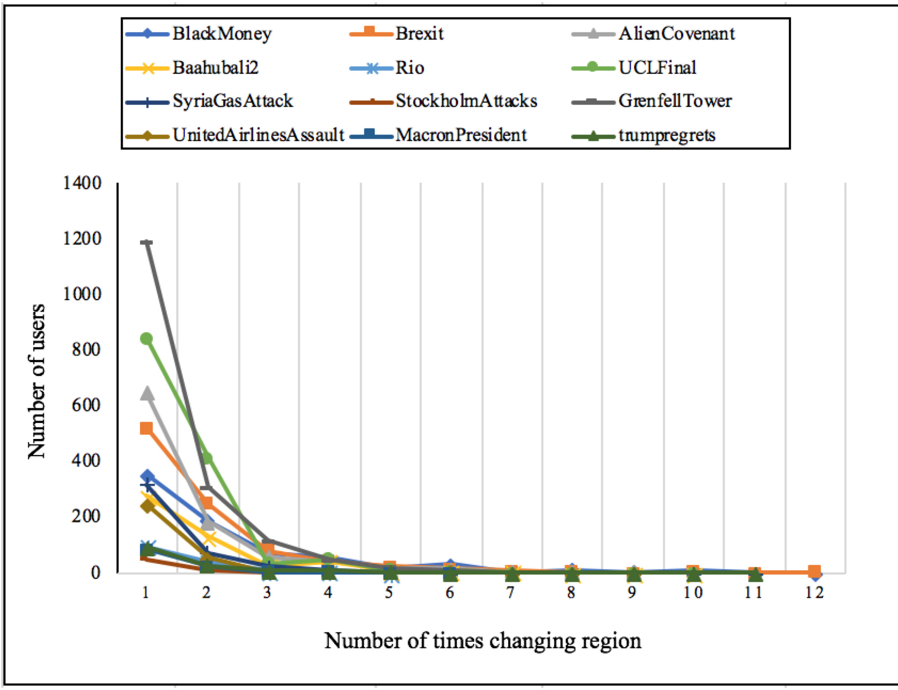


Fig. 6. Frequency of the user changing emotion region across topics.

user's opinion is often influenced by the incoming messages s/he receives. In this section, we attempt to understand the influential characteristics of different channels over the user's opinion by estimating the probability of the incoming emotion state coming through a channel agreeing with the user emotion state present in his post. As for example, given that emotion state $R1$ of the user and majority of the tweets that the user received, what is the likelihood that the user carrying the majority on an emotion state $R1$. In this section, we examine three types of social features; (i) incoming tweets with emotion state (i.e., $R1$, $R2$, $R3$ and $R4$), (ii) incoming tweets only from community (i.e., $InFL$, $InML$ and $InOL$), and (iii) incoming tweets only through conversation (InM, $InRT$, InR and InH). From the first features, we attempt to understand, if majority opinion can influence an individual's opinion. The second features try to understand if an individual's opinion can be biased by the opinions coming from the group/community that s/he belongs to. Last, we investigate if responses from the general public on previous posts of an individual influence the individual. We systematically explore the above questions by exploiting the dataset that we prepare in Section 3.

5.1 Can Majority Opinions Influence an Individual's Opinion?

To answer this, we examine distribution of the emotion states over all the incoming tweets that an individual receives before s/he posts her/his next tweet and check if the emotion state in her/his post agrees with any of the emotions in the incoming tweets. To systematically investigate the influential characteristics of the incoming message, we intend to understand the following sub-questions:

5.1.1 When an Individual Posts an Opinion, How Likely Does Her/his Emotion State Agree with That of Any of the Incoming Messages?. To answer this question, whenever a user posts a tweet, we

Table 3. Probability of an Individual's Emotion State in a Post Not Matching with the Emotion State of Any of the Incoming Messages

Emotion State	BlackMoneyDebate	Brexit	AlienCovenant	Baahubali	BadmintonRio2016	UCLFinal	SyriaGasAttack	StockholmAttacks	GrenfellTower	UnitedAirlinesAssault	MacronPresident	Trumpregrets	Avg. Across Topics
R1	0.464	0.510	0.422	0.600	0.194	0.397	0.664	0.466	0.538	0.237	0.351	0.594	**0.477**
R2	0.830	0.758	0.668	0.565	0.813	0.639	0.824	0.883	0.790	0.707	0.845	0.725	0.760
R3	0.903	0.888	0.898	0.819	0.974	0.976	0.970	0.755	0.917	0.918	0.925	0.858	0.896
R4	0.793	0.833	0.890	0.949	0.937	0.977	0.483	0.570	0.740	0.804	0.651	0.760	0.798
Avg. Across Emotion State	0.672	0.669	0.553	0.623	**0.246**	0.521	0.639	0.566	0.667	**0.332**	0.489	0.683	**0.645**

check in how many cases her/his emotion state matches with the emotion state of the incoming tweets s/he receives. Table 3 shows the probability of an individual's emotion state when s/he posts a tweet not matching with the emotion state of the incoming message across different topics. When an individual posts a tweet, if the emotion state of her/his tweet is matching with the emotion state of any of the incoming tweets, then we refer to it as `Matching`, otherwise `UnMatching`. The last row of Table 3 shows the percentage of `UnMatching` posts for each topic. It clearly shows that except for two out of twelve topics, the percentage of `UnMatching` posts is higher than that of the `Matching` posts. Across all topics, in 64.5% of the cases, the user's posts do not agree with any of the incoming tweets that s/he receives. It indicates that the majority of the user's opinion does not depend on the incoming opinion.

In rows ($R1$, $R2$, $R3$, and $R4$), it further shows the probability of `UnMatching`, if user posts a tweet with emotion state $R_i, i = 1, 2, 3, 4$, i.e., $Pr(UnMatching|R_i) = \frac{Pr(R_i|UnMatching)Pr(UnMatching)}{Pr(R_i)}$. It shows that user has higher chances of `Matching` when he posts a message with positive emotion (i.e., across all topics, the average of $Pr(UnMatching|R_1)$ is smaller than that of $R2$, $R3$, and $R4$). Similarly, chances of `UnMatching` is higher when s/he posts with low positive or high negative emotion state ($R3$ or $R4$). These observations are true for majority of the topics.

5.1.2 If Individual's Emotion State Matches with Incoming Emotion, Does S/he Agree with Majority?. To answer this question, we further estimate the probability of user emotion state matching with the majority emotion state of the tweets that user receives. Table 4(a) shows the probability of matching with the majority emotion state. In the table, M_i denotes ith majority emotion states, i.e., 1st, 2nd, 3rd, and 4th majority. An entry in R_i row and M_j column in Table 4(a) is the probability that user posts a tweet with emotion R_i and the emotion state of M_j is also R_i, i.e., $Pr(M_j = R_i|e(\uparrow m) = R_i)$ where $e(\uparrow m)$ is the emotion state of the user's outgoing tweet m.

The row with *total average* in Table 4, column (a), shows the probability of agreeing with $M_i, i = 1, 2, 3, 4$ if user's outgoing post has an agreement with an incoming tweet over all topics across different emotion state. It shows that probability of agreeing with M_1 is higher than that of M_2, M_3, and M_4. It means that if the user's emotion state in the tweet that he posted has an agreement with the emotion state of some of the incoming tweets that he received, it is likely to agree with the dominant emotion state among all the tweets he receives.

Further, the $Pr(R_i)$ column in Table 4(a) shows the probability of a user posting a comment/tweet with the emotion state R_i. It shows that in the majority of cases, user posts tweets with positive

Table 4. The Probability of an Individual's Emotion State in a Post Matching with the Emotion State of Any of the Incoming Messages

Dataset (#h)	Emotion State	(a) Agreement with Majority					(b) Community Channels			(c) Conversational Channels			
		Pr(R_i)	**M1**	**M2**	**M3**	**M4**	**ML**	**FL**	**OL**	**RT**	**H**	**R**	**M**
(1) BlackMoneyDebate	**R1**	**0.445**	**0.883**	0.095	0.022	0.001	**0.555**	0.441	0.004	0.877	0.079	0.022	0.022
	R2	0.217	0.300	0.423	0.075	0.040	0.481	0.515	0.004	**0.901**	0.068	0.014	0.017
	R3	0.161	0.154	0.290	0.381	0.018	0.481	0.518	0.002	0.796	0.027	0.005	0.173
	R4	0.177	0.058	0.347	0.417	0.044	0.541	0.457	0.002	0.868	0.090	0.018	0.024
	Avg.		**0.690**	0.169	0.089	0.051	**0.542**	0.454	0.004	**0.874**	0.076	0.020	0.030
(2) Brexit	**R1**	**0.465**	**0.964**	0.033	0.003	0.000	0.845	0.153	0.003	0.707	0.177	0.056	0.060
	R2	0.267	0.122	0.816	0.057	0.006	0.802	0.195	0.003	**0.728**	0.169	0.039	0.064
	R3	0.116	0.073	0.052	0.249	0.626	0.814	0.181	0.005	0.711	0.157	0.064	0.067
	R4	0.153	0.042	0.124	0.686	0.148	**0.870**	0.127	0.003	0.663	0.203	0.057	0.077
	Avg.		**0.694**	0.193	0.076	0.037	**0.837**	0.160	0.003	**0.708**	0.177	0.053	0.063
(3) AlienCovenant	**R1**	**0.593**	**0.973**	0.027	0.000	0.000	0.935	0.035	0.030	0.767	0.166	0.015	0.052
	R2	0.269	0.171	0.816	0.012	0.001	0.823	0.052	0.125	**0.814**	0.128	0.010	0.047
	R3	0.043	0.027	0.036	0.149	0.788	**0.939**	0.039	0.021	0.252	0.055	0.140	0.553
	R4	0.095	0.038	0.165	0.772	0.026	0.895	0.025	0.080	0.799	0.149	0.005	0.048
	Avg.		**0.781**	0.188	0.022	0.008	**0.911**	0.038	0.050	**0.767**	0.156	0.016	0.061
(4) Baahubali2	**R1**	**0.447**	**0.769**	0.229	0.002	0.000	**0.953**	0.038	0.008	**0.889**	0.073	0.012	0.027
	R2	0.400	0.501	0.495	0.003	0.000	0.925	0.045	0.030	0.851	0.115	0.006	0.027
	R3	0.127	0.128	0.108	0.753	0.011	0.826	0.047	0.127	0.852	0.129	0.002	0.017
	R4	0.027	0.019	0.038	0.192	0.750	0.817	0.087	0.096	0.750	0.163	0.048	0.038
	Avg.		0.604	0.344	0.049	0.003	**0.932**	0.042	0.026	**0.869**	0.096	0.009	0.027
(5) BadmintonRio2016	**R1**	**0.918**	**0.996**	0.004	0.000	0.000	0.595	0.391	0.014	**0.947**	0.025	0.002	0.026
	R2	0.075	0.190	0.805	0.006	0.000	**0.622**	0.359	0.020	0.907	0.063	0.001	0.028
	R3	0.003	0.000	0.500	0.500	0.000	0.500	0.000	0.500	0.250	0.250	0.500	0.000
	R4	0.004	0.250	0.750	0.000	0.000	0.417	0.333	0.250	0.750	0.000	0.083	0.167
	Avg.		**0.981**	0.019	0.000	0.000	**0.595**	0.391	0.014	**0.946**	0.026	0.002	0.026
(6) UCLFinal	**R1**	**0.563**	**0.972**	0.028	0.000	0.000	0.975	0.022	0.004	0.943	0.040	0.003	0.014
	R2	0.383	0.118	0.882	0.000	0.000	**0.982**	0.016	0.002	**0.974**	0.021	0.000	0.004
	R3	0.031	0.000	0.148	0.796	0.056	0.926	0.056	0.019	0.963	0.000	0.037	0.000
	R4	0.023	0.053	0.079	0.711	0.158	0.816	0.132	0.053	0.947	0.053	0.000	0.000
	Avg.		**0.723**	0.275	0.002	0.000	**0.977**	0.020	0.003	**0.952**	0.034	0.002	0.011
(7) SyriaGasAttack	**R1**	**0.432**	**0.864**	0.129	0.007	0.000	**0.873**	0.057	0.070	0.872	0.088	0.016	0.023
	R2	0.149	0.263	0.165	0.557	0.015	0.805	0.063	0.132	0.910	0.057	0.012	0.021
	R3	0.055	0.286	0.095	0.095	0.524	0.619	0.095	0.286	**0.952**	0.000	0.048	0.000
	R4	0.365	0.458	0.534	0.007	0.001	0.862	0.103	0.034	0.890	0.076	0.018	0.016
	Avg.		**0.606**	0.343	0.047	0.004	**0.861**	0.082	0.057	**0.884**	0.079	0.017	0.019
(8) StockholmAttacks	**R1**	**0.491**	**0.890**	0.079	0.031	0.000	0.567	0.009	0.424	0.842	0.113	0.023	0.022
	R2	0.073	0.542	0.083	0.125	0.250	**0.708**	0.042	0.250	0.625	0.292	0.042	0.042
	R3	0.120	0.844	0.000	0.065	0.091	0.083	0.455	0.117	**0.909**	0.039	0.026	0.026
	R4	0.310	0.438	0.556	0.006	0.000	0.651	0.009	0.340	0.683	0.228	0.052	0.037
	Avg.		**0.741**	0.220	0.027	0.011	**0.588**	0.017	0.395	**0.793**	0.147	0.033	0.027

(Continued)

Table 4. Continued

Dataset (#h)	Emotion State	(a) Agreement with Majority					(b) Community Channels			(c) Conversational Channels			
		Pr(R_i)	**M1**	**M2**	**M3**	**M4**	**ML**	**FL**	**OL**	**RT**	**H**	**R**	**M**
(9) GrenfellTower	**R1**	**0.486**	**0.991**	0.009	0.001	0.000	0.935	0.046	0.018	**0.873**	0.087	0.016	0.024
	R2	0.186	0.018	0.282	0.690	0.010	**0.947**	0.046	0.007	0.786	0.146	0.019	0.048
	R3	0.091	0.012	0.022	0.127	0.839	0.904	0.076	0.020	0.857	0.076	0.025	0.042
	R4	0.237	0.025	0.910	0.064	0.001	0.946	0.047	0.006	0.862	0.095	0.013	0.030
	Avg.		**0.676**	0.208	0.096	0.021	**0.938**	0.047	0.015	**0.860**	0.095	0.016	0.029
(10) UnitedAirlinesAssault	**R1**	**0.721**	**0.999**	0.001	0.000	0.000	0.672	0.014	0.314	0.723	0.160	0.038	0.079
	R2	0.138	**0.819**	0.118	0.063	0.000	0.173	0.007	0.819	**0.889**	0.048	0.044	0.018
	R3	0.029	0.000	0.125	0.125	0.750	**1.00**	0.000	0.000	0.375	0.563	0.000	0.063
	R4	0.112	0.388	0.374	0.238	0.000	0.687	0.034	0.279	0.707	0.177	0.041	0.075
	Avg.		**0.983**	0.010	0.005	0.003	**0.641**	0.014	0.345	**0.732**	0.155	0.038	0.075
(11) MacronPresident	**R1**	**0.655**	**0.985**	0.015	0.000	0.000	**0.876**	0.022	0.102	0.795	0.155	0.016	0.034
	R2	0.122	0.161	0.452	0.387	0.000	0.790	0.032	0.177	0.782	0.177	0.032	0.008
	R3	0.039	0.474	0.000	0.368	0.158	0.474	0.053	0.474	**0.842**	0.105	0.053	0.000
	R4	0.184	0.327	0.604	0.066	0.002	0.780	0.033	0.187	0.687	0.130	0.156	0.026
	Avg.		**0.869**	0.105	0.025	0.001	**0.858**	0.024	0.118	**0.782**	0.152	0.035	0.032
(12) Trumpregrets	**R1**	**0.485**	**0.932**	0.064	0.003	0.000	0.753	0.081	0.166	0.842	0.228	0.052	0.037
	R2	0.171	0.279	0.358	0.257	0.106	0.690	0.097	0.212	0.625	0.292	0.042	0.042
	R3	0.094	0.109	0.266	0.281	0.344	0.734	0.078	0.188	**0.909**	0.039	0.026	0.026
	R4	0.251	0.298	0.540	0.131	0.031	**0.796**	0.097	0.107	0.683	0.228	0.052	0.037
	Avg.		**0.681**	0.207	0.077	0.036	**0.751**	0.087	0.163	**0.793**	0.147	0.033	0.027
Total Average	**R1**	(**0.483**)	**0.941**	0.051	0.008	0.000	**0.766**	0.222	0.012	**0.814**	0.118	0.030	0.039
	R2	(0.242)	0.193	0.657	0.105	0.046	0.772	0.205	0.023	0.809	0.125	0.023	0.043
	R3	(0.117)	0.106	0.154	0.323	0.417	0.680	0.305	0.014	0.747	0.084	0.034	0.135
	R4	(0.158)	0.061	0.429	0.397	0.113	0.764	0.226	0.010	0.802	0.128	0.029	0.042
	Avg.		**0.711**	0.188	0.070	0.032	**0.764**	0.222	0.013	**0.810**	0.118	0.029	0.043

emotion R_1 irrespective of the topics. Overall, 48.3% percent of the tweets are in R_1. Interestingly, even for the events such as *(7) SyriaGasAttack* or *(8) StockholmAttacks*, the majority of the tweets are with positive emotion, i.e., 43.2% for *(7) SyriaGasAttack* and 49.1% for *StockholmAttacks*.

For different emotion states, it is observed that when a user posts a tweet with $R1$, it mostly agrees with dominant emotion in the incoming tweets, i.e., M_1. However, this is not the case when a user posts a tweet with other emotion states (other than $R1$). For example, when a user posts a tweet with $R3$ emotion state, it agrees mostly with either M_3 or M_4. It indicates that a significant number of users do not get influenced by what he receives.

5.1.3 Remarks. Coming back to our earlier question, i.e., *can majority opinions influence an individual's opinion?*, the above observations in Table 4(a), i.e., emotion state of a significant number of posts do not agree with the dominant emotion, indicates that influential ability of social propaganda on the social network is questionable.

5.2 Which Community Channel Is More Influential?

In the above section, we have considered all the incoming messages irrespective of the type of channels through which a user receives the messages. However, as indicated in Cha et al. [2010], different channels may have a different influential pattern. In this section, we investigate the influential characteristics of different channels over the individual opinion. Table 4(b) shows the probability of agreement with the dominant emotion state in each of the community channels—namely, *member-list* (ML), *following-list* (FL), and *other-list* (OL). An entry in R_i row and ML column in Table 4(b) is the probability that user posts a tweet with emotion R_i and majority of the tweets coming from ML have emotion state R_i, i.e., percentage of agreement with the dominant state in ML. Similarly, entries at FL and OL represent the percentage of agreement with their respective dominant state.

It is evident from Table 4(b) that ML has the highest probability of agreement as compared to FL and OL for all the emotion states $R_i, i = 1, 2, 3, 4$. It means that a message coming from ML has a higher potential for influencing users than the tweets coming from FL and OL. From the rows with *total average* in Table 4(b), it is observed that ML has 76% of agreements, whereas FL has only 22%. An interesting observation is that, though ML dominates FL for almost all the topics, the topics such as *BlackMoneyDebate*, *Brexit*, and *BadmintonRio2016* have comparable distribution between ML and FL. This is due to the fact that popular tweets propagate multiple times from the source by retweeting throughout the network. Watts and Dodds [2007] indicate that retweeting is a powerful mechanism in the social network where a group of users re-post the same tweet.

5.3 Which Conversational Channel Is More Influential?

In the previous section, it is observed that tweets coming from ML have higher potential of influencing a user's opinion. Further, tweets might be coming through different conversational channels such as hashtags (H), retweet (RT), mention (M), and reply (R). In this section, we further investigate influential characteristics of these conversational channels. Table 4(c) shows the probability of agreement with the dominant emotion state in each of the above conversational channels. An entry in R_i row and conversational channel in Table 4(c) is the probability that user posts a tweet with emotion R_i and the majority of the tweets coming from the channel also have emotion state R_i.

In almost all the cases over all the topics, RT dominates H, R, and M. It means that tweets coming from RT have higher potential for influencing a user's opinion than the tweets coming from others (H, R, M). Similar observations have also been reported in Suh et al. [2010]. Among H, R, and M, H has higher potential. From the row with *total average* in Table 4(c), it is observed that RT contributes in 81% of the agreements, H contributes in 12%, and the rest from M and R.

6 CHARACTERISTICS OF INCOMING TWEETS TOWARDS STATE TRANSITION

In Section 4, we observe that 63% of users change their opinions towards a topic at least once. This section investigates the distribution of the incoming tweets that an individual receives at the time of changing her/his emotion state while posting a tweet against a topic. It will help us to understand possible causal influence from different channels through which an individual receives incoming tweets. Like in Section 5, this section also considers the same three types of cases: *whole incoming tweets*, *community channels*, and *conversational channels*.

6.1 State Transition vs Incoming Dominant Emotion

Why does an individual change their opinion from their earlier emotion state against a topic? Has it been influenced by the emotion state of the majority opinion? To answer these questions, we study the distribution of the emotion state of all the incoming tweets that an individual receives before posting their next tweet with a different emotion state (emotion state different from their previous tweet). Figure 7 shows the distribution of the emotion state of the incoming tweets across different dominant emotion states for each possible state transition.

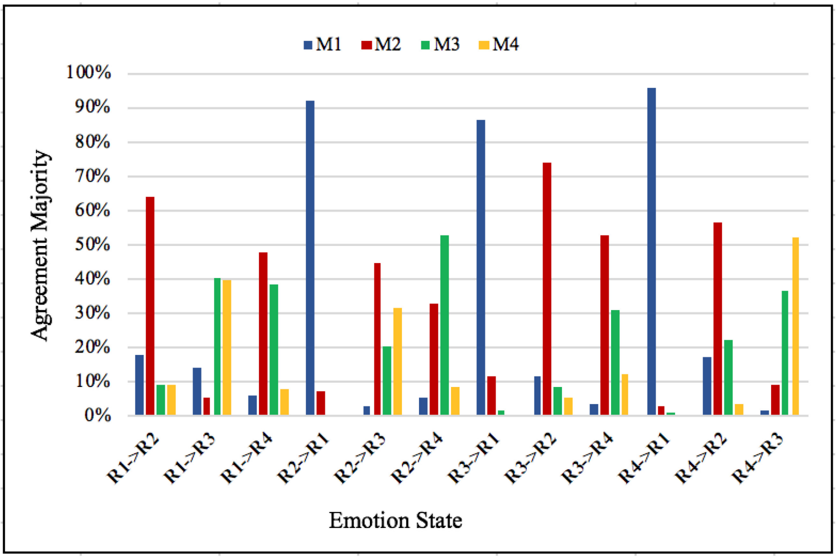


Fig. 7. Average probabilities of emotional agreement over all topics.

In Figure 7, the emotion transitions of a user is represented as $R_i \rightarrow R_j$ (where $i, j = 1, 2, 3, 4$). For each $R_i \rightarrow R_j$ transition, we have shown its agreement with the distribution of the incoming emotion state. A bar chart with M_k (where k = 1st, 2nd, 3rd, and 4th) against a state transition $R_i \rightarrow R_j$ represents the number of the cases (in percentage) in which the emotion state changes from R_i to R_j, and emotion state of the kth majority incoming tweet is R_j.

A user's agreement with 1st majority, i.e., M_1 at the time of state transition (change in emotion state of the user, i.e., $R_i \rightarrow R_j, i \neq j$), potentially reflects possible influence of changing state from the dominant incoming emotion. Similarly, a disagreement with the dominant emotion state at the time of changing the state of a user may also indicate a user's ability to make their own opinion (not biased by the dominant incoming emotion). Figure 7 shows two interesting observations. Whenever users change their emotion state to extreme positive from any other state, it always has an agreement with the majority (M_1), i.e., $R_i \rightarrow R_1, i \neq 1$. However, for any other changes where $R_i \rightarrow R_j, j \neq 1$, users' agreement with M_1 is very low. It potentially means that sharing positive emotion is more general, and sharing negative emotion is more personal. It is interesting to see that transition to extreme negative has agreement mostly with 2nd and 3rd dominant emotions, not with the majority. Figure 7 shows that when users change their emotion state from $R4 \rightarrow R1$ and $R1 \rightarrow R4$, the percentage of agreements with dominant incoming emotion are 96% and 6%, respectively. We can also see the percentage of agreement with dominant incoming emotion while the transition from low positive $R3$ to high positive $R1$ is higher than that of $R1$ to $R3$ (i.e., 87% and 14%).

From the above observations, it is evident that when a user changes their emotion state to non-positive states (i.e., $Rj, j \neq 1$), the user tends to share personal opinion. *How large is this proportion?* In our dataset, 40% of the state transitions do not agree with M_1, and 41% of these transitions belong to a non-positive state transition. Further, *how likely is a user to change their state if they had an agreement with the majority ?* It is observed from the dataset that in 2% of the cases a user tends to change their state from agreement to disagreement with the M_1, i.e., $R_i \rightarrow R_j, R_i = M_1, R_j \neq M_1$. It shows a significant proportion of the users are not influenced by incoming emotions.

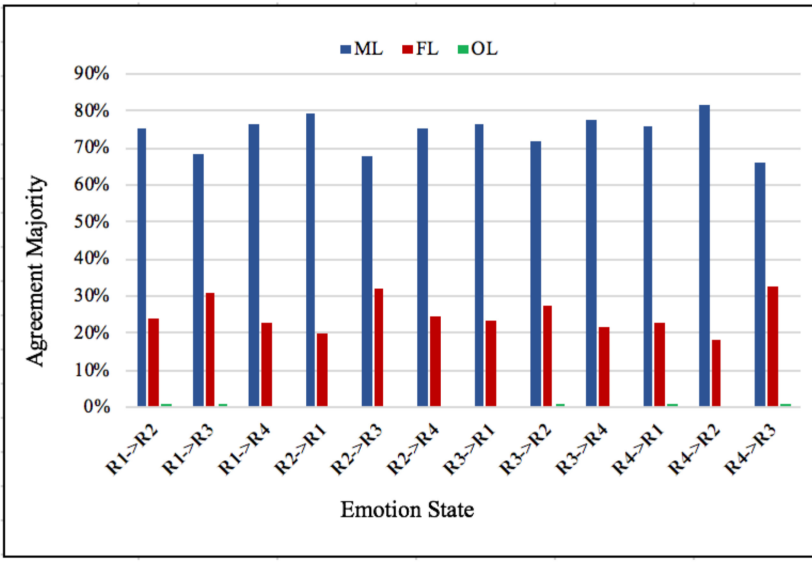


Fig. 8. Average probabilities of topological agreement over all topics.

6.2 Which Community Channel Is More Influential during Emotion State Transition?

In the previous section, we investigated over entire incoming tweets irrespective of the channels through which they receive the incoming tweets. In this section, we study the emotion distribution of the incoming tweets with respect to community channels, i.e., member list, following, and others. As in Section 6.1, we estimate the probability of user emotional state that matching with different channels through s/he receives during emotion transition. We calculate the total average probability of agreeing with the different channels over all topics in different categories. In Figure 8, the emotion transition refers to $R_i \rightarrow R_j$, where $i, j = 1, 2, 3, 4$ and for each $R_i \rightarrow R_j$ transitions, we have shown its agreement with majority for each community channel, i.e., *ML* for member list, *FL* for following, and *OL* for others. Each bar corresponding to a channel for a given transition $R_i \rightarrow R_j$ represents the percentage of its emotional agreement with the dominant emotional state in each channel, i.e., the dominant emotion state is R_j.

Figure 8 shows that if an individual changes their emotion state from one region to another, the average majority agreement of the member-list channel is always higher than other channels (i.e., 74%). It is true for all the $R_1 \rightarrow R_j, i \neq j$ pairs. From this observation, it is evident that *ML* has maximum contribution in causing the state change. Interestingly, emotion agreement with tweets coming from other (*OL*) channels is negligible. It shows that users are mostly influenced by tweets coming from either member list and following. Between member-list and following-list, member-list significantly dominates the following-list.

6.3 Which Conversational Characteristics Are More Influential during Emotion State Transition?

Individuals also receive tweets through conversational characteristics such as *Re-tweet, Hashtag, Reply,* and *Mention.* Which one of these is more influential in causing state transition? To acknowledge the above question, we investigate distribution of dominant emotion states over these channels in Figure 9. We calculate the total average probability of agreeing with different conversational characteristics over all topics in different categories. Like above, each bar in Figure 9 shows the

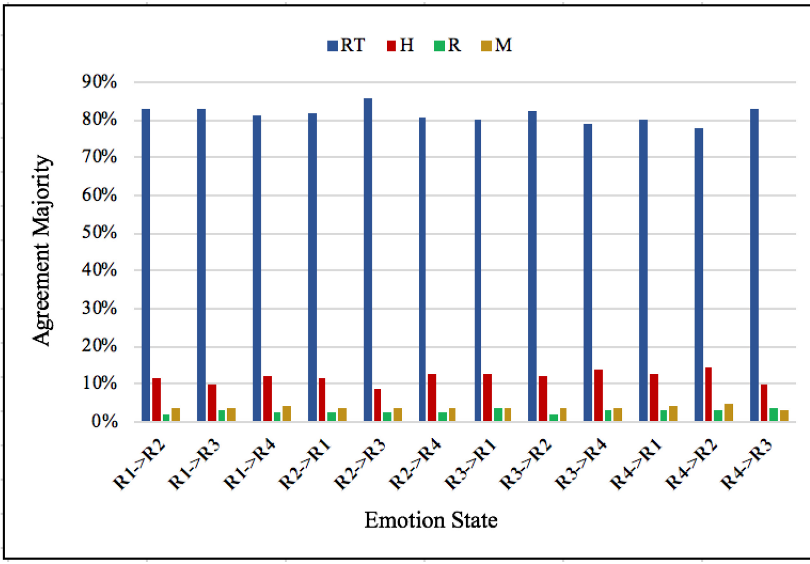


Fig. 9. Average probabilities of conversational agreement over all topics.

percentage of the instances of agreement with the majority in each characteristic against different possible state transition $R_i \rightarrow R_j, i \neq j$. It is evident from the figure that if an individual changes their emotion state from one region to another, then the retweet contributes the most with about 81% on average over all transitions. Further, hashtags contribute about 10%. The contribution from the reply and mention are negligible.

7 CONCLUSION

This article analyzes the emotion dynamics of users while posting public opinion through Twitter. This study has considered a dataset consisting of 17.65M tweets with about 69.36K users over 12 different topics. From this dataset, emotion dynamics of 12.91K users who have posted at least two tweets have been studied. Analysis has been investigated from three different perspectives: the user's emotion transition, the influence of the emotion of public opinion on an individual's opinion, and social parameters causing a change in an individual's opinion. First, we observe that 63% of the users change their opinion against a topic. People who share positive emotion against topics are likely to stay in the same emotional state in his/her subsequent tweets. Users in the highly negative state have the highest probability of changing state. If users change their emotional state, the probability of changing towards the highly positive state is higher than the probability of changing towards the highly negative state. It is observed that tweets coming from the member community have higher influential capability than the tweets coming from the follower community and other sources. Further, it is also observed that retweets can influence users more than hashtags, replies, and mentions.

To investigate systematically, we perform three different experiments over several categorical social topics/events on Twitter. First, we perform emotion state transition over entire conversation. Focusing on user emotion transition helps others to find someone's indisputable interest on the topic in the future. From the transition, we infer that people show positive opinion in their conversation, except for *Terrorism Attack* topics. We also infer that at the initial stage, people show high positive emotion; and while continuing their conversation, most people go towards a high positive direction. Second, we perform an analysis to understand influential characteristics of different channels over a user's opinion by estimating the incoming emotion state coming through a channel. From this analysis, we infer emotion state of a significant number of posts do not influence the dominant emotion on the social network. Finally, we investigate the influential characteristics towards state transition by approaching three types of cases (whole incoming tweets, community channels, and conversational characteristics). From this investigation, we infer that the majority of people agree with positive emotion when users change their emotion state from negative to positive. As a result, it is significant that the majority of people of state transition potentially reflect possible influence of changing state from the dominant incoming emotion.

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