4-2015

Measuring user influence, susceptibility and cynicalness in sentiment diffusion

Roy Ka-Wei LEE
Singapore Management University, roylee.2013@smu.edu.sg

Ee Peng LIM
Singapore Management University, eplim@smu.edu.sg

DOI: https://doi.org/10.1007/978-3-319-16354-3_45

Citation

LEE, Roy Ka-Wei and LIM, Ee Peng. Measuring user influence, susceptibility and cynicalness in sentiment diffusion. (2015). *Advances in Information Retrieval: 37th European Conference on IR Research, ECIR 2015, Vienna, Austria, March 29 - April 2, 2015. Proceedings*. 9022, 411-422. Research Collection School Of Information Systems.
Available at: https://ink.library.smu.edu.sg/sis_research/2453

Measuring User Influence, Susceptibility and Cynicalness in Sentiment Diffusion

Lee Ka-Wei Roy and Lim Ee-Peng

Living Analytics Research Centre *,
Singapore Management University
{roylee.2013,eplim}@smu.edu.sg

Abstract. Diffusion in social networks is an important research topic lately due to massive amount of information shared on social media and Web. As information diffuses, users express sentiments which can affect the sentiments of others. In this paper, we analyze how users reinforce or modify sentiment of one another based on a set of inter-dependent latent user factors as they are engaged in diffusion of event information. We introduce these sentiment-based latent user factors, namely *influence*, *susceptibility* and *cynicalness*. We also propose the *ISC model* to relate the three factors together and develop an iterative computation approach to derive them simultaneously. We evaluate the ISC model by conducting experiments on two separate sets of Twitter data collected from two real world events. The experiments show the top influential users tend to stay consistently influential while susceptibility and cynicalness of users could changed significantly across events.

Keywords: Twitter network, sentiment diffusion

1 Introduction

Motivation. Psychological research had shown that emotion induces and boosts social transmission of information [1, 11, 12]. In the context of online social networks, social transmission occurs mainly in the form of information diffusion. As social media becomes pervasive and users spend much time using them, it is now both important and feasible to study sentiment and user behavioral characteristics in information diffusion.

People generally believe that content with negative sentiment diffuse more readily than content with positive sentiment. Thelwall et al found that negative sentiment strength is more prevalent for popular events mentioned in Twitter [15]. Stieglitz and Linh conducted a study of political tweets and found that sentiment-charged tweets are more likely to be retweeted than neutral ones [14]. Tumasjan et al performed research on predicting the German Federal election outcome using sentiment charged tweets from Twitter users. They found that

* This research is supported by the Singapore National Research Foundation under its International Research Centre @ Singapore Funding Initiative and administered by the IDM Programme Office.

the online sentiments closely follow the political landscape of Germany during the period of time [16].

Most of the above studies, however, only considered the effects of the sentiment in tweet content, while neglecting the effects of user characteristics on driving the outcome of diffusion with sentiments. Consider the following scenario. When a user v expressed a sentiment towards a piece of content introduced to him by a friend, there are two possibilities. The first is that *there is no sentiment in the original content.* The sentiment from v is new suggesting that v has intrinsic sentiment towards the content. The second possibility is that *sentiment is found in the original content.* In this case, the sentiment from v can be affected by the sentiment-charged content from his friend. How likely v expresses sentiment and what sentiment polarity v would adopt for the incoming content would depend on the characteristics of both him and his friend.

Research objectives and contributions. In this paper, we aim to identify and model latent user characteristics that contribute to sentiment-charged content diffusion in a social network. In other words, we focus on the cases whereby users express sentiments after receiving content that carries sentiment. The adoption of same sentiment polarity by v from his friend (say u) may be due to: (i) the influential personality of u, (ii) the susceptibility of v to follow the sentiment polarities from others, or (iii) v's intrinsic sentiment polarity towards the diffused content. If v adopts a sentiment polarity opposite to that of the content diffused from u, this again may be due to: (i) the influential power of u, (ii) the cynicalness of v, and (iii) v's intrinsic sentiment polarity towards the diffused content. The three latent user characteristics, influence, susceptibility and cynicalness, are the focuses of this research. The intrinsic sentiment of v towards diffused content is a user-topic specific characteristics. In this research which focuses on user characteristics only, we assume that u is intrinsically neutral on any diffused content, and leave the user-topic characteristics to our future work.

We will focus on quantifying the three user characteristics, influence, susceptibility and cynicalness. We define the influence of a user to be how easy he or she could swing the sentiments of other users towards his, the susceptibility to be how easy the user adopts the same sentiments diffused by other users, the cynicalness to be how easy the user adopts opposing sentiments diffused by other users. The inter-dependency among the three user characteristics suggests that we need a model that derives them altogether. The scenario here is similar to HITS model where both authority and hub characteristics of web pages are to be measured together[7]. Our problem context is relatively more complex as there are three quantities to be measured. The involvement of content and sentiment polarity further complicates the model definition.

This work improves the state-of-the-art of user modeling in sentiment diffusion. To the best of our knowledge, there has not been any other work addressing the same research, i.e., considering sentiment diffusion in user characteristics modeling. Our main contributions in this work are as follows:

- We introduce user influence, susceptibility and cynicalness as the latent user characteristics affecting sentiment diffusion. These user characteristics are quantifiable and they together help to explain sentiment diffusion.
- We propose a novel model called ISC that utilizes the inter-dependency between the three characteristics to measure their corresponding values simultaneously.
- We develop an iterative computation algorithm to compute the model. The algorithm is simple and be easily implemented.

We also applied the proposed model and conducted a series of experiments on two separate Twitter datasets from two highly discussed real world events. Some of the interesting findings from the experiments include:

- Vast majority of users are non-influential, non-susceptible, and non-cynical.
- The top influential users, which are mainly news media and celebrities, tend to remain consistantly influential across the two real world events.
- The susceptibility and cynicalness of users could change significantly across events.

Paper outline. The rest of the paper is organized as follows. Section 2 reviews the literature related to our study. Section 3 presents our proposed ISC model for user characteristics relevant to sentiment diffusion. The experiments on the Twitter datasets gathered for two real world social events are described in Section 4. Section 5 highlights the experiment results and analysis before the conclusion in Section 6.

2 Related Work

The effects of emotions on information diffusion has been examined in both the psychology and information systems fields. Berger, in his psychological research, showed that emotions characterized by high arousal such as anxiety or amusement are likely to boost social transmission of information more than emotions characterized by low arousal such as sadness or contentment [1]. Other psychological researchers had also conducted similar experiments and obtained similar findings [11, 12].

In computer science, a number of research projects studied the effects of emotion in information diffusion for social networks such as Twitter. Stieglitz and Linh conducted a research study on political tweets in Twitter and found that sentiment-charged tweets are more likely to be retweeted than neutral ones [14]. Hansen et al, in their work, shown that negative news contents and positive non-news content are more likely to be retweeted by users in Twitter network [4]. Other research works had also shown that popular life events tend to generate more sentiment-charged tweets [15, 2]. These studies, though extensive, did not cover the latent user characteristics that contribute to sentiment diffusion.

There are some recent studies on latent user characteristics in information diffusion for social networks. Hoang et al proposed to measure the virality of Twitter users by their efforts in tweeting and retweeting viral tweets [6]. Janghyuk et al also conducted a study to measure the virality of a user in a marketing campaign by the amount of time taken by the user's friends to respond to the user's recommendation, and the number of unique friends that the user sends his recommendation after adopting an item [8]. Besides measuring virality of users, there are also research works on the susceptibility of users adopting an item in information diffusion [5]. Unlike these works, our paper considers sentiment in defining user characteristics. Hence, these user characteristics are unique. In particular, we introduce susceptibility and cynicalness according to the user's tendency to change of sentiment polarity.

3 User Model for Sentiment Diffusion

In this section, we introduce our proposed user model for sentiment diffusion. We first define sentiment diffusion as an instance of sentiment diffusing from one user to another. Based on a collection of sentiment diffusions, our proposed user model is then defined.

3.1 Sentiment Diffusion Representation

Tracking sentiment diffusion in the midst of many tweets received and generated by users is non-trivial. An approach to this is to focus on diffusion via retweeting whereby a user is said to be diffused when he retweets an incoming tweet. This approach is however very restrictive in the context of sentiment diffusion as it does not account for the case whereby the user generates a new "relevant" sentiment-charged tweet (instead of a retweet) after receiving an incoming sentiment-charged tweet. To identify the tweets (which also include retweets) relevant to sentiment diffusion, we have chosen to define sentiment diffusion for an event accordingly. In our experiments, we determine event tweets by a combination of event relevant keywords and user community. Similar and more sophisticated techniques [13, 3, 17] to find event tweets are available but are outside the scope of this paper.

We represent a set of users $i \in U$ and their *follower-followee* relationships by a directed graph $G = (U, E)$. A directed edge $(v, u) \in E$ represents v follows u. Here, an item refers to a tweet and the item sentiment x refers to the sentiment of a sentiment-charged tweet. Sentiment charged tweets, in the context of this study, are tweets that reveal the polarity, i.e. positive, negative or neutral, of the publishing user's sentiment on a certain event. We let $X(u)$ to denote the set of item sentiments that user u adopts. We give more notations and their definitions in Table 1.

Figure 1 illustrates an example of sentiment diffusion. User u adopts a positive (+) item sentiment while users $v1$ and $v2$, who are followers of u, had previously adopted neutral (0) item sentiment. Subsequently, $v1$ follows u's sentiment polarity and adopts a positive item sentiment while $v2$ adopts a negative

Table 1: Notation

$x(v)$	Item sentiment x adopted by user v before diffusion
$x'(v)$	Item sentiment x adopted by user v after diffusion
$X(u)$	Set of item sentiments adopted by user u
$X_d^{\rightarrow}(u)$	Set of item sentiments diffused by user u
$X_{ds}^{\leftarrow}(v)$	Set of item sentiments diffused to user v and v adopts the same item sentiment
$X_{do}^{\leftarrow}(v)$	Set of item sentiments diffused to user v and v adopts the opposite item sentiment
$X_i^{\leftarrow}(v)$	Set of item sentiments introduced to user v
$F_d^{\rightarrow}(u,x)$	Set of followers whom user u diffuses item sentiment x to
$F_{ds}^{\leftarrow}(v,x)$	Set of followees who diffuse item sentiment x to user v and v adopts the same item sentiment
$F_{do}^{\leftarrow}(v,x)$	Set of followees who diffuse item sentiment x to user v and v adopts the opposite item sentiment
$F_r(u)$	Number of followers of user u
$F_e(u)$	Number of followees of user u
$d^{\rightarrow}(u)$	Number of times user u diffused sentiment to his followers
$d^{\leftarrow}(u)$	Number of times user u is diffused sentiment by his followees

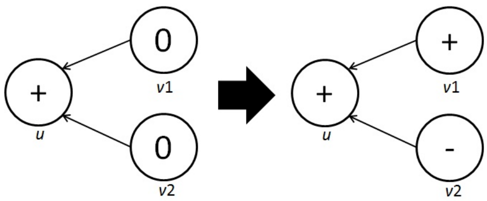

Fig. 1: Sentiment Item Diffusion

$(-)$ item sentiment which is opposite to u's. At the point of $v1$ and $v2$'s sentiment adoption, the positive $(+)$ item sentiment adopted by user u was the latest received tweet on $v1$ and $v2$'s Twitter timelines.

We say that u diffuses item sentiment x to v, if all the following conditions hold:(1) u adopts x before v adopts the same or opposing item sentiment x'. (2) v is a follower of u when v adopts x'. (3) u's tweet with sentiment x is the latest received tweet on v's Twitter timeline.

We assume that each user may receive and generate multiple item sentiments relevant to the same event. As a user adopts a sentiment item, he also introduces the item sentiment to his followers. A user can therefore diffuse item sentiments from multiple followees to multiple followers. We denote the set of item sentiments diffused by u to his followers by $X_d^{\rightarrow}(u)$. We also use $X_{ds}^{\leftarrow}(v)$ to denote the set of item sentiments diffused to v by his followees and v adopts the same sentiment polarities, and $X_{do}^{\leftarrow}(v)$ to denote set of item sentiments diffused to v and v adopts the opposite sentiment polarities. Every item sentiment $x(u)$ from user u has a value of 1 if x is positive, -1 if x is negative and 0 if x is neutral.

3.2 Proposed User Model

Sentiment diffusion in a network is an outcome of interactions among users. Depending on the characteristics of the diffusing and diffused users, the sentiment diffused may change accordingly. Thus, we propose a **Influence-Susceptibility-Cynical (ISC) Model** that measures user influence, susceptibility and cynicalness simultaneously based on a set of principles that help to distinguish each latent user characteristics from others. The three principles are:

- An influential user can get others, particularly the non-susceptible users and cynical users, to change and adopt the same item sentiment diffused by him.
- A susceptible user adopts same sentiments with sentiment-charged items diffused to him by non-influential users.
- A cynical user adopts opposite sentiments with sentiment-charged items diffused to him by non-influential users.

We denote the influence, susceptibility and cynicalness of a user u by $I(u)$, $S(u)$ and $C(u)$ respectively. $I(u)$ is assigned a value between 0 (denoting non-influential user) and 1 (denoting most influential user). The same applies to $S(u)$ and $C(u)$.

One of the important components of this study is the definition of change in sentiment of a follower v as a result of user u's influence. We represent this change in sentiment as $\triangle x(u, v)$ and introduce two functions to capture this change in sentiment. The first function, $f_s(x(u), x(v), x'(v))$, returns the change in sentiment when the follower v adopts same sentiment diffused by user u. Another function, $f_o(x(u), x(v), x'(v))$, returns the change in sentiment when follower v adopts the opposite sentiment diffused by user u. Both of the functions take in three parameters; $x(u)$ is the item sentiment value diffused by user u, $x(v)$ is initial item sentiment value adopted by follower v before the sentiment diffusion and $x'(v)$ is the item sentiment value adopted by v after the sentiment diffusion. Tables 2 and 3 show the definitions of $f_s(x(u), x(v), x'(v))$ and $f_o(x(u), x(v), x'(v))$ respectively. Unless specified in the tables, the function values are zero by default.

As shown in Table 2, the maximum change in sentiment (+2) is observed when v reverses his initial sentiment and adopted the same sentiment diffused by u. For example, v changes from an initial negative sentiment (-1) and adopts the same positive sentiment (1) diffused by u. In this example, the maximum change in sentiment is $|x'(v) - x(v)| = 2$. Likewise, If v changes from an initial neutral sentiment (0) and adopts the same positive sentiment (1) diffused by u, the change in sentiment is $|x'(v) - x(v)| = 1$. As a neutral sentiment diffused by u is not considered a strong sentiment, we assign a small value 0.5 to the change in sentiment when v changes from positive or negative to neutral sentiment due to the neutral sentiment diffusion by u. In contrast, Table 3 shows that the maximum change in sentiment is observed when v reverses his initial sentiment and adopts the opposite sentiment diffused by u. For example, v changes from an initial negative sentiment (-1) and adopts the opposite positive sentiment (1) diffused by u. i.e. maximum change in sentiment is $|x'(v) - x(v)| = 2$.

Table 2: Definition of $f_s(x(u), x(v), x'(v))$

$x(u)$	$x(v)$		
	1 (+ve)	0 (neutral)	−1 (−ve)
1 (+ve)	0	1 if $x'(v) = 1$	2 if $x'(v) = 1$; 1 if $x'(v)=0$
0 (neutral)	0.5 if $x'(v) = 0$	0	0.5 if $x'(v) = 0$
−1 (−ve)	2 if $x'(v) = -1$; 1 if $x'(v) = 0$	1 if $x'(v) = -1$	0

Table 3: Definition of $f_o(x(u), x(v), x'(v))$

$x(u)$	$x(v)$		
	1 (+ve)	0 (neutral)	−1 (−ve)
1 (+ve)	2 if $x'(v) = -1$; 1 if $x'(v) = 0$	1 if $x'(v) = -1$	0
0 (neutral)	0	0	0
−1 (−ve)	0	1 if $x'(v) = 1$	2 if $x'(v) = 1$; 1 if $x'(v) = 0$

We will use $f_s(x(u), x(v), x'(v))$ for $\triangle x(u, v)$ in influence and susceptibility score computation and $f_s(x(u), x(v), x'(v))$ for cynicalness computation.

In Equation 1, the *influence* of a user u is defined by the proportion of adopted items, $X(u)$, that are diffused, weighted by the proportion of diffused users having their sentiment influenced by u, $F_d^{\rightarrow}(u, x)$. Each diffused user v is further weighted by the change in sentiment of v due to u, $\triangle x(u, v)$, and the average of v's inverse *susceptibility*, $1 - S(v)$, and *cynicalness*, $C(v)$. To avoid giving high influence scores to users with very few followers diffusing sentiment well to the latter, we further weigh the influence score with $W_1(u)$, representing the amount of diffusing items from u as shown in Equation 4. N and M are large numbers to keep $W_1(u)$ within the range of $[0, 1]$. In our experiments, N and M are set to be 1000 (as 5% of users having at least 1000 followers) and 500 (as 5% of users have at least diffused sentiment to their followers for more than 500 times) respectively.

In Equation 2, the *susceptibility* of a user v is defined by the proportion of sentiment-charged items introduced to v , $X_i^{\leftarrow}(v)$, that are adopted with the same item sentiments by the set of users introducing the items, $F_{ds}^{\leftarrow}(v)$. Each user u who diffuses the sentiment-charged item to v is further weighted by the change in sentiment, $\triangle x(u, v)$, and his inverse *influence*, $1 - I(u)$. Finally, to avoid giving high susceptibility score to users with very few followees and getting diffused with sentiment, we introduce the weight $W_2(v)$ (see Equation 5) representing the amount of diffused items to. P and Q are large numbers to keep $W_2(v)$ within the range of $[0, 1]$. In our experiments, P and Q are set to be 1000 (as 5% of users having at least 1000 followees) and 20 (as 5% of users have at least been diffused sentiment by their followees for more than 20 times) respectively.

In Equation 3, the *cynicalness* of a user v is defined by the proportion of sentiment-charged items introduced to v, $X_i^{\leftarrow}(v)$, that are adopted with the opposite item sentiments by the set of users introducing the items, $F_{do}^{\leftarrow}(v)$. Each user u who diffuses the sentiment-charged item to v is further weighted by the change in sentiment, $\triangle x(u,v)$, and his inverse *influence*, $1 - I(u)$. Similar to susceptibility, we finally include the weight $W_2(v)$ (see Equation 5).

$$I(u) = \frac{W_1(u)}{|X(u)|} \cdot \sum_{x \in X_d^{\rightarrow}(u)} Avg_{v \in F_d^{\rightarrow}(u,x)} \Big(\triangle\, x(u,v) \cdot \frac{(1 - S(v)) + C(v)}{2} \Big) \tag{1}$$

$$S(v) = \frac{W_2(v)}{|X_i^{\leftarrow}(v)|} \cdot \sum_{x \in X_{ds}^{\leftarrow}(v)} Avg_{u \in F_{ds}^{\leftarrow}(v,x)} \big(\triangle\, x(u,v) \cdot (1 - I(u)) \big) \tag{2}$$

$$C(v) = \frac{W_2(v)}{|X_i^{\leftarrow}(v)|} \cdot \sum_{x \in X_{do}^{\leftarrow}(v)} Avg_{u \in F_{do}^{\leftarrow}(v,x)} \big(\triangle\, x(u,v) \cdot (1 - I(u)) \big) \tag{3}$$

$$W_1(u) = \frac{F_r(u)}{F_r(u) + N} \cdot \frac{d^{\rightarrow}(u)}{d^{\rightarrow}(u) + M} \tag{4}$$

$$W_2(v) = \frac{F_e(v)}{F_e(v) + P} \cdot \frac{d^{\leftarrow}(v)}{d^{\leftarrow}(v) + Q} \tag{5}$$

3.3 Model Computation

To compute the ISC model, we employ an iterative computation method. The algorithm first initializes $I(u)$, $S(u)$ and $C(u)$ for all users u's with 0.5. It then computes $I(u)$'s using the initial scores of $S(u)$'s and $C(u)$'s. The computed $I(u)$ values are then used to compute new set of values for $S(u)$ and $C(u)$. This process repeats until the values converge.

We found that the iterative computation method works well for our dataset and could achieve convergence in less than 50 iterations. The proof of convergence for this method is however difficult and we shall leave to the future research.

4 Datasets

In this section, we describe two Twitter datasets that were used to evaluate the ISC model. The first Twitter dataset contains tweets published by users from an asian city in a day within June 2013 where the city experienced the worse haze in its history. As the haze severely affected the livelihood of the local people and the local news media covered it widely, we expect strong sentiments and sentiment diffusion among the local Twitter users. The second Twitter dataset contains tweets published by the same set of users for an riot event which took place on in a day within December 2013. As riots in are rare in this city, the event attracted much attention and aroused strong sentiments within the local social media community. We again expect sentiment diffusion in the data which can be used in our experiments.

We first crawled tweet messages from about 150,000 Twitter users from the city on the events dates; on one day in June 2013 for the haze event and another day in December 2013 for the riot event. We selected tweets that contain keywords and hastags related to the events. These include "haze" and "worsehaze", etc., for the haze event and "riot", "police", etc., for the riot event. A total of 16,190 tweets generated by 5,570 users were collected for the haze event, while 18,933 tweets generated by the same set of 5,570 users were collected for the riot event. We also collected the follower-followee relationship among these users.

Next, we assign sentiment values to tweets using the sentiment classifier C_STANFORD, the Stanford's sentiment scoring API[1], which is widely used sentiment classifier based on maximum entropy. The training of the classifier makes use of tweets that are labeled based on positive and negative keywords and emoticons. The API returns a score of -1, 0, or $+1$ for a tweet detected to have positive, negative, or neutral sentiment respectively. We also assume that a user's previous published tweet was neutral when he published his first tweet.

5 Experiment Results

In this section, we discuss the results of the experiment by first examining the overall distribution statistics of *Influential, Susceptibility* and *Cynicalness* measures of users in both haze and riot events. Next, we compare the ISC model measures results of the two events using Pearson correlation and Jaccard similarity coefficient. Lastly we examine the characteristics of the influential users in greater detail and compare the ISC model influence measure with other traditional influence measures such as *In-Degree* and *PageRank*.

5.1 Distribution Statistics

Examining into the distribution of *influence*, *susceptibility* and *cynicalness* scores of users for both events, there are very few users have very high influence scores while majority of the users have very low or zero influence scores. The same can be said for susceptibility and cynicalness scores. This suggests that there are only few users who are highly influential, susceptible and cynical.

5.2 Comparision of Haze and Riot ISC Results

The pearson correlations of *influence*, *susceptibility* and *cynicalness* scores of users in the Haze and Riot events are 0.395, 0.045 and 0.034 respectively. The *influence* scores of users in the two events are more similar with each other than the other two measures. This suggests that influential users are consistently ranked in both events while the susceptibility and cynicalness of users changed significantly across events.

The same observation can be made in Table 4, which shows the Jaccard similarity coefficient between top k% for *influence*,*susceptibility* and *cynicalness*

[1] http://help.sentiment140.com/api.

Table 4: Jaccard similarity between top k% users in Haze and Riot events

k	Influence	Susceptibility	Cynicalness
1%	0.327	0.055	0.018
2%	0.227	0.073	0.036
3%	0.23	0.085	0.042
5%	0.182	0.116	-
10%	0.445	0.149	-
20%	0.785	0.212	-

Table 5: Comparison of top 1% influential users with average users

	Avg # followers	Avg # tweets	Avg # sentiment-charged tweets
All users	690	3	1
Top 1% users (haze)	22406	9	3
Top 1% users (riot)	22859	13	4

score users for both events. The Jaccard similarity coefficient for top 20% *influence* score users is 0.786, which suggest that most of the top 20% influential users remain highly influential between the two events. We observed some anomaly in the Jaccard similarity coefficient for top 2-5% *influence* score users. Examining into the data, we found that the top 1% influence score users tweeted intensively for both haze and riot event which resulted in some of them ranked highly for both events contributing to significantly higher Jaccard similarity coefficient. Whereas the top 2-5% users only tweeted intensively for only one of the two events, resulting in disparity for a user's ranking in two events and eventually a low Jaccard similarity coefficient. We did not compare the *cynicalness* score beyond top 3% because only 3% and 6% of the users have a non-zero *cynicalness* score for haze and riot event respectively.

5.3 Characteristics of Influential Users

As the influential users remain consistent across both events, we examine the characteristics of these users in greater detail. Table 5 shows the comparison between top 1% influential users with an average user. We observed that the top 1% influential users in both haze and riot events have an average of more than 20,000 followers, which is almost 30 times more than that of an average user. The top influential users also generate significantly more tweets than average users.

Table 6 shows the comparison of number of sentiment sent and diffused for top 1% influential users for In-Deg and ISC model. The number of sentiment sent by a user refers to the number of time the user's sentiment-charged tweets remain the first tweet on his follower's Twitter timeline at the point when his followers make a tweet. The number of sentiment diffused refers to the number of time the followers adopt the sentiments diffused by the user. We observed that although top 1% influential user under both measures have high average of

Table 6: Comparison of top 1% influential user for In-Deg and ISC model

	Avg Sentiment Sent (Haze)	Avg Sentiment Diffused (Haze)	Avg Sentiment Sent (Riot)	Avg Sentiment Diffused (Riot)
All users	5.52	0.045	6.585	0.034
Top 1% In-Deg	353.436	4.491	362.964	3.247
Top 1% ISC	334.566	5.438	368.127	3.833

Table 7: Pearson Correlation between Influence Measures

	INF_Riot	INF_Haze	In_Deg	PageRank
INF_Riot	1	0.395	0.475	0.597
INF_Haze	-	1	0.409	0.561
In_Deg	-	-	1	0.763
PageRank	-	-	-	1

sending sentiments to their followers, the influential users under the ISC model have a slightly higher average number of sentiment diffused to their followers.

5.4 Comparison of Influence Measures

Finally, we compare the influence measure of ISC model with other popular user influence measures, namely, *In-Degree* and *PageRank*. We define the *In-Degree* of a user by the number of his followers. *PageRank* defines the stationary probability of each user by performing a random walk from every user to his followees with equal transition probability.

Table 7 shows the Pearson Correlation between the different influence measures. The table shows that the *In-Degree* and *PageRank* are more similar with each other than the *Influence* measure in our proposed ISC model. Both the *In-Degree* and *PageRank* measures focus on the user's follower-followee relationships for computing user's influence. Although the ISC model's *Influence* measure considers the follower-followee relationships as well, it also considers the magnitude sentiment change when a user diffuses a sentiment item to his followers. This makes it more different from other influence measures.

6 Conclusion

In this paper, we propose a novel framework to model latent user characteristics that contribute to sentiment diffusion in a social network. We develop the ISC model to measure user influence, susceptibility and cynicalness simultaneously. The model determines how a user influences (or is influenced by) others by diffusing (or is diffused by) sentiment-charged tweets. We also propose the algorithm for implementing the model. We extract event relevant Twitter data for our experiment evaluation. Our experiment results have shown that different latent user characteristics can be derived from the observed sentiment diffusion. The ISC model however requires accuracy in sentiment analysis. In the future work, we can improve the accuracy of sentiment mining further to enhance the ISC model. We will also study more detailed emotions from users such as fear, anger, etc., in determining latent user characteristics.

References

1. J. Berger. Arousal increases social transmission of information. *Psychological Science*, 22(7):891–893, 2013.
2. J. Bollen, A. Pepe, and H. Mao. Modeling public mood and emotion: Twitter sentiment and socioeconomic phenomena. In *ICWSM*, 2011.
3. Deepayan Chakrabarti and Kunal Punera. Event summarization using tweets. In *ICWSM*, 2011.
4. L.K. Hansen, A. Arvidsson, F.A. Nielsen, E. Colleoni, and M. Etter. Good friends, bad newsaffect and virality in twitter. In *SocialComNet*, 2011.
5. T.-A. Hoang and E.-P. Lim. Virality and susceptibility in information diffusions. In *ICWSM*, 2012.
6. T.-A. Hoang, E.-P. Lim, P. Achananuparp, J. Jiang, and F. Zhu. On modeling virality of twitter content. In *ICADL*, 2011.
7. J.M. Kleinberg. Authoritative sources in a hyperlinked environment. *JACM*, 46(5):604–632, 1999.
8. J. Lee, J.-H. Lee, and D. Lee. Impacts of tie characteristics on online viral diffusion. *JAIS*, 24(1), 2009.
9. J. Leskovec, L.A. Adamic, and B.A. Huberman. The dynamics of viral marketing. *TWeb*, 1(1), 2007.
10. Y.-M Li, C.-H. Lin, and C.-Y. Lai. Identifying influential reviewers for word-of-mouth marketing. *ECRA*, 9:294–304, 2010.
11. O. Luminet, P. Bouts, F. Delie, A.S.R Manstead, and B. Rime. Social sharing of emotion following exposure to a negatively valenced situation. *Cognition and Emotion*, 14(5), 2000.
12. K. Peters, Y. Kashima, and A. Clark. Talking about others: Emotionality and the dissemination of social information. *European Journal of Social Psychology*, 39(2):207–222, 2009.
13. Takeshi Sakaki, Makoto Okazaki, and Yutaka Matsuo. Earthquake shakes twitter users: Real-time event detection by social sensors. In *WWW*, 2010.
14. S. Stieglitz and D.X. Linh. Emotions and information diffusion in social mediasentiment of microblogs and sharing behavior. *JMIS*, 29(4), 2013.
15. M. Thelwall, K. Buckley, and G. Paltoglou. Sentiment in twitter events. *JASIST*, 62(2):406–418, 2011.
16. A. Tumasjan, T.O. Sprenger, P.G. Sandner, and I.M. Welpe. Predicting elections with twitter: What 140 characters reveal about political sentiment. In *ICWSM*, 2010.
17. Wei Xie, Feida Zhu, Jing Jiang, Ee-Peng Lim, and Ke Wang. Topicsketch: Real-time bursty topic detection from twitter. In *ICDM*, 2013.