Modeling and Propagation Analysis on Social Influence Using Social Big Data

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Abstract. Although most existing models focus on the evaluation of social influence in online social networks, failing to characterize indirect influence. So we present a novel framework for modeling and propagation analysis on social influence using social big data. We design a method to transform the social big data into a social graph to characterize the connections between the social interaction and the spreading of short message service or multimedia messaging service (SMS/MMS) by using bidirectional weighted graph, and measure direct influence of individual by computing each node's strength, which includes the degree of node and the total number of SMS/MMS sent by each user to his/her friends. Then, we present an algorithm to construct an influence spreading tree for each node using the breadth first search algorithm, and measure indirect influence of individual by traversing the influence spreading tree. We extend the susceptible-infectious-recovery (SIR) model to characterize propagation dynamics process of social influence. Simulation results show that influence can spread easily in contact social network due to the good connectivity. The greater the degree of initial spread node is, the faster the influence spreads in social network.

Keywords: Social influence · Social big data · Influence evaluation · Influence propagation · Breadth first search · Propagation model

1 Introduction

Social networks [1] have been extensively used as an important communication media with exponential growth. Especially, 3G/4G and Web 2.0 technologies bring revolutionary changes to our daily lives in social networks. In the last decade, various social networks, such as Twitter, Facebook, LinkedIn, and smartphone-based 3G/4G communication networks, have emerged and tightly connected users all over the world. Users can use these networks to build their own friendship networks, and share their experiences, opinions, insights, information, and perspectives with each other. In addition, they can discover and

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propagate information by using various means, such as calls, messages, pictures, audios, and videos.

Social big data is a collection of very huge data sets of social networks with a great diversity (e.g., Twitter, Facebook, and LinkedIn). The 5V characteristics of social big data, including volume, velocity, variety, value, and veracity, make it difficult to handle such big data sets using traditional techniques, tools, and methods. Nowadays, the explosion of data in terms of high volume, high velocity, and high variety, fueled by stunning and exciting advances of the information technologies and web techniques, has become the focus of widespread attention. Applications of big data [2] lie in many scientific disciplines, such as biology, biogeochemistry, physics, medicine, astronomy, and so on.

Social influence [3] refers to the case that individuals change their behaviors under the influence of others. The strength of social influence depends on the relationship among individuals, the timing effect, the network distances, the characteristics of networks and individuals, etc. Lots of applications in real-world, such as viral marketing [4], online advertising and recommendation [5], can benefit from social influence by measuring quantitatively the influence of individuals or groups.

Social influence modeling and propagation analysis has become an important research topic in social networks. Thus, many efforts have been recently made to model social influence in social networks. Some schemes on social influence have been topic-oblivious [4,6–9]. In these models, social influence was measured either via the relative authority of individuals in their social network, or via the degree of information diffusion with the social network. Some schemes on evaluation of social influence have been topic-based [10–15]. In these models, social influence was measured by counting how much information related to a topic may be propagated in the network. In addition, some schemes are based on pairwise influence [5,16–20], which is defined on social ties and interactions between users.

It is still not well understood what fundamental rules the evaluation models for social influence must follow, although lots of existing methods for evaluation modeling and propagation analysis on social influence are available. Without a good answer to this question, the research for the evaluation modeling and propagation analysis on social influence is still not solid.

Motivated by this, we present a novel method for evaluation modeling and propagation analysis on social influence using social big data. First, we measure the direct influence of individual by computing each node's strength, which includes the degree of node and the total number of short message service or multimedia message service (SMS/MMS) sent by each user to his/her friends. Then, we use the breadth first search algorithm to construct an influence spreading tree for each node, and measure the indirect influence of individual by traversing the influence spreading tree. Our purpose is to develop a general method, which demonstrates the indirect influence of each individual on a given influence spreading tree. Our contributions are summarized as follows:

- We design a novel model to transform the social big data into a social graph, which represents the connections of social interaction and the spreading of short message service or multimedia messaging service (SMS/MMS). The social network graph is constructed using bidirectional weighted graph based on the real-world SMS/MMS-based big data set from people's daily lives for social interactions.
- We propose a new algorithm to measure social influence, includes both direct influence and indirect influence. The direct influence of individual is measured with the degree of node and the total number of SMS/MMS, and the indirect influence of individual is measured by traversing the influence spreading tree, which is constructed with the breadth first search algorithm.
- We also extend the susceptible-infectious-recovery (SIR) model to characterize propagation dynamics process of social influence under the selection of the top k influential nodes. Extensive experiments show that the greater the influence of initial spread node is, the more impact on the propagation of social influence in social networks.

The remainder of this paper is organized as follows: In Sect. 2, we provide a survey of related work, and provide evaluation modeling on social influence in Sect. 3. In Sect. 4, we provide an analysis of social influence propagation, and describe the experimental evaluation in Sect. 5. Finally, we conclude this paper and suggest future work in Sect. 6.

2 Related Work

In this section, we investigate related work in three dimensions. The first dimension is the topic-oblivious influence evaluation model; the second is related to the topic-based influence evaluation model; and the last is related to the pairwise-based influence evaluation model.

Domingos and Richardson [4] investigated social influence in the customer network. They proposed a model to identify customer's influence between each other in the customer network, and built a probabilistic model to mine the spread of influence for viral marketing. Li and Gillet [6] measured the academic influence of scholars based on the scientific impact of their publications using three different measures, and investigated their social influence using network centrality metrics. Sathanur and Jandhyala [7] investigated the information-theoretic measure called transfer entropy as a measure of directed causal influence in online social interactions. Wang et al. [8] presented a model, called dynamic social influence model, which simulates such social influencing processes that people dynamically change their attitudes when they communicate and exchange ideas with others. Ye et al. [9] presented a probabilistic generative model, namely social influenced selection, that explicitly quantifies and incorporates social influence from friends to a user.

Dietz et al. [10] presented a probabilistic topic model to explain the generation of documents. This model incorporated the aspects of topical innovation and topical inheritance via citations to predict the citation influences. Ding et al. [11] measured the influence of users using random walks on the multi-relational data (i.e. the retweet, the reply, the reintroduce, and the read) in Micro-blogging. Sang and Xu [12] presented a multimodal topic-sensitive influence model, which enables simultaneous extraction of node topic distribution, topic-sensitive edge strength, and the topic space. Tang et al. [13] studied a problem of conformity influence analysis in large social networks. They defined three major types of conformities to formulate the problem of conformity influence analysis. Cui et al. [14] presented a Hybrid Factor Non-Negative Matrix Factorization approach for modeling item-level social influence. Herzig et al. [15] presented an Author-Reader Influence model to evaluate the influence of various users on others by applying a retrospective analysis from an ordinary reader's point of view.

Peng et al. [16] introduced two factors to evaluate influence of each node. One factor is intimacy degree (ID), which is used to reflect the closeness between users. The other factor is activity degree (AD), which is used to determine which node is more active. Aral and Walker [17] presented a method by using vivo randomized experimentation to identify influence and susceptibility in networks. Su et al. [18] designed an algorithm based on the PageRank algorithm, called InfluentialRank, which calculates the influence of nodes based on the following relationship of users, retweet behaviours, and users' interests. Li et al. [19] presented a conductance eigenvector centrality model to measure peer influence in social networks. Phan et al. [20] presented the Topic-aware Community-level Physical Activity Propagation model, to capture the social influences of messages in the YesiWell study.

3 Evaluation Modeling on Social Influence

Social influence is a relationship established between two entities for a specific action. In particular, one entity influences the other to perform an action. For example, in a SMS/MMS-based social network, user u may influence v by sending SMS/MMS to v in daily social interactions. In this paper, the first entity is called the *influencer*, and the second one is called the *influencee*.

Definition 1 *[Direct Influence]***:** *Given two individuals u and v in a SMS/MMS-based social network, who are directly connected each other in the network, u has the effect of change in the opinion of v in a direct way. Let $DI_u(t)$ denote the direct influence of user u on its one-hop friends.*

Definition 2 *[Indirect Influence]***:** *Given two individuals u and v in a SMS/MMS-based social network, who are not directly connected in the network, u has a indirect impact on v. Let $II_{uv}(t)$ be the indirect influence of user u on v.*

Definition 3 *[Global Influence]***:** *Given a SMS/MMS-based social network, u exerts the power over the whole network, $I_u(t)$ is defined as the global influence of u at time t, which represents the global influential strength of u over the whole network.*

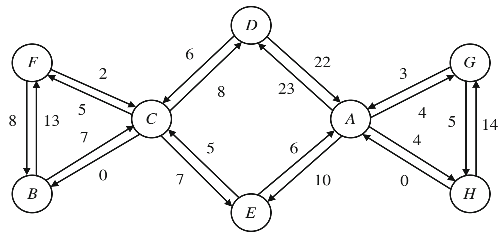

Fig. 1. A bidirectional weighted graph for social interactions in a week.

Table 1. The number of interactions between two cellular phone users in a week

Between two smartphones	The number of interactions	Between two smartphones	The number of interactions
$A \rightarrow D$	23	$D \rightarrow A$	22
$A \rightarrow E$	10	$D \rightarrow C$	6
$A \rightarrow G$	4	$E \rightarrow A$	6
$A \rightarrow H$	4	$E \rightarrow C$	5
$B \rightarrow C$	7	$F \rightarrow B$	8
$B \rightarrow F$	13	$F \rightarrow C$	2
$C \rightarrow B$	0	$G \rightarrow A$	3
$C \rightarrow D$	8	$G \rightarrow H$	5
$C \rightarrow E$	7	$H \rightarrow A$	0
$C \rightarrow F$	5	$H \rightarrow G$	14

3.1 Modeling on Smartphone Social Network

We model a mobile social network by a bidirectional weighted graph, $G(V, E_{ij}, W_{ij})$, where set V of vertices corresponds to the smartphones in cellular networks, set E_{ij} of directed edges corresponds to the traffic flow between any two cellular phones i to j, and set W_{ij} of weight values corresponds to the total number of SMS/MMS messages sent from cellular phone i to j in a given time period. In order to explain the idea of a smartphone social network, we take eight users from the data set and use them as an example. The data of this sample social network is listed in Table 1. According to Table 1, we treat each smartphone as a vertex, so a bidirectional directed, weighted social relationship graph can be obtained and is shown in Fig. 1.

3.2 Measuring Social Influence

(1) Computing direct influence

Let N be the total number of nodes in mobile phone based social networks, $N_i(t)$ be the number of one-hop friend nodes of node i in time t, and $C_{ij}(t)$ be the number of interactions between node i and k in time t. Thus, the total direct influence of i on its one-hop friend nodes is described as follows.

$$DI_i(t) = \omega_1 \frac{N_i(t)}{\max\{N_u(t)\}} + \omega_2 \frac{\sum_{k \in N_i(t)} C_{ik}(t)}{\max\{\sum_{v \in N_u(t)} C_{uv}(t)\}}, \tag{1}$$

where $i, k, u, v \in N$, $\omega_1 + \omega_2 = 1$.

(2) Constructing influence spreading tree

To characterize an individual exerting the power over the whole network, besides considering direct influence on its one-hop friend nodes, we also need to measure indirect influence on its two-hop friends or above. In this paper, we use the breadth first search algorithm to construct an influence spreading tree for each node for measuring the indirect influence of each individual by traversing the influence spreading tree.

To construct an influence spreading tree for each node, the each directed edge weight λ_{ik} is normalized as follows.

$$\lambda_{ik} = C_{ik}(t)/\max\{C_{uv}(t)\}, \tag{2}$$

where $i, k, u, v \in N$.

The construction algorithm of influence spreading tree is shown in Algorithm 1.

(3) Computing on indirect influence

According to Algorithm 1, the influence spreading tree of each node is obtained, and then we can measure the indirect influence of each nodes. For example, let r be the root node for a influence spreading tree. The influence of

Algorithm 1. Construction algorithm of influence spreading tree for all nodes.

Input: A social network $G(V, E, W)$ with total number of nodes N;
Output: A set of influence spreading trees T;

```
Network initialization. Compute direct influence for each node i using Equation
(1), and normalize each directed edge weight using Equation (2);
for i=1 to N do
    Add i into an empty queue Q_i;
    Build influence spreading tree T_i for node i, set i as root node in T_i;
    while Q_i is not empty do
        Pull out a node v in Q_i, find node u through which can obtain a path p from
        root node to i, which has maximum ∏_{e∈p} λ_e (λ_e is weight of edge e in p);
        Add v into T_i under the corresponding parent node u;
        Add all neighbors of node v into queue Q_i;
    end while
    Add T_i into T;
end for
return T;
```

root node r on its child j in the tree is denoted by $RI_{rj}(t)$, which is described as follows.

$$RI_{rj}(t) = \begin{cases} \lambda_{rj}, \\ \text{if } j \text{ is a child of root node } r; \\ (RI_{ri}(t)/Br_i(t)) \times \lambda_{ij}, \\ \text{if } j \text{ is not a child of root node } r, \\ \text{but is a child of } i; \end{cases} \tag{3}$$

where $RI_{ri}(t)$ denotes the influence of i on j, $Br_i(t)$ denotes the number of children of i, i and j belong to the same tree whose root node is r.

Thus, the indirect influence of r is described as follows.

$$II_r(t) = \sum\nolimits_{j \in R_r(t)} RI_{rj}(t), \tag{4}$$

where $R_r(t)$ denotes the set of non-direct reachable nodes of r in time t.

(4) Total influence of node

According to the above analysis, the total influence $I_i(t)$ of i is described as follows.

$$I_i(t) = \omega_3 DI_i(t) + \omega_4 II_i(t), \tag{5}$$

where $\omega_3 + \omega_4 = 1$.

The complete computing process of influence for all nodes is shown in Algorithm 2.

Algorithm 2. Influence computing algorithm for all nodes.

Input: A social network $G(V, E, W)$ with total number of nodes N, a set of influence spreading trees T;
Output: Global influence of each node;
for i=1 to N **do**
  Compute direct influence for each node i using Equation (1);
  Access influence spreading tree T_i for node i, set $II_i(t) = 0$;
  Add root i into an empty queue Q_i;
  while Q_i is not empty **do**
    Pull out a node k in Q_i;
    if k is not a one-hop neighbor of i **then**
      Compute indirect influence $RI_{ik}(t)$ using Equation (4), $II_i(t) = II_i(t) + RI_{ik}(t)$;
    end if
  end while
end for
return The global influence of each node;

According to Algorithm 1, we can construct an influence spreading tree for each node. Let us take Fig. 1 as an example, the influence spreading tree of node E is shown in Fig. 2.

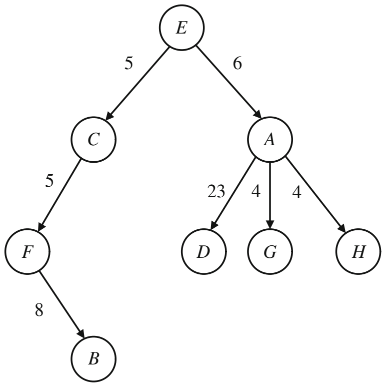

Fig. 2. Influence spreading tree of node E.

4 Analysis of Social Influence Propagation

According to the strength of social influence of individual, we use the minimum heap algorithm to select top k influential nodes. Then, we use SIR model to characterize propagation dynamics process of social influence under the immunization of the top k influential nodes in networks. The pseudo code of the mining algorithm for top k influential nodes is shown in Algorithm 3.

Algorithm 3. Mining algorithm for top k influential nodes.

Input: A social network $G(V, E, W)$ with total number of nodes N, the number of k, $\mathbf{K} = \emptyset$;
Output: A set of top k influential nodes;
1: Calls Algorithm 1 to build influence spreading tree for all nodes;
2: Calls Algorithm 2 to compute social influence for each node;
3: Selects the top k influential nodes by sorting the strength of social influence with minimum heap algorithm;
4: Adds these nodes into $\mathbf{K}$;
5: **return** $\mathbf{K}$.

It is well known that the classical influence diffusion models [4] in social networks include linear threshold model (LTM), independent cascade model (ICM), and weighted cascade model (WCM). However, influence diffusion model can also be seen as a specific case of the traditional epidemic models. In [21], SIR model was described in detail. In this paper, we extend SIR model to conduct the analysis of social influence spreading. It is shown in Fig. 3.

According to the spread property of virus in mobile social networks, the epidemic state of a node is divided as follows:

(1) Susceptible state (S): nodes have not been infected by any virus in the network but are prone to infection.

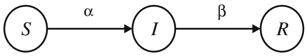

Fig. 3. SIR model.

(2) Infectious state (I): nodes have been infected by viruses in the network and they may infect nodes in state S.
(3) Recovered state (R): nodes that used to be infected by viruses have, and now recovered from the infection. Those nodes are cleaned and immune to the same type of cleaned viruses.

Due to that the SIR model can be mapped to the edge percolation process, many researchers use the SIR model to simulate the process of information and virus diffusion. In addition, the SIR model can be used to understand the influence propagation process and to obtain the exact solution for the theoretical analysis of the influence propagation process. In recent years, many researchers [22] have carried out a series of improvement and promotion of the SIR model, which makes it closer to the real propagation law, and more useful for the weighted directed graph. These analysis and studies have gained many new conclusions about the characteristics of dynamics propagation of information and virus.

Thus, we exploit the SIR model to evaluate the spreading ability of individual. In SIR epidemic model, we suppose a susceptible individual i (i.e. influencee), after successful contact with an infectious individual j (i.e. influencer), becomes infected. The above phenomenon shows that j influences i. Let α denote the probability with which a node in state S becomes a node in state I, β denote the probability with which a node in state I becomes a node in state R, and TT denote the transmission threshold through which a node i transforms from state S to state I. The rule for a node may change its states as follows.

(1) If an infected node u contacts with a susceptible node v, v may changes its state from S to I with probability α.
(2) If an infected node u contacts with a recovered node v, v may changes its state from I to R with probability β.
(3) The propagation process of infected nodes will not spread forever, and it will stop when these nodes change their states from I to R with a specific velocity V. According to the above transition rule of node state, the state transition algorithm is shown in Algorithm 4.

5 Performance Evaluation

To validate the effectiveness of the proposed model, we conduct extensive experiments using the message records collected by one of the largest cellular networks in China. In addition, we designed and developed a C# simulator to implement

Algorithm 4. State transition algorithm for all nodes.

Input: A social network $G(V, E, W)$ with total number of nodes N, a set of most influential k nodes;
Output: Influence spread in time t in a social network for a given set of most influential k nodes;

Network initialization. Compute social influence for each node i using Algorithm 2;
Node state initialization. The most influential k nodes are selected, and their states are set to be state I, and the states of other nodes are set to be state S;
Node i is accessed at time t, thus
while $i \leq N$ **do**
  if (The state of i is I) **then**
    The 1-hop and multi-hop neighbor nodes of i are accessed according to the influence spreading path;
    while $j \leq N_i$ **do**
      if (The state of its friend node j is S) and ($I_j(t)$ is not smaller than TT) **then**
        Node j changes its state from S to I with probability α;
      else
        Node j remains in its previous state;
      end if
    end while
    Node i changes its state from I to R with probability β;
  end if
end while
t equals to t plus Δt;

our proposed mechanism, which is an extension of the proposed model. Due to the huge scale of the real-world big data set, we preprocessed the big data set and took 119268 users (i.e., they are in same contact social network) for our experiments, rather than including all the users.

The influence diffusion is a metric to measure how many users can be influenced by the most influential k specific users (or called seed nodes). To test the influence spread, we use Algorithm 4 to propagate social influence. To obtain the influence spread of each model, we first select top k = (30, 50, 70, 90, 110) influential nodes as seeds, respectively. Besides degree centrality model, climb greedy model, set cover model, influence evaluation model, we also implement a random model as the benchmark, which selects seeds randomly.

Figure 4 shows the influence spread of the social influence evaluation model with different k and different infected probability α at time t. As can be seen from the results, as the value of k increases, the number of influence spread increases. The reason is the higher the most influential nodes, the more nodes can be influenced.

Figures 5 and 6 show the influence spread of different models with $k = 200$ influential nodes and $k = 300$ influential nodes, respectively, with infected probability $\alpha = 0.2$, at time t. From the results, it is can be seen that the influence

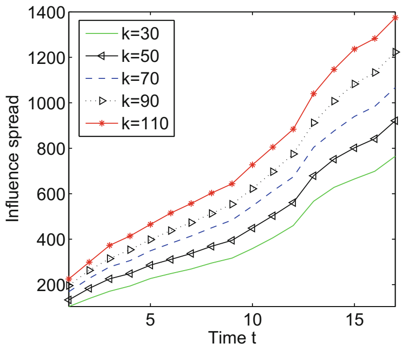

Fig. 4. A comparison of influence spread of the social influence evaluation model with different k influential nodes with infected probability ($\alpha = 0.2$).

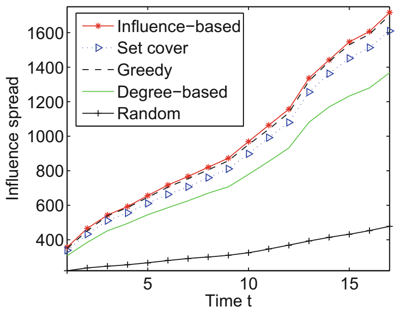

Fig. 5. A comparison of influence spread of different models with $k = 200$ influential nodes with infected probability ($\alpha = 0.2$).

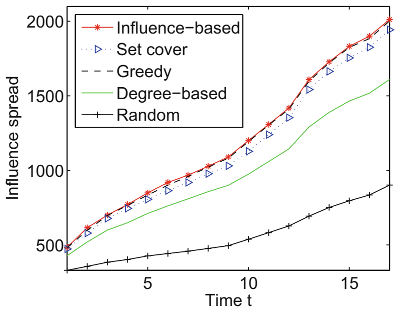

Fig. 6. A comparison of influence spread of different models with $k = 300$ influential nodes with infected probability ($\alpha = 0.2$).

spread of the social influence evaluation model is the best than the degree centrality model, set cover model, and the random model, and is approaching the climb greedy model. Except the random model, the influence spread increases slowly, as t changed from 1 to 10, and then, as the value of t increases, the number of influence spread increases quickly. This is because only the top 200 or 300 nodes are influential nodes and the succeeding nodes do not contribute to increasing the influence spread.

6 Conclusion and Future Work

In this paper, we present a novel method to quantify social influence in a smartphone-based social network. The social influence of individuals is measured through the analysis on the SMS/MMS-based communication behaviors among mobile users. In addition, we reveal and characterize the social relations among mobile users by analyzing the degree of node and the total number of SMS/MMS sent by each user to his/her friends. Extensive analytical results demonstrate that the influence spread of our proposed method is better than that of the random method, the degree-based method, and the set cover method. As for our further work, we will focus on describing the impact of casual relationship on social influence, and distinguishing positive influence, negative influence, and controversial influence.

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