Influence Strength Aware Diffusion Models for Dynamic Influence Maximization in Social Networks

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Abstract—Social network plays a fundamental role as a medium for the spread of influence among its individuals. During the influence spreading process, one favorable goal is achieving influence maximization in social marketing. Thus diffusion model which identifies a set of individuals to initiate this spread so that more individuals can be triggered at last is very critical. However, to the best of our knowledge, all current diffusion models only consider the dynamics during diffusion and ignore the dynamically changing influence strength during information propagation. In this paper, taking account of both dynamics and influence strength during information diffusion, we propose two diffusion models in social networks for dynamic influence maximization. The first one is the Time-dependent Comprehensive Cascade (TCC) model, which considers that the activation probability between two individuals is dependent on previous activation trials. The second one is the Dynamic Variable Threshold (DVT) model, which considers that the activation threshold of an individual could be changed based on the individual’s attitude towards the propagated information. Theoretical analysis show that our proposed two diffusion models are more practical compared with previous diffusion models.

Keywords—social networks; influence maximization; diffusion model; influence strength

I. INTRODUCTION

In recent years, the importance of social networks as a marketing tool is growing rapidly and the use of social networks as a marketing tool spans diverse areas. Considering that a company wishes to promote its new camera, a promising way these days would be through popular social networking services (e.g., Facebook, Blogosphere, Twitter), rather than using classical advertising channels [1] [2] [3]. Moreover, the company needs to convince several key persons in each social network to adopt (or try) the new camera, then the company can obtain an effective marketing campaign and enjoy the diffusion effect over the network. Further, if we assume that it costs a certain amount of money to invite each key person to “spread” advertisement for increasing the reputation of the new product, then a natural problem is as follows: given a social network, how can we detect the key persons through whom we can spread the new camera in the most effective way?

This problem, referred to as influence maximization, would be of interest for many corporations as well as individuals that want to promote their products, services, innovative ideas, etc. Diffusion models provide good opportunities to address this problem, because they are connecting a huge number of people and they collect a huge amount of information about the social network structures and communication dynamics [8]. For the state of art, there are a lot of work about diffusion models. Among these diffusion models, the Linear Threshold Model and Independent Cascade Model are the most commonly used models in both static social networks [1], [7], [8], [9], [10], [11] and dynamic social networks [12]. However, these two models only consider the dynamics during diffusion and overlook the influence strength with dynamic changes when propagating information. Actually, the influence strength can be quite mutative. For example, if an individual is not activated during previous trials, then this individual is very likely not to be influenced this time. Also, if an individual accepts the diffused information, then the influence probability of this individual should be increased. Similarly, if the propagated information is rejected by this individual, the influence probability of this individual should be decreased.

In this paper, considering both dynamics and the influence strength, we put forward two novel diffusion models for dynamic influence maximization in social networks. The first diffusion model is the Time-dependent Comprehensive Cascade (TCC) model, in which the activation probability between two individuals is dynamically changing based on previous activation trials. The second diffusion model is the Dynamic Variable Threshold (DVT) model, which considers that the activation threshold of an individual should be changed if the individual’s attitude towards the propagated information is muted. Further, we also provide the prediction
approach regarding when the influence strength should be changed in these two models. To the best of our knowledge, our paper is the first work considering the influence strength of diffusion model, which clearly demonstrates our scientific contribution for diffusion models in social networks.

For the rest of this paper, it is organized as follows. Section II presents preliminaries about dynamic network, dynamic influence maximization as well as decision information system in rough set theory. Our proposed influence strength aware diffusion models are shown in Section III. The prediction approach of the influence strength state change in these two models is presented in section IV. Section V discusses and compares our proposed two new models with previous diffusion models. Finally, section VI concludes this paper.

II. PRELIMINARIES

A. Dynamic Network

Let \{1, \ldots, T\} be a finite set of discrete time stamps. Let \( I = \{1, \ldots, n\} \) be a set of individuals. Let \( G_t = (V_t, E_t) \) be a graph representing the snapshot of a static network at time \( t \). \( V_t \) is a subset of individuals \( I \) at time \( t \) and \((u_t, v_t) \in E_t\) if individuals \( u \) and \( v \) interact at time \( t \). A dynamic network \( G = <G_1, \ldots, G_T> \) is the graph \( G = (V, E) \) of the time series of graphs \( G_t \) such that \( V = \bigcup_t V_t \) and \( E = \bigcup_t E_t \cup \bigcup_{t<\tau} (v_t, v_{t+1}) \).

B. Dynamic Influence Maximization

Given a dynamic social network graph \( G = <G_1, \ldots, G_T> \) over \( T \) time stamps and an integer \( k \), the dynamic influence maximization problem is to find an initial set of individuals \( A_0 \) whose size |\( A_0 | = k \), so as to make the expected size of the set of active individuals |\( \sigma(A_0) | = |A_T | \) in \( G \) after \( T \) time stamps.

C. Decision-making Information System in Rough Set Theory

Information System (IS) is a quaternary presentation \( S = (U, A, V, f) \), in which \( U \) denotes a non-empty, finite set of objects called the universe and it is expressed as \( U = \{x_1, x_2, \ldots, x_n\} \) [6]. \( A \) denotes a non-empty, finite set of attributes and \( A = \{a_1, a_2, \ldots, a_m\} \). \( V \) is the range of attributes. \( V = \{v_1, v_2, \ldots, v_m\} \) where \( v_i \) is a value of \( a_i \). \( f \) is an information function, \( f : U \times A \rightarrow V, f(x_i, a_i) \in V_i \).

Decision-making Information System (DIS) is a quaternary presentation \( S = (U, C \cup D, V, f) \), where \( A = C \cup D \) and \( C \cap D \neq \emptyset \). \( C \) is the set of conditional attributes and \( D \) is the set of decision attributes [6]. Let \( S = (U, A, V, f) \) be a decision-making information system, where \( A = C \cup D \) and \( C \cap D \neq \emptyset \). \( X_i = U/C \) and \( Y_j = U/D \). Decision-making rules are defined as follows. \( r_{ij} : des(X_i) \rightarrow des(Y_j) \). \( X_i \cap Y_j \neq \emptyset \). \( des(X_i) \) denotes the description of each object on conditional attributes, and \( des(Y_j) \) denotes the description of each object regarding decision-making attributes. Reliability gene of each rule is defined as follows. 

\[ \mu(X_i, Y_j) = |X_i \cap Y_j|/|X_i| \], \( 0 \leq \mu(X_i, Y_j) \leq 1 \). If \( \mu(X_i, Y_j) = 1 \), then \( r_{ij} \) is certain. If \( 0 < \mu(X_i, Y_j) < 1 \), then \( r_{ij} \) is uncertain.

III. INFLUENCE STRENGTH AWARE DIFFUSION MODELS

A. Time-dependent Comprehensive Cascade Model

Traditionally, the independent cascade model (e.g., [7] [8]) describes a spreading process comprising of two sets of individuals, active individuals and inactive individuals. The process unfolds in discrete time stamps. In each time stamp, each individual attempts to activate its neighbors independently. In the dynamic network, the activation probability of each individual actually depends on the historical activations from other neighbors. And we propose the following time-dependent comprehensive cascade model (TCC) model to show the influence diffusion in a dynamic network. Specifically, in TCC model, an active individual \( u_t \) in time stamp \( t \) activates each of its currently inactive neighbors \( v_t \) only once with a probability \( p_{u_t,v_t} \), which is dependent on how many individuals has already tried to activate the \( v_t \). We assume that there exists a state (increase, decrease, stable) function from the historical activations to new activations.

Figure 1 shows the activation and diffusion mechanism of TCC model. In Figure 1, red nodes indicate the active nodes and white node indicates the inactive node. Before time \( t \), the active nodes have tried to activate the inactive node, but failed. At time \( t \), a newly active node \( u_t \) comes in and it should try to activate the inactive node again with a certain influence probability \( p_{u_t,v_t} \). Particularly, this influence probability \( p_{u_t,v_t} \) is calculated as follows. Let \( S_t \) be the set of \( u \)'s neighbors who have already tried to activate \( u \) but failed before the time stamp \( t \). The influence probability \( p_{u_t,v_t} \) from active individual \( u \) to inactive neighbor \( v \) at time stamp \( t \) is as follows.

\[
p_{u_t,v_t} (S_t) = p_{u_t,v_t} - K \times \frac{|S_t|}{|V|} p_{u_t,v_t}
\]

\[
p_{u_t,v_t} = \frac{f_{u_t,v_t}}{\sum_{n=1}^{N} f_{u_t,v_t}} \tag{1}
\]

\(|V| \) is the number of individuals in the network. \( S_t \in N(v) \). \(|S_t| \) is the size of \( S_t \) and \( N(v) \) is the neighbor set of \( v \). \( p_{u_t,v_t} \)
is the initial influence probability from \( u_t \) to \( v_t \). \( f_{u_t,v_t} \) is the influence from individual \( u_t \) to \( v_t \). Here we first assume \( K = \{-1, 0, 1\} \) as a parameter to control the state change. Specially, if \( K = -1 \), then \( p_{u_t,v_t} \) will grow. And it means that the inactive node will be easily activated by the new activation. If \( K = 1 \), \( p_{u_t,v_t} \) should be decreased, which means the inactive node will not be activated by the new activation. If \( K = 0 \), then \( p_{u_t,v_t} \) is the same as the initial influence probability, which indicates that the state of the inactive node should be changeless. In fact, TCC model will be degraded as independent cascade model if \( K = 1 \). And the detailed prediction approach regarding \( K \) will be shown in section IV.

B. Dynamic Variable Threshold Model

The dynamic variable threshold (DVT) model also describes the spread over two sets of individuals, active and inactive. Each inactive individual has a certain susceptibility to become active, which is denoted by the individual’s “threshold”. Each active individual has a certain “weight” of influence over each of its inactive neighbors. An individual becomes active if the accumulated weight of all its active neighbors becomes larger than the individual’s susceptibility threshold.

Specially, the DVT model is defined by two parameters. For each individual \( v \), a threshold \( \theta_v \leq 1 \) represents the latent tendency of this individual to be activated. For each edge \( (u_t, v_t) \) \( \in E_t \), the weight \( b_{u_t,v_t} \) is the influence of individual \( u \) on individual \( v \), i.e., \( u \)’s ability to activate \( v \), \( \forall v_t, \sum u_t b_{u_t,v_t} \leq 1 \). And the diffusion process described by DVT model in a dynamic network graph starts with a given set of initial thresholds \( \theta_v \) assigned to each individual randomly. The initial set of active individuals is \( A_0 \). And the process unfolds in discrete time stamps, \( 1, \cdots, T \). At each step \( t \), each inactive individual \( v_t \) is influenced by the set of its active neighbors. The inactive individual \( v_t \) becomes active at time stamp \( t+1 \), if \( \sum b_{u_t,v_t} \geq \theta_v \). If \( \sum b_{u_t,v_t} < \theta_v \), then \( v \) remains inactive at time stamp \( t+1 \), and a new attempt is made to activate \( v_{t+1} \) by the set of its neighbors active at time \( t+i \). Each attempt is independent of any previously made attempt. However, the threshold of individual \( v_t \) is dependent on the previously made attempts \( b_{i,v_t}, i \in \{0,\cdots, t\} \) and previously thresholds \( \theta_v, i \in \{0,\cdots, t\} \). Obviously, the thresholds of individuals are dynamically changed due to the time unfolding in DVT model. Therefore, it is easy to know that there exists a mapping from previously attempts and previously thresholds to current thresholds in DVT model.

Figure 2 shows the entire diffusion mechanism of DVT model. Specially, at time \( t = 0 \), which is the initial state for diffusion in DVT, we randomly assign the thresholds to all the individuals. Let’s take the green node as our current target active individual. Two active individuals (red nodes) have already tried to activate the current target individual, but failed. However, the threshold of the target individual will be changed \( (\theta_0 \rightarrow \theta^1) \) in terms of the interaction between individuals. In the same way, at time \( t = 2 \), another active individual tries to activate the current target individual, the threshold of target individual will be change again \( (\theta^1 \rightarrow \theta^2) \). Hence, we formalize this mapping as follows. Let \( S_t \) be the set of \( u \)’s neighbors who have already tried to activate \( u \) but failed before the time stamp \( t \). The threshold of \( u \) at time stamp \( t \) is as follows.

\[
\theta_t(S_t) = \theta^{t-1} - K \times \frac{|S_t|}{|V|} \theta_t^{t-1}
\]

(2)

Here, \(|V|\) is also the number of individuals in the network. \( S_t \in N(v) \) and \(|S_t|\) is the size of \( S_t \). \( \theta_0 \) is the initial threshold of individual \( v \). We also assume the state change parameter \( K = \{k\} \in \{0, 0, 1\} \) first and section IV presents the detailed prediction approach about \( K \).

The above process continues until no more activation is possible. The outputs are the set of individuals active at time \( T \) and \( |A_T| \) is the size of that set \( A_T \). \( \sigma(A_0) = A_T \) denoting the correspondence between the initial set \( A_0 \) and the resulting set of active individuals \( A_T \).

IV. PREDICTION APPROACH OF PARAMETER K

\( K \) is an important parameter in our proposed two diffusion models and it decides the dynamics of the model. For example, the parameter \( K \) in TCC model controls the variation of influence probability \( p_{u_t,v_t} \). And \( K \) in DVT model is related to the dynamical variation of influence thresholds of individuals. In previous section, we simply select \( k \) randomly. Actually, since the two adapted diffusion models are dependent on time, we consider that the parameter \( K \) is dependent on the historical data. And time series analysis methodology is adopted to predict the \( K \) in this section. In this paper, we utilize the approach in [13] to predict \( K \).

A. Time series and trending structure sequence

Time series is a series of observation data according to a certain time sequence [4]. It is an aggregate which owns both time and event characteristics. Time series is also a data set in the planar or multidimensional space. Time-series data mining is an important way which obtains some useful and potential knowledge from a great deal of time-series data mining system is an important way which obtains some useful and potential knowledge from a great deal of time-series data. And time series possess the following characteristics. 1) In a planar time series \( X \), a certain point \( x_t(t, x) \) is composed of x-axis coordinate \( t \) (time) and y-axis coordinate \( x \) (time series) in planar space \( T \times X \). 2) Time series is not reversible. 3) Information transfer is unilateral and not reversible. Information transfer direction is the same as the time elapse direction. For example, for a time series \( X = \{x_t|t = 1, 2, \cdots, n\} \), the information will be transferred from \( x_{t1} \) to \( x_{t2} \) (\( t_1 < t_2 \)).
As for trending structure sequence, as the time series can be wrote in vector form $X = \{x_1, x_2, \ldots, x_n\}$, let $X = \{x_t| t = 1, 2, \ldots, n\}$ be time series and $T_r = \{\delta_1, \delta_2, \ldots, \delta_{n-1}\}$. Then $T_r$ is a trending structure sequence of $X$. Obviously, $T_r$ is also a time series. $\delta_i = \text{sgn}(x_{i+1} - x_i)$ $(i = 1, 2, \ldots, n-1)$, $\text{sgn}(\cdot)$ is a symbol function. And

$$\delta_i = \text{sgn}(x_{i+1} - x_i) = \begin{cases} 1, & x_i < x_{i+1} \\ 0, & x_i = x_{i+1} \\ -1, & x_i > x_{i+1} \end{cases}$$

Further, let $X = \{x_t| t = 1, 2, \ldots, n\}$ be time series, $T_r = \{\delta_1, \delta_2, \ldots, \delta_{n-1}\}$ be trending structure sequence of $X$. $(x_i, x_{i+1}, \ldots, x_{i+k-1})$, $(\delta_j, \delta_{j+1}, \ldots, \delta_{j+k-1})$ $(i = 1, 2, \ldots, n - k + 1; j = 1, 2, \ldots, n - k)$ are called k-time sub series for $X$ and $T_r$ respectively. Particularly, $\{\delta_h, \delta_{h+1}, \ldots, \delta_{h+k-1}\}$ is a trending structure sequence of time sub series $\{x_h, x_{h+1}, \ldots, x_{h+k-1}\}$ in $T_r$, in which $\delta_m = \text{sgn}(x_{m+1} - x_m)$, $m = h, h+1, \ldots, h+k-1$ $(h+k-1 < n)$ and $x_i \in X$. $(x_h, x_{h+1}, \ldots, x_{h+k-1})$ is a latest time sub series whose length is $k$. And k-time sub series is defined as follows.

$$S(X, k) = \{(x_i, x_{i+1}, \ldots, x_{i+k-1})|(i = 1, 2, \ldots, n-k+1)\}$$

(3)

$$S(T_r, k) = \{\{\delta_j, \delta_{j+1}, \ldots, \delta_{j+k-1}\)|(j = 1, 2, \ldots, n-k)\}$$

(4)

Here, $|S(X, k)| = n-k+1$, $|S(T_r, k)| = n-k$.

Moreover, suppose $s_1, s_2 \in S(X, k) = \{(x_{n-k+1}, x_{n-k+2}, \ldots, x_n)\}$, $l_1, l_2 \in S(T_r, k)$ and $l_1, l_2$ are trending structure sequence of $s_1, s_2$ respectively, if $d(l_1, l_2) = 0$, then the trending structure of $s_1$ is the same as that of $s_2$. $d(l_1, l_2)$ denotes the Euclid distance.

$$d(l_1, l_2) = \sum_{i=1}^{k} |\delta_{l_1} - \delta_{l_2}|. l_1 = \{\delta_{11}, \delta_{12}, \ldots, \delta_{1k}\}$$

and

$$l_2 = \{\delta_{21}, \delta_{22}, \ldots, \delta_{2k}\}.$$ 

B. Prediction of Parameter K based on Trending Structure Sequence and Rough Set

In TCC model and DVT model, there exists a time series $p_{uv} = \{p_{u_1,v_0}, p_{u_1,v_1}, \ldots, p_{u_1,v_{t-1}}\}$ and $\theta_v = \{\theta^1_v, \theta^2_v, \ldots, \theta^t_v\}$, its corresponding trending structure sequences are $T_{\text{CC}} = \{\delta^1_{\text{CC}}, \delta^2_{\text{CC}}, \ldots, \delta^t_{\text{CC}}\}$ and $T_{\text{DVT}} = \{\delta^1_{\text{DVT}}, \delta^2_{\text{DVT}}, \ldots, \delta^t_{\text{DVT}}\}$. Hence, we can construct the trending structure predictable information systems shown in Table I and Table II.

$$\delta^1_{\text{CC}} = \text{sgn}(p_{u_{t-1},v_t} - p_{u_{t-1},v_{t-1}})$$

and $\delta^1_{\text{DVT}} = \text{sgn}(\theta^{t-1}_v - \theta^t_v)$ are our prediction aims in TCC model and DVT model. $(\delta_{n-1} = 0, 1)$, $s_q = \{\delta_{-k+1}, \delta_{-k+2}, \ldots, \delta_{-n+1}\}$ and $H(q,m) = \{l \in S(T_r, k)|\text{Hamming}(s_q, l) = 2m\}$, $m = 0, 1, \ldots, k-1, h(q,m) = |H(q,m)|$. Hamming$(s_q, l)$ is the hamming distance between $s_q$ and $l$.

To obtain the prediction aim $K$, the mathematical expectation of Hamming distance is calculated.

$$E(K = -1, 0, 1) = \sum_{m=0}^{k-1} 2m \left( \frac{h(q,m)}{\sum_{m=0}^{k-1} h(q,m)} \right)$$

5
Eq. (5) denotes the mathematical expectation of Hamming distance between \( s_q \) and 1. The smaller \( E(K = -1, 0, 1) \) is, the more trusty \( K \) is.

Finally, after \( K \) can be predicted, the influence probability \( p_{ur,v_t} \) in the TCC model and the threshold of DVT model can be replaced by the more accurate definitions which are shown as follows.

Let \( S_t \) be the set of \( u \)'s neighbors who have already tried to activate \( u \) but failed before the time stamp \( t \). The influence probability from active individual \( w \) to inactive neighbor \( u \) at time stamp \( t \): \( p_{w,v_t} \) is redefined as follows.

\[
p_{u,v_t}(S_t) = p_{u,v_t} = \left( \arg \min_{K \in \{-1,0,1\}} \sum_{m=0}^{k-1} 2m \left( \frac{h(q,m)}{\sum_{m=0}^{k-1} h(q,m)} \right) \right) \\
\times \frac{|S_t|}{|V|} p_{u,v_t} \\
p_{u,v_t} = \frac{f_{u,v_t}}{\sum_{v_t \in S_t} f_{u,v_t}}
\]

where \( K = \{k \} \) \(-1, 0, 1\), \( |V| \) is the number of individuals in the network. \( S_t \in N(v) \), \( |S_t| \) is the size of \( S_t \), \( N(v) \) is the neighbor set of \( v \), \( p_{u,v_t} \) is the initial influence probability from \( u_t \) to \( v_t \). \( f_{u,v_t} \) is the influence from individual \( u_t \) to \( v_t \).

Let \( S_t \) be the set of \( u \)'s neighbors who have already tried to activate \( u \) but failed before the time stamp \( t \). The threshold of \( u \) at time stamp \( t \) is redefined as follows.

\[
\theta^t_v(S_t) = \theta^{t-1}_v - \left( \arg \min_{K \in \{-1,0,1\}} \sum_{m=0}^{k-1} 2m \left( \frac{h(q,m)}{\sum_{m=0}^{k-1} h(q,m)} \right) \right) \\
\times \frac{|S_t|}{|V|} \theta^{t-1}_v \\
\theta^0_v = \text{Random}(0, 1)
\]

where \( K = \{k \} \) \(-1, 0, 1\), \( |V| \) is the number of individuals in the network. \( S_t \in N(v) \), \( |S_t| \) is the size of \( S_t \), \( \theta^0_v \) is the initial threshold of individual \( v \).

V. MODELS FEATURES DISCUSSION AND COMPARISON

Table III lists the features of four models with respect to general influence maximization and dynamic influence maximization. To sum it up, our proposed diffusion models have a good adaptability for dynamic network. The main difference between TCC, DVT models and IC, LT models is the dependency of influence diffusion and feature of TCC and DVT model. In addition, we also incorporate the methodology of individual ethology to evaluate the influence probability in TCC model and threshold in DVT model. For example, traditional IC diffusion model is a kind of attenuation models. But our TCC model considers that an influence probability could be decreased, increased or changeless. Similarly, traditional LT model assumes that the thresholds of individuals are not be changed. But DVT model considers the threshold of individual might be decreased, increased, changeless in terms of individuals’ sentiment, attitude and other social behaviors. Furthermore, there are also some interesting relationships between those models. The TCC model is a generalized model of IC model, TCC model can be degraded to attenuation model with dependency of influence diffusion and time feature when \( K = 1 \). The DVT model can also be degraded as a kind of LT model when \( K = 0 \).

VI. CONCLUSIONS

Existing diffusion models overlook the influence strength during spread. Taking account of both the dynamics of interactions and influence strength, we propose two influence strength aware diffusion models for dynamic influence maximization in social networks. Theoretical analysis and comparison of the model features show that both the Time-dependent Comprehensive Cascade (TCC) model and the Dynamic Variable Threshold (DVT) model can deal with the dynamically changing influence probability problem quite well. Furthermore, we also utilize the trending structure sequence of time series data to predict the state change parameter \( K \) in our proposed diffusion models. We believe that proposed models can simulate the dynamics of interactions as well as the time feature in social networks. And they are both beneficial for dynamic influence diffusion modeling and analysis.

REFERENCES


### Table III

#### Models Features Comparison

<table>
<thead>
<tr>
<th>Model</th>
<th>Independent Cascade (IC) Model</th>
<th>Linear Threshold (LT) Model</th>
<th>TCC Model</th>
<th>DVT Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Influence Maximization</td>
<td>1) Information attenuation model. 2) Each active individual attempts to activate each of its neighbor independently. 3) After the single attempt, the active individual becomes latent.</td>
<td>1) Each node has a random threshold. 2) The threshold will not be changed.</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Dynamic Influence Maximization</td>
<td>The active individuals never become latent during the spreading process.</td>
<td>Each active individual is allowed only one attempt to activate any of its inactive neighbor.</td>
<td>The influence probability might be increased, decreased, or changeless. It depends on the previous activation trials.</td>
<td>The threshold of each node can be changed. It depends on the previous activation trials.</td>
</tr>
</tbody>
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