DM-NAI: Dynamic Information Diffusion Model Incorporating Non-Adjacent Node Interaction

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***Abstract*—Describing the dynamics of information diffusion within social networks poses a formidable challenge. Despite multiple endeavors aimed at addressing this issue, only a limited number of studies have effectively replicated and forecasted the evolving course of information diffusion. In this paper, we propose a novel model, *DM-NAI*, which not only considers the information transfer between adjacent users but also takes into account the information transfer between non-adjacent users to comprehensively depict the information diffusion process. Extensive experiments are conducted on six datasets to predict the information diffusion range and the diffusion trend of the social network. The experimental results demonstrate an average prediction accuracy range of 94.62% to 96.71%, respectively, significantly outperforming state-of-the-art solutions. This finding illustrates that considering information transmission between non-adjacent users helps *DM-NAI* achieve more accurate information diffusion predictions.**

***Index Terms*—Social network, Information Diffusion, Cascade Model, Non-Adjacent Users, Influence Calculation**

I. Introduction

The continuous development of online social networks expands the way people share information and inevitably promotes the spread of false information, causing certain damage to social order and even affecting national stability. Therefore, precisely describing the trends in information diffusion on social network platforms has become an ongoing research focus, crucial for timely event comprehension and the effective management of diverse social effects [1, 2].

Existing social network information diffusion model research is mainly based on two classic models: the *Independent Cascade (IC) Model* [3] and the *Linear Threshold (LT) Model* [4]. For example, based on the *IC* model, researchers have carried out a large number of studies considering the influence of time [5–7], user emotions [8–10], topics [11–14], and individual preferences [14–18].

However, previous studies have solely focused on information transfer between adjacent users. The diffusion of information among non-adjacent users in social networks also significantly impacts the overall information diffusion. In this paper, we propose a novel information diffusion model, called *DM-NAI*, which incorporates dynamic changes in user attitudes and considers the influence of non-adjacent users. By continuously updating users' attitude distribution and incorporating the information diffusion mechanism among non-adjacent users, *DM-NAI* facilitates a more comprehensive prediction of the information diffusion process.

II. Related Work

Understanding the diffusion mechanisms behind vast amounts of information is crucial in various research fields, including viral marketing, social recommendations, community detection, and social behavior prediction. Researchers from diverse fields, such as epidemiology, computer science, and sociology, have conducted extensive studies and proposed various models of information diffusion to accurately describe and simulate this intricate process.

Kempe et al. originally introduced two fundamental models of information diffusion: the Independent Cascade Model (IC) [3] and the Linear Threshold Model (LT) [4]. Considering the influence of time, [5] introduced the T-IC model, effectively capturing the temporal aspects of the network. A new model called the cycle-aware intelligent method was proposed by [6]. [7] introduced the GT diffusion model by considering the influence of time on user behavior. Accounting for the influence of user emotions, [8] proposed the E-SFI model. [9] proposed a novel model based on user sentiment. A et al. proposed CECM [10]. Taking into account the influence of topics, [11] proposed a novel topic-aware influence-driven diffusion model. [12] introduced a topic-aware community-based independent cascade model. [13] presented a topic-aware social influence diffusion model. [14] proposed NSTI-IC model. Accounting for the influence of spatial factors, [12] introduced a community-based independent cascade model. Taking into account the influence of individual preference factors, [14] proposed the NSTI-IC model. [16] developed a topic-enhanced sentiment diffusion model.

III. Problem Formulation

As illustrated in Fig. 1, the social network is modeled as a directed graph denoted as $G = (V, E, T)$. Each node $v_i \in V$ corresponds to a topic set $T_i = \{t_{i\_1}, t_{i\_2}, t_{i\_3}, \ldots\ldots, t_{i\_z}\}$, which reflects user i's attitude towards information on all

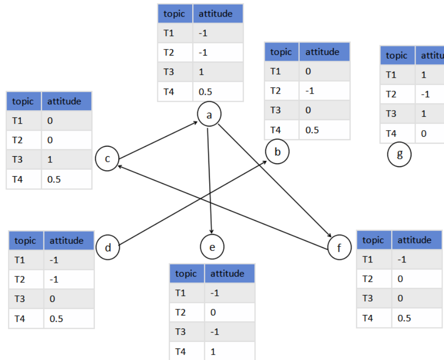


Fig. 1. User Network.

topics, where $t_{i\_k} \in \{-1, 0, 0.5, 1\}$,$t_{i\_k}$ is used to represent user i's attitude towards topic k. The values -1, 0, 0.5, and 1 correspond to the user's stances, representing four states: unknown, positive, neutral, and negative. Tab. I provides an overview of frequently utilized symbols along with their corresponding interpretations.

Definition 1 (**Activation action**). *Activation action can be represented by user u being influenced by a sequence of information related to topic i at time t. Consequently, there is a probability of the user's attitude towards topic i changing.*

Definition 2 (**Attitude distribution similarity**). *The attitude distribution similarity between users can be described as $sim(u, v)$. Assuming that the attitude distributions of users u and v are $T_u = \{t_{u\_1}, t_{u\_2}, t_{u\_3}, \ldots, t_{u\_z}\}$ and $T_v = \{t_{v\_1}, t_{v\_2}, t_{v\_3}, \ldots, t_{v\_z}\}$, this value can be obtained by analyzing the similarity of the distributions of T_u and T_v.*

Definition 3 (**Information diffusion**). *We define the conditions for information diffusion in social networks as follows:$(1)(u, v) \in E$; $(2)(u, v) \notin E$, but $sim(u, v) > \tau$. Here,τ represents the threshold for controlling information diffusion. When either condition (1) or condition (2) is satisfied, there is a certain probability of information diffusion occurring between users u and v.*

Definition 4 (**Social influence**). *For user u and user v in a social network, we define $P_i(u, v)$ to represent the influence of user u on user v's attitude regarding topic i.*

Definition 5 (**User attitude's perseverance**). *For user v, we define A_v^i to represent the perseverance of user v's attitude towards topic i, which is the probability of change in user v's attitude towards topic i.*

IV. The Proposed Model

A. Attitude Distribution Similarity

In the social network model of this paper, the user is depicted as the distribution of attitudes towards various topics. The similarity [22] of attitude distribution among users affects the probability of information diffusion. Given two nodes u and v, the topic similarity $sim(u, v)$ between nodes u and v is measured as follows:

$$sim(u, v) = 1/\left(\left(\sqrt{z} + \sqrt{\sum_{i=1}^{z} \left(t_u^i - t_v^i\right)^2}\right)/\sqrt{z}\right) \tag{1}$$

where a higher value of $sim(u, v)$ indicates greater similarity in the attitude distribution between nodes u and v, leading to a higher probability of information diffusion between them.

B. Influence Evaluation between Users

In a social network, there exists a corresponding influence between users when they transmit information [23]. Users can leverage this influence to assess whether and how their attitudes will change. We define r_{uv}^i as the diffusion rate between users u and v regarding topic i. A larger value denotes a higher rate of information diffusion.

Assuming that user u transmits information about topic i to user v within time τ_i, the probability that the information cannot be transferred from u to v can be obtained by multiplying the probability of non-transfer in each small time interval $\triangle t$, that is

$$P_i(u, v) = (1 - W_i(u, v)) * sim(u, v) * f(t_v^i, t_u^i) \tag{2}$$

$$W_i(u, v) = 1 - \lim_{\triangle t \to 0} \left(1 - r_{uv}^i \triangle t\right)^{\tau_i/\triangle t} = 1 - e^{-r_{uv}^i t} \tag{3}$$

$$f(t_v^i, t_u^i) = \begin{cases} 1, & t_v^i = -1, 0.5 or t_v^i = t_u^i \\ \lambda, & |t_v^i - t_u^i| \leq 0.5 \\ \mu, & else \end{cases} \tag{4}$$

where λ and μ are control parameters used to regulate the influence weight between user u and user v regarding topic i. Regardless of the existence of a connection relationship between two users and the similarity of the attitude distribution between the two users, there is a certain probability of mutual influence.

C. Attitude Change Probability

Considering the different attitudes of users on topics and the intricacies of the information received, the probability of changes in users' attitudes may vary. We define A_v^i as the attitude perseverance of user v towards topic i, which serves as a metric to gauge the likelihood of the user's attitude change. A_v^i is calculated as follows:

$$A_v^i = A_v^i - \sum_{u=1}^{k} \left(|t_u^i - t_v^i| * P_i(u, v) - (\overline{t_u^i \oplus t_v^i}) * P_i(u, v)\right)/k \tag{5}$$

when user v encounters information that conflicts with his attitude, A_v^i is reduced, indicating an increased possibility of attitude change towards topic i. Conversely, when user v

TABLE I
IMPORTANT MATHEMATICAL SYMBOLS.

Notation	Description
$G=(\boldsymbol{V},\boldsymbol{E},\boldsymbol{T})$	Represents a social network, where $\boldsymbol{V}$ is a set of nodes with a size of n, $\boldsymbol{E}$ is a set of edges with a size of m [19], and $\boldsymbol{T}$ is a set of topics with a size of z.
P_e	Probability of information diffusion on edge e [20].
$n=\lvert\boldsymbol{V}\rvert$	The number of nodes in G.
$m=\lvert\boldsymbol{E}\rvert$	The number of edges in G[21].
$\boldsymbol{T_i}=<t_{i\_1},t_{i\_2},\ldots\ldots,t_{i\_z}>$	Attitude held by user i towards information on all topics.
$z=\lvert\boldsymbol{T}\rvert$	The number of topics in G.
$\delta,\lambda,\mu,\epsilon$	Control parameter.

receives information that aligns with his existing attitude on topic i, A_v^i increases, indicating a decreased possibility of attitude change for user v towards topic i.

D. Attitude Change Mechanism

In social networks, changes in a user's attitude towards a particular topic are determined by the user's attitude and the information that the user has received. The mechanism for user v's attitude change at the next moment is as follows:

$$t_v^i=\begin{cases} t_u^i, & P_i(u,v)\geq A_v^i \\ 0.5, & else \end{cases} \tag{6}$$

that is if user v has not been exposed to relevant information about the topic i before time t, the change in user v's attitude at the next moment is determined by the similarity of attitude distributions between users and the perseverance of user v's attitude towards topic i. The higher the similarity between the attitude distributions, the greater the likelihood that user v will be influenced by the other user's attitude.

When user v has been exposed to relevant information about the topic before time t, the mechanism for the user's attitude change at the next moment is as follows:

$$t_v^i=(\overline{t_u^i\oplus t_v^i})*t_v^i+(t_u^i\oplus t_v^i)*(t_v^i\pm\varepsilon*0.5) \tag{7}$$

where ε is a constant parameter. When $P_i(u,v)>A_v^i$, ε is 1. When $P_i(u,v)<A_v^i$,ε is 0. The symbol $\pm$ is used to control the direction of the stance change of node v. When the initial t_v^i is 0, indicating that node v initially holds an opposing stance on topic t_i, we assign a positive sign (+). Conversely, we assign a negative sign (-).

V. ALGORITHM

A. Information Dissemination Process

Our model assumes that user v can access information not only from its neighboring nodes but also from non-neighboring nodes. Additionally, the model assumes that the information posted by user v at any time t_1 may be received by user u at a later time t_2 (where $t_2>t_1$). The specific diffusion process is illustrated in Algorithm 1.

$\boldsymbol{V}\backslash\boldsymbol{V_{adj}}$ denotes the difference set between the set $\boldsymbol{V}$ and the set $\boldsymbol{V_{adj}}$. In the algorithm 1, the adjacency node $\boldsymbol{V_{adj}}$ and the non-adjacency node $\boldsymbol{V_{\sim adj}}$ are comprehensively considered.

Algorithm 1 DM-NAI

Input: $G=(\boldsymbol{V},\boldsymbol{E},\boldsymbol{T})$, initial set of topics $\boldsymbol{T_k}=\{\boldsymbol{T_1},\boldsymbol{T_2},\ldots\ldots,\boldsymbol{T_z}\}$,initial topic number j,number of diffusion K.
Output: The updated network G=(V,E,T).
function DM-NAI$(G,\boldsymbol{T_k},j,K)$
  $\boldsymbol{T_{j-0}^{now}}=\boldsymbol{T_{j-0}}$, $\boldsymbol{T_{j-0.5}^{now}}=\boldsymbol{T_{j-0.5}}$, $\boldsymbol{T_{j-1}^{now}}=\boldsymbol{T_{j-1}}$
  $\boldsymbol{V_j^{new}}=\boldsymbol{T_{j-0}^{now}}\cup\boldsymbol{T_{j-0.5}^{now}}\cup\boldsymbol{T_{j-1}^{now}}$
  $\boldsymbol{V_{adj}}=\emptyset$, $\boldsymbol{S}=\emptyset$
  for k = 1 to K **do**
    for v in $\boldsymbol{V_j^{new}}$ **do**
      $\boldsymbol{S}=\{u\vert(u,v)\in\boldsymbol{E}\}$
      for q $\in\boldsymbol{S}$ **do**
        if q $\notin\boldsymbol{V_{adj}}$ **then**
          $T_{cur}=T_q^j$
          $A_q^j=Eq.(4)$
          $T_q^j=ATT(G,q,v,j,A_q^j)$
          $\boldsymbol{V_{adj}}\leftarrow q$
        end if
        if $T_{cur}=-1$ and $T_q^j!=-1$ **then**
          $\boldsymbol{T_{j-T_q^j}}\leftarrow q$
          $\boldsymbol{V_j^{new}}\leftarrow q$
        end if
      end for
    end for
    $\boldsymbol{V_{\sim adj}}\leftarrow\boldsymbol{V}\backslash\boldsymbol{V_{adj}}$
    $NADJ(G,j,\boldsymbol{V_{\sim adj}},\boldsymbol{V_j^{new}})$
  end for
  return G
end function

B. Node State Change Process

During the information diffusion process, the stance of a node towards the current topic may continuously change. We consider the node's current stance and the influence of all the different stance information it has received up until time t to determine the possible stance changes at the current time t. The specific calculation process is shown in Algorithm 2.

C. Diffusion in Non-adjacent Nodes

Nodes also influence their non-neighboring nodes during the information diffusion process. Whether these nodes are in a known or unknown state for the current topic, there

Algorithm 2 ATT

Input: $G = (\boldsymbol{V}, \boldsymbol{E}, \boldsymbol{T})$, node q,v, the topic number j,A_q^j.
Output: T_q^j.

function ATT(G, q, v, j, A_q^j)
  $T_{cur} = T_q^j$
  if $T_q^j = 0.5$ or -1 **then**
    $T_q^j = Eq.(5)$
  else
    $T_q^j = Eq.(6)$
  end if
  if $T_{cur}! = T_q^j$ **then**
    $\boldsymbol{T_{j-T_q^j}} \leftarrow q$
    $\boldsymbol{T_{j-T_{cur}}} \leftarrow q$
  end if
  return T_q^j
end function

is a certain probability that they will be influenced by the information from the node. The specific diffusion process is shown in Algorithm 3.

Algorithm 3 NADJ

Input: $G = (\boldsymbol{V}, \boldsymbol{E}, \boldsymbol{T})$,$\boldsymbol{V_{adj}}$, $\boldsymbol{V_j^{new}}$,the number of diffusion k, the topic number j, the parameters r1,r2.
Output: The updated network $G = (\boldsymbol{V}, \boldsymbol{E}, \boldsymbol{T})$.

function NADJ($G, \boldsymbol{V_{adj}}, \boldsymbol{V_j^{new}}, k, j, r1, r2$)
  Generating collections $\boldsymbol{V^{new}}, \boldsymbol{V_{adj}^{new}}, \boldsymbol{V^{new}} = \{v | v \in \boldsymbol{V_j^{new}}\}$
  $|\boldsymbol{V^{new}}| = r1 * |\boldsymbol{V_j^{new}}|$
  $\boldsymbol{V_{adj}^{new}} = \{\boldsymbol{U} \cup \boldsymbol{V} | u, v \in \boldsymbol{V_{adj}}, u \in \boldsymbol{T_j}, v \notin \boldsymbol{T_j}\}$
  $|\boldsymbol{V_{adj}^{new}}| = r2 * |\boldsymbol{V_{adj}}|$
  for $q \in \boldsymbol{V_{adj}^{new}}$ **do**
    $T_{cur} = T_q^j$
    for $v \in \boldsymbol{V^{new}}$ **do**
      $A_q^j = Eq.(4)$
      $ATT(G, q, v, j, A_q^j)$
      if $T_{cur} = -1$ and $T_q^j! = -1$ **then**
        $\boldsymbol{V_j^{new}} \leftarrow q$
        $\boldsymbol{T_j} \leftarrow q$
      end if
    end for
  end for
  return G
end function

where, $r \in [0.5, 1], a \in [0, 0.5), r + a = 1$. $\boldsymbol{T_j}$ represents the set of users for whom topic j is known, and $\boldsymbol{V_{adj}^{new}}$ contains a subset of non-neighboring users for node v.

VI. Experiment

A. Dataset

The datasets utilized in the experiments of this paper are sourced from actual microblog data. Each dataset features varying numbers of topics and microblog posts. Tab. II provides detailed information about the datasets.

TABLE II
THE DATASET.

Dataset	nodes	edges	topics	Number of seed nodes
Dataset I	1331	8737	1	20
Dataset II	1109	7723	1	23
Dataset III	1801	8493	1	27
Dataset IV	2351	14739	2	41
Dataset V	2817	13283	2	45
Dataset VI	4028	23151	3	69

TABLE III
AUC VALUES FOR IC, LT, EMIC, EIC, TIC AND DM-NAI.

Dataset	IC	TIC	EMIC	EIC	DM-NAI
Dataset I	61.54%	77.01%	78.63%	84.48%	95.90%
Dataset II	61.50%	76.92%	77.92%	84.64%	96.71%
Dataset III	59.10%	76.68%	77.01%	84.97%	95.82%
Dataset IV	65.35%	75.49%	78.15%	83.12%	95.01%
Dataset V	59.30%	75.97%	76.69%	82.89%	94.67%
Dataset VI	56.28%	74.82%	76.43%	82.77%	94.62%

TABLE IV
STANCE PREDICTION ACCURACY.

Dataset	Stance prediction accuracy
Dataset I	79.40%
Dataset II	76.92%
Dataset III	77.41%

B. Analysis of Diffusion Results

Based on the six datasets, we conduct experiments to analyze the accuracy of the model. A comparison is made with the IC model, as well as existing models based on user sentiment or topic, namely TIC [11], EMIC [24], and EIC [18]. The experimental results are presented in Tab. III. The results demonstrate that the proposed model outperforms existing models in terms of accuracy. Furthermore, Fig. 2 illustrates the dynamic changes of the affected users when information is propagated through the DM-NAI, IC, TIC, EMIC, and EIC models, respectively, for each of the six datasets. The similarity between our model and the real information diffusion process is further highlighted by comparing it with the real diffusion process in social networks.

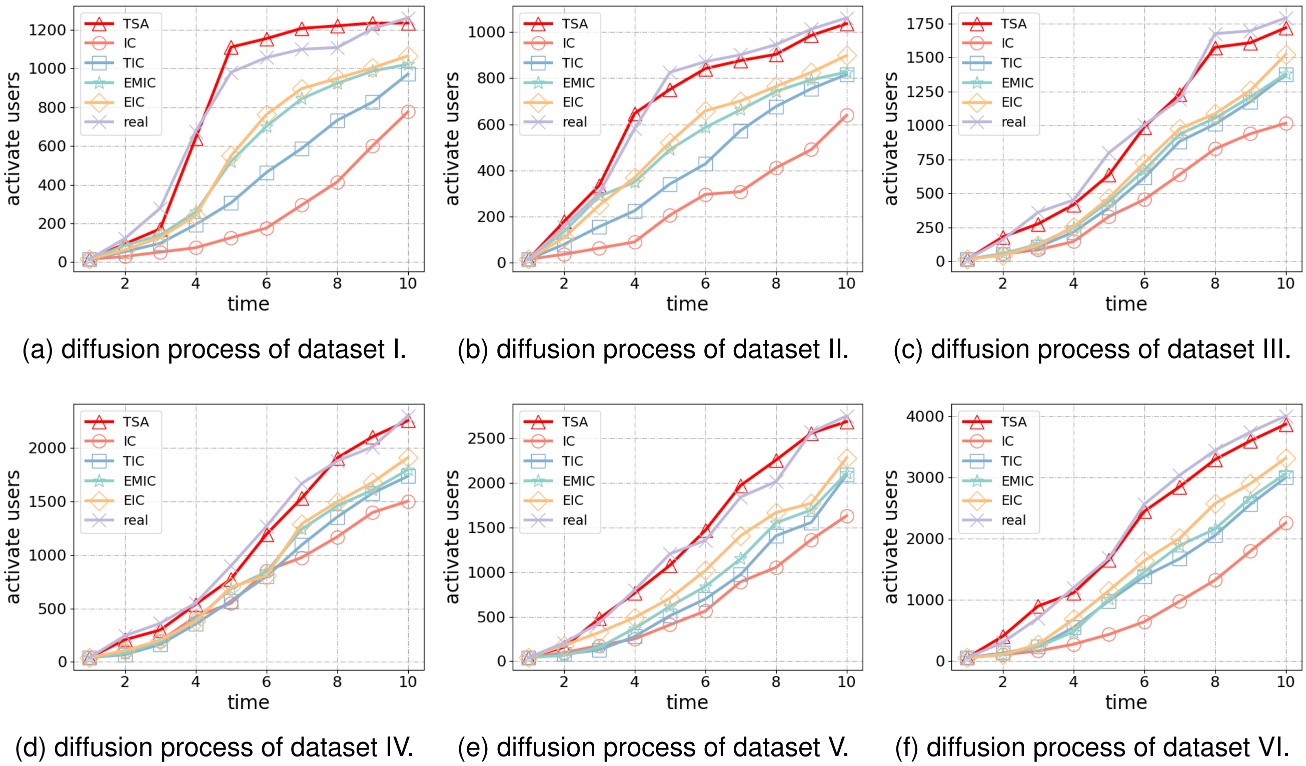
C. Stance Change Analysis

In this paper, experimental data setsI, II, and III, are used to analyze change of users' stance, and the experimental results are shown in Tab. IV.

The results indicate that users with different stances undergo continuous changes during the information diffusion process. Additionally, influenced by network dynamics, users tend to adopt a negative attitude towards public opinion topics. Moreover, as information spreads, users who initially held a supportive or neutral stance may also be influenced and shift towards a negative stance.

VII. Conclusion

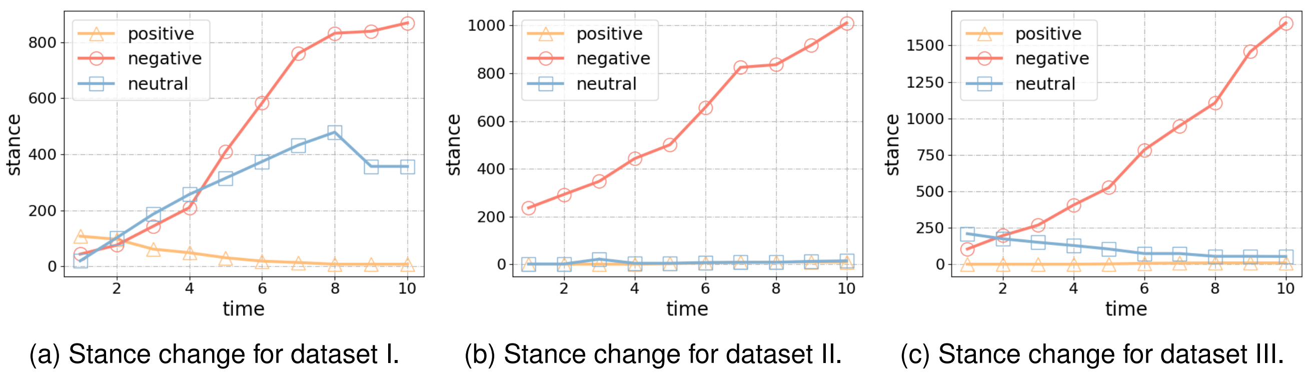
In this paper, we propose a novel model, *DM-NAI*, which considers information transfer between non-adjacent users.



(a) diffusion process of dataset I. (b) diffusion process of dataset II. (c) diffusion process of dataset III.

(d) diffusion process of dataset IV. (e) diffusion process of dataset V. (f) diffusion process of dataset VI.

Fig. 2. The diffusion process from dataset I to dataset VI.



(a) Stance change for dataset I. (b) Stance change for dataset II. (c) Stance change for dataset III.

Fig. 3. The stance change process from dataset I to dataset III.

By continuously calculating the similarity of changing attitude distribution and the probability that one node influences another non-adjacent node, *DM-NAI* effectively incorporates the impact of user attitude changes and interactions with non-adjacent nodes on information diffusion. Extensive experiments are conducted on six different datasets to predict the information diffusion range and the diffusion trend of the social network. The experimental results demonstrate that the proposed algorithm outperforms traditional information diffusion models in simulating the information diffusion process in current social networks, providing valuable insights for early warning of adverse social events.

VIII. Acknowledge

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