UAPE: Information Propagation Model Based on User Attitude and Public Opinion Environment

Xinyu Li*, Jinyang Huang* §, Xiang Zhang† §, Peng Zhao*, Meng Wang*,
Guohang Zhuang*, Huan Yan‡, Xiao Sun*, and Meng Wang*

*School of Computer and Information, Hefei University of Technology, Hefei, China.

†CAS Key Laboratory of Electromagnetic Space Information, University of Science and Technology of China, Hefei, China.

‡ School of Big Data and Computer Science, Guizhou Normal University, Guiyang, China.

§Corresponding Authors: Jinyang Huang, Xiang Zhang   Email: hjy@hfut.edu.cn, zhangxiang@ieee.org

***Abstract*—Modeling the information propagation process in social networks is a challenging problem. Despite numerous attempts to address this issue, existing studies often assume that user attitudes have only one opportunity to alter during the information propagation process. Additionally, these studies tend to consider the transformation of user attitudes as solely influenced by a single user, overlooking the dynamic and evolving nature of user attitudes and the impact of the public opinion environment. In this paper, we propose a novel model, *UAPE*, which considers the influence of the aforementioned factors on the information propagation process. Specifically, *UAPE* regards the user's attitude towards the topic as dynamically changing, with the change jointly affected by multiple users simultaneously. Furthermore, the joint influence of multiple users can be considered as the impact of the public opinion environment. Extensive experimental results demonstrate that the model achieves an accuracy range of 91.62% to 94.01%, surpassing the performance of existing research.**

***Index Terms*—Information Propagation, Online Social Networks, Cascade Model, User Attitude, Dynamic Change**

I. Introduction

The growth of online social networking has minimized geographical constraints on information propagation[1]. However, the rapid spread of diverse, opinion-laden content remains a concern. This phenomenon can influence people's judgment to a certain extent and give rise to various social effects, such as affecting the fairness of elections, impacting the stock market, and even jeopardizing national stability. Therefore, accurately predicting the information propagation trends in social networks plays a crucial role in scientifically responding to various emergent events [2, 3].

Initially, Kempe et al. proposed *the Independent Cascade (IC) Model* [4] and *the Linear Threshold (LT) Model* [5] to predict the information propagation trends. Later researchers found that apart from the neighboring nodes considered by the aforementioned models, additional factors also exert influence on the information propagation process. Consequently, a substantial body of research has emerged, which incorporated different elements, e.g., user-interest topics [6–9], individual preferences [9–11], information propagation timing [12, 13], and user emotions [14–16], into *IC* model.

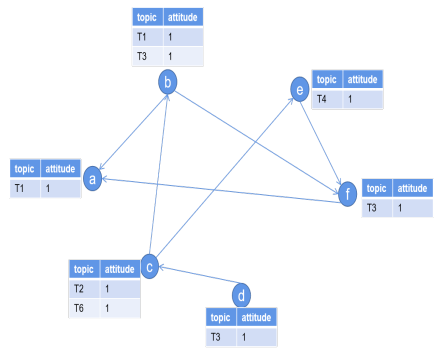


Fig. 1: Traditional Network Model.

However, previous research has ignored the dynamic nature of user attitudes and the influence of the public opinion environment, which greatly affects the prediction accuracy. Therefore, in this paper, we consider these two factors to simulate the dynamic process and trends of information propagation to achieve a more accurate prediction.

II. Related Work

A large number of studies have explored the information diffusion process. Kempe et al. proposed *the Independent Cascade (IC) Model* [4] and *the Linear Threshold (LT) Model* [5]. Considering the influence of topic, Qin et al. introduced a topic-aware community-based Model that incorporated both the structural characteristics of communities and thematic features [6]. [7] considered the influence of similar topics between nodes and proposed a new model. [9] proposed *NSTI-IC* model. [17] proposed a topic-aware model.

In addition to the user's interests and the topics they are interested in, individual factors, such as emotions, will also affect the information dissemination in social network. Therefore, considering the influence of individual factors, Zhang et al. introduced the *NSTI-IC* model that incorporated the impact of individual preferences [9]. Wang et al. developed a unified probabilistic framework by considering

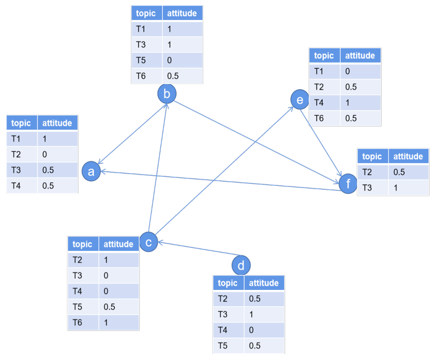


Fig. 2: Initial Network Model.

users' historical emotional states, tweet topic distributions, and social structure [10]. Dai et al. proposed the *EIC* model to elucidate the impact of group polarization effects and individual preferences [11]. [15] proposed an emotion-based independent cascade model that integrates user features, structural features, tweet features, and more. [16] established an information propagation model based on node sentiment.

Since the effective time of information dissemination can impact the dissemination range, taking this factor into account, [12] proposed the *T-IC* model. Zhou et al. introduced a cycle-aware intelligent prediction method [13].

III. Problem Formulation

Unlike previous social network models, as shown in Fig. 1, which only consider the topics that users are initially interested in, ignoring the impact of other topics, we model the social network as a directed graph G [19], as shown in Fig. 2, taking into account all topics with users' different attitudes. Each node i is associated with a topic set $\boldsymbol{T_i} = \{t_{i\_1}, t_{i\_2}, t_{i\_3}, \ldots\ldots, t_{i\_k}\}$, reflecting the user's attitudes towards different topics. Specifically, $t_{i\_k} \in \{0, 0.5, 1, -1\}$, and t_{i_k} is used to express the attitude of user i towards topic k. The values -1, 0, 0.5, and 1 indicate the user's stance, representing the four conditions: unknown, positive, neutral, and negative. Tab. I summarizes the commonly used symbols and their respective meanings[20].

A. Influence Evaluation Mechanism

Given two nodes u and v, the topic sets corresponding to these two nodes are $\boldsymbol{T_u} = \{t_{u\_1}, t_{u\_2}, t_{u\_3}, \ldots\ldots, t_{u\_n}\}$ and $\boldsymbol{T_v} = \{t_{v\_1}, t_{v\_2}, t_{v\_3}, \ldots\ldots, t_{v\_m}\}$. We employ the Degrootian model [21] to calculate the changes in users' attitudes toward each topic during information propagation:

$$O_{i\_v}(t+1) = \frac{T_{i\_v}(t) + \sum_{j \in T_i(t)} T_{j\_v}(t)}{|T_i(t)| + 1} \tag{1}$$

For topic i, the influence P_i of node u on node v is measured as follows:

$$Pr\{v \rightarrow i\} = \frac{\frac{1}{|O_{i\_v}(t) - O_i| + 0.01}}{\sum_{j \in T_i(t)} \frac{1}{|O_{i\_v}(t) - O_j| + 0.01}} \tag{2}$$

Algorithm 1 UAPE

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,Time threshold K.
Output: The updated network G=(V,E,T).

function UAPE$(G, \boldsymbol{T_k}, j, K)$
  $\boldsymbol{V_j} = \boldsymbol{T_{j-0}} \cup \boldsymbol{T_{j-0.5}} \cup \boldsymbol{T_{j-1}}$
  $\boldsymbol{V_{adj}} = \emptyset$, $\boldsymbol{S} = \emptyset$
  for k = 1 to K **do**
    for v in $\boldsymbol{V_j}$ **do**
      $\boldsymbol{S} = \{u|(u,v) \in \boldsymbol{E}\}$
      for q $\in \boldsymbol{S}$ **do**
        $T_{cur} = T_q^j$
        $A_q^j = Eq.(2)$
        $T_q^j = Get\_Att(G, q, v, j, A_q^j)$
        if q $\notin \boldsymbol{V_{adj}}$ **then**
          $\boldsymbol{V_{adj}} \leftarrow q$
        end if
        if $T_{cur} = -1$ and $T_q^j != -1$ **then**
          $\boldsymbol{T_{j-T_q^j}} \leftarrow q$
          $\boldsymbol{V_j} \leftarrow q$
        end if
      end for
    end for
  end for
  return G
end function

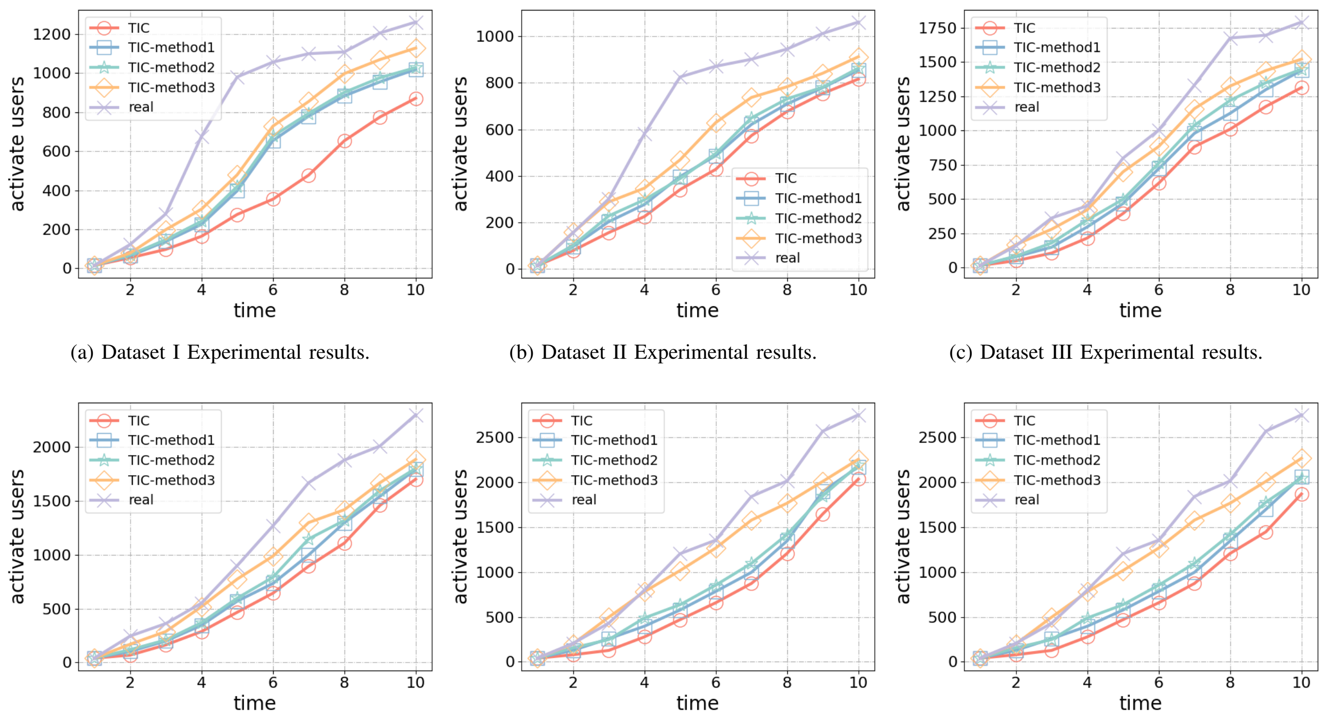
Algorithm 2 *Get_Att*

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

function $Get\_Att(G, q, v, j, A_q^j)$
  $T_{cur} = T_q^j$
  if $T_q^j = 0.5$ or -1 **then**
    if $P_j(q,v) > A_q^j$ **then**
      $T_q^j = T_v^j$
    else
      $T_q^j = 0.5$
    end if
  else
    $T_q^j = (T_q^j \oplus T_v^j) * T_q^j + (\overline{T_q^j \oplus T_v^j}) * (T_q^j \pm \varepsilon * 0.5)$
  end if
  if $T_{cur} != T_q^j$ **then**
    $\boldsymbol{T_{j-T_q^j}} \leftarrow q$
    $\boldsymbol{T_{j-T_{cur}}} = \boldsymbol{T_{j-T_{cur}}} - q$
  end if
  return T_q^j
end function

TABLE I: FREQUENTLY USED NOTATION.

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, and $\boldsymbol{T}$ is a set of topics with a size of z.
P_e	Probability of information propagation on edge e [18].
$\boldsymbol{T_i} =< t_{i\_1}, t_{i\_2}, \ldots\ldots, t_{i\_z} >$	The set of user i attitudes towards all topics.
$sim(u, v)$	Interest similarity between nodes u and v.
$A_v i$	Attitude value of node v for topic i.



(a) Dataset I Experimental results. (b) Dataset II Experimental results. (c) Dataset III Experimental results.

(d) Dataset IV Experimental results. (e) Dataset V Experimental results. (f) Dataset VI Experimental results.

Fig. 3: Experimental results of *TIC* model.

$$P_i(u, v) = Pr\{v \to i\} * \sqrt{\sum_{i=1}^{k} \left(\left(t_u^i - t_v^i \right) \oplus 0.5 \right)^2 / IN(v)} \tag{3}$$

where $Pr\{v \to i\}$ is used to calculate the level of interest of user v in topic i. The denominator 0.01 is utilized to handle exceptional cases, a similar approach to the one employed in the study [22]. The variable k represents the size of the set of topics in which both nodes u and v are interested, and $IN(v)$ represents the in-degree of node v.

B. The Attitude Persistence of A Node to A Topic

For every topic t_i within the social network, each node holds a specific attitude towards it. During each iteration, the information received by a node regarding the same topic may contain varying attitudes. These diverse attitudes can influence the node's persistence in its attitude, potentially leading to changes in the node's attitude. Therefore, in this paper, we propose a computational system that quantifies the persistence of nodes to their respective attitudes, providing insights into the likelihood of attitude changes concerning topic t_i.

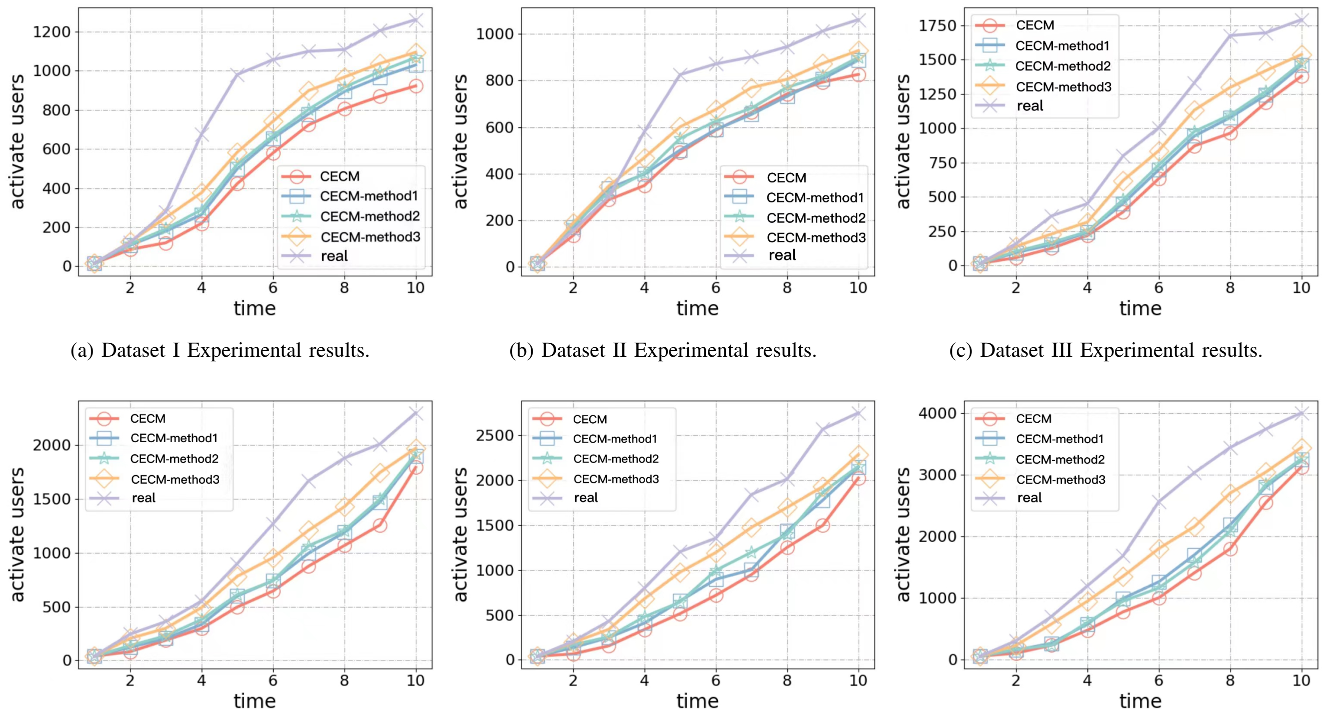
$$A_v^i = A_v^i - \sum_{u=1}^{q} \left(|t_u^i - t_v^i| * P_i(u, v) - (\overline{t_u^i \oplus t_v^i}) * P_i(u, v) \right) / q \tag{4}$$

where, q represents the number of messages received by node v so far, and A_v^i represents node v's persistence of attitude towards topic t_i.

IV. Algorithm

A. Information Propagation Model

Based on the *IC* model and considering the dynamic changes in user attitudes during the information propagation



(a) Dataset I Experimental results.
(b) Dataset II Experimental results.
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(d) Dataset IV Experimental results.
(e) Dataset V Experimental results.
(f) Dataset VI Experimental results.

Fig. 4: Experimental results of *CECM* model.

process, along with the combined influence of multiple neighboring users, we present the *UAPE* model. The detailed process of the model is outlined in Algorithm 1. Where V_{adj} denotes the set of adjacent nodes of all nodes in the existing seed set S, T_{cur} represents the state of the node before it is affected.

B. Node Attitude Change Process

During the process of information propagation[23] in social networks, the attitudes of nodes towards topics undergo continuous changes. Therefore, it is crucial to track the evolving attitudes of nodes towards various topics throughout the information propagation process. To achieve this, we propose an algorithm Get_Att, that comprehensively considers all the information received by the node about the specified topic up to the current moment and calculates the node's attitude towards the specified topic. The detailed process of the model is outlined in Algorithm 2.

V. Experiment

A. Dataset

The datasets used in this study are all obtained from real Weibo data. Datasets I,II and III contain original tweets and comments related to a particular topic, respectively. Datasets IV and V contain original tweets on two specific topics and comments related to them. Dataset VI contains all original Weibo posts and comments on three topics. Tab. II provides detailed information about the dataset.

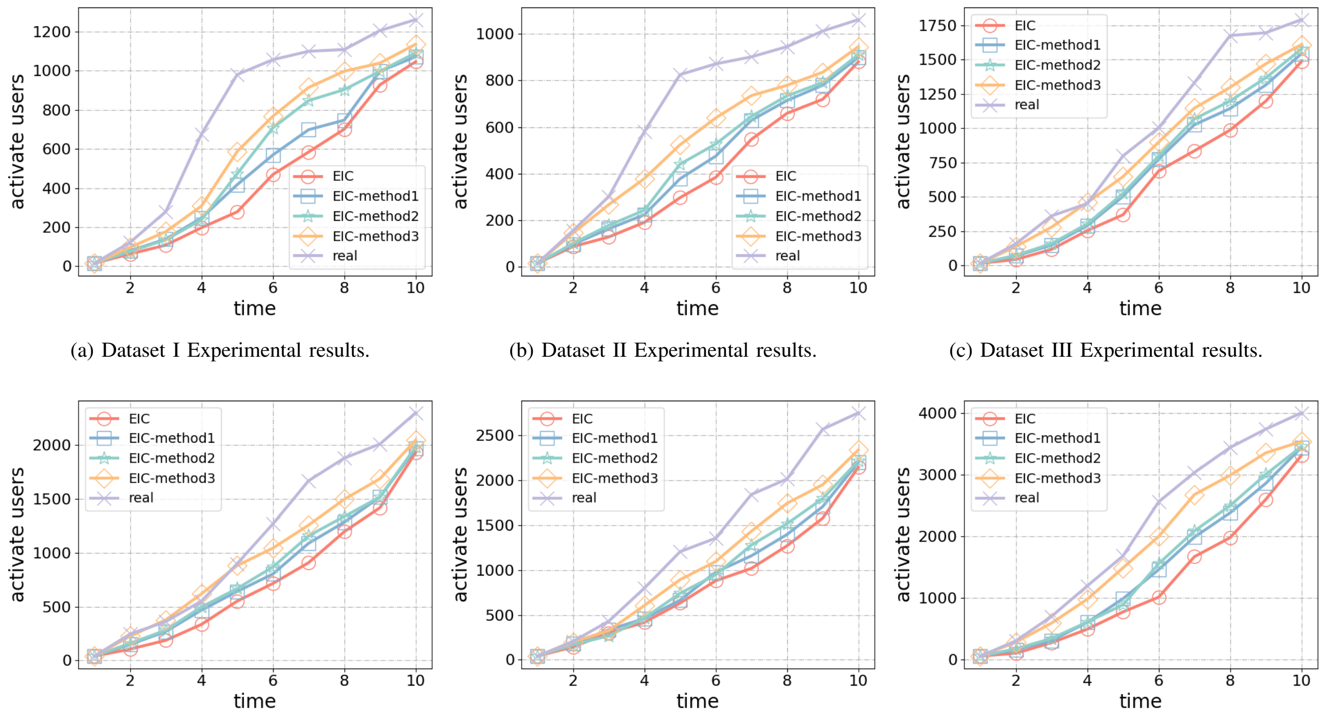
B. Comparison Methods

The *UAPE* model is compared with the *TIC* model, which solely considered topics in reference [24]. Additionally, we compare it with the *EIC* [11] and the *CECM* [14] model, both of which considered user sentiment or individual preferences. Specifically, the methods evaluated and compared in the experiments are as follows:

- Method 1: Considering the dynamic changes in user attitudes during the information propagation process to make predictions.
- Method 2: Taking into account the collective influence of multiple neighboring users to make predictions.
- Method 3: Considering the dynamic changes in user attitudes during the information propagation process and the combined influence of multiple neighboring users to make predictions.

C. Experimental Results

(a) to (f) of Fig. 3, Fig. 4, and Fig. 5 represent the *TIC*, the *CECM*, and the *EIC* model on the six datasets, respectively. We compare the prediction process of our model with



(a) Dataset I Experimental results. (b) Dataset II Experimental results. (c) Dataset III Experimental results.

(d) Dataset IV Experimental results. (e) Dataset V Experimental results. (f) Dataset VI Experimental results.

Fig. 5: Experimental results of *EIC* model.

TABLE II: The Details of 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 *TIC*, *CECM*, *EIC* and *UAPE*.

Dataset	TIC	CECM	EIC	UAPE
Dataset I	77.01%	80.63%	84.48%	93.90%
Dataset II	76.92%	79.92%	84.64%	93.71%
Dataset III	76.68%	80.01%	84.97%	92.82%
Dataset IV	75.49%	80.15%	83.12%	94.01%
Dataset V	75.97%	79.69%	82.89%	93.67%
Dataset VI	74.82%	79.43%	82.77%	91.62%

the actual information propagation process. It is evident that both the dynamic changes in user attitudes during information propagation and the joint effect of multiple neighboring users significantly affect information propagation.

In addition, we conduct experiments on the *UAPE* model proposed in this paper and compare its performance with that of the *TIC*, *CECM*, and *EIC* models. The experimental results, as depicted in Tab. III, clearly demonstrate a substantial improvement in prediction accuracy achieved by our model in comparison to the other models.

VI. CONCLUSION

In this paper, we propose a novel model, *UAPE*, which considers the impacts of dynamically changing user attitudes and the public opinion environment on the information propagation process to accurately depict information propagation in online social networks. Specifically, dynamically changing user attitudes and the joint effects of multiple neighboring users are considered essential reference indicators to realize the accurate prediction of the information propagation trend. Extensive experiments demonstrate that *UAPE* can achieve more satisfactory prediction accuracy on the propagation trend.

VII. ACKNOWLEDGE

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