Automated Influence Maintenance in Social Networks: an Agent-based Approach

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Abstract—Social influence modelling and maximization appear significant in various domains, such as e-business, marketing, and social computing. Most existing studies focus on how to maximize positive social impact to promote product adoptions based on static network snapshots. Such approaches can only increase influence in a social network in short-term, but cannot generate sustainable or long-term effects. In this research work, we study on how to maintain long-term influence in a social network and propose an agent-based influence maintenance model, which can select influential nodes based on the current status in dynamic social networks in multiple times. Within the context of our investigation, the experimental results indicate that multiple-time seed selection is capable of achieving more constant impact than that of one-shot selection. We claim that influence maintenance is crucial for supporting, enhancing and assisting long-term goals in business development. The proposed approach can automatically maintain long-lasting impact and achieve influence maintenance.

Index Terms—Influence maintenance, influence diffusion, long-lasting influence, agent-based modelling

1 Introduction

With the prevalence and advancement of the Internet, on-line social networks have become an important and efficient channel for information propagation. The propagation relies on one of the social phenomena, i.e., social influence, indicating that one's opinions or behaviours are affected by his or her contactable neighbours in the social network [1], [2]. Influence message is a common and concrete representation of social influence, which 'travels' rapidly through the network topologies via users' sharing and posting behaviours. By leveraging the power of social influence, a great many business owners attempt to expand the market and increase the brand awareness through the 'word-of-mouth' effect (or called viral marketing) [3]. In recent years, influence maximization draws tremendous attention to both researchers and domain experts. Influence maximization attempts to identify a set of influential users committed to spreading a piece of influence message to their neighbours, such as adopting a product, expecting that they can propagate influence and maximize the positive impact across the entire network [4]. The selected group of influencers is called *seed set*, and the seeding process is named as *seed selection*.

From a business perspective, influence maximization corresponds to short-term marketing effects, which tend to cause sudden profit spikes that rarely last [5]. Whereas, long-term marketing is typically more beneficial since it emphasizes on long-term and sustainable business goals. Specifically, long-term influence can establish brand awareness and continually produce results even years down the road; thus, without having long-term marketing strategies, short-term success may be short-lived [6]. Motivated by this background, in this research, we aim to achieve constant impact for long-term marketing by investigating the preservation of a particular type of influential situation or status, called *influence maintenance*.

There are many limitations for short-term (or even one-shot) influence maximization when being utilized in real business cases. First, it focuses on how to maximize the influence of one-shot investment. Based on the risk management theory and best practice [7], with the same budget, the multiple-time investment could enable a better business strategy. In this way, the next action can be planned and carried out based on the outcome of the previous investment. For example, in a stock market, very few investors purchase stocks with all the money at only one time. Second, a great many business owners intend to expand the lifespan of influence, so that the brand awareness can be enhanced and increased in the long run [8]. Influence maintenance not only cares about the quantity of users being affected but also considers constant influence impact.

Influence maintenance needs to be supported by a formal influence diffusion model which possesses two attributes: **(1)** the model is capable of capturing the temporal feature of a social network; **(2)** the model can monitor the status of a particular influence. On the other side, in most existing on-line social media applications, information cannot be delivered to the users directly, but cached in individual's message repository, pending for users to access. The timeliness of a particular influence message becomes an important factor to be considered. More specifically, an individual reading list in on-line social networks, such as Weibo[1], is typically presented as a stack, which turns out

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1. http://www.weibo.com

to be last-post-first-read. Thus, the accessing priority of a particular message keeps decreasing over time, and posting or sharing behaviours are not supposed to be triggered without reading it.

In [9], we conducted very preliminary research work on modelling maintaining influence under a particular social context. In this paper, we systematically elaborate and formulate the influence maintenance problem, which tends to maximize the constant impact of a particular influence by considering time-series. Meanwhile, a decentralized influence propagation model, i.e., the Agent-based Timeliness Influence Diffusion (ATID) model, is proposed. In the ATID, the diffusion process is considered as a networked evolutionary phenomenon, users are modelled as autonomous agents, and each maintains its local information incorporating friendship affiliation list, message repository and posting histories. Furthermore, we propose the Timeliness Increase Heuristic (TIH) algorithm for solving the influence maintenance problem. Extensive experiments are conducted by using three real datasets. The experimental results show that: (1) multiple-time selection can maintain influence better than one-shot selection; and (2) the TIH algorithm outperforms the other traditional seed selection algorithms regarding maintaining influence in social networks; and (3) seed-set variation is associated with both selection approaches and network properties. To summarize, the contributions of this research work are as follows.

- We formally defined the influence maintenance problem. To the best of our knowledge, this is the first literature describing the maintenance of influence in on-line social networks, which is significantly different from the adaptive influence maximization problem (clarified in the related work).
- We proposed a novel decentralized influence diffusion model to accommodate to the influence maintenance problem. The proposed model is capable of capturing two major elements for maintaining long-lasting influence, i.e., the temporal feature of a social network and the status of a particular influence.
- We proposed a novel timeliness-based seed selection algorithm to maximize the influence lifespan.

The rest of this paper is organized as follows. Section 2 reviews the literature related to this research work. Section 3 introduces the preliminaries, formal definitions and problem description. Section 4 systematically elaborates the influence maintenance using the proposed decentralized diffusion model, and the TIH algorithm is also described. In Section 5, experimental results are presented to evaluate the performance of the proposed model. Our conclusions and future works are detailed in Section 6.

2 Related Work

2.1 Adaptive Influence Maximization

A rich body of research works has been devoted to the influence maximization problem over the past ten years [4], [10]. The majority of these studies fall into either full-feedback or non-feedback models [11]. In the former, all the seeds are committed based on the networked features or specific heuristics. Namely, there is no adaptive seed selection policy applied. Whereas, the latter utilizes the observations during the seeding process, where the rules for identifying influencers are also known as adaptive policies. Based on the full-feedback model, some researchers extend the influence maximization problem by exploring the adaptive budget allocations [11], [12], [13]. Hatano et al. address budget allocation for maximizing influence by considering adaptive strategies [14]. Yang et al. model the continuous influence maximization problem and devise a coordinate descent framework [15]. Similarly, Rodriguez and Schölkopf study influence maximization in continuous time diffusion networks by developing INFLUMAX model that accounts for the temporal dynamics underlying diffusion process [16].

Our research work departs from the body of the studies mentioned above mainly in two aspects. First, the existing studies focus on investigating adaptive policies on the basis of the concept of adaptive submodularity [11]. Whereas, we concentrate on modelling the influence maintenance, achieving a constant impact by considering the timeliness degrees, though adaptive seeding algorithms are proposed to accommodate to the model. Second, these research works do not give a clear concept of time-series, and the networked evolutionary trend driven by influences is not captured. While, in this paper, the time-series can be presented and the global observation of a social network status can be captured since *Agent-Based Modelling (ABM)* [17], [18] has been applied in our model.

2.2 Dynamic Social Streams

Dynamics is one of the major features of social networks. Users join and quit, and links are forming and vanishing over time. The influence propagation tendencies among the users also can be altered dramatically with the involvement of any breaking news. Many research works have been dedicated to the dynamic social streams, which aim to investigate the possible solutions for real-time influence maximization in a dynamic environment. Konstantin et al. present STRIP, the first streaming method computing influence probabilities [19]. Subbian et al. propose an influence-query framework to mine influencers in a time-sensitive fashion from streaming social data [20]. Wang et al. propose the Influential Checkpoints framework and a Sparse Influence Checkpoints framework to tackle the stream influence maximization querying processing [21].

Whereas, nearly all the literature of dynamic social streams still focus on the mining the influencers and enlarging the global activation coverage, but fail to track the status of any influence message. By contrast, the objective of influence maintenance is set to maintain the popularity of a particular influence message in a dynamic environment.

2.3 Influence Diffusion Modelling

Most researchers investigate influence diffusion and influence maximization problems based on two popularly adopted influence diffusion models, i.e., Independent Cascade (IC) model and Linear Threshold (LT) model [4]. Many studies are conducted under various extended influence diffusion models. Wang et al. propose the IMIC-OC model to explain how users build opinions during the process of information spreading [22]. Goyal et al. research learning influence probabilities in social networks based on the users' past actions, and successfully predict the time by which a user may be expected to perform an action [23]. Tang et al. propose topical affinity propagation to model the topic-level social influence and measure the strength quantitatively [24]. Chen et al. formulate the influence maximization problem by focusing on the temporal factors based on the heat diffusion model [25], a realistic model that simulates the social influence in accordance with a physical phenomenon, i.e., heat flow [26].

Most of the existing research works oversimplify the influence diffusion process, and the propagation models concentrate on the activation state of each individual. Whereas, the users' features and behaviours affecting the influence acceptance have not been considered. Moreover, the dynamic status of influence messages over time is neglected. By contrast, the proposed ATID model for influence maintenance is decentralized, focusing on modelling individuals' personalized traits and behaviours. Furthermore, the ATID is capable of capturing the evolutionary network trend based on time-series, as well as the status of influence messages.

2.4 Agent-based Modelling for Influence Diffusion

Agent-Based Modelling (ABM) has demonstrated many advantages in modelling complex systems, simulating continuous variations and analysing the trend of a particular phenomenon [17], [18]. Moreover, it is more suitable for exploring the macro world through defining a micro level of a social system [27], [28]. Some researchers model the influence diffusion in a social network by leveraging ABM. Jiang et al. survey the influence diffusion in social networks from a multi-agent perspective [29]. Li and Tang analyse the group polarization based on ABM [30]. Van Maanen and Van der Vecht propose a multi-disciplinary approach for studying on-line social network influence [31]. Similarly, Li et al. propose an agent-based influence diffusion model, where the influence propagation demonstrates an evolutionary process, and the model is applicable in a dynamic environment and functions even without the network topology [32]. In their studies, the factors affecting the activation cost are considered, including individual's personalities, i.e., the degree of stubbornness, predisposition, i.e., prior commitment level, and social pressure. Li et al. exploit influence maximization using a novel decentralized approach, i.e., the stigmergy-based influence maximization model, where the influence propagation process is modelled as ants crawling across the network topology [33]. However, the message timeliness feature has been ignored in nearly all of these studies. With an exception, Han et al. propose a novel algorithm for addressing the influence maximization problem, which incorporates time delay for timeliness, opportunistic selection for acceptance ratio and broad diffusion for influence breadth [34]. Nevertheless, their proposed BICOT model in [34] neglects the long-term trend of a social network.

On the other side, most agent-based models for influence diffusion are user-centred, which follow the rule that a user activates users through direct interactions. The evident disadvantages are reflected in two aspects, i.e., lacking the model of influence instances and having difficult in estimating the influence probabilities. The former fails to track the state of influence; the latter shows a non-trivial task in calculating the weight of influential links, i.e., the 'cost' of activating one user by the neighbours [23], [35].

Different from the studies and models discussed above, the proposed ATID model captures the properties of the influences existed in the same environment as that of the individuals'. Therefore, the observations of the disseminated influence messages can also be reflected from the ATID model. Moreover, the influence activation is channelled through accessing messages in the repository, which mitigates the complexity of modelling the influential relationships among the individuals.

3 Preliminaries and Problem Formulation

3.1 Social Networks and Newsfeed

Most on-line social networks can be classified into two categories, depending on whether the newsfeed is re-organized.

First, some popular on-line social networks, such as Facebook[2], create personalized activity feeds for increased interactions and content contributions [36]. For example, Facebook previously employed the *EdgeRank* algorithm[3] to determine which stories appear as newsfeed for each user by considering three original elements, i.e., affinity, weight and time decay [37]. Therefore, to maximize the impact of a particular influence, social media marketers need to stay informed of the changes to the latest newsfeed algorithms. Nowadays, newsfeed algorithms have become much more sophisticated. For example, Facebook has begun to employ a more complex ranking algorithm based on machine learning [36], [37], [38]. In this sense, it is nearly impossible for researchers to investigate the influence diffusion modelling in such social networks, as the outcome is much dependent on the newsfeed algorithms.

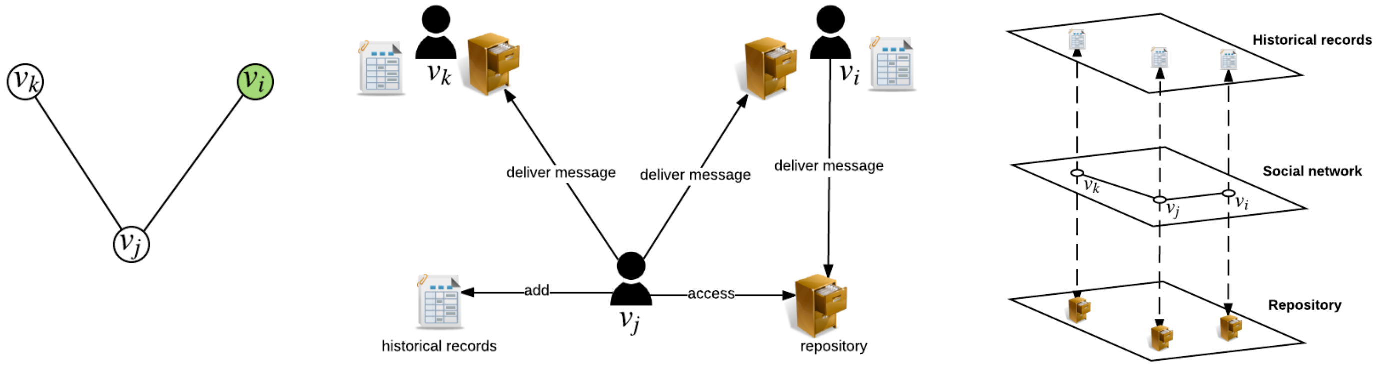
Second, on-line social networks, like WeChat[4], enable users to share daily moments with friends. The newsfeed is generated instantly based on the timeline. Moreover, the social interactions among the individuals, such as 'comments' and 'like', are only visible if friendship connections are established. Different from Facebook, such kind of social networks allow duplicate messages propagating through the network, and no newsfeed algorithms are applied. Moreover, 'posting a message' or 'forwarding a message' can be regarded an influential behaviour, while 'like' and 'comments' weigh less due to the visibility and privacy restrictions.

In this research, we mainly focus on the second category of social networks and investigate influence maintenance, where the timeliness degree of a message plays a pivotal role in organizing the newsfeed.

3.2 Agent-based Influence Diffusion

ABM simulates the influence diffusion process by emphasizing individualized features and behaviours. Users in social networks have been modelled as autonomous interactive

2. https://www.facebook.com/
3. http://edgerank.net/
4. http://www.wechat.com/en/



(a) Social Network Graph (b) Agent-based Influene Diffusion Model (c) Influence Diffusion Facets

Fig. 1. General Idea of the Proposed Model

agents, and they have their interests and behaviours. Based on the influence theory, homophily and influence are driven by the users' preferences. Thus, individuals have different tendencies of reading and posting different types of topics [39]. The messages wrapped with influence are supposed to be delivered to the repository of corresponding recipients, where the repository is filled with the influence messages from the neighbours. Each agent has a different frequency of accessing its repository. Based on agent's preference and message timeliness degree (see Definition 4), the agent determines whether the information is to be shared with its adjacent neighbours. If an agent is influenced (*activated*), i.e., posting action is triggered, then, the influence message reaches its neighbours' repositories. Whereas, in the recipient's repository, the timeliness degree of this message keeps decreasing over time, but this will be refreshed if the repository owner is activated or the same message has been received again.

In Figure 1, a toy example has been demonstrated, which represents the general idea of our proposed model. Figure 1a shows an ordinary social network graph in traditional influence diffusion models. Let v_i be an initial influencer who attempts to activate v_j with a certain success rate. While v_j intends to influence its adjacent neighbour v_k if v_j is activated by v_i. Figure 1b describes our model from a microscopic point of view. Individual's influence activation is achieved by accessing the repository. More specifically, if a user is influenced (activated), the influence message is supposed to be delivered to all the neighbours' repositories. Meanwhile, this message is archived as one of the sender's historical records. From a macroscopic viewpoint, apart from the topological structure of a social network, two more factors are affecting the influence propagation, i.e., the historical records and the repository, which is illustrated in Figure 1c.

Since the individual's activation is achieved through reading influence messages in the repository, the user-user influential relationship in this model does not directly affect the influence acceptance. Namely, the model is developed based on the assumption that the influence activation is only driven by the existing messages in the repository and past posting behaviours. Moreover, with consideration of different activation cost for each agent, the model would become a rather complicated one.

TABLE 1
Frequently Used Notations

Notation	Description
v_i	user agent
msg_p	influence message
φ	timeliness degree
r	influence attenuation constant
λ	the speed of influence decay
R_{v_i}	incoming message repository of v_i
H_{v_i}	historical records of v_i
A	seed set
ϱ_{msg_p}	global activation coverage (GAC) of msg_p
$\xi^{t_n}_{msg_p}$	global timeliness degree (GTD) of msg_p at t_n
Ω_{msg_p}	global cumulative timeliness degree (GCTD) of msg_p
$\Delta\Omega$	incremental timeliness contribution
$P(.)$	probability
$g(.)$	timeliness gain

The detailed modelling will be elaborated in Section 4. Before moving on to the technical parts of this paper, we summarise the frequently used notations in Table 1.

3.3 Formal Definitions

Definition 1: A user agent $v_i, (v_i \in V)$ is defined as a vertex in a social network $G = (V, E)$, where $V = \{v_1, ..., v_n\}$ denotes a set of agents and E represents a set of edges, $E = \{e_{ij} | 1 \leq i, j \leq n\}, i, j \in \mathbb{N}^+, \{v_i, v_j\} \subseteq V$. v_i has a neighbour set $\Gamma(v_i)$. If agent v_j is a neighbour of v_i, then $\{e_{ij}\} \subseteq E, v_j \in \Gamma(v_i)$. While, E_{v_i} indicates the edge set connected with v_i, where $E_{v_i} = \{e_{ij} | v_i \neq v_j \wedge v_j \in \Gamma(v_i)\}$. $|V|$ and $|E|$ denote the cardinality of agents and edges respectively. The affiliation information is maintained by each agent locally. In addition, agent v_i has a binary state $s^{msg_p}_{v_i}$ towards a particular influence message msg_p (see Definition 3), where $s^{msg_p}_{v_i} \in \{0, 1\}$, representing inactive and active, respectively.

Definition 2: Environment ε_{v_i} is an ego network representing the local influence diffusion context or the local view of a particular agent v_i. The environment of v_i is denoted by using a four-tuple, $\varepsilon_{v_i} = (\Gamma(v_i), E_{v_i}, R_{v_i}, H_{v_i})$, where R_{v_i} and H_{v_i} represent the repository and historical records of v_i, respectively (see Definitions 4 and 5). Each agent is capable of accessing all the resources in its environment.

Definition 3: Influence message msg_p is defined as a particular piece of information sent from one person to his or her contactable recipients, affecting their opinions or behaviours. It is a common and concrete representation of social influence in on-line social networks. In the current settings, each influence message msg_p belongs to a particular topic τ_x, i.e., $msg_p \in \tau_x$. If agent v_i is influenced after accessing msg_p, then $s_{v_i}^{msg_p} := 1$; meanwhile, v_i attempts to deliver the influence message to the repositories of neighbours $\Gamma(v_i)$.

Definition 4: Timeliness degree of an influence message is a real value, describing the position of an influence message in a user's repository at a particular time. Timeliness degree not only reflects the status of the influence message, but also implies whether a specific piece of news arrives at a suitable time. In reality, it happens more than often that users check the friend-circle or moments update right after a message has been posted. Subsequently, this influence message has a higher chance to draw the user's attention than that of the others. Mathematically, we define the timeliness degree of message msg_p in v_i's repository at time t_m using the notation $\varphi(v_i, msg_p, t_m)$.

Inspired by the behaviour analysis approach introduced in [40], [41], we assume that the effect of influence satisfies the principle of natural decay; thus, the exponential decay, i.e., e^{-r}, can be leveraged to describe the attenuation of influence, where r denotes the attenuation constant. Suppose message msg_p has been delivered to v_i's repository at t_b, then the timeliness degree is formulated in Equation 1.

$$\varphi(v_i, msg_p, t_m) = e^{-r\cdot(m-b)} \tag{1}$$

The timeliness degree of any message equals to 1 when arriving at the repository, i.e., $m = b$, and starts to decrease over time. Therefore, the speed of influence decay λ is described in Equation 2, which shows the speed is gradually slowing down.

$$\begin{aligned} \lambda &= \varphi(v_i, msg_p, t_{m-1}) - \varphi(v_i, msg_p, t_m) \\ &= e^{-r\cdot(m-1-b)} - e^{-r\cdot(m-b)} \\ &= (e^r - 1)\cdot e^{-r\cdot(m-b)}, m \geq b \end{aligned} \tag{2}$$

We assume msg_p is supposed to be ignored by agent v_i after time t_e, subject to $e \in \mathbb{N}$, $e > m - b$ and $\varphi(v_i, msg_p, t_e) \geq \sigma(msg_p)$, where $\sigma(msg_p)$ denotes the valid timeliness degree threshold of msg_p. Likewise, the higher timeliness degree, the greater probability that the influence message can be accessed by the user when visiting the repository.

Definition 5: Repository $R_{v_i}^{t_m} =< r_1, r_2, ..., r_n >$ refers to a cached container of agent v_i at time step t_m. It incorporates all the valid incoming messages from neighbours $\Gamma(v_i)$ to agent v_i. Each agent has a different frequency of accessing the repository. An element in $R_{v_i}^{t_m}$ can be represented as a three-tuple, i.e., $r_k = (v_j, msg_p, \varphi)$, where v_j denotes the agent who posts the influence message msg_p, $v_j \in \Gamma(v_i) \cup \{v_i\}$ and $\varphi \geq \sigma(msg_p)$. For simplification purposes, we regard φ as the timeliness degree of the corresponding message at t_m, which is equivalent to $\varphi(v_i, msg_p, t_m)$.

Definition 6: Historical records refer to past outgoing influence messages delivered from a particular user to the neighbours. Historical records $H_{v_i} = \{txn_1, txn_2, ..., txn_n\}$ is defined as a collection of user v_i's past sharing transactions, i.e., posted messages. An element of H_{v_i} can be denoted by a three-tuple, i.e., $txn_n = (msg_p, \varphi, t_m)$, where φ represents the message timeliness degree when posted (clarified in Definition 5), $\varphi \geq \sigma(msg_p)$. While, t_{now} refers to the current time step, and Δt describes the valid lifespan of a transaction, $t_{now} - t_m \leq \Delta t$. Given $t_{now} - t_m > \Delta t$, the corresponding transaction is supposed to be removed from the collection. Historical records H_{v_i} is also an implication of agent v_i's interests or preferences.

3.4 Problem Description

Influence maintenance in this paper is defined as the process of preserving a particular type of influential situation or the status of influence being preserved. The concept is derived from influence maximization. Specifically, given a finite budget k (seed set size) and a limited time span $[t_0, t_m]$, an investment (seed selection) occurs once every n time steps, thus, the investment time steps $I = \{t_{N\times n} | N \in \mathbb{N} \wedge N \times n < m\}$, where $t_{N\times n}$ represents a particular seed selection point. There are $|I|$ times of investment considered for maintaining the influence.

Influence maintenance aims to find a solution of identifying the seed set $A_{t_{N\times n}}$ for each time step $t_{N\times n}$ to maximize the influence lifespan of msg_p. Thus, the selected seed set A is a collection of seeds identified from each investment time step, i.e., $A = \{A_t | t \in I\}$ and

$$\sum_{t \in t_{N\times n}} |A_t| = k \tag{3}$$

We assume that the same amount of seeds are supposed to be selected for each selection point, and any seeds cannot be selected more than once. In other words, given $\{A_i, A_j\} \subseteq A$, $|A_i| = |A_j|$, $A_i \cap A_j = \emptyset$.

The *Global Timeliness Degree (GTD)* of msg_p at a particular time step t_n is represented as $\xi_{msg_p}^{t_n}$, which can be calculated by using Equation 4. The popularity trend of a particular influence message can be reflected by connecting the GTD of the corresponding influence in each time step.

$$\xi_{msg_p}^{t_n} = \sum_{v_i \in V} \varphi(v_i, msg_p, t_n) \tag{4}$$

The overall effective influence lifespan of msg_p in the entire social network is evaluated by using *Global Cumulative Timeliness Degree (GCTD)* of a specific time span $[t_0, t_m]$, i.e., Ω_{msg_p}, which can be derived by using Equation 5.

$$\Omega_{msg_p} = \sum_{t_0}^{t_m} \xi_{msg_p}^{t_n} = \sum_{t_0}^{t_m} \sum_{v_i \in V} \varphi(v_i, msg_p, t) \tag{5}$$

The objective of influence maintenance is to maximize Ω_{msg_p}. Furthermore, the traditional influence effectiveness evaluation metrics, i.e., Global Activation Coverage (GAC), is taken into consideration as well. GAC of influence message msg_p is denoted using the notation ϱ_{msg_p}, indicating the number of users in the social network getting affected or activated by msg_p. It is formulated in Equation 6.

$$\varrho_{msg_p} = \sum_{v_i \in V} |\{v_i | s_{v_i}^{msg_p} = 1\}| \tag{6}$$

4 Influence Maintenance Model

4.1 The Agent-based Timeliness Influence Diffusion (ATID) Model

The ATID model is a decentralized influence diffusion model which utilizes the advantages offered by ABM. The influence propagation in social networks demonstrates a networked evolutionary pattern driven by individuals' actions. In this model, each agent maintains its ego-network and makes decisions of performing social activities based on both timeliness degree of the influence message and its preference.

There are many reasons to make a user to carry out a social behaviour, such as influence from neighbours in the same social networks, affected by any external events, or the user actively posts some messages without getting influenced by anybody [23]. In the proposed model, we assume users deliberately post messages after influenced by the neighbours, and each individual's repository and historical records contain enough evidence for statistical analysis. Furthermore, each user agent (e.g., v_i) has a different frequency of accessing its repository, i.e., $freq(v_i)$, which can be calculated by using Equation 7. It can be seen that $freq(v_i)$ is equivalent to the probability of v_i accessing a particular message msg_p in its repository at time t_m, i.e., $P_f(v_i, msg_p, t_m)$.

$$\begin{aligned} freq(v_i) = & P_f(v_i, msg_p, t_m), \\ & subject\ to\ \varphi(v_i, msg_p, t_m) \geq \sigma(msg_p) \end{aligned} \tag{7}$$

One important task of influence diffusion modelling is to identify the probability of getting activated after reading message msg_p of topic τ_x at time t_m, where the influence probability may not remain constant independently of time [23]. Therefore, in the proposed model, a user agent has the capability of adapting its probability of posting message msg_p based on two major factors, i.e., the attention degree of influence message msg_p and the user preference derived from the latest k posts. Therefore, the probability of user agent v_i posting message msg_p at time t_m can be estimated in Equation 8:

$$P(msg_p | R_{v_i}^{t_m}, H_{v_i}) = P(msg_p | R_{v_i}^{t_m}) P(\tau_x | H_{v_i}, msg_p \in \tau_x) \tag{8}$$

In Equation 8, $P(msg_p | R_{v_i}^{t_m})$ represents the attention degree of influence message msg_p in v_i's repository at time t_m, i.e., the probability of getting attracted by msg_p, which is associated with the message timeliness degree $\varphi(v_i, msg_p, t_m)$. While $P(\tau_x | H_{v_i}, msg_p \in \tau_x)$ denotes the probability of sharing topic τ_x at time t_m on the basis of v_i's past behaviours.

Thus, the attention degree of influence message msg_p in v_i's repository at time t_m is formulated in Equation 9.

$$P(msg_p | R_{v_i}^{t_m}) = \frac{\sum\limits_{r_n \in R_{v_i}^{t_m} \wedge r_n.msg = msg_p} \varphi(v_{r_n}, r_n.msg, t_{r_n})}{\sum\limits_{r_n \in R_{v_i}^{t_m}} \varphi(v_{r_n}, r_n.msg, t_{r_n})}, \tag{9}$$

where $t_{r_n} = t_m - t_n$, t_n denotes the time when the message r_n arrives the repository.

According to v_i's historical records, the probability of sharing topic $\tau_x, msg_p \in \tau_x$ at time t_m can be derived from the weighted average of topic τ_x's timeliness difference. Specifically, if msg_p has been posted when its timeliness degree $msg_p.\varphi$ is low, this implies that the user is very interested in the topic of msg_p (i.e., $msg_p.\tau$), and the message timeliness degree will not significantly impact the chances of posting such messages. Hence, $P(\tau_x | H_{v_i}, msg_p \in \tau_x))$ is represented in Equation 10.

$$P(\tau_x | H_{v_i}, msg_p \in \tau_x)) = \frac{\sum\limits_{msg_p \in \tau_x} (1 - msg_p.\varphi)}{\sum\limits_{msg_q \in H_{v_i}} (1 - msg_q.\varphi)} \tag{10}$$

4.2 Diffusion Process under the ATID

Benefited from ABM, individual's features, behaviours and the local environment can be considered in the ATID. As the ATID is a decentralized influence propagation model, the diffusion algorithm under the ATID corresponds to an agent's response when accessing its repository. The diffusion process in the ATID is described in Algorithm 1.

Algorithm 1 The Influence Diffusion Algorithm under the ATID

Input: $v_i, t_m, msg_p, msg_p \in \tau_x$
Output: v_i's social behaviour (posting / not)

1: Generate random decimal $rand_1$
2: **if** $rand_1 \leq freq(v_i) \wedge \Phi(msg_p | H_{v_i}) = 0$ **then**
3:     Compute $P(msg_p | R_{v_i}^{t_m})$ using Equation 9
4:     Compute $P(\tau_x | H_{v_i}, msg_p \in \tau_x))$ using Equation 10
5:     Compute $P(msg_p | R_{v_i}^{t_m}, H_{v_i})$ using Equation 8
6:     Generate random decimal $rand_2$
7:     **if** $P(msg_p | R_{v_i}^{t_m}, H_{v_i}) \leq rand_2$ **then**
8:         **for** $\forall v_j \in \Gamma(v_i) \cup \{v_i\}$ **do**
9:             $R_{v_j}^{t_{m+1}} := R_{v_j}^{t_m} \cup \{(v_i, msg_p, 1)\}$
10:         **end for**
11:         $H_{v_i} := H_{v_i} \cup \{(msg_p, \varphi, t_m)\}$
12:     **end if**
13: **end if**
14: **for** $\forall r_n \in R_{v_i}^{t_{m+1}} \setminus \{(v_i, \tau_x, \varphi)\}$ **do**
15:     $r_n.\varphi := r_n.\varphi - \lambda$
16: **end for**

In Algorithm 1, the inputs incorporate user agent v_i, time t_m, the influence message msg_p and msg_p's corresponding topic τ_x; while the output is v_i's social behaviour, i.e., post msg_p at time t_m or not. Line 2 checks the precondition of sharing msg_p, where $\Phi(msg_p|H_{v_i})$ is an indicator function, which returns 0 if msg_p is not posted by v_i before, and 1 otherwise. Lines 3-5 aim to compute the probability of posting msg_p by v_i at t_m. Lines 8-11 update the repositories of agents in v_i's ego-network, as well as its own historical records. Lines 14-16 demonstrate that the message timeliness attenuation occurs in v_i's repository.

4.3 The Timeliness Increase Heuristic (TIH) Algorithm

There are some classic seed selection algorithms, such as degree-based, greedy, random and Degree Discount Heuristic (DDH) selections [4], [42]. These algorithms are developed based on either the node features or influence diffusion models. More specifically, degree-based approach identifies the influencers by considering the node degree. Greedy algorithm attempts to reach the maximum influence marginal gain in each selection, but it is not scalable. DDH extends the rank-based algorithm that once a node is selected, the degree of corresponding neighbours is deducted by one. Random selection does not follow any heuristics, which selects seeds randomly.

The rationale of developing TIH algorithm is clarified as follows. Since influence maintenance is newly proposed, no existing algorithms are exclusively designed for this problem. We attempt to leverage the classic approaches tailored from the influence maximization problem, and set further improvement of the performance as one of the future works. Based on the brief introduction of several state-of-the-art seeding algorithms in the traditional influence maximization problem, greedy selection is one of the fundamental algorithms, coming with a $(1-1/e)$ approximation guarantee. This results from properties of monotonicity and sub-modularity that the spread function exhibits under some diffusion models [4]. Meanwhile, DDH is a simple and popular algorithm, which is developed based on the fact that many of the most central nodes may be clustered; thus, it is not necessary to target all of them [42].

Inspired by the key features of greedy algorithm and the intuitiveness of DDH, we utilize the similar concepts to maintain an influence. Namely, the influence fading-out zone should be first targeted to achieve influence maintenance, and each selection is conducted based on the assumption that previous seed is selected. Therefore, TIH algorithm is presented in Algorithm 2. For selecting each seed, the TIH tends to search for the user v^*, who can bring the maximum message timeliness gain, which is calculated in Equations 11 and 12.

$$v^*_{t_m} = \underset{v_i}{\operatorname{argmax}} \sum_{v_j \in \{v_i\} \cup \Gamma(v_i)} g(v_j, msg_p, t_m) \tag{11}$$

$$g(v_j, msg_p, t_m) = 1 - \varphi(v_j, msg_p, t_m) \tag{12}$$

In Equations 11 and 12, $g(v_j, msg_p, t_m)$ denotes v_j's message timeliness gain if v_i is selected as a seed. The selection of the next seed is based on the assumption that if previously identified seeds are selected. Thus, the TIH selection is described in Algorithm 2.

The inputs include the social network G, the number of seeds to be selected k_m, the time step t_m and influence message msg_p; the output is the selected seed set at t_m. Lines 2-4 replicate all the user agents' current timeliness degree of msg_p to a temporary variable. Lines 6-11 calculate the global timeliness gain for all the users in G, in other words, this evaluates the influence impact of each individual. Lines 12-13 aim to find the most 'beneficial' user. Lines 15-16 update the temporary timeliness variables of all the users in v^*'s ego network with the assumption that if v^* is activated and selected as a seed. The worst-case time complexity of the TIH algorithm is determined by Lines 5-8. As k_m is a constant, the complexity is $O(n^2)$.

Algorithm 2 The TIH Algorithm

Input: $G=(V,E), k_m, t_m, msg_p$
Output: A_m
1: Initialize $A_m := \emptyset$
2: **for** $\forall v_i \in V$ **do**
3: $\quad v_i.\varphi' := v_i.\varphi$
4: **end for**
5: **while** $|A_m| < k_m$ **do**
6: $\quad$ **for** $\forall v_i \in V$ **do**
7: $\quad\quad g_{sum}(v_i, msg_p, t_m) := 0$
8: $\quad\quad$ **for** $\forall v_j \in \{v_i\} \cup \Gamma(v_i)$ **do**
9: $\quad\quad\quad g(v_j, msg_p, t_m) = 1 - v_j.\varphi'$
10: $\quad\quad\quad g_{sum}(v_i, msg_p, t_m) += g(v_j, msg_p, t_m)$
11: $\quad\quad$ **end for**
12: $\quad$ **end for**
13: $\quad$ Find v^* using Equation 11
14: $\quad A_m := A_m \cup \{v^*\}$
15: $\quad v^*.selected := true$
16: $\quad$ **for** $\forall v_j \in \{v^*\} \cup \Gamma(v^*)$ **do**
17: $\quad\quad v_j.\varphi' := 1$
18: $\quad$ **end for**
19: **end while**

It can be seen that the seed set selected by TIH algorithm is the local optimal solution, following the heuristic that the largest timeliness fading-out zone should be firstly targeted. Moreover, the TIH demonstrates its advantages in maintaining the influence of a hypothesis message.

$$
\begin{aligned}
\Delta\Omega &= \sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} \sum_{t=t_m}^{t_{m+n}} \varphi'(v_j, msg_p, t) - \varphi(v_j, msg_p, t) \\
&= \sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} (\sum_{t=t_m}^{t_{m+n}} \varphi'(v_j, msg_p, t) - \sum_{t=t_m}^{t_{m+n}} \varphi(v_j, msg_p, t)) \\
&= \sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} (\sum_{i=0}^{n} e^{-i\cdot r} - \sum_{i=0}^{n} e^{-(m_j+i)\cdot r}) \\
&= \sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} (\frac{1-e^{-(n+1)\cdot r}}{1-e^{-r}} - \frac{1-e^{-(n+1)\cdot r}}{1-e^{-r}} \cdot e^{-m_j\cdot r}) \\
&= \sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} \frac{1-e^{-(n+1)\cdot r}}{1-e^{-r}} \cdot (1-e^{-m_j\cdot r}) \\
&= \frac{1-e^{-(n+1)\cdot r}}{1-e^{-r}} \sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} (1-e^{-m_j\cdot r}) \\
&= \frac{1-e^{-(n+1)\cdot r}}{1-e^{-r}} \sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} (1-\varphi(v_j, msg_p, t_m)) \\
&= \frac{1-e^{-(n+1)\cdot r}}{1-e^{-r}} \sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} g(v_j, msg_p, t_m)
\end{aligned}
\tag{13}
$$

Theorem 1. *TIH is a kind of greedy algorithm.*

Proof. Given current time step t_m, and $\varphi(v_j, msg_p, t_m) = e^{-m_j\cdot r}$, where m_j denotes the time difference between when msg_p arrives and t_m. If node v_i has been selected as a seed, the corresponding timeliness degree of node set $\{v_j | v_j \in \{v_i\}\cup\Gamma(v_i)\}$ is supposed to be reset back to 1, i.e., $\varphi'(v_j, msg_p, t_m) = 1$. Therefore, the incremental timeliness contribution of activating v_j, i.e., $\Delta\Omega$ can be derived using Equation 13.

In Equation 13, $n \in \mathbb{N}$, representing the difference between the total time steps and the current time step, and $e^{-m_j\cdot r}$ denotes the timeliness degree of a particular message in v_j's repository at t_m according to Equation 1. It is obvious that $\frac{1-e^{-(n+1)\cdot r}}{1-e^{-r}}$ is a coefficient, $\sum_{v_j \in \{v_i\}\cup\Gamma(v_i)} g(v_j, msg_p, t_m)$ exactly corresponds to the objective function of TIH algorithm in Equation 11. Therefore, TIH is a kind of greedy algorithm. □

Lemma 2. *Let S be the seed set selected by TIH and S^* be the seed set that maximizes Ω_{msg_p}. $\Omega_{msg_p}(S)$ be the GCTD of msg_p with seed set S. Then $\Omega_{msg_p}(S) \geq (1-1/e)\cdot\Omega_{msg_p}(S^*)$. In other words, the theoretical guarantee for TIH in the influence maintenance problem is $1-1/e$.*

Proof. Let A be the initial seed set and $X =< v_1, v_2, ..., v_h >$ be one of the paths activated by A. $f(A)$ represents the GCTD of msg_p caused by A. $f_X(A)$ denotes the GCTD accumulated by path X. Similar to the calculations in Equation 13, we have:

$$f_X(A) = \sum_{j=1}^{h} \sum_{t=t_{m+j}}^{t_{m+n}} g(v_j, msg_p, t)$$

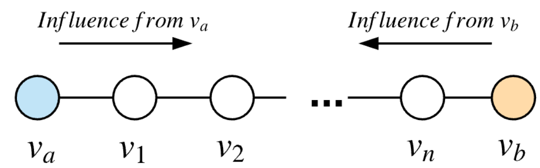


Fig. 2. One of the Overlapped Influence Diffusion Paths

, where $g(v_j, msg_p, t_m)$ is defined in Equation 12, and $0 \leq g(v_j, msg_p, t) \leq 1$. It is easy to proof that $f_X(A)$ is sub-modular. Hence:

$$f(A) = \sum_{outcomes\ x} Prob|X| \cdot f_X(A)$$

, which is also sub-modular since the non-negative linear combination of sub-modular functions is sub-modular. As we clarified in Theorem 1 that TIH is a kind of greedy algorithm. According to Theorem 2.4 in [4], we have $f(A) \geq (1-\frac{1}{e})f(A^*)$, where A^* denotes the set that maximizes $f(.)$ over all k-element sets.

Let $f(S) = \Omega_{msg_p}(S)$, the lemma is proofed.

□

4.4 Influence Maintenance Analysis

We analyse the influence maintenance by considering the timeliness gain contributed by two seeds v_a and v_b under both scenarios, i.e., one-shot selection and multiple-time selection, where the time discrepancy of selecting both users is denoted by using m_0. In the former, no time discrepancy is presented, i.e., $m_0 = 0$, while in the latter, $m_0 \neq 0$.

Suppose that enough time is given for the influence decay, i.e., $n \to \infty$, if any node is activated, the theoretical timeliness gain would be $1/(1-e^{-r})$ according to Equation 13. If all the influence-diffusion paths of active users fail to overlap with each other, the global timeliness gain of one-shot selection would be the same as that of the multiple-time selection. Whereas, in reality, this rarely happens. Therefore, we consider the situation when the influence-propagation paths cover same partial nodes with each other.

Suppose the influences disseminated from v_a and v_b can reach each other. In other words, path $\overrightarrow{v_{a,b}} =< v_a, v_1, v_2, ..., v_n, v_b >$ exists in the network, which is illustrated in Figure 2. Moreover, for simplification purpose, we assume that the influence propagation probability remains the same.

For any node v_x in path $\overrightarrow{v_{a,b}}$, the corresponding $\Delta\Omega$ is explicitly determined by the time discrepancy of the influences ΔT from two sources, v_a and v_b, where ΔT is associated with the number of nodes in between, i.e., n and the time difference in activating v_a and v_b, i.e., m_0. Hence, values of influence maintenance related parameters are described in Table 2.

In Table 2, T_{v_a} is an n-tuple, having a finite ordered list of n elements, where each element denotes the time step when the influence initiated from v_a arrives at the corresponding node, and the sequence implies the influence-diffusion path. Meanwhile, $\Delta T = (T_{v_b} - T_{v_a})$, where each element indicates

TABLE 2
Influence Maintenance Parameters

	v_1	v_2	...	v_n
T_{v_a}	d_0	d_0+1	...	d_0+n-1
T_{v_b}	m_0+d_0+n-1	m_0+d_0+n-2	...	m_0+d_0
ΔT	$\lvert m_0+n-1\rvert$	$\lvert m_0+n-3\rvert$	...	$\lvert m_0+n-(2n-1)\rvert$
$\Delta\Omega$	$\sum_{i=0}^{\lvert m_0+n-1\rvert-1} e^{-ir}$	$\sum_{i=0}^{\lvert m_0+n-3\rvert-1} e^{-ir}$	...	$\sum_{i=0}^{\lvert m_0+n-(2n-1)\rvert-1} e^{-ir}$

the absolute value of the difference between the elements in T_{v_b} and T_{v_a} at the same position.

If ΔT is odd, ΔT starts from m_0+n-1, decreasing by 2 further down the influence-diffusion path, and begins to increase by 2 for each hop when the value reaches 1. Similarly, if ΔT is even, ΔT drops by 2 and then is added by 2 after reaching 0. For example, given $n=6$, we can obtain the data in Table 3.

TABLE 3
Example: value variation of ΔT (n=6)

m_0 (even)	ΔT (odd)	m_0 (odd)	ΔT (even)
0	$(5,3,1,1,3,5)$	1	$(6,4,2,0,2,4)$
2	$(7,5,3,1,1,3)$	3	$(8,6,4,2,0,2)$
4	$(9,7,5,3,1,1)$	5	$(10,8,6,4,2,0)$
6	$(11,9,7,5,3,1)$	7	$(12,10,8,6,4,2)$

Apparently, in both scenarios where ΔT is even or odd, merely one different element can be seen when m_0 increases by 2.

Lemma 3. $\forall k\in\mathbb{N}$, $\Delta\Omega(m_0=k+2)>\Delta\Omega(m_0=k)$.

Proof.

$$\begin{aligned}\Delta\Omega' &= \Delta\Omega(m_0=k+2)-\Delta\Omega(m_0=k)\\ &= \sum_{i=0}^{|k+2+n-1|-1} e^{-ir} - \sum_{i=0}^{|k-n+1|-1} e^{-ir}\\ &= \sum_{i=|k-n+1|}^{|k+n+1|-1} e^{-ir} > 0, \{n,k\}\in\mathbb{N}, n\geq 1\end{aligned}$$

□

According to Lemma 3, $\forall k\in\mathbb{N}$, we have:

$$\begin{aligned}&\Delta\Omega(m_0=0)<\Delta\Omega(m_0=2)<...<\Delta\Omega(m_0=2k)\\ &\Delta\Omega(m_0=1)<\Delta\Omega(m_0=3)<...<\Delta\Omega(m_0=2k+1)\end{aligned} \tag{14}$$

Theorem 4. *Multiple-time selection maintains a particular influence more effectively than that of one-shot selection.*

Proof. Based on Equation 14, we only need to proof $\Delta\Omega(m_0=1)>\Delta\Omega(m_0=0)$. Assume that the path length between two active nodes has an equal chance to be even or odd. In other words, $P(n=2h)=P(n=2k+1)$, where $k,h\in\mathbb{N}$. The values of ΔT and $\Delta\Omega$ under different parameters are listed and compared in Tables 4 and 5. Then we can obtain Equations 15 and 16.

$$\begin{aligned}&\Delta\Omega(n=2k+1,m_0=1)-\Delta\Omega(n=2h,m_0=0)\\ &=2\sum_{i=0}^{2h}e^{-ir}+...+2\sum_{i=0}^{2k-2}e^{-ir}+\sum_{i=0}^{2k}e^{-ir}\end{aligned} \tag{15}$$

$$\begin{aligned}&\Delta\Omega(n=2h,m_0=1)-\Delta\Omega(n=2k+1,m_0=0)\\ &=-(\sum_{i=0}^{2h-1}e^{-ir}+2\sum_{i=0}^{2h+1}e^{-ir}+...+2\sum_{i=0}^{2k-1}e^{-ir})\end{aligned} \tag{16}$$

Suppose $h>k$, then by adding Equation 15 to Equation 16, we can obtain:

$$\begin{aligned}&(\Delta\Omega(n=2h,m_0=1)+\Delta\Omega(n=2k+1,m_0=1))\\ &\quad-(\Delta\Omega(n=2k+1,m_0=0)+\Delta\Omega(n=2h,m_0=0))\\ &=e^{-2hr}+...+e^{-2(2k-2)r}+e^{-2kr}\\ &\quad-(e^{-(2h+1)r}+...+e^{-(2k-1)r})\\ &=(e^{-2hr}-e^{-(2h+1)r})+...\\ &\quad+(e^{-(2k-2)r}-e^{-(2k-1)r})+e^{-2kr}\\ &\quad>e^{-2kr}>0\end{aligned} \tag{17}$$

The same proof can be applied when $h\leq k$. Therefore, $\Delta\Omega(m_0=1)>\Delta\Omega(m_0=0)$. □

5 Experiments and Analysis

We conducted three major experiments for this research work. The first one aims to compare the difference in influence impact between one-shot and multiple-time investment. The second experiment evaluates the performance of the TIH algorithm. In the third experiment, we further compare one-shot selection against multiple-time selection by exploring the variations of selected seeds based on the ATID model.

5.1 Experiment Setup

Datasets. In the experiments, the following three datasets are used.

- **Ego-Facebook**[5] dataset, collected by McAuley et al. using a Facebook application, which is archived in Stanford Large Network Dataset Collection [43]. It contains profile and network data from 10 ego-networks, consisting of 193 circles, 4,039 users and 88,234 edges.

5. http://snap.stanford.edu/data/egonets-Facebook.html

TABLE 4
Value Comparison for $\varDelta T$ and $\varDelta \Omega$ (n = 2h)

	v_1	...	v_h	v_{h+1}	v_{h+2}	...	v_{2h}
$\varDelta T(n=2h, m_0=0)$	$2h-1$		1	1	3		$2h-1$
$\varDelta \Omega(n=2h, m_0=0)$	$\sum_{i=0}^{2h-2} e^{-ir}$		$\sum_{i=0}^{0} e^{-ir}$	$\sum_{i=0}^{0} e^{-ir}$	$\sum_{i=0}^{2} e^{-ir}$		$\sum_{i=0}^{2h-2} e^{-ir}$
$\varDelta T(n=2h, m_0=1)$	$2h$		2	0	2		$2h-2$
$\varDelta \Omega(n=2h, m_0=1)$	$\sum_{i=0}^{2h-1} e^{-ir}$		$\sum_{i=0}^{1} e^{-ir}$	0	$\sum_{i=0}^{1} e^{-ir}$		$\sum_{i=0}^{2h-3} e^{-ir}$

TABLE 5
Value Comparison for $\varDelta T$ and $\varDelta \Omega$ (n = 2k+1)

	v_1	...	v_k	v_{k+1}	v_{k+2}	...	v_{2k+1}
$\varDelta T(n=2k+1, m_0=0)$	$2k$		2	0	2		$2k$
$\varDelta \Omega(n=2k+1, m_0=0)$	$\sum_{i=0}^{2k-1} e^{-ir}$		$\sum_{i=0}^{1} e^{-ir}$	0	$\sum_{i=0}^{1} e^{-ir}$		$\sum_{i=0}^{2k-1} e^{-ir}$
$\varDelta T(n=2k+1, m_0=1)$	$2k+1$		3	1	1		$2k-1$
$\varDelta \Omega(n=2k+1, m_0=1)$	$\sum_{i=0}^{2k} e^{-ir}$		$\sum_{i=0}^{2} e^{-ir}$	$\sum_{i=0}^{0} e^{-ir}$	$\sum_{i=0}^{0} e^{-ir}$		$\sum_{i=0}^{2k-2} e^{-ir}$

- **Email-Enron**[6] dataset, which covers all the email communication. It has been posted to the web by the Federal Energy Regulatory Commission [44]. The Enron email network has 36,692 nodes and 367,662 Edges. To diminish the computing time, we capture a sub-graph with 10k nodes for the experiment.
- **Wiki-Vote**[7] dataset, which incorporates administrator elections and votes history data from 3 January 2008. There are 2,794 elections with 103,663 total votes and 7,066 users participating in the elections. Nodes refer to Wikipedia users and edges represent votes from one user to another [45].

System Setup. We simulate the social context by creating a number of user agents based on the public datasets. Each user agent manages its local information, including a friendship list, a repository and historical records. We assume a hypothesis influence message is supposed to be maintained and each agent has a different tendency of posting this message. In the meanwhile, the reporting agent is responsible for monitoring the entire multi-agent system and collecting global information. The system has three types of states as follows:

- **Evolve**: user agents perform actions, incorporating accessing the repository, reading the message and making decisions (share the post or not) based on both past experiences and timeliness degrees.
- **Pause**: the entire system pauses, and stops functioning temporarily. This state allows seed selection algorithms to identify influential users and select seeds based on the current network status. In other words, further investment happens at this point. The system evolution resumes as soon as the seed selection is completed.
- **Stop**: All the user agents decompose, and the system terminates.

6. https://snap.stanford.edu/data/email-Enron.html
7. https://snap.stanford.edu/data/wiki-Vote.html

TABLE 6
Experiment Parameters

Parameter	Value(s)
Fixed time steps for seed selections	100
Fixed time steps in total	150
Number of seeds to be selected for each selection points	25, 5, 1
The interval (time steps) of seed selection	100, 20, 4
Seed set size	25
attenuation constant r	0.1
General action frequency of user agents (times per second)	5

By setting up the system, the parameters for the experiments are given in Table 6. We assume that the observations of network evolution are within a fixed interval, and the same amount of seeds are supposed to be selected at each seed selection point. To reduce the bias of measuring the performance of different strategies, additional time steps, i.e., 50 time steps in our experiments, are given after the final seed selection for the influence dissemination and attenuation. Furthermore, the budget is limited, in other words, the seed set size is limited. The overall action frequency of user agents controls the speed of network evolution.

Evaluation Metrics. As introduced in Section 3.4, three major evaluation metrics are taken into consideration, i.e., GTD, GCTD and GAC, which have been explained and formulated in Equations 4, 5 and 6, respectively. GCTD and GAC were applied in both Experiment 1 and Experiment 2 for comparing the performance of different selection strategies. GTD has been mainly utilized in Experiment 1 for tracking the variation of timeliness degree of a particular influence message in different time steps. In Experiment 3, some distance indices were facilitated to measure the variation of seed sets.

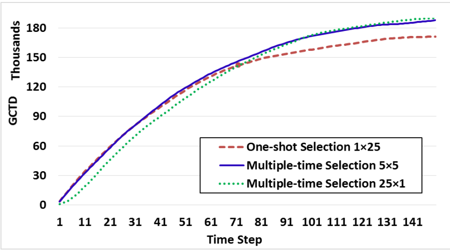


Fig. 3. Rank-based (GCTD)

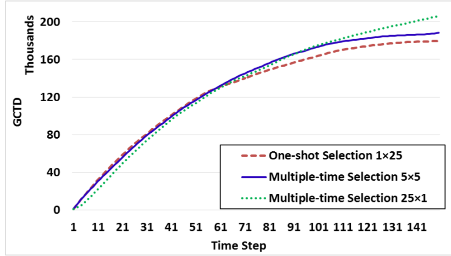


Fig. 4. DDH Selection (GCTD)

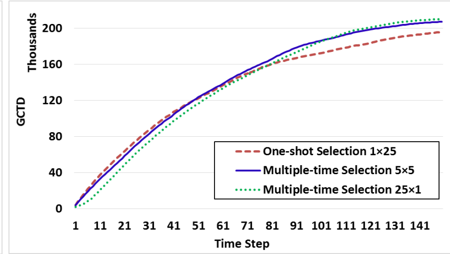


Fig. 5. TIH Selection (GCTD)

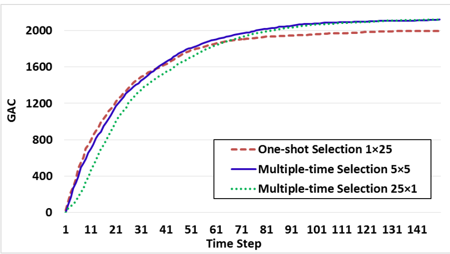


Fig. 6. Rank-based (GAC)

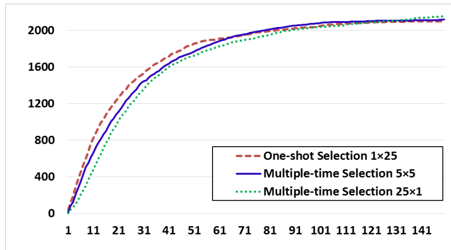


Fig. 7. DDH Selection (GAC)

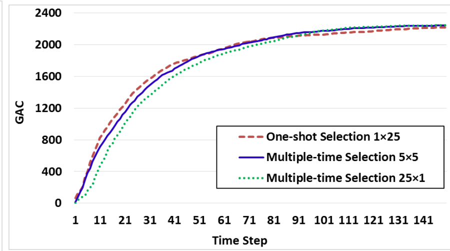


Fig. 8. TIH Selection (GAC)

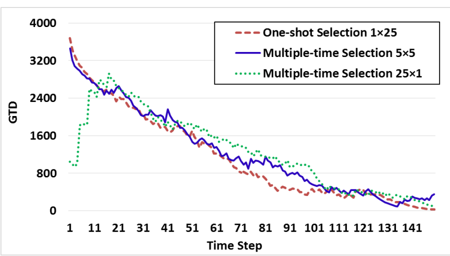


Fig. 9. Rank-based (GTD)

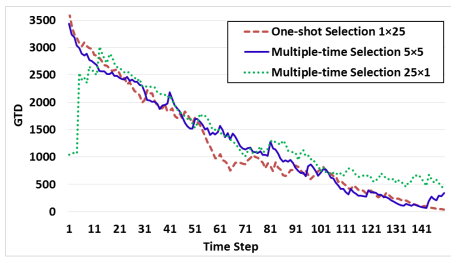


Fig. 10. DDH Selection (GTD)

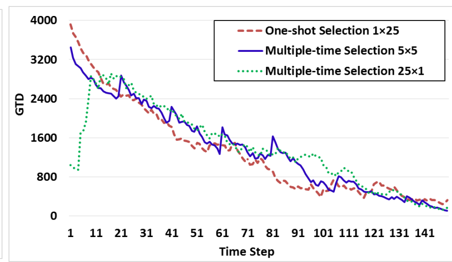


Fig. 11. TIH Selection (GTD)

5.2 Experiment 1: One-shot vs multiple-time selection

Experiment 1 compares one-shot investment against the multiple-time by facilitating different seed selection algorithms, i.e., rank-based, DDH and the TIH selection. In this experiment, the Ego-Facebook dataset is applied for the explorations. The notations of selection approaches are listed in Table 7.

TABLE 7
Notations of Selections

Notation	Meaning
1×25	One-shot selection, 25 seeds
5×5	5-time selection, select 5 each time
25×1	25-time selection, select 1 each time

As we can observe from Figures 3, 4 and 5 that multiple-time selections can produce higher GCTD. The gap between one-shot selection and multiple-time selection turns out to be evident over time. 5×5 and 25×1 give pretty close performance, but 25×1 shows slightly better, especially after 100 time steps when the selections are completed. By comparing the GAC in Figures 6, 7 and 8, the multiple-time selection also outperforms the one-shot selection. One-shot selection demonstrates a rapid influence activation coverage, but unfortunately it loses the leading position halfway.

Based on the results in Figures 3 - 8, we can observe that with the same budget, increasing the frequency of investments generally carries out higher GCTD and GAC, subject to additional time for influence diffusion and attenuation provided. This is due to the reason that the last-round investment in multiple-time selections is not supposed to give much credit without additional time for influence spread and decay. The results also explicitly reveal that multiple-time selections target the reward in the long-run, but may yield short-term performance. If an organisation intends to maintain an influence by considering both effectiveness and time required for GCTD to reach a certain level, selection strategies with extremely high frequencies (25×1 in our experiment) may not be advocated, since it takes longer time to reach the maximum GCTD. Whereas, 5×5 balances the trade-off between time and GCTD, which is a better option under such a scenario. The same rule also applies to GAC.

To drill down into the details, we explore timeliness variations of the influence message after adopting different selection strategies in Figures 9, 10 and 11. One-shot selection has the highest starting point, but it declines faster than that of 5×5 and generally falls behind the others after around 20 time steps. Obvious spikes can be observed in multiple-time selections and appear to be more prominent in the TIH 5×5. Whereas, 25×1 demonstrates a different pattern. It climbs to the peak point, which is higher than that of the other two selection approaches, then falls gradually. The organisation expects a sharp upward trend after each investment. However, this is not guaranteed based on the results. For example, no obvious increase can be observed at time steps 60 and 20 of rank-based 5×5 and DDH 5×5, respectively. In contrast, the TIH 5×5 sees an evident spike after each investment.

5.3 Experiment 2: The TIH Seed Selection Evaluation

Experiment 2 aims to evaluate the performance of the TIH algorithm. We compare the proposed TIH algorithm against state-of-the-art algorithms. Since the diffusion model is probabilistic based, the results are obtained by averaging multiple trials. To reduce the bias, we evaluate the TIH algorithm by using the three datasets mentioned previously, i.e., Ego-Facebook, Email-Enron and Wiki-Vote.

The experimental results are demonstrated in Table 8. It can be seen that the TIH outperforms the others in all the three datasets. By using any selection strategy, the TIH performs the best in terms of GCTD and GAC.

Another intriguing finding from the experimental results is concerning the relationship between GCTD and GAC. More specifically, given the same budget, GCTD rises with the increment of selection trails. In general, GAC gains when GCTD increases. However, by adopting rank-based 25×1, the GAC yields that of the 5×5, though GCTD rises. This phenomenon implicitly shows that the outcome of influence maintenance is not always in accordance with that of the influence maximization. Whereas, the relationship between GCTD and GAC tends to be affected by the applied business strategies. In other words, the strategies created for long-term marketing can possibly suppress the short-term growth of the product adoptions.

5.4 Experiment 3: Seed Set Variation Analysis

With the same budget, different selection approaches inevitably produce different seed sets. To understand the outcome of various strategies, in this experiment, we further compare one-shot selection against multiple-time selection by exploring the variations of selected seeds based on the ATID model. The TIH algorithm has been applied for the seeding procedures in three social networks mentioned previously.

Three evaluation metrics are adopted for measuring the distance (*referring to variation or dissimilarity*) between any two seed sets, i.e., Jaccard distance $d_{jcd}(A_1, A_2)$, Dice dissimilarity $d_{dic}(A_1, A_2)$ and sequential distance considering the index of the elements $d_{sqc}(A_1, A_2)$, which are formulated in Equations 18, 19 and 20, respectively. In these three equations, A_1 and A_2 denote two different seed sets, having the same cardinality, i.e., $A_1 \neq A_2, |A_1| = |A_2|$. $I(c|A_1)$ refers to the index of element c in set A_1.

$$d_{jcd}(A_1, A_2) = 1 - \frac{|A_1 \cap A_2|}{|A_1 \cup A_2|} \tag{18}$$

$$d_{dic}(A_1, A_2) = 1 - \frac{2|A_1 \cap A_2|}{|A_1| + |A_2|} \tag{19}$$

$$d_{sqc}(A_1, A_2) = \frac{1}{|A_1|}\left(\sum_{c \in A_1 \cap A_2} \frac{|I(c|A_1) - I(c|A_2)|}{|A_1|} + |A_1 \setminus A_2| \right) \tag{20}$$

As the influence diffusion appears to be probabilistic-based, different sets of the nodes could be selected by using the same algorithm. To reduce the bias, results are averaged over multiple trials. Figure 12 compares the variations of the seed sets produced by using different strategies. It explicitly shows that the seed-set variations between one-shot selection and multiple-time selection appear to be more prominent when having a higher frequency of selections. Two multiple-time selection approaches, i.e., 5×5 and 25×1, share a larger overlapping seeds than that of one-shot selection.

To investigate the correlations between network properties and seed-set variations, we list the detailed results in Table 9, where *"Average Path Length" (APL)* refers to the average number of steps along the shortest paths for all possible pairs of nodes. APL is one of the key metrics to measure the transitivity of the network [46]. A shorter APL generally indicates that less time is required for any influence travelling from one node to another.

It can be seen from Table 9 that a greater average path length corresponds to a higher seed-set variation. The reason behind is that in shorter APL networks, influences become relatively easier to reach any node, thus $e^{-r\cdot(m-b)}$ in Equation 1 appears to be lower as b shrinks. Subsequently, timeliness gain turns out to be less prominent. Therefore, based on Equations 11 and 12, the TIH algorithm has a higher chance to carry out similar seed sets under such circumstances.

5.5 Discussion

We simulated a social environment and the process of influence maintenance in a social network. Through the experiments, we demonstrated the advantages of applying ATID to model the influence propagation process. Two critical factors required by the influence maintenance can be presented clearly in the ATID, i.e., the temporal feature of the social network and the status of a particular influence. Furthermore, the seed-set variations are compared after applying different selection approaches. We also evaluate the effectiveness of various seed-selection algorithms in maintaining an influence. The TIH algorithm surpasses some selected traditional selection algorithms by using three different datasets.

More importantly, three empirical laws can be drawn from the experimental results. **(1)** Given the same budget, the multiple-time investment is generally more beneficial for achieving the long-lasting influence of a particular product than that of the one-shot investment. **(2)** Influence maintenance is not always in accordance with that of the influence maximization. In other words, sustaining a long-term impact of a particular influence cannot ensure a large fraction of activation coverage; the long-term marketing strategies may hinder the profit spikes. **(3)** Seed-set variation is not only associated with the frequency of selections, but also affected by the network property. A greater average path length of social networks leads to a higher seed-set variations.

TABLE 8
Seed Selection Performance Comparison

Social Network	Algorithm	Metrics	One-shot Selection 1×25	Multiple-time Selection 5×5	Multiple-time Selection 25×1
Ego-Facebook	TIH	GCTD	**195,951**	**207,115**	**209,675**
Ego-Facebook	TIH	GAC	**2,222**	**2,242**	**2,249**
Ego-Facebook	RANK	GCTD	170,966	187,696	189,968
Ego-Facebook	RANK	GAC	1,996	2,124	2,118
Ego-Facebook	DDH	GCTD	181,994	190,653	205,774
Ego-Facebook	DDH	GAC	2,097	2,123	2,151
Ego-Facebook	Random	GCTD	168,733	175,899	188,300
Ego-Facebook	Random	GAC	1,889	1,988	2,003
Email Eron	TIH	GCTD	**341,418**	**358,722**	**384,861**
Email Eron	TIH	GAC	**4,307**	**4,445**	**4,331**
Email Eron	RANK	GCTD	328,026	352,744	362,992
Email Eron	RANK	GAC	4,082	4,391	4,365
Email Eron	DDH	GCTD	338,803	355,452	373,218
Email Eron	DDH	GAC	4,227	4,255	4,492
Email Eron	Random	GCTD	324,994	337,380	338,269
Email Eron	Random	GAC	4,181	4,189	4,196
Wiki Vote	TIH	GCTD	**254,710**	**267,810**	**272,292**
Wiki Vote	TIH	GAC	**2,868**	**3,001**	**2,953**
Wiki Vote	RANK	GCTD	247,659	264,417	267,213
Wiki Vote	RANK	GAC	2,826	2,944	2,878
Wiki Vote	DDH	GCTD	249,977	265,950	270,906
Wiki Vote	DDH	GAC	2,843	2,954	2,829
Wiki Vote	Random	GCTD	247,626	253,349	257,599
Wiki Vote	Random	GAC	2,813	2,843	2,824

TABLE 9
Network Properties and Seed Sets Variations

Dataset	Average Path Length	one-shot selection vs. multiple-time selection 5×5			one-shot selection vs. multiple-time selection 25×1			multiple-time selection 5×5 vs. multiple-time selection 25×1		
		Jaccard	Dice	Sequence	Jaccard	Dice	Sequence	Jaccard	Dice	Sequence
Email Enron	3.123	0.442	0.284	0.365	0.498	0.332	0.424	0.094	0.051	0.113
Wiki Vote	3.247	0.622	0.452	0.540	0.730	0.576	0.650	0.424	0.270	0.394
Ego-Facebook	3.693	0.768	0.624	0.631	0.792	0.656	0.668	0.477	0.315	0.383

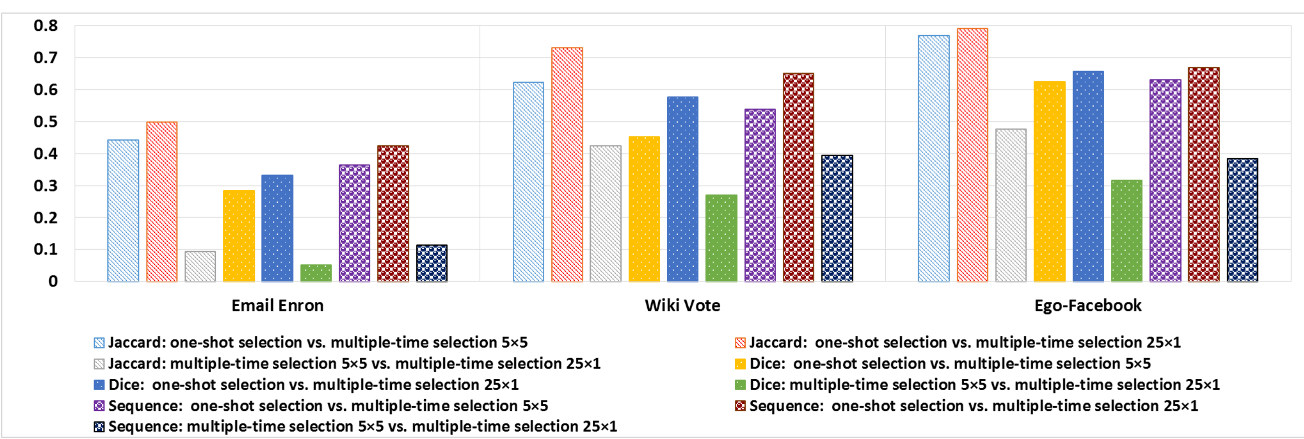


Fig. 12. Seed Set Variation Comparison under Different Strategies

6 Conclusions and Future Work

In this paper, we systematically studied the influence maintenance problem, which targets the long-term and sustainable business goals. To the best of our knowledge, this paper is the first full research work that characterizes the influence maintenance in social networks. The distributed influence diffusion model, i.e., the ATID, presented in this article can also pave the way in exploring influence propagation social pheromone, since it concentrates on modelling the agent's personalized traits and behaviours, tracking the temporal feature of a social network, as well as the status of influence messages. Many features of both individuals and influences can be enabled in the ATID when analysing the social influence diffusion phenomenon. We have also proposed a novel seed selection algorithm, i.e., the TIH, which is capable of maintaining long-term influence effectively. Extensive experiments are conducted, and the empirical results show that the proposed model is capable of enhancing long-term influence. Given the same budget and limited time frame, multiple-time investment is superior to one-shot investment in terms of influence maintenance. Moreover, the experimental results also explicitly show that the TIH performs better than the other traditional selection algorithms by considering GCTD and GAC. We believe that our findings can shed light on the understanding of influence maintenance for long-term marketing.

In the future, we plan to free up the assumptions. Specifically, we will try to explore the solutions for the situations, where (1) the time step is not fixed; (2) for each investment, the seed set size is not fixed; and (3) the seed selection point can be a variant.

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