Modelling Multiple Influences Diffusion in On-line Social Networks

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ABSTRACT

In on-line social networks, innovations in the presence of one or more influences disseminate through the topological structure of the networks rapidly. In reality, various influences normally coexist in the same context and have subtle relations, such as supportive, contradictory and competitive relations, affecting the users' decisions of adopting any innovations. Therefore, modelling diffusion process of multiple influences is an important, yet challenging research question. By employing the agent-based modelling, in this paper, a distributed approach has been proposed to model the diffusion process of multiple influences in social networks. The proposed model has been applied in the undesirable influence minimisation problem, where the time series is taken into consideration. The experimental results show our model can be utilised to minimise the adverse impact of a certain influence by injecting other influences. Furthermore, the proposed model also sheds light on understanding, investigating and analysing multiple influences in social networks

KEYWORDS

Multiple influences; agent-based modelling; influence diffusion; influence minimisation

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1 INTRODUCTION

Nowadays, with the prevalence of on-line social networks, influence diffusion analysis and modelling has attracted tremendous attention to both researchers and practitioners due to many important applications [27], such as influence maximisation [13]. The influence propagation process usually relies on the fact that an individual's decision on adopting a particular product, opinion or innovation has been significantly influenced by the choices made by the adjacent neighbours in social networks [3]. Based on such a common phenomenon of innovation dissemination, most researchers investigate the pairwise influence diffusion by focusing on the coverage of a specific influence but ignoring the impact of other influences.

In reality, multiple influences of various topics normally coexist within the same context, and their divergent relationships impact each other regarding individual's influence acceptance. Intuitively, influences of the same topic can be either supportive or contradictory to each other. Influences usually propagate in the presence of a wide variety of rich content, i.e., influence messages, which can be images, videos, long articles or even short comments, conveying the opinions or ideas towards the one or more innovations. When multiple influence messages with the same opinion flood into one's friend circle, he or she has a high tendency of adopting the opinion. Whereas, individuals usually struggle with taking a side when adverse opinions of the corresponding topic emerge. In addition, different influences appear to be associated with each other indirectly by competing for the 'common resources', i.e., the users' attention. More specifically, nobody can take care of all the influence messages due to the limited vigour of human nature. Instead, individuals usually get attracted by the information that they care most. In other words, each individual possesses a finite capacity of considering and absorbing the impact of influences, and the corresponding attention is always focused on particular influence messages. Meanwhile, the existing information keeps fading out of the public attention, especially when other significant influences are injected into the same context. This feature becomes more prominent in time-sensitive social networks, such as microblogging platforms [6].

There are several motivations to model and analyse multiple influences diffusion in social networks. A non-trivial incentive is to investigate effective approaches for rationally alleviating or even suppressing the impact of a particular undesirable influence message, e.g., a rumour. Based on the contemporary research work, when any adverse opinions are propagating through a social network, some researchers recommend blocking a particular group of nodes [31] or a bunch of links [14] from on-line social networks to control the influence contaminations. However, these approaches can only be facilitated to a few types of networks, such as virus or epidemic networks [1]. As for those ordinary or customer-based social networks, any user or affiliation link is not supposed to be blocked or removed. Furthermore, the topological structure of a network is out of control in most cases. Therefore, approaches without

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restricting users' behaviours or altering the networked structure are highly recommended. This scenario frequently arises in the real world: when a piece of sensational news fast disseminates, public attention tends to be diverted by other news eventually. Inspired by this social phenomenon, the subtle relationships among multiple influences and the individualised features of users can be utilised to achieve the undesirable influence minimisation.

In this paper, we proposed an Agent-based Multiple Influences Diffusion (AMID) model to analyse multiple influences propagation in social networks by considering their relationships. The influence diffusion process is modelled in a decentralised manner by using Agent-Based Modelling (ABM) [4, 22, 30]. Each user's personalised traits, preferences, behaviours and social context have been taken into consideration. Influential relationships among the entities, including *user and user, user and influence, influence and influence,* have been considered in the proposed model. Furthermore, we utilise undesirable influence minimisation as a typical application of the proposed model. Extensive experiments have been conducted, and the results suggest that by using the proposed model, introducing external influences can suppress the adverse influence effectively. The major contributions of this paper are summarised as follows.

- We formally define a multiple influences diffusion model. To the best of our knowledge, this is the first literature systematically articulating the multiple influences and their relationships.
- We propose a novel decentralised multiple influences diffusion model by considering the influential relationships, as well as individual's personalised traits, such as interests and trusts.
- We explore the intriguing discoveries and insights through modelling the relationships of divergent influences and evaluate the effectiveness of different approaches in minimising the undesirable influences by facilitating the proposed model.

The rest of this paper is organized as follows. Section 2 reviews the literature related to this research work. Section 3 introduces the modelling of multiple influences diffusion using ABM and the formal definitions. Section 4 systematically elaborates the influential relationships modelling. In Section 5, experiments and experimental results are presented by using a typical application, i.e., undesirable influence minimisation. Conclusions and future works are detailed in Section 6.

2 RELATED WORK

2.1 Influence Diffusion

Domingos and Richardson attempt to mine the value of customers in social networks by considering influence diffusion [7]. Kempe et al. address the influence maximisation problem based on two fundamental propagation models, i.e., the Independent Cascade (IC) model and the Linear Threshold (LT) model [13]. Based on these early works, many follow-up studies have been conducted for social influence propagation modelling. Goyal et al. [8] and Saito et al. [24] research learning influence probabilities by measuring pairwise influences among the individuals. Li et al. investigate cross-layers cascade and investigate the information-diffusion speed variations in multiplex networks [20]. Zhang et al. study social influence locality for modelling users' re-tweet behaviours in microblogging network [35]. Li et al. model influence diffusion in social networks by using agent-based modelling [19].

However, in nearly all the research work mentioned above, only one influence is considered. In other words, these studies focus on the adoption of a particular product or opinion, while other influences in the same context have been ignored. With an exception, Tang et al. propose topical affinity propagation to model the topic-level social influence, which can identify the experts in different topics and measure the strength quantitatively [27]. Nevertheless, Tang's work is developed based on the assumption that no dependencies are presented among the various topical influences. Different from the aforementioned research work, we model the influence propagation by considering the impacts and relationships among the multiple influences.

2.2 Competitive Influence

Many researchers study the competitive influence diffusion and its corresponding influence maximisation problem by extending the fundamental propagation models, i.e., the IC model and the LT model. Bharathi et al. extend the IC model and focus on the scenario when multiple innovations are competing within a social network [3]. Based on the traditional IC model, Zhu et al. present the C-IC model to characterise how various influences are competing with others in social networks [36]. Borodin et al. propose an extended version of the LT model to handle the competitive influence diffusion of two different technologies [5]. Liu et al. extend the LT model to establish the diffusion-containment model, i.e., D-C model, by incorporating the realistic specialities of the containment of the competitive influence spread [21]. He et al. attempt to tackle the influence blocking maximisation problem and extend the LT model to incorporate competitive influence diffusion [10]. Kostka et al. present the rumour game which models the dissemination of competing information in social networks [16]. Similarly, Trpevski et al. model the competitive rumour spreading by extending a well-known epidemic SIS model [29]. Goyal and Kearns study the product adoption competition between two firms by developing a game-theoretic framework [9].

There are three major limitations in most of the studies of competitive influence, including the research work mentioned above. **(1)** The studies focus on the influential competitive relationships among the social influence and ignore other factors, such as supportive influences and the impact of other innovations. For example, the introduction of Samsung phone competes with that of the Apple phone for the public attention [32]. Whereas, the emergence of Samsung 3D Glasses tends to be a supportive influence for Samsung phones due to its compatibility, but becomes a subtle force of discouraging the adoption of Apple phones. **(2)** A major assumption in most of current approaches is that each user possesses a single adoption when given multiple choices, e.g., various products from different firms. Whereas, users may adopt the multiple products or innovations, e.g., a customer can purchase both Samsung phone and Apple phone. **(3)** Nearly all of the research work extends the IC or LT model to accommodate the competitive influence dissemination. However, due to the nature of both models, i.e., centralised

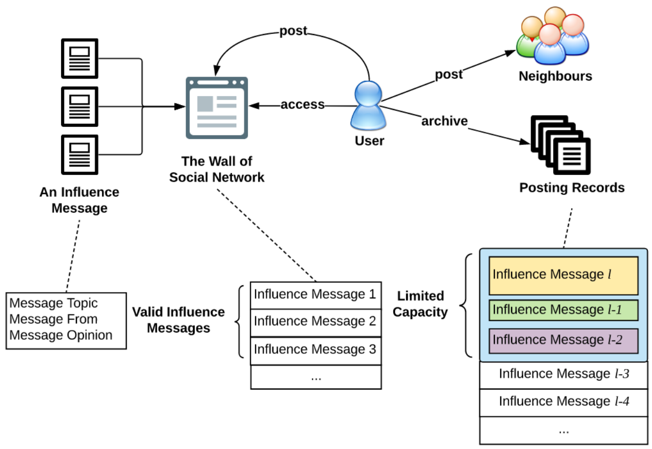

Figure 1: The Framework of an Agent-based Multiple Influences Diffusion Model

influence diffusion models [17], the extended IC and LT models can neither capture the dynamics of social networks nor track the long-term trend of a social network driven by influence propagation [18, 19].

To cover the limitations mentioned above, our study models multiple influences diffusion by considering the various corresponding relationships. We leverage an agent-based diffusion model to capture the evolutionary trend of a social network, as well as the individual's features and behaviours. Thus, the multiple adoptions of different innovations by a particular user at different time steps can be enabled.

2.3 Negative Influence Minimisation

By extending the influence maximisation problem [13], many researchers explore the approaches to minimise the adverse impact of a particular existing influence in a social network. A bulk of studies attempt to block an influence in a very straightforward way, i.e., altering the structure of a social network. For example, Kimura et al. claim to minimise the spread of influence contaminations by removing links [14, 15]. Similarly, Wang et al. suggest minimising the negative influence by blocking a limited number of nodes in social networks [31], and Yao et al. adopt the same solution from a topic modelling perspective [33]. These approaches can only be applied based on the assumption that the organisation is authorised to manage network topological structures. However, in reality, such modifications are generally not applicable.

On the other side, some researchers tend to achieve the negative influence minimisation by levering the power of competitive influence. In other words, the negative influence minimisation becomes one of the typical applications of competitive influence modelling. For example, He et al. address the influence blocking maximisation problem by selecting seed nodes to inject the positive opinions to fight against the negative rumour [10]. Most studies relying on the competitive influence models intent to suppress an undesirable impact by introducing the opposite influence only. However, the influential effects originated from other influences are neglected, and these 'irrelevant' influences can be even more powerful in distracting users from focusing one opinion. Moreover, the individual's features, such as preference and information intake capacity, are not taken into consideration. These factors can affect a user's influence acceptance to a large extent.

By contrast, we attempt to alleviate the negative influence minimisation problem in a real situation when multiple influences coexisted in the same social context. Furthermore, three possible relationships among the influences, i.e., support, competitiveness and irrelevance, are taken into consideration.

3 MULTIPLE INFLUENCES DIFFUSION

3.1 An Agent-based Multiple Influences Diffusion Model

To analysis and model multiple influences diffusion in social networks, traditional propagation models, such as IC model and LT model, only concentrate on the diffusion process and activation status of each node, ignoring the interactions between users and influence messages, as well as the co-actions among influences. Motivated by this background, a novel propagation model is necessarily required.

The AMID proposed in this paper models the propagation process in a decentralised manner. In the AMID model, users have been modelled as a set of interactive autonomous agents that possess their own personalised traits and behaviours. Meanwhile, influence messages appear to be another type of entities in the same context which can be interacted with the agents directly. From a macroscopic point of view, the influence diffusion demonstrates a networked evolutionary pattern driven by the individuals' actions, i.e., interactions with various influences.

Figure 1 shows the framework of the proposed AMID model. An ordinary influential behaviour of a particular user agent incorporates only two simple sequential steps, i.e., reading messages from the wall of on-line social networks and getting influenced by posting an influence message. More specifically, in time-sensitive social networks, such as Twitter, various influence messages of different topics are constantly posted to a user's wall. He or she tends to be influenced by the received influence messages based on the interests and peer trust relationships [11]. Subsequently, an influence message is not only posted to the adjacent neighbours, but also archived as one of the posting records, reflecting the user's latest interests. In this model, three major attributes of an influence message are taken into consideration, including the topic, delivered from and the opinion.

We assume that only a particular number of the latest messages are regarded as valid, accessible information, and each user has a limited and different-size capacity (vigour) for taking care of the influence messages. Once a new message has been posted, a certain amount of space is occupied. The space it takes depends on the peer trust and the user's interests. In addition, the old ones are fading out of the user's attention.

3.2 Formal Definitions

Definition 1: A User Agent $v_i, (v_i \in V)$ refers a node in a time-sensitive social network $G = (V, E)$, where $V = \{v_1, ..., v_n\}$ denotes a set of agents and E represents a set of edges, $E = \{e_{ij} | 1 \leq i, j \leq$

$n\}, i, j \in \mathbb{N}^+, \{v_i, v_j\} \subseteq V$. User agent v_i has a set of neighbours $\Gamma(v_i)$, and such affiliation information is maintained by the agent locally. If 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 $E_{v_i} = \{e_{ij} | v_i \neq v_j \wedge v_j \in \Gamma(v_i)\}$. In addition, each user agent has a local view, which covers all its neighbours and the corresponding posting records (refer to Definition 4).

Definition 2: An Influence Message $msg_p, (msg_p \in M)$ in general refers to a communication containing some information, which potentially affects users' opinions and behaviours, where $M = \{msg_1, msg_2, ..., msg_k\}$ denotes the influence message set in a social network. $msg_p^{(v_j \to v_i)}$ refers to msg_p delivered from v_j to v_i, subject to $v_j \in \Gamma(v_i)$.

Given a finite number of n influence topics $T = \{\tau_1, \tau_2, ..., \tau_n\}$, each influence message is associated with all the topics with different membership degrees. Therefore, the relationships among influence message msg_p and the topics T can be represented as a fuzzy set:

$$\begin{aligned} S_{msg_p} &= (T, m_p) \\ &= m_p(\tau_1)/\tau_1 + m_p(\tau_2)/\tau_2 + \ldots + m_p(\tau_n)/\tau_n, \end{aligned} \tag{1}$$

where $m_p(.)$ is a membership function, and $m_p(\tau_k) \in [0,1], k \in [1, n]$ quantifies τ_k's membership degree of topic τ_k in the fuzzy set. An influence message msg_p can be expressed by using a two-tuple: $msg_p = (S_{msg_p}, o_p)$, where $o_p \in \{0, 1\}$ refers to the general opinion of msg_p, $o_p = 1$ means positive, and negative otherwise.

Definition 3: Social Network Wall $W_{t_m}^{(v_i)}$ refers to a dynamic area on a time-sensitive social network profile or home page of user agent v_i at time step t_m, displaying the latest n influence messages posted by $\Gamma(v_i)$ in a reverse chronological order. $W^{(v_i)}$ generally represents v_i's wall in a predefined context. Mathematically, $W_{t_m}^{(v_i)} = \langle msg_p^{(v_j \to v_i)} | v_j \in \Gamma(v_i), msg_p \in M \rangle$ describes a sequential vector, incorporating n messages delivered to v_i. User agent accesses the messages from $W_{t_m}^{(v_i)}$ at time t_m and determines which message to be posted.

Definition 4: Posting Records $PR_{t_m}^{(v_i)}$ describes a collection of historical influence messages delivered by user agent v_i. Similar to social network wall, the posting records also can be represented by using a sequential vector $PR_{t_m}^{(v_i)} = \langle msg_p^{(v_i \to v_j)} | v_j \in \Gamma(v_i), msg_p \in M \rangle$, which reflects v_i's preferences. For simplification purpose, $PR^{(v_i)}$ denotes v_i's posting records in a predefined context.

Definition 5: Capacity $c^{(v_i)}$ is defined as v_i's capability to take care of the influence messages, which implies the limited vigour or attention of a user agent. When an influence message $msg_p^{(v_j \to v_i)}$ arrives or pre-exists, a particular amount of capacity $\widehat{A}(msg_p^{(v_j \to v_i)})$ is supposed to be occupied if the message has been accepted (see Relationship 3). In addition, the old influence messages are suppressed and fading out of the user's attention.

4 INFLUENTIAL RELATIONSHIP MODELLING

Relationship 1: User and User. Users are far more likely to be influenced by the people they know and trust, rather than from any strangers or systems [25]. In the current setting, $TR(v_i, v_j)$ describes the trust relationship established between two users, i.e., truster v_i and trustee v_j. In this paper, we borrow the definition of trust of [12], and it can be interpreted truster' engagement probability respected to the influence messages posted by the trustee.

When user v_i accesses influence message $msg_p^{(v_j \to v_i)}$, there is a possibility that $msg_p^{(v_j \to v_i)}$ will be posted (or shared) by v_i. If v_i posts the same message, we say v_i trusts v_j on the topics of $msg_p^{(v_j \to v_i)}$. Therefore, the trust value of v_i to v_j can be estimated from the number of times that v_i shares v_j's posting records. As each user agent is able to access the posting records of its neighbours, the trust relationships are obtained by individuals locally.

There are two possibilities of an action towards an influence message, i.e., post or not post. Therefore, the probability density over these binary events can be expressed as Probability Density Function (PDF), i.e., $beta(\alpha, \beta)$. A simplified subjective logic approach in [12] can be applied to estimate the trust degree. Here we do not consider transitive trust. We denote s, u, a as the number of posted, unshared messages, and the priori, which is the default value that can be assigned to users.

Then α and β can be determined as:

$$\alpha = s + 2a, \qquad \beta = u + 2(1 - a) \tag{2}$$

As only two possible responses exist in the environment, a can take 0.5. With s shared and u unshared messages, the a posteriori distribution is beta PDF with $\alpha = s + 1$ and $\beta = u + 1$. To capture the dynamic sharing behaviours, a forgetting factor λ is used to weight a message at time t_{now}:

$$f_{msg_p} = \lambda^{(t_{now} - t_{msg_p})}, \tag{3}$$

where $0 \leq \lambda \leq 1$, t_{msg_p} is the time at which the message was posted. After that, we measure the trust relationship using all posts related to v_i and v_j. We denote the cumulative post and not post rate as $\bar{s}$ and $\bar{u}$. They can be aggregated by summing up the weights of the posted and not posted messages, respectively, using the following equations.

$$\bar{s}_{v_i, v_j} = \sum_{msg_h \in PR^{(v_i)}} f_{msg_h^{(v_j \to v_i)}} \tag{4}$$

$$\bar{u}_{v_i, v_j} = \sum_{msg_h \in W^{(v_i)} \setminus PR^{(v_i)}} f_{msg_h^{(v_j \to v_i)}} \tag{5}$$

The trust relationship between v_i and v_j can be estimated by aggregating the evidence from both users, while the base trust value a is involved in the case that both users have never interacted before. The trust values of v_i to v_j can be obtained by calculating the mean of their distribution:

$$TR(v_i, v_j) = E[beta(\bar{s}_{v_i, v_j} + 1, \bar{u}_{v_i, v_j} + 1)] \tag{6}$$

Apply the mean value of beta distribution, Equation 6 can then be normalised to:

$$TR(v_i, v_j) = \frac{\bar{s}_{v_i, v_j} + 1}{\bar{s}_{v_i, v_j} + \bar{u}_{v_i, v_j} + 2} \tag{7}$$

Relationship 2: User and Influence. User's influence acceptance of a particular influence mainly depends on two major factors, i.e., the peer trust relationships and individual's interests. Similar to an influence message, a user agent's topical level interests can also be expressed as a fuzzy set:

$$\begin{aligned} S^{(v_i)} &= (T, m^{(v_i)}) \\ &= m^{(v_i)}(\tau_1)/\tau_1 + m^{(v_i)}(\tau_2)/\tau_2 + \ldots + m^{(v_i)}(\tau_n)/\tau_n, \end{aligned} \tag{8}$$

where the membership degree $m^{(v_i)}(\tau_k)$ represents v_i's interest towards influence topic τ_k, which can be evaluated by user agents locally based on the past posting records $PR^{(v_i)}$. Thus, $m^{(v_i)}(\tau_k)$ can be formulated in Equation 9.

$$m^{(v_i)}(\tau_k) = \frac{1}{|PR^{(v_i)}|} \sum_{msg_p \in PR^{(v_i)}} \frac{m_p(\tau_k) \cdot f(t)}{\sum_{\tau_x \in T} m_p(\tau_x)}, \tag{9}$$

where $|PR^{(v_i)}|$ denotes the cardinality of posting records, $m_p(\tau_k), \tau_k \in T$ refers to the membership degree of msg_p, and $f(t)$ is an attenuation function formulated in Equation 10.

$$f(t) = e^{-t \cdot k}, \ k > 0 \tag{10}$$

The relationship between user agent v_i and the message msg_p is presented as the Cartesian product of the topical fuzzy set of msg_p and user's interest fuzzy set, which is described in Equation 11.

$$\begin{aligned} R(v_i, msg_p) &= S_p \times S^{(v_i)} = (T, \mu_R^{(v_i)}) \\ &= \mu_R^{(v_i)}(\tau_1)/\tau_1 + \mu_R^{(v_i)}(\tau_2)/\tau_2 + \ldots + \mu_R^{(v_i)}(\tau_n)/\tau_n, \end{aligned} \tag{11}$$

The fuzzy relationship $R(v_i, msg_p)$ is a mapping from Cartesian space to the interval, and the strength of the mapping can be expressed by using the membership function $\mu_R^{(v_i)} : S_p \times S^{(v_i)} \to [0, 1]$. Therefore, we can derive the user agent v_i's acceptance to message msg_p sent from neighbour v_j by using Equation 12.

$$\begin{aligned} A(msg_p^{(v_j \to v_i)}) &= g(R(v_i, msg_p), TR(v_i, v_j)) \\ &= \gamma R(v_i, msg_p) + (1 - \gamma) TR(v_i, v_j), \end{aligned} \tag{12}$$

where $g(.)$ is a weighted average function and γ represents a trade-off factor balancing the peer trust relationship and the individual's interests.

Relationship 3: Influence and Influence. Different from user agents, influences are not capable of interacting with each other directly, but their relations and impacts are mediated by user agents. Individuals have high chances to adopt the opinion strongly supported by most of the adjacent neighbours, which complies a common social phenomenon, i.e., social conformity [28]. In other words, messages of similar topics with the same opinion are supportive to each other, and contradictory otherwise. As aforementioned, fuzzy set S_p represents the degree of topical belongingness of msg_p. Therefore, to obtain the topical similarity between msg_x and msg_y, i.e., $Sim_T(msg_x, msg_y)$, is equivalent to measure the similarity between fuzzy sets S_x and S_y. The most obvious way of calculating fuzzy sets similarity is based on the distance of their membership degrees [2]. Thus, $Sim_T(msg_x, msg_y)$ is formulated in Equation 13 by using normalised Hamming distance, namely, one of the most widely used distances for fuzzy sets [26].

$$Sim_T(msg_x, msg_y) = 1 - \frac{1}{|T|} \sum_{\tau_k \in T} |m_x(\tau_k) - m_y(\tau_k)| \tag{13}$$

The comprehensive strength exerting on v_i to accept the opinion of msg_p is formulated in Equation 14, where θ denotes the similarity threshold.

$$\begin{aligned} &\varphi(msg_p) = \sum_{msg_q \in W^{(v_i)}} A(msg_q^{(v_j \to v_i)}) \\ &\text{subject to } Sim_T(msg_p, msg_q) \geq \theta, \ msg_p.o_p = msg_q.o_q \end{aligned} \tag{14}$$

Similarly, the comprehensive strength of declining the opinion of msg_p, i.e., $\varphi'(msg_p)$, stems from the similar messages with adverse opinions, thus $\varphi'(msg_p)$ can be formulated in the same way as $\varphi(msg_p)$, but with a different constraint, i.e., $msg_p.o_p \neq msg_q.o_q$. We can derive the probability that v_i accepts the opinion of msg_p by using Equations 15 and 16.

$$p(msg_p) = 0, \varphi(msg_p) \leq \varphi'(msg_p) \tag{15}$$

Otherwise:

$$\begin{aligned} p(msg_p) &= \frac{\varphi(msg_p) - \varphi'(msg_p)}{\varphi(msg_p)} \cdot \frac{\varphi(msg_p) + \varphi'(msg_p)}{\sum_{msg_q \in W^{(v_i)}} \varphi(msg_q) + \varphi'(msg_q)} \\ &= \frac{\varphi(msg_p)^2 - \varphi'(msg_p)^2}{\varphi(msg_p) \cdot \sum_{msg_q \in W^{(v_i)}} \varphi(msg_q) + \varphi'(msg_q)} \\ &\leq \frac{\varphi(msg_p)^2 - \varphi'(msg_p)^2}{\varphi(msg_p)^2} \leq 1 \end{aligned} \tag{16}$$

As mentioned previously, the influence competitive relations are reflected from the limited capacity of each user agent. Once an influence message $msg_p^{(v_j \to v_i)}$ has been accepted, the amount of occupied capacity can be represented as the normalised value of user acceptance to $msg_p^{(v_j \to v_i)}$, i.e., $\widehat{A}(msg_p^{(v_j \to v_i)})$. In addition, $C(PR^{(v_i)})_{t_m}$ denotes the influence message set drawing v_i's attention at time t_m, which appears to be a subset of $PR_{t_m}^{(v_i)}$, i.e., $C(PR^{(v_i)})_{t_m} \subseteq PR_{t_m}^{(v_i)}$, subject to:

$$\sum_{msg_n^{(v_j \to v_i)} \in C(PR^{(v_i)})_{t_m} \wedge v_j \in \Gamma(v_i)} \widehat{A}(msg_n^{(v_j \to v_i)}) \leq c^{(v_i)} \tag{17}$$

Algorithm 1 describes a user agent's response towards an incoming influence message. The inputs include $msg_p^{(v_j \to v_i)}$ and wall $W_{t_m}^{(v_i)}$ at the time step t_m, while the output of the algorithm produces an influence message set that attracts user agent v_i's attention at the following step t_{m+1}. Lines 1-2 calculate the probability of accepting the $msg_p^{(v_j \to v_i)}$ and the influence message set drawing v_i's current attention. Lines 3-4 initialise the variables. Lines 5-7 determine if $msg_p^{(v_j \to v_i)}$ is posted by v_i, and update the posting records by adding msg_p to the head of $C(PR^{(v_i)})_{t_m}$. Lines 8-14 tend to construct the influence message set drawing v_i's attention in time step t_{m+1} by replicating the influence messages until user agent's capacity reaches the limit.

Algorithm 1 Multiple Influences Diffusion Algorithm

Input: $msg_p^{(v_j \to v_i)}$, $W_{t_m}^{(v_i)}$
Output: $C(PR^{(v_i)})_{t_{m+1}}$

Calculate $p(msg_p)$ by using Equations 15 and 16.
Obtain $C(PR^{(v_i)})_{t_m}$ by using In-equation 17.
Initialise $C(PR^{(v_i)})_{t_{m+1}} = \emptyset$
Generate a random decimal $rand$
if $rand \leq p(msg_p)$ **then**
  $PR^{(v_i)} := PR^{(v_i)} \cup \{msg_p^{(v_j \to v_i)}\}$
  $C(PR^{(v_i)})_{t_m} := \{msg_p\} \cup C(PR^{(v_i)})_{t_m}$
  Initialise temp variable $c_{temp}^{(v_i)} := \widehat{A}(msg_p^{(v_j \to v_i)})$
  for $\forall msg_q \in C(PR^{(v_i)})_{t_m}$ **do**
    if $\widehat{A}(msg_q) + c_{temp}^{(v_i)} \leq c^{(v_i)}$ **then**
      $C(PR^{(v_i)})_{t_{m+1}} := \{msg_q\} \cup C(PR^{(v_i)})_{t_{m+1}}$
      $c_{temp}^{(v_i)} := c_{temp}^{(v_i)} + \widehat{A}(msg_q)$
    end if
  end for
end if

5 EXPERIMENTS AND ANALYSIS

Two experiments have been conducted to evaluate the proposed model. In both experiments, we have applied the AMID model in an extended version of the influence maximisation problem [13] by considering how to suppress and minimise the constant impact of a particular influence message or opinion within a fixed time-span [34]. The objective of the experiments is set to suppress an undesirable influence by utilising various strategies based on the AMID model. In the experiments, three major types of influences are involved:

- *Irrelevant Influence:* the topics of the influences are not relevant to any of the existing influences. In other words, the influence messages are not topically related at all.
- *Opposite Influence:* the topics of the influences are close to the existing ones but with an adverse opinion.
- *Relevant Influence:* the topics of the influences are strongly related the existing ones, and the opinion appears to be supportive.

The differences between the two experiments are reflected as follows: In the first experiment, we aim to explore and analyse the trend of the undesirable influence after adopting different strategies. Whereas, the second experiment tends to measure and compare the effectiveness of different approaches, including blocking nodes [14], by varying the seed set size and aggregating the results in each time step.

5.1 Problem Formulation

Assume that an undesirable influence msg_p is spreading across the social network $G = (V, E)$, and new messages with same opinion keep emerging over time. An organisation aims to suppress the impact of such opinions as much as possible in a fixed time-span, i.e., $[t_0, t_m]$. We regard the targeting influence message/opinion msg_p has been suppressed successfully if msg_p has been faded out of users' attention. Specifically, we leverage **Active Influence Coverage Degree (AICD)** as the evaluation metric, which implies how much the users care about a particular opinion at a specific time step, and the value can be derived from the users' latest posting records. Furthermore, **Cumulative AICD** measures the influence impact within a timespan. Therefore, the problem can be represented as an optimisation problem, expecting to minimise the objective function:

$$min \sum_{t=t_0}^{t_m} \sum_{v_i \in V} \sum_{msg_p \in C(PR^{(v_i)})_t \wedge v_j \in \Gamma(v_i)} \widehat{A}(msg_p^{(v_j \to v_i)}) \quad (18)$$

5.2 Experiment Setup

Dataset and settings. The experiments have been conducted by using the Facebook-like social network, which is originated from an on-line community for students at the University of California, Irvine. The public dataset is collected by Opsahl and Panzarasa [23], which incorporates 1,899 users and 20,296 directed links.

Since how to estimate individuals' topical interests and how to generate fuzzy sets for a particular influence message are not part of the major purpose of the experiments, thus, to make it simple, we extend the dataset by giving the following settings and assumptions:

- The individuals' capacities are randomised by following the Gaussian distribution.
- There are ten pre-defined topics in the social network, i.e., $T = \{\tau_1, \tau_2, ..., \tau_{10}\}$.
- Users' interests towards these ten topics are randomly generated. Peer trust and user's interests are equally important for an individual to accept any influence, i.e., $\gamma = 0.5$.
- There are four pre-existing influence messages in the context, which are not topically related to each other.
- Among the four influence messages, *Influence Message 2* in Figures 2-7 is targeted to be suppressed.
- Each individual's social network wall is initialised by filling with randomised influence messages.
- Measures are not supposed to be taken until the evolution of the network reaches the 30th time step.

Comparison methods. Based on the settings mentioned above, given such a social network with several pre-existing influence messages, users interact and exert influences on each other by disseminating influence messages to the adjacent neighbours. The evolution of the network pauses after some time steps. Next, based on this state, we attempt various strategies to navigate the direction of the networked evolution. Two scenarios are involved in the experiments. **(1)** The social network is under the control of this organisation, having the privileges to manipulate the topological structure of the social network. **(2)** The organisation does not possess any control to the social network. Therefore, any nodes or links are not supposed to be blocked or removed. In the former, we attempt to identify the most negative influencers and block their capabilities of spreading the designated undesirable influence. While, in the latter, three types of influences are supposed to be injected into the same environment to suppress the existing undesirable influence, which are

- the influences topically irrelevant to any of the existing influences
- the influences holding the opposite opinion towards the undesirable influence

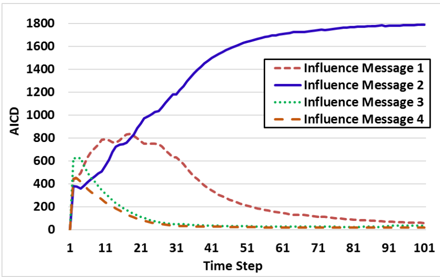

Figure 2: No Strategies Applied - Without Injecting any Influences

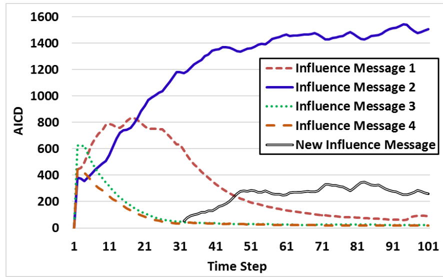

Figure 3: Inject Irrelevant Influence (Seed Set Size = 20)

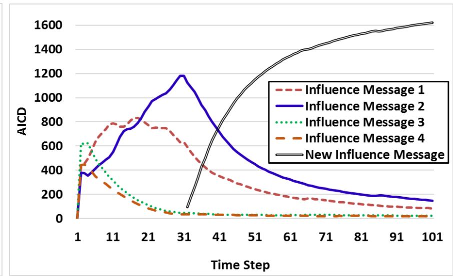

Figure 4: Inject Irrelevant Influence (Seed Set Size = 30)

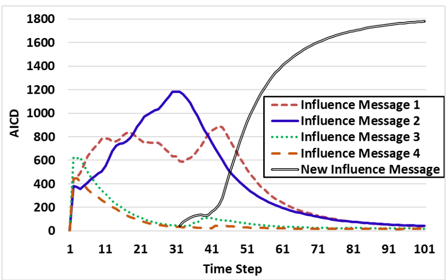

Figure 5: Inject Relevant Influence (Seed Set Size = 10)

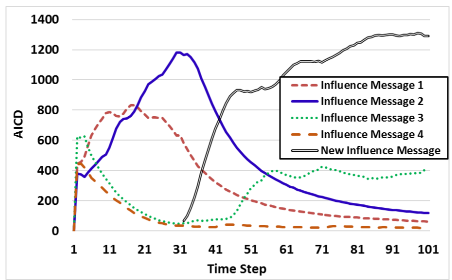

Figure 6: Inject Opposite Influence (Seed Set Size = 10)

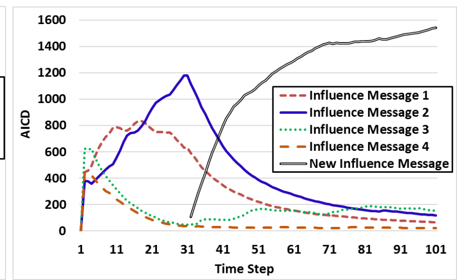

Figure 7: Inject Opposite Influence (Seed Set Size = 30)

- the influences strongly associated with the existing influences but excluding the undesirable influence

The process of identifying influential users are named as *seed selection*; the selected users are called *seed set*; the size of seed set refers to the *budget*. In the experiments, the greedy selection algorithm [13] has been applied for all the approaches. The approach which can minimise the Cumulative AICD of undesirable influence (refer to Equation 18) with less budget is regarded as the optimal solution.

5.3 Experiment 1

In the first experiment, we aim to explore and analyse the trend of the undesirable influence after adopting different strategies. As aforementioned, among four pre-existing influence messages, *Influence Message 2* is undesirable and supposed to be minimised. In Figures 2 - 9, the x-axis represents the networked evolving time steps, and the y-axis denotes the AICD. Various strategies are only supposed to be adopted after the 30th time step when the adverse influence does not fully dominate the network.

Figure 2 demonstrates the evolutionary trend of the social network without taking any measures. As we can observe that the undesirable influence message spreads rapidly and dominates the entire social network after 50 time steps. Whereas, others keep fading out of context gradually. During the evolving process, Influence Message 1 seems competitive and shows a spike around the 20th time step, but loses the public attention eventually.

Next, we inject a new influence message into the social network to compete with the existing ones for the resources, expecting that the undesirable influence message could be suppressed. The injected influence is totally independent and not associated with any existing influences in terms of topics. Unfortunately, as we can see from Figure 3 that given investment budget as 20 (seed set size), the undesirable influence still attracts most users' attention, though an upper shaking trend is spotted. As illustrated in Figure 4, by increasing the seed set size (up to 30) of the same injected influence message, the undesirable influence demonstrates a sharp downward trend and is fading out of the users' attention eventually. In addition, the injected influence dominates the entire social network.

Moreover, we attempt to inject an influence message, which is topically associated with two of the existing influence messages, i.e., Influence Messages 1 and 3. In Figure 5, the expected outcome can be achieved with merely ten seeds. In addition, an interesting phenomenon can be observed from Figure 5 that the associated influences, i.e., both Influence Messages 1 and 3 rise up when the new influence message has been injected into the social network, and this is due to topical similarities among the three influence messages.

Another ordinary strategy is introducing influences with opposite opinions. According to Figures 6 and 7, undesirable influence stops expanding and demonstrates a sharp downward trend after injecting an opposite influence. However, the injected message shows different growing tendencies when varying the seed set size. In Figure 6, the injected message increases and starts to oscillate when reaching the 45th time step. Meanwhile, Influence Message 3 shows an upper trend from the same point and steadily rises to 400. A higher budget in Figure 7 can ensure a relatively smooth increase, though other influences still show a slightly upper trend.

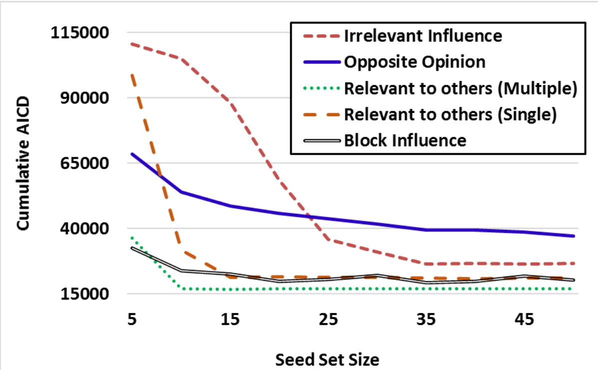

Figure 8: Undesirable Influence (Cumulative AICD)

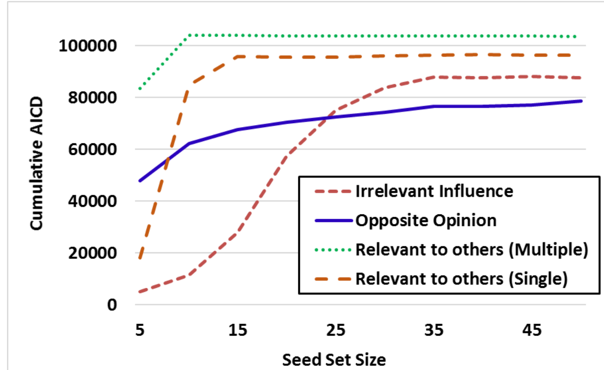

Figure 9: Injected Influence (Cumulative AICD)

5.4 Experiment 2

Experiment 2 tends to measure and compare the effectiveness of different approaches in suppressing an undesirable influence, including injecting irrelevant influences, opposite opinions, relevant influences and blocking nodes, by employing the proposed AMID model.

Figure 8 describes the trend of the undesirable influence by applying various strategies. The AMID model employs probabilistic methods. Therefore, the results are averaged over 100 trials in the experiment. By varying the seed set size, the traditional approach, i.e., blocking influential nodes, performs very well, especially when the budge is so limited. However, the administrative privileges of the social network must be granted to adopt this approach. By contrast, without any authorisations, injecting a new influence topically associated with multiple existing influences can produce an even better performance than that of blocking nodes. Overall, injecting a relevant influence topically associated with one or more existing influences appears more effective than that of bringing in opposite opinions or irrelevant influences. Furthermore, utilising irrelevant influences is not cost-efficient compared with others, but it outperforms that of adopting the adverse-opinion influence when the seed set size increases up to 25.

We also measure and compare the dissemination of newly injected messages when any strategy has been adopted. It can be seen from Figure 9 that the influence message topically relevant to multiple existing ones can easily dominate the social network, and a low budget of approximate ten seeds can almost achieve the maximum spread. Whereas, a new message requires a much higher budget and appears not cost-efficient.

5.5 Discussions

Based on the experimental results, we can derive that the fast dissemination of the newly injected influence message can generally suppress the expansion of the undesirable influence effectively. The results also suggest that to suppress an undesirable influence, introducing new influences topically associated with the existing ones appears more cost-efficient than that of injecting an influence message of brand new topics. Meanwhile, the supportive strength of the new influence message encourages the spread of the pre-existing influence messages with similar topics. On the other side, involving influences with opposite opinions does not carry out a desirable result unless the budget reaches a certain threshold. If the opposite influence appears not strong enough, i.e., limited budget, such strategy may cultivate the growth and spread of other influences, since their competitions and the contradicting opinions reduce the probability of being shared. As an ordinary approach, blocking nodes has been widely acknowledged as an effective method to alleviate the spread of any undesirable influence, especially when having a low budget. However, the targeting nodes are usually those influences of the social network, and such approaches are not applicable in most of the scenarios. From the above analysis and discussions, we can conclude that the undesirable influence can be suppressed by injecting other influences based on the AMID. The experiments also prove the rationality of applying AMID in analysing influence propagation when multiple influences involve. Our proposed model can shed light on understanding, investigating and analysing multiple influences in social networks.

6 CONCLUSION AND FUTURE WORK

In this paper, we studied the problem of multiple influences diffusion in social networks and proposed an Agent-based Multiple Influences Diffusion (AMID) model to describe the problem by using the concepts from multi-agent systems. In this model, we precisely formulated three types of influential relationships among different entities, i.e., user and user, user and influence, influence and influence. A distributed multiple influences diffusion algorithm was presented to show the user agent's response towards an influence message, where the personalised features, behaviours and social context were considered. To evaluate the proposed model, we applied it to the undesirable influence minimisation problem. The experimental results revealed that the proposed model was capable of alleviating the adverse impact of a particular influence by injecting other influences. The approach is also applicable in cases where the organisation does not possess the control of the social network.

In the future, we plan to investigate how to identify an appropriate injecting influence message to minimise the undesirable influence, and explore the situations when multiple new influences can be injected into the social network.

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