Agent-based Influence Maintenance in Social Networks (Extended Abstract)

Weihua Li
Auckland University of Technology
Auckland, New Zealand
weihua.li@aut.ac.nz

Quan Bai
Auckland University of Technology
Auckland, New Zealand
quan.bai@aut.ac.nz

Tung Doan Nguyen
Auckland University of Technology
Auckland, New Zealand
tung.nguyen@aut.ac.nz

Minjie Zhang
University of Wollongong
Wollongong, NSW, Australia
minjie@uow.edu.au

ABSTRACT

We study on how to maintain long-term influence in a social network by proposing an agent-based influence maintenance model. Within the context of our investigation, the experimental results reveal that multiple-time seed selection is capable of achieving more constant impact than one-shot selection.

Keywords

Influence maintenance, influence diffusion, long-term marketing, 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 and innovation propagation [7]. The diffusion relies on one of the fundamental social phenomena, i.e., social influence, where information is travelling rapidly through the networks via users' sharing and posting behaviours. By leveraging the power of social influence, a great many business owners attempt to expand the market through the 'word-of-mouth' effect (or called viral marketing) [10]. In recent years, influence maximization draws tremendous attention to both researchers and domain experts. Influence maximization aims to identify a small subset of influential users from a particular social network, expecting that they can propagate influence and maximize the positive impact across the entire network [1, 2, 4].

From a business perspective, influence maximization actually corresponds to short-term marketing effects, which attempts to cause sudden profit spikes that rarely last [11]. Whereas, long-term marketing are typically more beneficial, since it emphasizes on long-term and sustainable business goals. Specifically, long-term influence is able to establish brand awareness and constantly produce results even years down the road, thus, without having long-term marketing strategies, short-term success may be short-lived [1, 8]. 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 state, called *influence maintenance*.

Appears in: *Proc. of the 16th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2017), S. Das, E. Durfee, K. Larson, M. Winikoff (eds.), May 8–12, 2017, São Paulo, Brazil.*

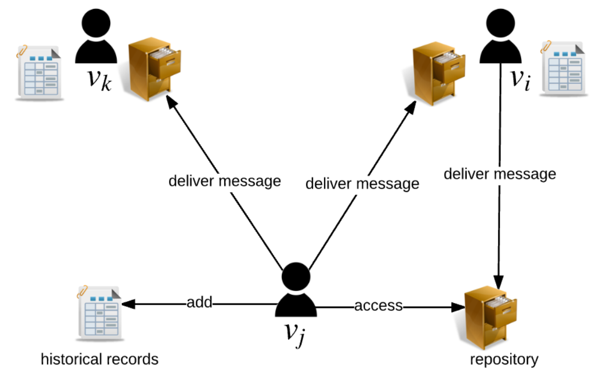

Figure 1: Agent-based Influence Diffusion

An essential factor to be considered for formulating influence maintenance is *timeliness* of a particular influence message. Specifically, an individual reading list in on-line social networks is normally presented as a stack, turning out to be last-post-first-read. Thus, the accessing priority of a particular received influence message keeps decreasing over time, and posting or sharing behaviours are not supposed to be triggered without reading it. Moreover, the timeliness degree also implies the "state" of the corresponding influence message. A low timeliness degree indicates the message is fading out of the user's attention and superseded by other innovations. Whereas, a high timeliness degree implies its great popularity.

On the other hand, a novel influence diffusion model is required, since traditional models, such as Independent Cascade (IC) model and Linear Threshold (LT) model [2], are oversimplified and not capable of capturing the constant impact of an influence message. Therefore, we propose an influence diffusion model by using Agent-Based Modelling [6, 5], which is demonstrated in Figure 1. From a microscopic point of view, each individual's influence activation is achieved by accessing the repository. If a user becomes active, the influence message is supposed to be delivered to all

Table 1: Notations

Symbol	Descriptions
v_u	a user agent
msg_p	an influence message
t_m	a time step
$\varphi(.)$	timeliness degree function
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

the neighbours' repositories. Furthermore, this message will be added to the sender's historical records. From a macroscopic viewpoint, the entire social network demonstrates an evolutionary pattern driven by the actions of individuals.

The relevant notations are listed in Table 1, where $\varphi(.)$ is a function of calculating timeliness degree. $\varphi(v_i, msg_p, t_m)$ denotes the timeliness degree of message msg_p in v_i's repository at time t_m. The influence maintenance formulation is detailed in Section 2.

2. PROBLEM FORMULATION

The influence maintenance is defined as the process of preserving a particular type of influential situation or the state of influence being preserved, which derives from the influence maximization problem. Specifically, given a finite budget k (seed set size) and a limited timespan $[t_0, t_m]$, 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 sets A is a collection of seeds identified from each investment time step, i.e., $A = \{A_t | t \in I\}$ and $\sum_{t\in t_{N\times n}} |A_t| = k$.

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 $\{A_i, A_j\} \subseteq A$, then $|A_i| = |A_j|, A_i \cap A_j = \emptyset$. 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 timespan $[t_0, t_m]$, i.e., ξ_{msg_p}. The *Global Timeliness Degree (GTD)* of msg_p at a particular time step t_n can be calculated by using Equation 1.

$$\xi^{t_n}_{msg_p} = \sum\nolimits_{v_i \in V} \varphi(v_i, msg_p, t_n) \qquad (1)$$

Thus, we can obtain ξ_{msg_p} by using Equation 2. The objective of influence maintenance is to maximize ξ_{msg_p}.

$$\xi_{msg_p} = \sum_{t_0}^{t_m} \xi^{t_n}_{msg_p} = \sum_{t_0}^{t_m} \sum\nolimits_{v_i \in V} \varphi(v_i, msg_p, t) \qquad (2)$$

3. EXPERIMENT AND RESULTS

Ego-Facebook dataset[1] has been used for the experiment[9, 3], which contains profile and network data from 10 ego-networks, consisting of 193 circles, 4,039 users and 88,234 edges.

[1]http://snap.stanford.edu/data/egonets-Facebook.html

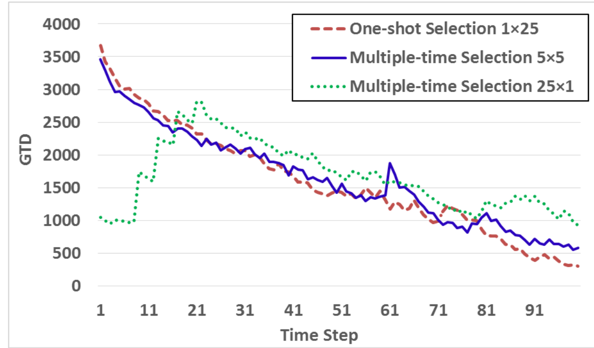

Figure 2: GTD Comparison

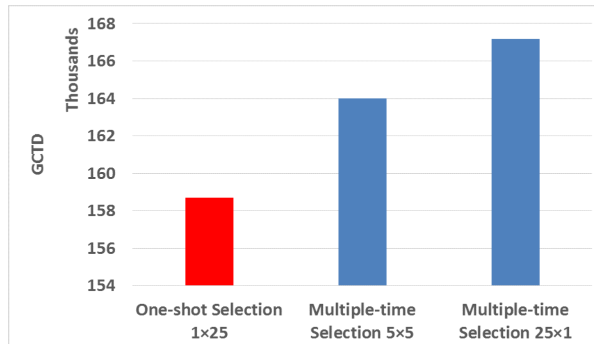

Figure 3: GCTD Comparison

The experiment aims to compare one-shot investment against the multiple-time by facilitating rank-based seed selection algorithm, i.e., selecting seeds based on the degree of node. As observed in Figure 2, 5×5 multiple-time selection has a pretty high starting point after the initial investment, and demonstrates steady downward trends afterwards. Compared with 25×1 one-shot selection, the GTD is a little bit lower at the beginning, but one-shot selection declines faster and eventually looses its advantages. Whereas, 1×25 multiple-time selection demonstrates a different pattern. It climbs up to the peak point, which is higher than the other two selection approaches, then falls gradually. Furthermore, by comparing the GCTD of the three approaches in Figure 3, it is evident that multiple-time selection is a better choice for maintaining a particular influence, and multiple-time selection 25×1 is even more prominent.

4. CONCLUSIONS

In this paper, we addressed the influence maintenance problem. An agent-based influence diffusion model was proposed, which can be applied to investigate the strategies for long-term marketing. Experiments were conducted to evaluate the proposed model. The experimental results revealed that given the same budget and limited time frame, multiple-time investment is superior than one-shot investment in terms of influence maintenance. We believe that our findings can shed light on the understanding on influence maintenance for long-term marketing.

REFERENCES

[1] D. Hatano, T. Fukunaga, and K.-i. Kawarabayashi. Adaptive budget allocation for maximizing influence of advertisements. In *Proceedings of the 25th International Joint Conference on Artificial Intelligence IJCAI-16*, pages 3600–3608, 2016.

[2] D. Kempe, J. Kleinberg, and É. Tardos. Maximizing the spread of influence through a social network. In *Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 137–146, Washington, DC, USA, 2003. ACM.

[3] J. Leskovec and A. Krevl. SNAP Datasets: Stanford large network dataset collection. http://snap.stanford.edu/data, Jun 2014.

[4] W. Li, Q. Bai, C. Jiang, and M. Zhang. Stigmergy-based influence maximization in social networks. In *Proceedings of Pacific Rim International Conference on Artificial Intelligence*, pages 750–762. Springer, 2016.

[5] W. Li, Q. Bai, and M. Zhang. Agent-based influence propagation in social networks. In *IEEE International Conference on Agents (ICA)*, pages 51–56. IEEE, 2016.

[6] C. M. Macal and M. J. North. Agent-based modeling and simulation. In *Proceedings of the Winter Simulation Conference*, pages 86–98. IEEE, 2009.

[7] L. Marcolino, A. Lakshminarayanan, A. Yadav, and M. Tambe. Simultaneous influencing and mapping social networks. In *Proceedings of the Fifteenth International Conference on Autonomous Agents and Multiagent Systems (Short Paper)(AAMAS 2016)*, 2016.

[8] L. Marketing. What are your short-and long-term marketing strategies?, August 2015. [Online; posted 26-August-2015].

[9] J. J. McAuley and J. Leskovec. Learning to discover social circles in ego networks. In *NIPS*, volume 2012, pages 548–56, 2012.

[10] J. Moran and F. Cordaro. Understanding the hit-rate dynamics of a large website with an agent-based model. In *Processing of 8th International Conference on Autonomous Agents and Multiagent System (AAMAS 2009)*, pages 105–109, 2009.

[11] A. Valencia. Short-term vs. long-term online marketing, August 2013. [Online; posted 22-August-2013].