

COMPETITIVE INFLUENCE DIFFUSION THROUGH SOCIAL NETWORKS

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Abstract: The dynamic of the information distribution is complex and affects the everyday life, especially with the multiple ideas that are being released in social networks. These multiple ideas often have competing nature for the same nodes of the network. In this paper we will discuss two competitive influence diffusion models in social networks. First, we take in consideration the competitive cascade model and at a certain point, the network will behave according to a competitive linear threshold dynamic model. We will assume that when a certain number of the nodes will have a specific information and when this number will grow up beyond a critical percentage of the active nodes, then we will reach an automatic collective change behavior of the network. Each node in the network can be inactive or active (positively or negatively). If we can control the diffusion processes of the information in the network, we can predict the popularity of the innovation introduced. Since is a challenging task to predict the popularity of an innovation, by analyzing the dynamic of the network according to the competitive diffusion models as extended of single item diffusion. By joining the two models for the diffusion of the information on the directed networks, we will better understand the dynamic of the information distribution through the network, and how this distribution is affected from the different attitudes of the individuals when they firstly have this information. By combining and analyzing the two competitive diffusion models, extending them with two influence distribution functions, we take as a result as a better way to outperform in term of efficiency and effectiveness.

Keywords: information diffusion, influential nodes, competitive models.

1. INTRODUCTION

The diffusion processes are strongly connected with the spread of information and innovation ideas or new trends on social networks. In both cases, the distribution ability of the idea that is being propagated on the network, is not affected only from the idea but even from the structure and the dynamic of the network. Each diffusion process has an initial point, where special individuals (or nodes) are the first to adopts the new idea propagated in the network, which will affect the distribution to the other nodes. To fully understand the social behavior or how nodes communicate with each other, we must know the structure through the information is distributed. In this paper we will show how the information is distributed in a directed network, knowing the structure of the network and changing the dynamics of the network. First, we take in consideration the competitive cascade model [1-4] and at a certain point, the network will behave according to a competitive linear threshold dynamic model [5-7]. In order to reach at this point, we will assume that when a certain number of the nodes will have a specific information (the new idea that is being propagated in the network), and this number will grow up beyond a critical percentage of the active nodes, then we will reach an automatic collective change behavior of the network. Each node in the network can be inactive or active (positively or negatively). Some nodes will not like the new trend that is spreading in the network, but even by being negative influencer, they are sharing the new idea just by mentioning it: an anti-advertisement, is an advertisement too. By joining the two models for the diffusion of the information on the directed networks, we will better understand the dynamic of the information distribution through the network, and how this distribution is affected from the different attitudes of the individuals when they firstly have this information. We must mention that now more then ever the digital marketing can influence in being or not successful for an innovation that is released in the network. All the success of the digital marketing, by the other hand, will depend from the influencer nodes, where usually are positive influencer nodes and they will recommend to their neighbors, but of course bad influencer can be part of the network, and affect too. Since everybody can be part of the digital marketing, similar products are being released from different companies, and each of them aim to attract as much as possible the attention of the individuals. These companies (or they can be individuals) will compete by using influential nodes of the network, aiming to increase and maximize their influence. Another famous diffusion model proposed by *Clifford et al.* [8] is the voter model. In this model individuals are positioned at the nodes of the network, and connected with each other with the same probability, and at each time step, one of the nodes will randomly chose one of the neighbors and adopt the new idea. Li et al. [14] extended the voter model by considering the competition of the positive influential nodes and negative influential nodes for the same innovation released in the market. The references [9-12] are extended literature for the competition of multiple ideas released in

social networks and the approaches of diffusion processes in order to describe the overall dynamic of the distribution of the idea released in the network as an innovation.

2. MATERIALS AND METHODS

The competitive influencers in directed are defined as proposed in the section below, where we are considering the nodes in three states. Nodes can be active, and by being active they could be positive or negative influencer related to the new idea released in the network. Even though they are positive or negative influencer, nodes are all connected. At the beginning we will fix the number of nodes, and the degree distribution of the nodes. The network is created depending on the degree distribution and the closeness of the nodes. We randomly chose one node and this node connects with the closest neighbor. We will repeat the process until the network will have the degree distribution that we asked at the beginning of the simulation.

At the competitive cascade model each node has positive and negative influence probabilities $p^+(u, v)$ and $p^-(u, v)$, where u - is an active node, v - is an inactive node. Let's denote with $A_t^+(v)$ the positive successful attempt set and $A_t^-(v)$ negative successful attempt. Node u will be positively influenced if u 's attempt to activate v with independent probability $p^+(u, v)$ is successful, $u \in A_t^+(v)$. The opposite, the same node will negatively be influenced if influenced if u 's attempt to activate v with independent probability $p^-(u, v)$ is successful, $u \in A_t^-(v)$. The *competitive cascade model* will follow the rules:

$$\bullet \begin{cases} \text{If } A_t^+(v) \neq \emptyset \wedge A_t^-(v) = \emptyset: v \in S_t^+ \\ \text{If } A_t^-(v) \neq \emptyset \wedge A_t^+(v) = \emptyset: v \in S_t^- \\ \text{If } A_t^+(v) \neq \emptyset \wedge A_t^-(v) \neq \emptyset: \text{breaking rule} \end{cases} \quad (1)$$

Another classical case would be to apply the tie breaking role for fixed probability, for example v is positive with probability $\emptyset$ and negative with probability $1 - \emptyset$. In this case we can obtain positive or negative dominance by applying the rule:

$$\bullet \text{ Fixed probability}(1)/\text{Fixed Probability}(0) \quad (2)$$

We can apply breaking rule with proportional probability as follows:

$$\bullet \begin{cases} V \text{ is positive with probability } \frac{A_t^+(v)}{A_t^+(v) + A_t^-(v)} \\ V \text{ is negative with probability } \frac{A_t^-(v)}{A_t^+(v) + A_t^-(v)} \end{cases} \quad (3)$$

When we need to apply a breaking rule, we first have to check the priority order the node $u \in A_t^+(v) \cup A_t^-(v)$ that is order first wins, and v takes the state of u .

Let's now describe briefly the competitive linear threshold model, knowing that in this model we will use weighted nodes to measure the positive and negative influence in the network. Initially each node v selects a positive threshold θ_v^+ and a negative threshold θ_v^- independently from $[0, 1]$. At each time step, using respective weights and thresholds, we propagate positive influence and negative influence separately. If both attempts are successful, then we use fixed probability tie breaking rules according to equation (1) and equation (3).

The next addressed problem with the competitive diffusion models (CIC and CLT) is to find *how we can maximize the influence* for a given idea or item that we want to spread all over the network? Let $\sigma(S)$ denote the final influence spread of node set S . Given a social graph (G) , under the competitive diffusion models introduced, we have to find a positive node set $S_0^+ \in V/S_0^-$ with at most of the k -node sets such that the positive influence spread of S_0^+ given to negative node sets S_0^- , $\sigma^+(S_0^+, S_0^-)$ is maximized. We can solve this problem by computing:

$$S_0^+ = \operatorname{argmax} \sigma^+(S_0^+, S_0^-) \quad (4)$$

Each edge is sampled once, since only one item or idea can propagate through each edge.

If we chose the case of homogeneous network, we have fixed probability for each set of nodes $0 < \theta < 1 \rightarrow$ not sub modular (Figure 1). Black nodes are negative influencer. Figure 2 shows that the homogeneous CLT dynamic of the network is not sub modular.

Figure 1 Homogeneous Competitive Cascade model:
Sub modularity of σ^+

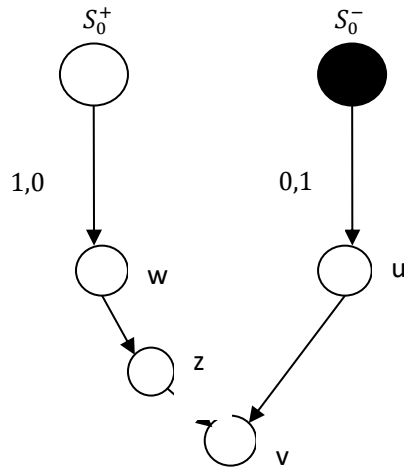
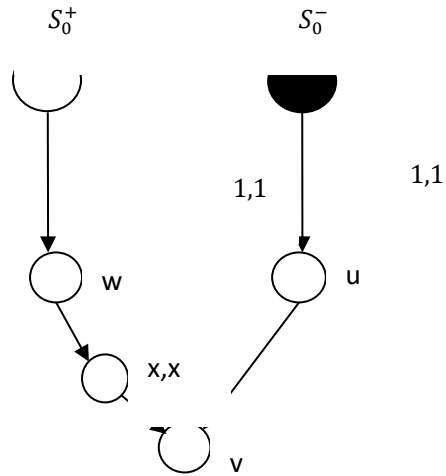


Figure 2 Homogeneous Competitive Linear Threshold model:
Sub modularity of σ^+



1-x,1-x

We will set how many nodes will have the new idea and will initiate the distribution at the beginning of the simulation. At each time step, each node will decide to spread the innovation to their neighbors. Here we find the motivation to find a way for blocking influence maximization, if needed, to stop the rumor spreading or, another example would be node vaccination, which ones will not likely spread positive influence.

3. RESULTS

By combining the competitive diffusion models, we can highlight the popularity for an item or idea presented which can be improved by considering two item diffusion: positive influencers and negative influencers. Figure 3 shows the percentage of active nodes at the beginning of the simulations, and figure 4 shows the percentage of new nodes that are hearing the new idea or item propagated for the first time at each time step of the simulation.

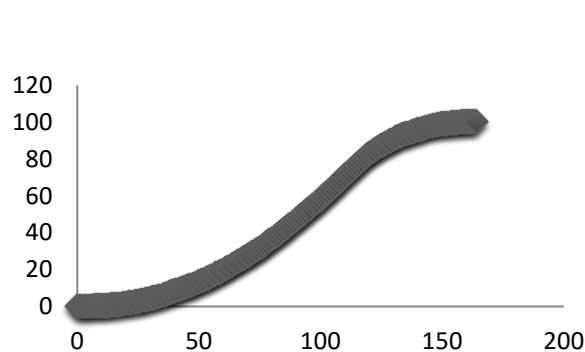


Figure 3 The % of activated nodes

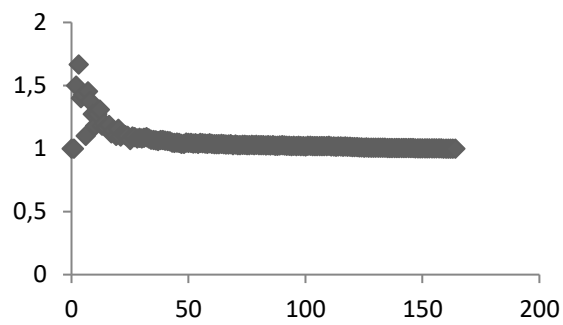


Figure 4 The % of new nodes that are hearing the new idea at each time step

Figure 5 shows the percentage of the nodes that are being positively or negatively activated. At each time step, every person who knows the new idea randomly chooses a neighbor to tell the new idea too. The simulation keeps track of

who knows the new idea propagated, how many people know the new idea, and how many “repeated telling” of the new idea occur.

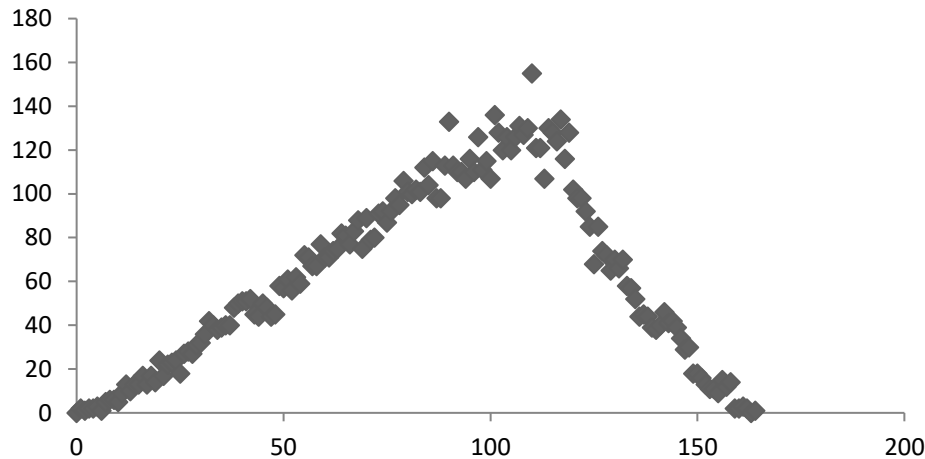


Figure 5 The % of new nodes who are being activated at each time step

Each node has an assigned probability to have the new idea and to share it with her neighbors. The information is proportional with the number of links of the nodes that already have it. If the node does not have outgoing links, we will assume that this node will stay inactive until some outgoing links are settled. The distribution of the information will depend on the size of the network and the number of the active nodes of the network.

4. DISCUSSIONS

We extended the competitive cascade and classical linear threshold model to maximize the influence in directed social networks. We proposed two influences distribution functions, if similar innovation ideas are released, and nodes will compete for attention. We have applied these competitive models in the simplest setting where the diffusion probability is described in equation (1) and equation (3). The combined study of the models helps us to better realize the distribution of the information affected by both type of active nodes (negative/positive). To improve this study, we must consider the preferential attachment model as a good approximation of the distribution of the information in our network.

5. CONCLUSIONS

In this paper, we have presented and analyzed two competitive diffusion models, by extending them with two influence distribution functions as a better way to outperform the results in term of efficiency and effectiveness. Further showed that the proposed method can predict how to maximize influence of the node sets accurately. An on-going direction for future work is to validate more data and at the same time to take in consideration more models for which provable approximation can be achieved.

NOTE

We, as author(s) of this paper, welcome any kind of suggestion to improve the idea presented in this material.

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