COMPETITIVE INFLUENCE DIFFUSION THROUGH SOCIAL NETWORKS

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INTRODUCTION

- The dynamics of the information distribution is complex and affects the everyday life, especially with multiple ideas that are being released in social networks.
  - These multiple ideas often have competing nature for the same nodes of the network
- 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 behaviour of the network.
  - Each node in the network can be inactive or active
- If we can control the diffusion processes of the information in the network, we can predict the popularity of the innovation introduced.
- 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 is not affected only from the idea, but also from the structure and dynamics of the network.
- Each diffusion process has an initial point, where nodes are the first to adopt the new idea propagated in the network and change the dynamics of the network.
- To fully understand the social behaviour, we must know the structure through which the information is distributed.

Models

1. **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.

Node u will be positively influenced if u's attempt to activate v with independent probability $p^{+}(u,v)$ is successful, $u \in A_t^{+}(v)$. with $A_t^{+}(v) \longrightarrow$ the positive successful attempt set and $A_t^{-}(v) \longrightarrow$ negative successful attempt.
The ***competitive cascade model*** will follow the rules:

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

2. **Competitive linear threshold model**: in this model we will use weighted nodes to measure the positive and negative influence in the network.
   i. Initially each node v selects a positive threshold θ_v^{+} and a negative threshold θ_v^{-} independently from [0,1].
   ii. At each time step, we propagate positive influence and negative influence separately.

– How can we maximize the influence for a given idea or item that we want to spread all over the network?

We have to find a positive node set $S_0^{+} \in V/S_0^{-}$ with 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. By computing:

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

we can solve this problem.

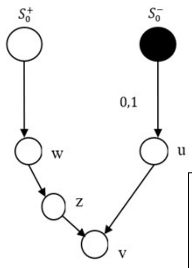

Figure 1: Homogeneous Competitive Cascade model: Sub modularity of σ+

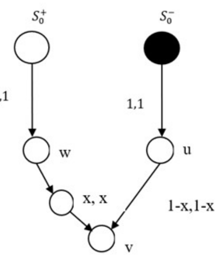

Figure 2: Homogeneous Competitive Linear Threshold model: Sub modularity of σ+.

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.

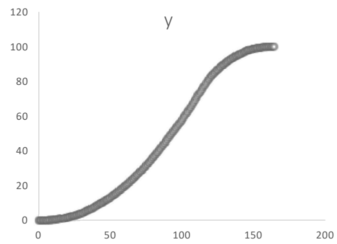

FIGURE 3: THE PERCENTAGE OF ACTIVATED NODES

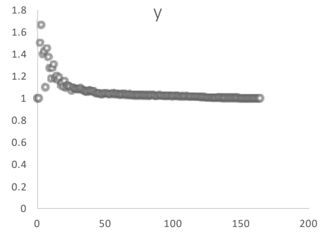

FIGURE 4: THE PERCENTAGE OF NEW NODES THAT ARE HEARING THE NEW IDEA AT EACH TIME STEP

- 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 neighbour to tell the new idea to.

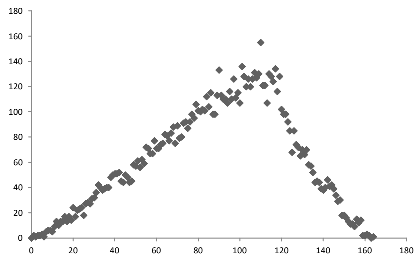

Figure 5

- 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.
- The distribution of the information will depend on the size of the network and the number of the active nodes of the network.

CONCLUSIONS

- We presented and analysed 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.
- Showed that the proposed method can predict how to maximize influence of the node sets accurately.

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