

Product Promotion Strategies for Influencers in Social Network Associations

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Abstract. The development of the Internet has given birth to a new type of promotion mode, and the selection of promotion agents has become a hot issue. The influence index of the agent itself and the type of its association structure become the key factors affecting the degree of product promotion. In this study, we analyze different types of influencers and their community structure in social networks, study the influence of influencers' community structure and influence on information dissemination, and try to find out the agent selection strategy to obtain the highest promotion efficiency under the lowest budget. Based on these findings, this paper proposes an agent selection strategy for product promotion that integrates influencer type and association structure. The strategy suggests that firms first identify the social network structure of their target market and then select the combination of influencers that maximizes the effect of information dissemination. The findings of this study provide a new perspective and methodology for enterprises to promote their products in social networks, which helps them to utilize social network resources more effectively and enhance the effectiveness and efficiency of product promotion.

Keywords: social networks; influencer types; association structure.

1. Introduction

Studies have shown that there are differences in product promotion effects and promotion costs for influencers with different numbers of followers on social networks, and given the importance of product promotion agents in decision support for enterprises, many scholars both at home and abroad have analyzed how to enhance consumer purchase intention through influencer selection from multiple perspectives, such as the type of product promoted, customer interest in the product, the upper limit of the investment in the brand, and other factors. Different from the research direction of previous scholars, this study will first categorize influencers based on their number of followers, and analyze the differences in influence metrics and selection guidelines of different types of influencers. Then, it will analyze the optimal product promotion agent selection strategy based on influencer type and network association structure under a limited budget. This study focuses on influencer types and cost differences. Firms and brands choose different types of influencers for product representation at different costs, resulting in differences in decision-making. For different types of influencers, the metrics are not the same, and the role of influencer type on the metrics is considered and included in the evaluation system. Previous studies have rarely linked network association structure to product agency promotion, but this paper analyzes the effect of product promotion under the influence of different association structures, which seems to be a new idea at present.

2. Theory and Experiment

2.1 Relevant Theories

2.1.1 Impact Metrics

The most dominant approach to the criteria for classifying influencers is to classify the type of influencer based on the number of followers of the influencer. Campbell et al[1] classified influencers as celebrity influencers (with some followers greater than or equal to 1 million), mega influencers (with several followers greater than or equal to 1 million), macro influencers (between

100,000 and 1 million followers), micro influencers (between 10,000 and 100,000 followers) and nano influencers (less than 10,000 followers) five categories. Different types of influencers bring different profits to the promotion of corporate products, so the selection of influencers has become a key concern of modern social media, a good choice can not only bring effective promotion of the company's products but also save money under the same influence effect pointed out to achieve the optimal. Although influencer marketing activities have been increasingly emphasized by enterprises, there are very few studies on the influence metrics of different types of influencers, the selection strategies of different types of influencers, and the differences in the product promotion effects of different types of influencers. 61% of marketers believe that it is difficult to find the right influencers for their marketing campaigns[2]. Some survey data suggest that micro-influencers may bring better marketing results than celebrity influencers in influencer marketing, and micro-influencers have higher engagement[3]. Some scholars point out that enterprises should choose a few super Vs in the network to promote their products, and trigger the diffusion of product information through these super Vs[4]; while some other scholars point out that consumers are usually embedded in small associations, and choosing multiple mini-Vs based on the community structure to promote their products will be more effective [5].

To sum up, combining the actual needs of enterprises and theoretical debates, this project will classify influencers based on the number of their followers, and first analyze the differences in the influence metrics and selection criteria of different types of influencers; then, the study will analyze the optimal product promotion agent selection strategy based on the type of influencers and the structure of the network associations under the constraints of the capital budget and explore the differences in product promotion effects of different types of influencers. promotion effects of different types of influencers.

2.1.2 Information Dissemination Model

Our study is based on the following model.

Independent Cascade (IC) Model.In the study of social network propagation, we consider a graph $G(V, E)$ consisting of a collection of nodes V and a collection of edges. In this network, each node has two states: active and inactive. Information propagation between nodes is performed with a given propagation probability $P_{u,v}$. For a given set of activated seed nodes A , each seed node u in the activated state tries to activate its neighbor node v in the inactivated state with probability $P_{u,v}$. It is worth noting that each node has only one chance to activate its neighbor node, and if the activation fails, the node will remain inactivated forever. When multiple nodes in the activated state try to activate the same neighbor node in the inactive state at the same time, the activation process will be performed in random order to ensure that the activation is completed at the same moment. In this propagation process, when node v is activated at moment t , it has one chance to activate its neighbor node w . At the moment $t+1$, whether v succeeds in activating w or not depends on the probability $P_{v,w}$. If w has more than one node that has been activated, then these nodes affect it randomly and independently. However, regardless of whether the activation is successful or not, v cannot affect w 's later states. The whole propagation process will continue until there are no nodes that can be activated, thus completing the process of information propagation.

Liner Threshold (LT) Model.In social network communication research, the linear threshold model emphasizes the cumulative process of influence more than the independent cascade model. In this model, each node v in the social network graph $G(V, E)$ is assigned a threshold value θ_v belonging to the range of $[0,1]$. At the same time, each node has a probability of propagation between nodes in the range of $[0,1]$ $P_{u,v}$. Given a set of activated nodes A , each node u in the set activates its neighboring node v with a probability $P_{u,v}$. It should be noted that the sum of the weights of all the edges connected to node v needs to satisfy the constraint $\sum P_{u,v} \leq 1$, where $u \in \Gamma(v)$ and $\Gamma(v)$ represent all neighbor nodes of node v . Node v will be activated when the sum of the influence of all the neighbor nodes of node v on it is greater than or equal to its threshold value θ_v ;

otherwise, it remains inactive. The propagation process will continue until no node in the social network performs the activation behavior.

We improve on the above model, we consider the role of node degree on node influence, in addition to directly adjacent nodes, adding the influence of second-hop and third-hop neighbors, and the inter-node influence decreases with the increase of inter-node degree, which means that a node's first-hop, second-hop, and third-hop neighbors all influence the probability of its activation, and the combination of the above ideas generates our information dissemination model.

2.2 Simulation Experiment

2.2.1 Experimental Procedure

We used the LFR network generation function to generate 4000 random network nodes, which are self-contained with the association attribute, and the random network divided these nodes into a total of 20 associations. To avoid chance caused by the small number of experiments, which affects the results of the experiments, we perform a Monte Carlo simulation for each association separately, averaging over a total of 100 cycles. In this simulation, we calculate the influence, cost, and score of the nodes, then select seed nodes and calculate the expense of hiring seed nodes, which are disseminated using the information dissemination model, and subsequently calculate values such as the average customer acquisition cost.

We classify the node types based on the relative size of the node degree, which is found by dividing the degree of the node itself by the degree of the node with the largest degree in the network. These network nodes are categorized into six groups V1, V2, V3, V4, V5, and V6.

In the algorithm for assigning scores to nodes, we use the following public notices:

$$\text{score} = \gamma * \text{cost_effective} + (1 - \gamma) * \text{norm_influence} \quad (1)$$

Where γ is a value set by yourself, norm_influence is the standardized influence, divide the standardized influence by the standardized cost to get effective, and standardize again to get cost_effective .

In selecting seed nodes, we take the largest degree in the network as the budget under which nodes with high scores in V are selected as far as possible.

2.2.2 Experimental results

To facilitate the observation of the variability between the seed nodes of each group, we visualized and analyzed the experimental results, and presented the resultant data in the form of line graphs, with a total of 20 association nodes analyzed in the graphs, and Fig. 1 demonstrates the results of the data derived from Monte Carlo simulation for the first six of them.

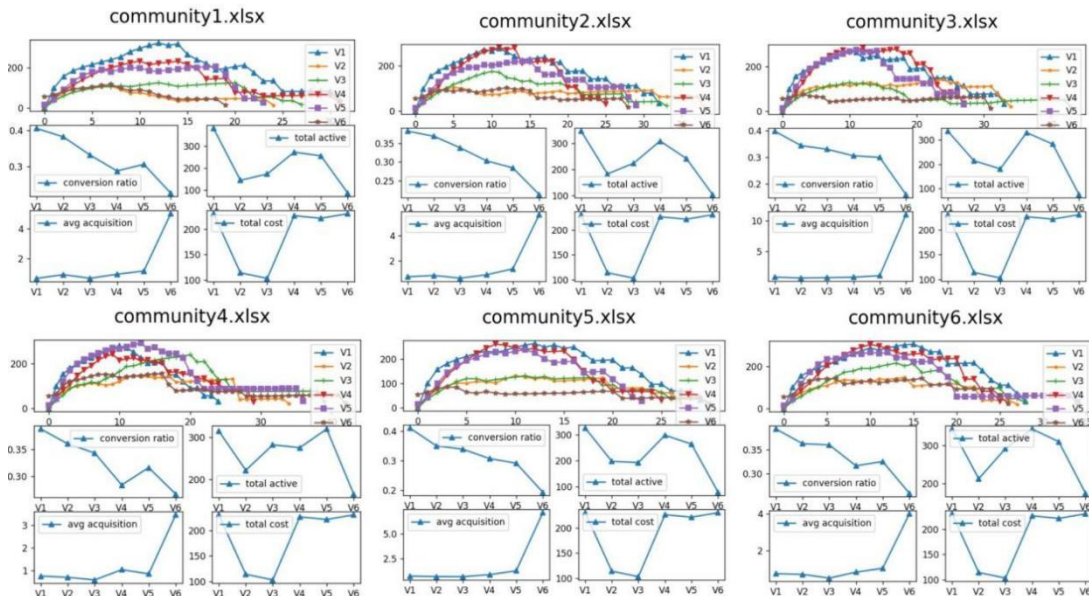


Figure 1: Visualization of the results of the simulation experiments (partial)

According to the purpose of our experiment, we need to select the object with higher active under less cost, i.e., divide total active by total cost to get average acquisition, and according to the visual analysis and comparison, the group of seed nodes in V1, V2, and V3 have the least average acquisition. According to the comparison of visual analysis, it is concluded that the seed node group in V1, V2, and V3 has the least average acquisition, i.e., it best meets our needs.

This paper provides a new idea for enterprises to promote their products in social networks, i.e., the number of followers of an influencer does not always have a positive effect on the effectiveness of product promotion, and it may be wiser to choose an influencer with fewer followers in the process of product promotion of an enterprise.

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