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Research Article

Channel Optimization of Marketing Based on Users' Social Network Information

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Marketing in the social network environment integrates current advanced internet and information technologies. This marketing method not only broadens marketing channels and builds a network communication platform but also meets the purchase needs of customers in the entire market and shortens customer purchases. The process is also an inevitable product of the development of the times. However, when companies use social networks for product marketing, they usually face the impact of multiple realistic factors. This article takes the maximization of influence as the main idea to find seed users for product information dissemination and also considers the users' interest preferences. The target users can influence the product, and the company should control marketing costs to obtain a larger marginal benefit. Based on this, this paper considers factors such as the scale of information diffusion, user interest preferences, and corporate budgets, takes the influence maximization model as a multi-objective optimization problem, and proposes a multiobjective maximization of influence (MOIM) model. To solve the NP-hard problem of maximizing influence, this paper uses Monte Carlo sampling to calculate high-influence users. Next, a seed user selection algorithm based on NSGA-II is proposed to optimize the above three objective functions and find the optimal solution. We use real social network data to verify the performance of models and methods. Experiments show that the proposed model can generate appropriate seed sets and can meet different purposes of information dissemination. Sensitivity analysis proves that our model is robust under different actual conditions.

1. Introduction

As for social networks, they have a wide audience, information dissemination is faster with the support of the internet, and more and more people participate in social work. Enterprises should reasonably understand the interactive activities between users in social networks, analyse the support of social networks for their own network marketing work on the basis of understanding social networks, and then propose the working way and way of marketing based on social networks for enterprise marketing work [1–3]. For enterprises, a reasonable information communication strategy of social networks is to select a small number of influential users as seed users to spread information. The efficient place of the social network facilitates the connection between enterprises and users and provides a platform to spread business information [4]. Influence maximization is a problem of identifying a few seed nodes to maximize the spread of influence on social networks [5].

A common approach to the problem of influence maximization is to simulate the cascade of influence through a diffusion model based on the existence of network links. Qiu et al. [6] proposed the study of influence maximization as a model for algorithmic problems. Trivedi and Singh [7] formalized the impact maximization problem as a discrete optimization problem and proposed an independent cascade model (ICM) and a linear threshold model (LTM). Among many existing influence diffusion models, the most popular and widely cited are the independent cascade (IC) model [8, 9] and the linear threshold (LT) model [10, 11]. The IC model regards the activation of a user by multiple neighbors as an independent process, while the LT model regards the activation of the user as a joint process of multiple neighbors. Tang et al. [12] proved that the influence maximization

problem is an NP-hard problem and designed a greedy algorithm to select the approximate optimal seed set. However, the shortcomings of the IC model and the LT model are their limitations in scalability and operational efficiency for large datasets. Therefore, researchers have proposed many improved models to improve the efficiency of influence maximization [13–15]. Banerjee et al. [16] designed a new heuristic algorithm for the prefix elimination maximum influence tree (PMIA) model and proposed the LDAG algorithm of the LT model. He et al. [17] proposed a new upper bound lazy forward (UBLF) algorithm to identify a set of top-k influence nodes. Avetisyan et al. [18] used the user's participation mode and information diffusion rate to model the information flow and identify effective personalized information recommendations. Jiang et al. [19] proposed a model that can quickly find group seed nodes based on large networks to ensure that all nodes in the social network can be affected. Taking into account the impact of information dissemination after product recommendation, Dou et al. [20] updated personalized information recommendation according to the user's personality characteristics by integrating collaborative filtering and information dissemination processes. Banerjee et al. [21] discussed the whom-to-mention scheme to identify suitable candidates for social information, and this can trigger a large-scale cascading information diffusion process. Breza et al. [22] studied the expected diffusion of social information, intending to maximize total user participation through socialized perception diffusion. The problem of maximizing influence is widely used in the viral marketing of social networks. Companies try to promote their products and services through information diffusion mechanisms.

Through the analysis of the above research work, the actual communication effect of marketing information is the result of the comprehensive effect of multiple factors, different users have different interests in different products, and it is meaningless to spread the information to users who are not interested in it. On the contrary, the enterprise promotion cost is in direct proportion to the user influence; the greater the influence, the higher the user communication cost. Factors such as the structural influence of seed users, the users' interest in marketing information affected by the seed set, and the enterprise budget all have an important influence on the selection and decision of seed users. How to balance among different factors is an important issue faced by enterprises in social marketing. Therefore, this paper takes the influence maximization model as a multiobjective optimization problem to maximize the influence scale and interest while minimizing the diffusion budget. Our model is more realistic and can provide useful suggestions for social network marketing recommendation applications.

2. Theories about Social Networks and Optimization

2.1. Social Networks. A social network is a social structure composed of individuals or organizations and a collection of interaction relationships between them; a social network service is an online platform used to create content and share similar interests, activities, backgrounds, or realities with other individuals or social network [23]. The network structure is the carrier of information transfer between social network users, and the characteristics of the network structure affect and determine the evolution of the spread of information on the network. These basic characteristics include small-world networks, scale-free networks, and centrality.

2.2. Measuring the Influence of Social Network Information. Social network information can not only affect the behavior of users but also analyse the dynamic evolution of the network. The measurement of information influence can help predict the behavior of internet users, understand the trend of information dissemination among users, and provide technical support for marketers to choose better information strategies. Starting from the importance of nodes in the network, this article introduces some methods for measuring the importance of network nodes to measure the influence of users in social network information.

2.2.1. Degree Centrality. Its idea is that the nodes with high importance in the network have more neighbor connection edges. In an undirected graph, the number of directly connected edges between a node and all its neighbors is regarded as its degree. The greater the degree is, the higher the degree centrality of the node is and the higher its influence is. The standardized measurement of degree centrality is

$$\text{Center}(\text{node}) = \frac{D_{\text{node}}}{M-1} = \frac{\sum_{\text{node}\in N} A_{\text{node}}}{M-1}. \tag{1}$$

Among them, D_{node} represents the degree, $\sum_{\text{node}\in N} A_{\text{node}}$ is the cumulative sum of all neighbors of the node, and M is the total number of network nodes.

2.2.2. Tight Centrality and Betweenness Centrality. Close centrality describes the average distance between a node and other nodes in the network. The greater the tight centrality of a node is, the smaller the average shortest path to other nodes is and the closer it is to the center of the network. Its general calculation formula is as follows:

$$\text{Close}(\text{node}) = \frac{(P_{\text{node}}-1)^2}{(M-1)\sum_{p\in P_{\text{node}}} \text{Dis}(\text{node}, p)}. \tag{2}$$

Among them, P_{node} is the number of all vertices in the connected block containing the node and $\text{Dis}(\text{node}, p)$ represents the shortest path distance between the node pair.

The betweenness centrality in betweenness represents the ratio of the total number of shortest paths between the network node pairs through the shortest paths of the node. By calculating the shortest path between all pairs of nodes, the number of shortest paths passing through the node is found. The more paths passed and the greater the betweenness, the higher the importance of the node on the

network. Formula (3) expresses the calculation method of betweenness centrality:

$$\mathrm{Bet}(\mathrm{node}) = \frac{\sum_{\mathrm{node}\neq p} R_{(\mathrm{node},r)}(\mathrm{node})}{\sum_{\mathrm{node}\neq p} \mathrm{all\_Dis}(\mathrm{node}, r)}, \quad (3)$$

where $\mathrm{all\_Dis}(\mathrm{node}, r)$ is the number of all shortest paths between the node and r and $R_{(\mathrm{node},r)}(\mathrm{node})$ is the number of paths that pass p.

2.2.3. Feature Vector Centrality. It is described that the importance of a node in the network depends on the neighbor nodes of the node, including the number of neighbor nodes and the importance of neighbor nodes. If the neighbor status of a node is more important, then it is also in a more important position in the network. From the perspective of influence, the greater the influence of a network user's neighbors is, the more the user's influence will increase with the accumulation of the influence of its multiple neighbors and vice versa. Formula (4) can express the user's influence:

$$\mathrm{Max\_}I_{\mathrm{user}} = \sum_{i=1}^{M} A_{(\mathrm{node},r)} * I_i. \quad (4)$$

2.3. Marketing Strategy Characteristics of Social Network Services

2.3.1. Based on a Huge User Scale and an Open Network Platform. Social network services have a huge user scale and cover a wide range of people. Users of social networking services generally use social networking sites, microblogs, mobile social networking platforms, and other platforms for online interaction, and the registered accounts in each platform may not be unique. Open network platform and sharing user resources are the operating and marketing principles that social network services always adhere to. This is in line with the development trend and requirements of the internet and has also attracted a large number of brand advertisers, third-party application developers, and other types of cooperation websites to enter and interconnect.

2.3.2. Rich and Flexible Online Interaction Methods, High User Enthusiasm for Participation. When the themes of marketing activities are combined with hot topics, they can resonate with users and attract users' attention and participation in activities. The marketing interaction mode of social network services realizes two-way communication between users and brand owners, allowing users to experience product functions in a virtual network environment and provide brand owners with feedback information in the first time.

2.3.3. Brand Owners Get Free Secondary Communication. Brands have to pay for marketing and promotion activities on social networking sites, Weibo, and other platforms. However, the secondary dissemination of brand information in user groups driven by marketing activities does not require any cost. Attracted by the promotional and interactive links that brand owners paid for in the early stage, a large number of users came to participate in the experience, forming the first exposure of brand products on the platform. If users are interested in branding or marketing activities, forward the content of related activities to friends, and post participation information on their personal homepages, this will form the second exposure and dissemination of brand products on social network service platforms, where more popular people can be found out.

2.3.4. Combination of Online Activities and Offline Activities. In the marketing activities of Weibo and WeChat, there are brands integrating online and offline activities. While creating product exposure opportunities and increasing visibility, brand owners are also paying more and more attention to transforming user attention into actual purchases, realizing the extension of online activities to offline.

2.3.5. Development to Mobile Terminals Has Become a Trend. The rapid development of WeChat has further focused the market's attention on the mobile internet field. With the further popularization and improvement of mobile social applications, the marketing strategies of brands that cooperate with them will more reflect the characteristics of mobile and localization. Because there is more than one platform commonly used by users of social network services and across the desktop and mobile terminals, brand owners can carry out large-scale marketing and promotion on the desktop side and launch shopping discounts for users on the mobile side to achieve online propaganda and offline consumption model. The development of social network services in mobile terminals provides more choices for brand owners to formulate and implement marketing strategies.

3. Marketing Channel Optimization Model Based on User Social Network Information

3.1. Model Construction. The current literature on influence maximization focuses on selecting high-impact users as few as possible to maximize information dissemination, with the aim of ultimately influencing the maximum number of users in the social network. However, true information dissemination applications usually have characteristics of multiple uses. An application scenario would be for a company to spread product promotions through social networks and make them known to as many people as possible, but the company absolutely wants to spread promotions to people who are interested in the product, and online promotions are often limited by budgets. All this means that companies should make tradeoffs when using social networks to spread information.

Figure 1 depicts three social networks with $L = 9$ users and $P = \{p1, p2, p3, p4, p5, p6, p7, p8, p9\}$. In the traditional method of information dissemination, users with higher out-degree values are more likely to be selected as seed nodes to disseminate information. As shown in Figure 1,

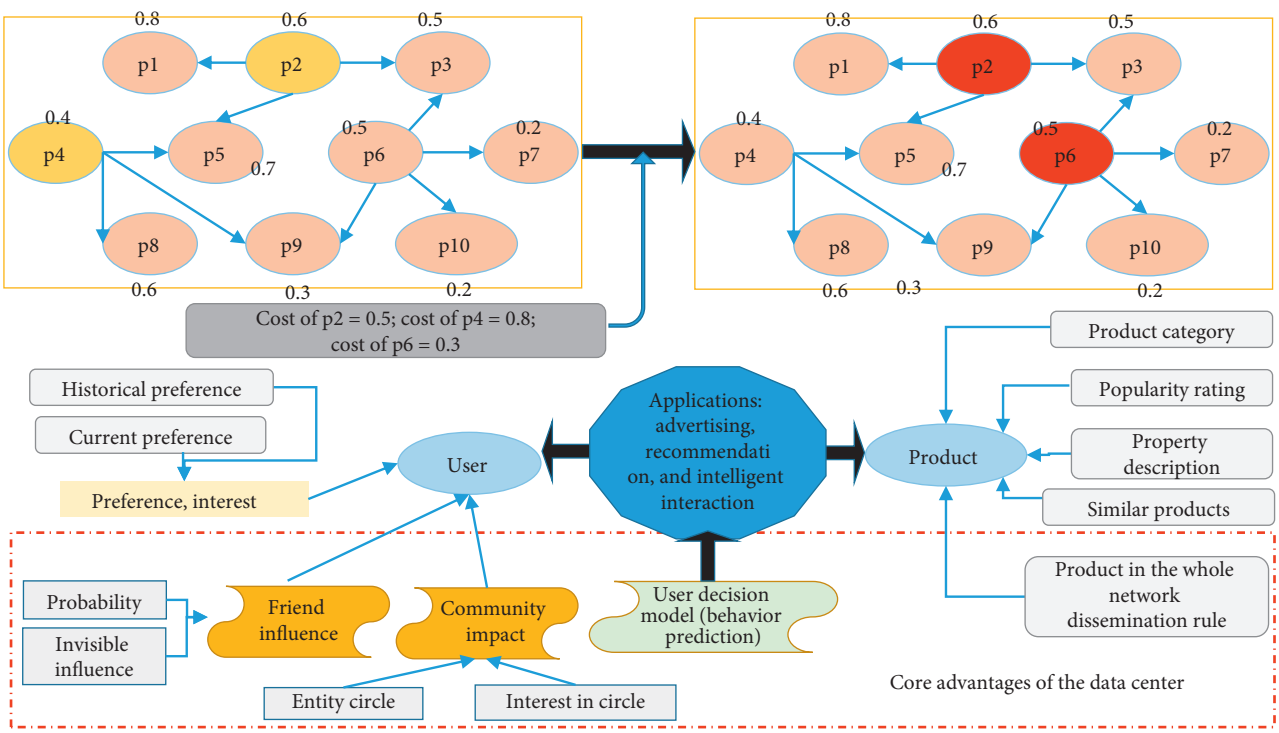

Figure 1: Examples of multiobjective maximization.

data center is the set of out-degree values, and {p2, p4, p6} will be selected to spread the information. However, if we consider user interest preferences, most users affected by user p6 have low interest in the product. Therefore, using p6 is not a suitable seed; at this time, we choose {p2, p4}. Furthermore, we consider the budget for information dissemination. Assuming that the maximum budget for dissemination of information is 1, user p4 may be excluded from the seed set because p4 is too expensive. If p4 is selected, then we have no budget to hire other seeds. In this sense, hiring p6 has become an optional decision because p6 is relatively cheap, which may produce unexpected good results. The above description shows that when the problem of maximizing influence encounters multiple goals, we need new methods to make more flexible and effective decisions.

This article optimizes the performance of marketing channels from the perspective of diffusion scale and user interest and ensures that diffusion activities are under budget control. As shown in Figure 2, first obtain social network data. The connection relationship between nodes in the data can reflect their influence spreading relationship. Then, according to the problem raised in Figure 1, combined with the social network node network structure and node attributes, a multiobjective impact maximization model is constructed, and a model solving algorithm is proposed. In the modeling phase, this paper considers the influence of social network information, user interest preferences, and corporate budgets to construct a multiobjective optimization model. In the model solving stage, a simulation calculation method based on a reliable subset of user influences based on Monte Carlo sampling is first proposed to approximate the node influence and to calculate other target values of each user in the model. Then, a seed node search and selection algorithm based on NSGA-II and a designed genetic operator is proposed to solve the multiobjective optimization function, and the Pareto nondominated target seed user set is searched and combined.

3.1.1. Maximize Influence. The goal of maximizing influence is to use a small number of influential seed users to disseminate information to the network, allowing users who follow them to see the information and generate further information forwarding and spreading behavior and disseminating the information to fans who follow these users. This cycle of transmission continues to achieve the largest network coverage of information and maximize the number of users receiving information.

In the social network probabilistic information diffusion model, the reliable subset A_p of user p is defined as a set of information that can diffuse from p to subusers with high probability. Assuming that B is the candidate set of seed nodes, the influence scale B' can be modelled in the following way:

$$B' = \arg\max_{p} \sum_{i=1}^{L} C_p \left(\sum_{j \in A_p} D_{ij} \right). \tag{5}$$

Among them, D_{ij} and C_i, respectively, represent the control variables of whether user j is in the reliable subset of user i and whether user i is the selected seed user:

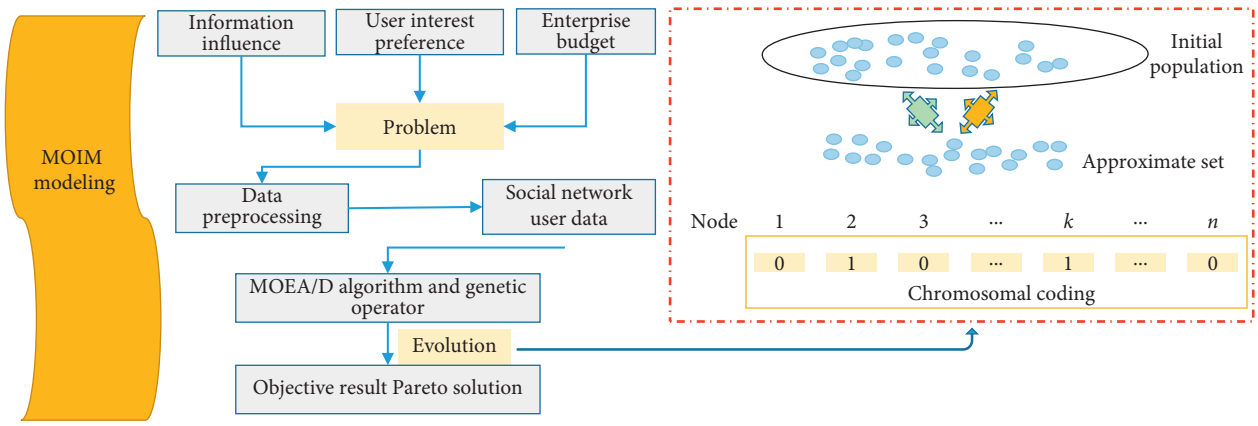

Figure 2: Schematic diagram of the process of multiobjective influence maximization models and methods.

$$D_{ij} = \begin{cases} 1, & j \in A_p, \\ 0, & \text{else}, \end{cases}$$
$$C_i = \begin{cases} 1, & i \in B, \\ 0, & \text{else}. \end{cases} \tag{6}$$

The scale of influence target means that the MOIM model aims to select seed users to maximize the scale of influence spread. Because one subuser may be affected by multiple seed users, in order to eliminate the repeated influence of multiple seed users on a single subuser, if user v is affected by multiple candidate seed users u, we constrain $\sum j \in A_p$ and $D_{ij} = 1$ to ensure the accuracy of the results.

3.1.2. Maximize User Interest. On social networking platforms, the same user has different preferences for different products, and different users have different concerns for the same product, and there is almost no common concern. While using the method of maximizing influence for product advertising, it is also necessary to consider the personal interest preferences of the audience and users and disseminate the information as much as possible to potential consumers who have a higher interest in the product to achieve precision marketing and improve product sales conversion rate. The maximization of interest preference is to maximize the total value of interest preferences of all users that can be affected by the influence of multiple candidate seed users. To simulate the total interest of the candidate seed set, we expand the first objective function by introducing the interest value of each user, as shown in the following formula:

$$H' = \arg\max_{p} \sum_{i=1}^{L} C_i \left(\sum_{j \in A_p} F_{ij} \right),$$
$$F_{ij} = \begin{cases} 1, & j \in A_p, \\ 0, & \text{else}, \end{cases} \tag{7}$$

where F_{ij} represents the interest preference F_j of the subuser j affected by the seed user i for a given product. The interest preference goal means that the subusers affected by the candidate seeds are not always interested in the information, and we should disseminate the information to those interested in it.

3.1.3. Minimize Business Costs. The purpose of marketing activities for enterprises is to maximize the marginal utility of costs, increase product sales through advertising and promotional activities, and increase sales revenue and profits. The budget is the total cost of the company's plans to promote its product on social networks. Assuming that the constant K refers to the cost that the company needs to pay to the user p to disseminate information, the cost objective function can be modelled as

$$L' = \arg\max_{p} \sum_{i=1}^{L} C_i K_i, \tag{8}$$

$$\sum_{i=1}^{L} C_i K_i \leq \text{money}. \tag{9}$$

Formula (8) means that our goal is to minimize expenses in the pursuit of maximizing influence and to ensure that the company obtains higher returns.

This article considers various problems and challenges encountered by companies in real-life product marketing activities, takes the social network influence maximization problem as the research direction, combines the interest and preference attributes of internet users with corporate marketing budgets, etc., and proposes the multiobjective maximization of influence (MOIM) model that integrates the maximization of influence, the maximization of interest preference, and the minimization of corporate costs. The mathematical model of MOIM is as follows:

$$
\begin{aligned}
B' &= \operatorname{argmax}_p \sum_{i=1}^{L} C_i \left(\sum_{j \in A_p} D_{ij} \right), \\
H' &= \operatorname{argmax}_p \sum_{i=1}^{L} C_i \left(\sum_{j \in A_p} F_{ij} \right), \\
L' &= \operatorname{argmax}_p \sum_{i=1}^{L} C_i K_i, \\
\text{s.t.} \quad D_{ij} &= \begin{cases} 1, & j \in A_p, \\ 0, & \text{else}, \end{cases} \\
C_i &= \begin{cases} 1, & i \in B, \\ 0, & \text{else}, \end{cases} \\
F_{ij} &= \begin{cases} 1, & j \in A_p, \\ 0, & \text{else}, \end{cases} \\
\sum_{i=1}^{L} C_i K_i &\leq \text{money}.
\end{aligned}
\tag{10}
$$

The above model shows that the goals of MOIM are inconsistent or conflict with each other. Therefore, this paper needs a flexible method to solve the model. The basic assumption of multiobjective is to find a reliable subset of each user. To obtain the reliable subset and solve the multiobjective model of information diffusion, this paper uses a Monte Carlo sampling parallel algorithm to obtain the reliability of each user subset and the corresponding total interest degree and proposes a multiobjective optimization algorithm based on NSGZ-II to search for the Pareto optimal solution of the model.

3.2. Node Influence Calculation Based on Monte Carlo Sampling. In this paper, the user influence dissemination weight in social network information dissemination can be regarded as a kind of similar random probability event. Probability distribution sampling is used to simulate the information dissemination weight and user interest preference to estimate the average activation of each node after iterative calculation number of nodes. Here, we use the uniform distribution function to obtain mutually independent random number sequences.

We use Monte Carlo sampling to calculate the reliable subset A_p, the total interest value h_p, and the diffusion cost l_p of the user p. To ensure that the user p diffuses the information with a higher probability to obtain A_p, we set the probability threshold $\alpha \in [0, 1]$ to ensure that only edges with a probability greater than α will be sampled during the sampling process. At the same time, we set the shortest path threshold thr to limit the extent of information reduction in the process of information transmission.

The basic idea of this sampling algorithm is as follows:

(1) According to the directed connection relationship and attribute information between users in social networks, define the information dissemination probability of directed edges between users and the unique interests and preferences of each user, and construct a directed probability graph of social networks.

(2) A predefined probability threshold α and shortest path threshold thr are used to find edges with greater propagation probability and nodes with strong propagation capabilities.

(3) For each iteration of each source node p, use the distribution function to randomly sample to generate a random probability value to compare with α and the directed edge propagation probability in the directed probability graph, and take the edge with the larger probability value to construct a sample to determine Sub.

In the algorithm, the directed probability graph is converted into an M-order matrix, which represents the social relationship between users and the transmission probability from each user to its fans. We obtain the set of deterministic subgraphs of all users from the directed probability graph. Then, for each user's subgraph Sub, calculate the reliable subset A_p reachable from user p. Each user p has its attribute interest value h_p for a specific product. Finally, we select high-influence users as candidate seed set B and as the input for subsequent work.

3.3. Model Optimization Based on NSGA-II. The influence maximization problem studied in this paper is defined as a multiobjective problem, which requires maximization of influence, maximization of user interest, and minimization of costs. This article uses the elitist nondominated sorting genetic algorithm (NSGA-II) with an elite strategy. NSGA-II first generates the initial population, then continuously optimizes through replication, crossover, and mutation, and retains the elite solution in the process of evolutionary optimization. Figure 3 shows the evolution and elite solution retention process of NSGA-II.

Elite solution retention strategy:

(1) The elite solution of the first generation: the first level of nondominated individuals after the nondominated sorting of the initial population. This is the first solution set in the elite solution retention process.

(2) The elite solution in the evolution process: add the offspring obtained from each genetic operation (crossover and mutation) to the elite solution of the previous generation, and then use Pareto nondominated sorting to select the first level of nondominated individual, which is the elite solution of the generation.

(3) Exclude extreme elite solutions: if there is only one node in the seed set and the influence of the node is 0, the seed set is discarded.

The initial population is usually randomly generated to ensure evolutionary diversity. In this paper, the initial population size m is set to 100. This paper proposes a multiobjective optimization model with three objectives,

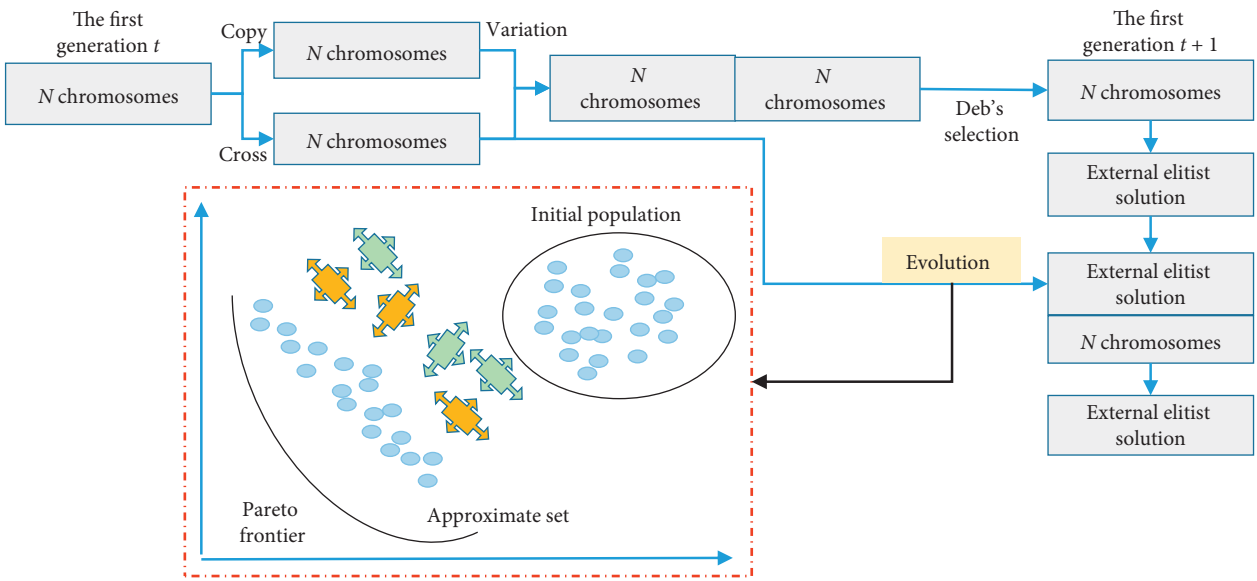

Figure 3: Multiobjective evolutionary algorithm.

one of which is to minimize the cost within the budget, and each chromosome here represents an initial population, so the cost of each chromosome cannot exceed the budget.

The purpose of crossover and mutation is to generate new solutions and accelerate the evolution of the population. First, part of the parents' genes is passed directly to the offspring. A random number is generated in the interval [0, 1] for the remaining positions in each child. If this number exceeds 0.5, then the offspring will receive the corresponding allele of the first parent; otherwise, it will receive the second parent. The crossover probability is usually between 0.25 and 1. The probability of mutation is usually around 0.001.

4. Results and Discussion

4.1. Experimental Dataset. To ensure the validity of the experimental results, this paper selects three sets of real social network data with different statistical characteristics to verify the proposed method. The dataset used in our experiment comes from the real social network data p2p-Gnutella06, p2p-Gnutella08, and p2p-Gnutella09 of SNAP. The three networks have 8,717, 6,301, and 8,114 users and 31,525, 20,777, and 26,013 links.

4.2. Analysis of Optimization Results. Figure 4 shows the planar projection of the target value, showing the inconsistency between influence, corporate budget cost, and user interest. The "cost compared with influence" projection shows that when the budget cost exceeds the threshold, the growth rate of influence will drop sharply. Therefore, we should flexibly weigh the cost and influence decisions. The "cost compared with interest" plane projection shows that high costs do not always get more interested users. As the cost increases, the number of interested users will gradually decline. The "influence compared with interest" plane projection shows that the influence is proportional to interest. Therefore, in the actual information dissemination, we should balance cost and interest and pay the budget to the appropriate users.

4.3. Sensitivity Analysis

4.3.1. Probability Threshold Experiment. In the experiment, the probability threshold α in the Monte Carlo sampling method is an important factor to control which edges have the opportunity to diffuse information. We use probabilities 0.5, 0.6, and 0.7 to sample p2p-Gnutella06 to test the robustness of this method. The probability density curve in Figure 5 shows that when α has different values, this method can effectively estimate the user's influence.

As shown in Figure 5, smaller α (for example, $\alpha = 0.5$) means that more edges have the potential to spread information, and users have greater potential to spread information. If we conservatively set larger α ($\alpha = 0.7$), the diffusion scale will be narrowed, and the number of users affected by the seed will decrease. The probability density of the influence scale shows that the proposed Monte Carlo sampling-based node influence calculation is robust, and the results obtained are consistent with the existing results in the literature.

4.3.2. Diffusion Budget Experiment. The diffusion budget is an important factor in deciding which users can be chosen as seeds. In the practice of information dissemination, if we have more budgets, we can choose users with high influence capabilities as seeds. However, if the budget is limited, the wise decision is to avoid all high-impact users and choose the right users to meet the budget constraints. In this experiment, we set the diffusion budget to 100,000, 200,000, and 300,000 to solve the MOIM model.

Figure 6 shows the cost of the Pareto optimal solution obtained in three experiments and shows that the proposed

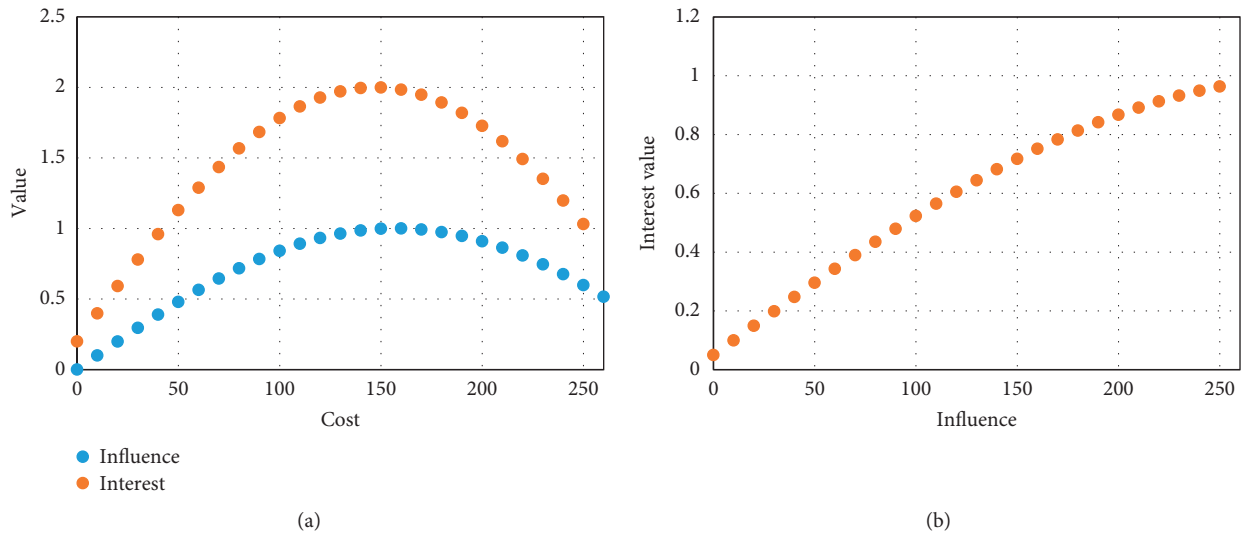

Figure 4: Planar projection of the multiobjective solution. (a) Cost compared with influence and interest. (b) Influence compared with interest.

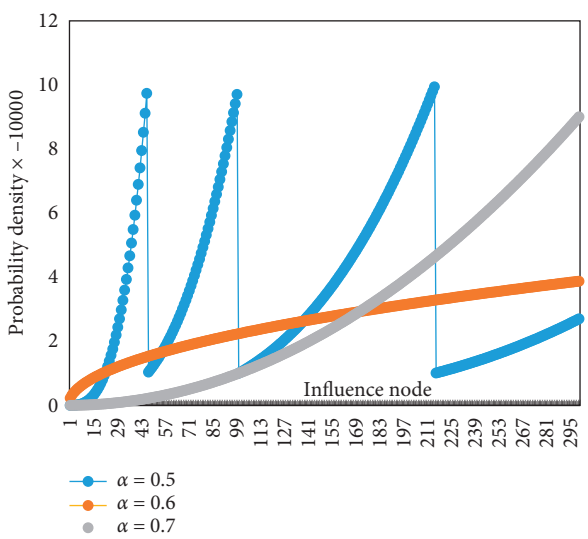

Figure 5: The probability threshold of α.

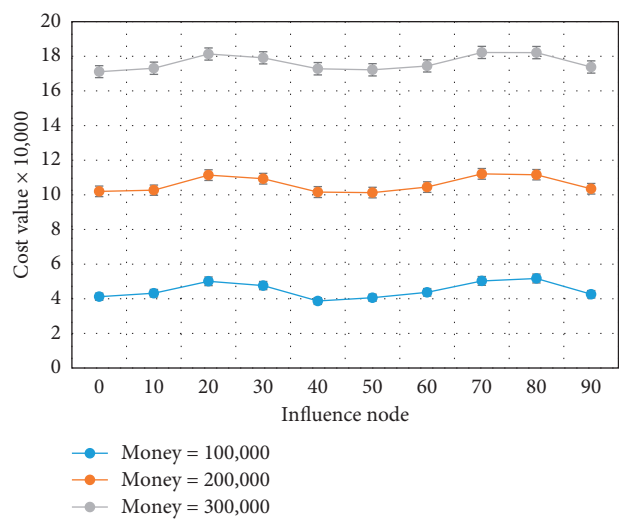

Figure 6: Diffusion budget.

model is robust in terms of diffusion budget and can find a flexible and reliable satisfactory solution no matter how much the budget changes.

4.4. Experimental Comparison. To compare the advantages and disadvantages of the method proposed in this paper with the classic algorithm degree centrality, tight centrality, and betweenness centrality, this paper designs comparative experiments for the three networks of p2p-Gnutella06, p2p-Gnutella08, and p2p-Gnutella09.

Suppose the size of the seed set is 100. This article uses three classic algorithms to find the 100 most influential nodes, calculates the node's influence index, interest index, and cost index, and compares them with the optimal value of the 100 nodes found in this paper. The influence index, interest index, and cost index are compared. The experimental results are shown in Figures 7–9. By analyzing the figures, it is not difficult to find that compared with the classic algorithm, the model proposed in this paper can always find a set of seeds with better indicators. Because this method comprehensively optimizes the influence index, interest index, and cost index, it can provide enterprises with a more flexible set of marketing decision-making schemes.

5. Discussion

Marketing activities based on social network service platforms are the process of developing and utilizing the market value of social media. Their core idea is to turn the user scale advantage of social network services into revenue. The

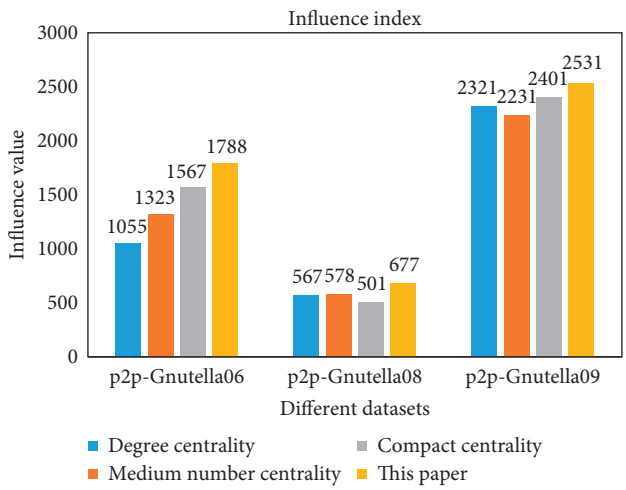

Figure 7: Influence index comparison of different methods.

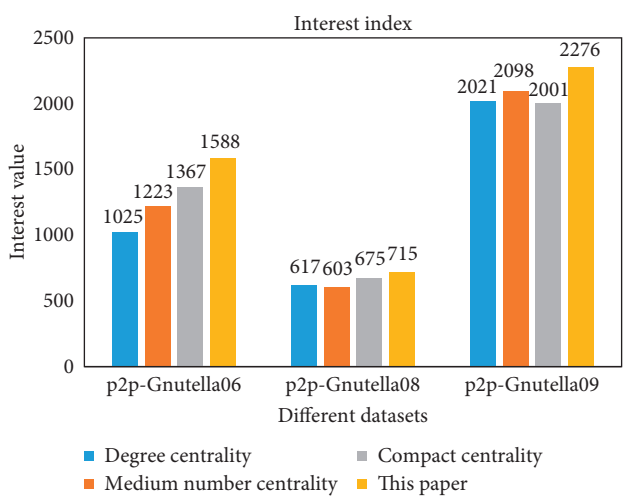

Figure 8: Interest index comparison of different methods.

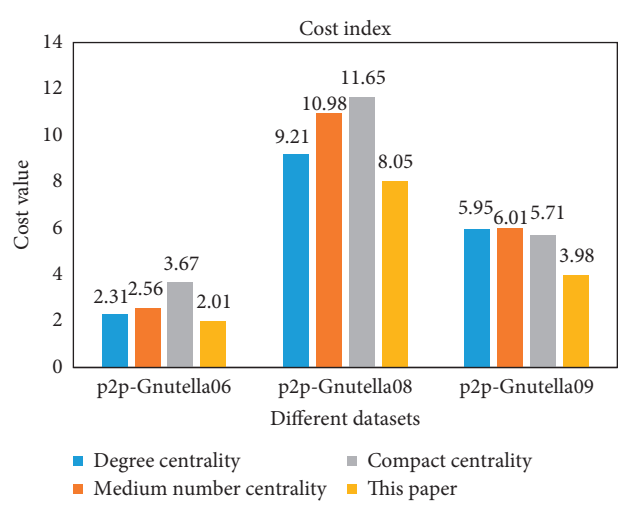

Figure 9: Cost index comparison of different methods.

research results of [24] show that different types of information sources improve consumers' online shopping performance and realize business intelligence. By comparing the fixed amount of time the participants spent on AOI, it was demonstrated that consumers' online comment search behavior was significantly affected by the degree of human exposure.

In this paper, the influence maximization model is taken as a multiobjective optimization problem to maximize the influence scale and interest while minimizing the diffusion budget. In order to prove that our model is closer to the actual situation, this paper selects four groups of real social network data with different statistical characteristics to verify the proposed method. By analyzing the probability density curve, 3d target value, and sensitivity of the social network, it can be seen that the algorithm in this paper has a better seed set of indicators than the current algorithm. Since the method in this paper comprehensively optimizes the indicators such as influence index, interest index, and cost index, it can provide enterprises with a more flexible set of marketing decision plans and provide useful suggestions for the recommendation application of social network marketing.

6. Conclusion

Social networks have penetrated all aspects of life, and the use of social networks for marketing and promotion by enterprises has also become a hot research issue. A social network is a kind of complex network, which follows the characteristics of a complex network. Therefore, it is often used to maximize the influence to study the selection of social network seed nodes. In actual corporate marketing, there are more practical factors besides influence, namely, user interest and corporate cost. In social networks, when a user receives product information, he may purchase or promote it because he is interested or he may fail to disseminate information because of disinterest or dislike and even bring negative effects. Enterprise cost is a measure of whether the cost of the seed set is within the enterprise budget. This paper proposes a multiobjective impact maximization model, combining the three objectives of maximizing influence, maximizing user interest preferences, and minimizing cost, constructs an objective function, and proposes a model solution method. First, the Monte Carlo sampling method is used to calculate the reliable subset of the user's reachable influence, to estimate the user's approximate influence, and to calculate the user's total interest and employment cost. Next, a seed user selection algorithm based on NSGA-II is proposed to optimize the above three objective functions and find the optimal solution. Finally, the effectiveness and robustness of the proposed model are verified through experiments in real social networks. Because we need to find the optimal solution of the impact maximization model, this process is very time-consuming because our next work is to optimize the solution process of the optimal solution.

Data Availability

The data used to support the findings of this study are available upon request to the author.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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