Research on Product Marketing Recommendation Methods Based on Maximizing Individual User Influence in the Context of Globalization

Zefeng Shao [1], Dalong Yu [2,*]

{641804082@qq.com[1], yudalong2288@163.com[2]}

[1.] The National University of Malaysia - Graduate School of Business

[2.] Universiti Kebangsaan Malaysia-Graduate School of Business

Abstract. Product marketing recommendation is an important tool for companies to gain competitive advantage and increase market share in the context of globalization, how to accurately recommend products to users has become a challenging problem. In view of this, the study proposes a product marketing recommendation method based on influence maximization, in which the process overlaps user influence, introduces greedy greedy algorithm for calculation and optimization, and performs accurate recommendation marketing by analyzing the user's degree of hesitation and interest. The experimental results show that the research method can reach a maximum of 3.4, 12 and 2.3 in the three datasets when conducting influence gain test; when conducting influence calculation number test, the maximum number of calculations of the research method is 726 when the node subset size is 40; the running time of the research method is only about 30ms in the Viki-Vote dataset when the number of companies is 1; the research The study method achieves a user purchase rate increase of 19% or more in all five companies. All of these results show that the research method has good performance in product marketing recommendation and can achieve significant increase in user purchase rate, which provides a new method reference for product marketing recommendation.

Keywords: product marketing; greedy; influence maximization; mixed integer programming algorithm; social influence

1 Introduction

In the context of globalization, product marketing recommendations have become more and more important and challenging. With the rapid development of the Internet and social media, the influence of individual users is playing a key role in product promotion[1] . Consumers want personalized and accurate recommendation services, while companies need to attract users and increase sales through effective recommendation mechanisms[2] . How to accurately assess the influence of individual users is a complex issue. Influence is not only related to the user's social network connections, but also influenced by other factors, such as the user's activity level, content quality, etc.[3-4] . Traditional advertising push and marketing models often fail to meet the needs of personalized and precise recommendations, and face the dilemma of low promotion effect and unsatisfactory user feedback[5] . Influence maximization is an important strategy to find the individual users with the greatest influence

ICIDC 2023, June 02-04, Nanchang, People's Republic of China

DOI 10.4108/eai.2-6-2023.2334690

so that product recommendations can spread more widely in social networks. Greedy algorithms can be used to optimize the solution to the influence maximization problem by iterating and optimizing the strategy to improve the recommendation effectiveness. Mixed integer programming algorithms can take into account the complexity of multiple factors and provide a more comprehensive consideration of product recommendation strategies. In this context, a product marketing recommendation method based on maximizing individual user influence is proposed, which urgently needs to effectively improve the effectiveness of product marketing recommendations and bring new technical references for product marketing.

2 Product marketing recommendation method based on maximizing individual user influence

2.1 Influence gain-based product recommendation method for social users

In the context of globalization, the influence spreading ability of social networks has been demonstrated and is gradually applied in the business field . Influence maximization is to analyze the probability of spreading among users based on the influence spreading model, so that the overall influence of a group of users in the network is maximized in the network, and the product message is endorsed by this group of users to expand the spreading range of the product message . The influence maximization problem belongs to a basic problem in viral marketing, and the mathematical form is shown in equation (1).

$$S = \arg\max_S f(S),\ s.t.\ c(S) \le B \quad (1)$$

In equation (1), S represents a group of users; $f(S)$ represents the overall influence of a group of users in the network; $c(S)$ represents the expenditure of the user group for product endorsement or promotion; and B represents the budget. The influence of users in social networks is mainly spread through a network of connections between users, and establishing connections with new users created in the network can increase influence more directly. However, simply connecting users does not maximize influence gain, so influence overlap is needed, and the influence overlap in the network is shown in Figure 1.

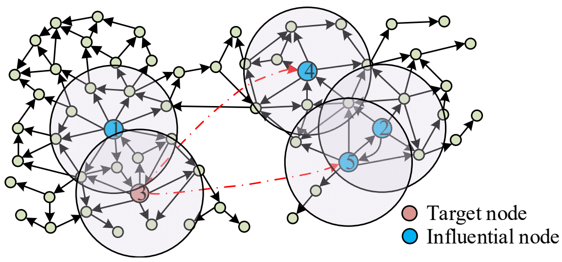

Fig 1 Overlapping influence in the network

As seen in Figure 1, after setting node 3 as the target node, it is preset to connect with 2 other nodes to improve its influence, and the most influential subset of nodes {1,2} is obtained by the influence maximization solution. However, in fact, the influence gain from the connection of node 3 with node subset [1,2] is not as large as that with node subset {4,5}, because there is a certain area of influence overlap between node 3 and node 1. The influence overlap of node 3 with node 4 and node 5 is almost zero, and the influence gain from making the connection is relatively greater. In order to model the individual influence propagation, a directed graph is set up to represent the influence network. The optimization of individual influence maximization is defined as shown in equation (2).

$$\arg\max_S \Re(S) = \left\{ f_{t\to}^{S} - f_{t\to V} \right\},\ s.t., |S| \le K \quad (2)$$

In equation (2), t represents the target user node; S represents a subset of nodes; $\Re(S)$ and $f_{t\to}^{S} - f_{t\to V}$ represent the influence gain of a node after connection establishment with a subset of nodes; K represents the budget for establishing a new connection; and V represents the number of nodes in the network. Setting a candidate node, the influence gain of the target node and is shown in equation (3).

$$f_{t\to V}^{\{c\}} - f_{t\to V} = \sum_{i\in V} \left(f_{t\to i}^{\{c\}} - f_{t\to i} \right) = \lambda_c \left(1 - f_{t\to c}\right) \sum_{i\in V} \left(1 - f_{t\to i}\right) f_{c\to i} \quad (3)$$

In Eq. (3), C represents any candidate node; i represents any node in the network; $f_{t\to i}$ represents the influence of the target node on i ; $f_{t\to c}$ represents the influence of the target node on c .The influence calculation is performed using the greedy greedy algorithm, and the delay calculation method is introduced to optimize the computational efficiency. When the network size reaches a certain order of magnitude, the computation of the greedy greedy algorithm is too large, so the linear social influence model is used for optimization . Under the linear social influence model, the influence of each node on other nodes has an upper bound, as shown in equation (4).

$$f_{i\to V} = \sum_{j=1}^{n} f_{i\to j} \le a_i \cdot \left(I - DT\right)_i^{-1} e \quad (4)$$

In equation (4), D represents a diagonal matrix; I represents the unit matrix of $n\times n$; e represents an all-1 vector of $n*1$; and T represents the propagation probability matrix. The upper bound theorem is translated into vector form as shown in equation (5).

$$\left[\Re(\{1\}), \Re(\{2\}), \ldots, \Re(\{n\}) \right]' \le diag\left(\lambda_1, \lambda_2, \ldots, \lambda_n\right) \cdot diag\left(a_1, a_2, \ldots, a_n\right) \cdot \left(I - DT\right)^{-1} e \quad (5)$$

In equation (5), $\left(I - DT\right)^{-1} e$ is calculated quickly by the Guass-Seidel method. The obtained linear time complexity calculation does not lose the quality of the solution, and the obtained influence gain is the maximum gain value available.

2.2 Multi-influence based product potential user recommendation method

In a real world environment, users are influenced by the products of multiple competing companies, and if they are influenced by multiple companies with similar influence, these users are called hesitant users under multiple influences . When making product marketing recommendations, it is more effective to select customers who are interested in the product but are hesitant to recommend it. In order to improve the efficiency of recommendation, a generalized computational framework was built, as shown in Figure 2.

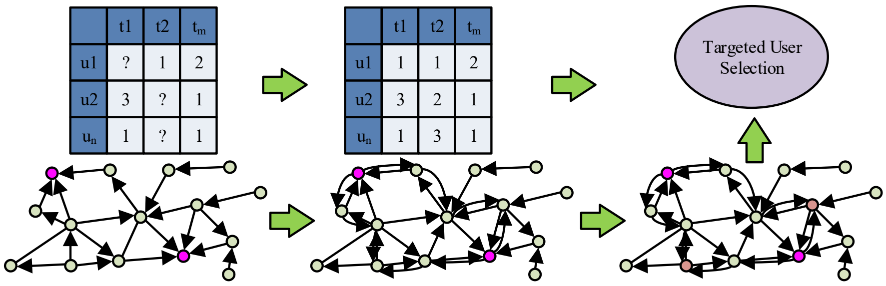

Fig 2 Universal computing framework

As seen in Figure 2, a mixed integer programming algorithm is used in the framework to build the influence matrix and construct a function to represent the user's hesitation for a product under multiple influences. The user's consumption behavior is recorded and analyzed, and the user's interest is inferred using collaborative filtering to build a utility function to measure the user's interest in a product. Afterwards, the two functions are combined and a weight parameter is added to select the products that users are interested in but hesitant. The influence of the company on the node is defined as shown in equation (6).

$$f_{i\leftarrow j}=\sum\nolimits_{k\in N(i)}t_{ik}f_{k\leftarrow j},i\in\{V-C\} \tag{6}$$

In equation (6), $N(i)$ represents the set of in-degree neighbor nodes of the user. The mixed integer programming algorithm first initializes the matrix, after which it performs multiple influence propagation and resets the company-to-company influence, and continuously performs influence propagation and resets until the matrix converges. Sub-matrix splitting of influence matrix and propagation probability matrixDuring the iteration, the first c rows of the influence matrix will be reset continuously, so it will not change, but the post-remaining rows will change, and the post-remaining rows of the influence matrix are calculated as shown in equation (7).

$$F_{|U|}=\lim_{x\to\infty}T^{'}_{|U||U|}F^{0}_{|U|}+\sum\nolimits_{i=1}^{t}T^{t-1}_{|U||U|}T_{|U|c}F^{0}_{c} \tag{7}$$

In Eq. (7), F^0 is the initial matrix. $I-T_{|U||U|}$ is strictly diagonally dominant, so the mixed integer programming algorithm eventually converges to a fixed point. The hesitation property of the user is calculated as shown in Eq. (8).

$$H_E(u)=\sum_{j=1}^{|C|}\left(-f_{uj}\log_{|C|} f_{uj}\right), H_D(u)=\sum_{j=1}^{|C|}\frac{f_{uj}}{1+f_{uj}} \quad (8)$$

In equation (8), $H_E(u)$ is the hesitation function from information entropy; $H_D(u)$ is the hesitation function from with information diversity; u represents the user. The higher the value of the hesitation function, the more serious the hesitation of the user. Collaborative filtering is one of the similarity calculation methods, and the central idea is to project the user's preferences based on the user's historical behavior, and make product recommendations to the user based on the user's preferences or the choices of other users with similar preferences. Such recommendations are generally based on the user's behavioral data only, and do not require processing of item information and user information. The study uses item-based collaborative filtering method and user-based collaborative filtering method for user interest identification.

3 Performance analysis of the product marketing recommendation method based on maximizing individual user influence

The influence gain increases with the increase of the number of nodes, and the influence gain of Random and LongDist increases very weakly. In Wiki-Vote, the influence gain of OutDeg, PageRank and HighestInf reaches about 2.75 when the number of nodes reaches 50; the influence gain of IMseeds reaches about 3.3; the influence gain of the research method reaches about 3.4. In Weibo, the influence gain of OutDeg, PageRank and HighestInf reaches about 10 when the number of nodes reaches 50; the influence gain of IMseeds reaches about 11; the influence gain of the research method reaches about 12. In Cit-HepPH, the influence gain of PageRank and HighestInf reaches about 1.8; the influence gain of IMseeds and research methods reaches about 2.3. It shows that the influence gain effect of the research method is better.

The number of computations increases with the size of the node subset in all datasets. In Wiki-Vote, when the node subset size increases from 10 to 40, the number of computations of the greedy algorithm increases from 70391 to 280957; the number of computations of the lazy algorithm increases from 7171 to 7331; and the number of computations of the research method increases from 53 to 297. In Weibo, the number of calculations of the greedy algorithm increases from 73646 to 330616; the number of calculations of the lazy algorithm increases from 7446 to 7917; the number of calculations of the research method increases from 98 to 726. In Twitter, the number of calculations of greedy algorithm increases from 45137 to 53716; the number of calculations of lazy algorithm increases from 6837 to 8164; the number of calculations of the research method increases from 43 to 254. It shows that the research method significantly reduces the number of influential calculations in the process.

In all five companies, both the random recommendation method and the research method significantly boosted user purchase rates. In Weibo, the random recommendation method had the smallest lift of about 4% at Delta and the largest lift of about 14% at Charlie; the research method had the smallest lift of about 22% at Charlie and the largest lift of about 30% at Delta. In Twitter, the random recommendation method has the smallest lift of about 5% in Bravo and the largest lift of about 11% in Alpha; the research method has the smallest lift of about 19%

in Charlie and the largest lift of about 32% in Echo. This indicates that the research method is effective in increasing the product purchase rate of users with a higher lift.

4 Conclusion

In order to improve the accuracy and personalization of product marketing recommendations, the study proposes a method based on maximizing individual user influence. The experimental results show that the maximum gain of the research method can reach about 12 when performing influence gain, which is higher than other algorithms; when performing influence calculation, the maximum number of calculations of the research method is only 98 for a node subset size of 10; when running time tests are performed on the research algorithm, the In the user purchase rate test, the increase in user purchase rate of the research algorithm is higher than that of the random recommendation method, and the lowest increase is about 0.8 times that of the random recommendation method. It indicates that the research method has good computational efficiency and can effectively improve the sales of products when making product marketing recommendations. However, the research method is only tested in the case of no price change, and will be subsequently tested in the context of discount and deflation to enrich the experimental results and optimize the method.

Author Introduction:

Zefeng Shao,Master of Business Administration,Intermediate Economist,Graduated from the National University of Malaysia in 2023,The National University of Malaysia - Graduate School of Business,Consumer Behaviour and Globalisation, Marketing, Behaviour. Dalong Yu,Master of Business Administration,Intermediate Economist,Universiti Kebangsaan Malaysia(2023),Universiti Kebangsaan Malaysia-Graduate School of Business,Globalisation and international development，Global Marketing，The impact of economic globalization on consumer behavior.

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