Medical Research Infused Analysis of Marketing Strategy for Community Agricultural Products Based on Consumers' Psychological Demands for Nutrition and Health

Wei Tao[1*]

[1]School of Finance & Business, Zhenjiang College, Zhenjiang 212028, Jiangsu, China

Corresponding author: Wei Tao, taowz2004@zjc.edu.cn

Abstract. To explore the marketing strategy of community agricultural products based on the psychological needs of consumers' nutrition and health, this paper combines the psychological needs of consumers to carry out community agricultural product marketing innovation, improve the marketing effect of community agricultural products, and meet the needs of consumers' psychological health. Moreover, this paper proposes a probabilistic propagation model based on network embedding as an influence propagation model in social media. In addition, this paper analyzes the nature of information dissemination networks on social media and studies some of the characteristics of high-influence users. The data simulation study shows that the algorithm and model proposed in this paper can play a specific role in analyzing the marketing strategy of community agricultural products based on the psychological needs of consumers' nutrition and health.

Keywords: consumers; nutritional health; psychological needs; community agricultural products; Medical Research Infused.
DOI: https://doi.org/10.14733/cadaps.2024.S24.145-156

1 INTRODUCTION

1.1 Related Work

Internet + strategy: It combines the information of all walks of life with the Internet through information communication technology so that the traditional fields of all walks of life will glow with a new vitality and form a comprehensive platform. The abbreviation is Internet + agriculture = Internet agriculture. However, its cases do not simply add to each other [5]. Instead, it is to combine the Internet and agriculture organically. Internet agriculture has begun to influence traditional production links from e-commerce and other sales platforms, bringing opportunities for agricultural development and broadening conventional agriculture development [7]. Based on a new type of community experience and data analysis in the background, the e-commerce of agricultural products has entered a new marketing track [1]

Farmer-community docking connects farmland with the community to realize direct marketing [9]. Under the new marketing model of farmer-community docking, farmers can plant according to community residents' needs and determine the number of plants according to the actual sales of agricultural products. This method can not only better meet the needs of residents but also make agricultural products more A relatively stable sales channel can avoid the waste of farm products and build a more suitable sales environment [4].

In implementing the new model of farmer-community docking marketing, certain influencing factors in the community have certain constraints on the development of the farmer-community docking model. To maintain internal cleanliness and order in some communities, they cannot accept the connection with the farming community [2]. The community needs to build a particular vegetable procurement area. The community department must be responsible for environmental sanitation and buying and selling orders. The hygiene and safety of vegetables and the community need to be paid a certain amount of extra to help the operation of the farm cooperative [6]. After the construction of agricultural product sales places, the increase in the flow of people inside and outside the community, the safety of vehicle traffic, and the consumption of water and electricity also had a particular impact on community management. Secondly, implementing the connection between farmers and cooperatives makes the required procedures more complicated and troublesome for farmers. Therefore, many farmers "retreat," and it is challenging to realize the connection mode of farmers' cooperatives successfully. The effect of promotion in different provinces is also relatively significant [8]. Some local governments do not have enough support for the new marketing model of peasant cooperatives, and they lack understanding of this model, which makes it difficult to effectively promote the peasant cooperatives docking model so that they cannot provide relevant preferential policies and subsidies for communities and agricultural cooperatives, which makes the model difficult to upgrade. The popularization and use of it are more difficult to achieve [3]

1.2 Objectives

This paper combines the needs of consumers' health and psychology to carry out community agricultural product marketing innovation, improve the marketing effect of community agricultural products, and meet the consumers' psychological health needs.

2 METHODOLOGY

This paper improves the marketing algorithm based on the actual needs of modern agricultural product community marketing and enhances the information dissemination effect of intelligent community agrarian product marketing.

2.1 Research on Influence Maximization Problem Based on Information Dissemination Network Embedding

The IC model is a probabilistic model. Even if the same seed node is selected, the last activated node may differ for each propagation. Figure 1 shows an example of an IC model. In this network, if node A is assumed to be selected as the seed node to propagate information, then the probability of node B and node C being activated is 0.6 and 0.4, respectively. Moreover, node A has a probability of 0.3 to start node D through the edge (A→D) directly and 0.6'0.5 to activate node D indirectly through path A→B→D. Therefore, the influence expansion degree of node A as a seed node is the sum of the probabilities of other nodes being activated:

$$\rho(A) = 0.6 + 0.7 + (0.3 + 0.6 \times 0.5) = 2 \tag{1}$$

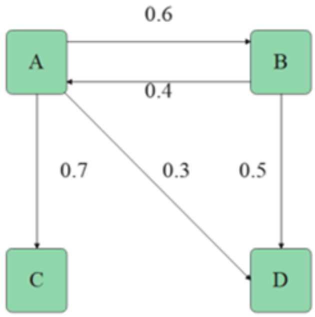


Figure 1: Example of an independent cascade model.

The LT model is a type of threshold model. An example of the LT model is shown in Figure 2. In this network, if node A is selected as the seed node, node C is only affected by node A. However, the influence weight of node A on node C, 0.7, is less than the activation threshold of node C, 0.8, so node C will not be affected. Similarly, node A can directly activate node B but cannot directly activate node D. The influence expansion degree of node A is $\sigma(A)=2$.

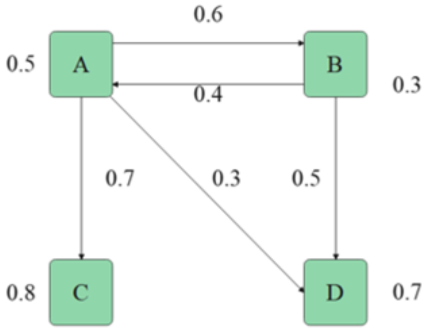


Figure 2: Example of the linear threshold model.

The CTIC (Continuous Time Independent Cascade) model is a commonly used model that considers the likelihood of pairwise propagation between nodes as a continuous time distribution. A typical temporal arousal impact distribution is an exponential model, that is:

$$p(t_v \mid t_u; \alpha_{u,v}) = \begin{cases} \alpha_{u,v} \cdot e^{-\alpha_{u,v}(t_v - t_u)} & \text{, if } t_v > t_u \\ 0 & \text{, else} \end{cases} \quad (2)$$

Another commonly used continuous-time model is the DynaDiffuse model, which considers the exponential decay of the propagation rate between nodes with time.CTIC and DynaDiffuse are very similar.

2.2 Influence Propagation Model Based on Network Embedding

This paper proposes a probabilistic propagation model based on network embedding as an influence propagation model in social media. Different from the IC model and its extended models, each edge (v, u) in the IC model has a propagation probability. In some early studies, when only the social media attention network structure is known, the propagation probability of edges is usually randomly generated or set according to some metric. For example, the DE (Degree-based) method assumes that the edge propagation probability is the reciprocal of the in-degree of the end node:

$$p_{vu} = \frac{1}{\text{Indegree}\,(u)} \tag{3}$$

When having information dissemination records within a period, it is possible to know the fundamental relationship strength of two users more accurately and set a more reasonable probability of edge dissemination. For example, the ST (StaticModel) method assumes that the edge propagation probability is:

$$p_{vu} = \frac{A_{vu}}{A_v} \tag{4}$$

Among them, Avu represents the number of times that node v affects node u, and Av is the total number of times that node v affects other nodes.

Two d-dimensional vectors, X_v and Y_v, represent the user's characteristics as an information disseminator and an information receiver, respectively. The strength of the ability of node v to influence node u depends on the communicator feature vector X_v of node v and the receiver feature vector Y_u of node u:

$$inf(v,u) = X_v \cdot Y_u + b_v + b'_u \tag{5}$$

Among them, b_v and $b_u^{\prime}$ are both 1-dimensional embeddings; b_v represents the node's ability to influence others, and $b_u^{\prime}$ represents the bias of the node's difficulty in being influenced by others.

When the random walk passes through node u at a particular step, the probability of walking to node v through the meta-path in the next step is:

$$p_{rw}(u \to v) = \frac{w_{u,v}}{\sum_{x,(x,v)\in E} w_{x,v}} \tag{6}$$

After obtaining the set of random walk sequences, this paper uses the skip-gram model to learn the node embedding representation of the network by maximizing the overall conditional probability of co-occurrence between a given node and its adjacent reachable nodes. The objective function is:

$$argmax\ _{\theta} \sum_{v\in\mathcal{V}}^{\Sigma} \sum_{b\in\mathcal{N}(v)}^{\Sigma} log \tag{7}$$

Among them, $\mathcal{N}(v)$ represents the set of adjacent reachable nodes of node v, and the co-occurrence probability here is also set as a softmax function:

$$p(c \mid v;\theta) = \frac{e^{inf(v,c)}}{\sum_{u\in V} e^{inf(v,u)}} \qquad = \frac{e^{X_v\cdot Y_c+b_v+b'_c}}{\sum_{u\in V} e^{X_v\cdot Y_u+b_v+b'_u}} \tag{8}$$

The sampling size K of negative sampling and the negative sampling distribution $\mathrm{P(u)}$ are given, and $\mathrm{u^k}$ is the $k(k \le K)$ -th negative sample collected according to this distribution, then the objective function to be minimized can be expressed as:

$$\mathcal{O} = log\,\sigma\,(inf(v,c)) + \sum_{k=1}^{K} \mathbb{E}_{u^k\sim P(u)}\,[log\,\sigma\,(-\,inf(v,u^k))] \tag{9}$$

Among them, $\sigma(x)$ is still a sigmoid function:

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{10}$$

The stochastic gradient descent algorithm optimizes the objective function to learn the network node embedding, and the gradient of the corresponding parameter is:

$$\frac{\partial \mathcal{O}}{\partial X_v} = (1-\sigma(inf(v,c)))\cdot Y_u + \sum_{k=0}^{K}\left(\sigma(-inf(v,u^k))\right)\cdot Y_{u^k}$$
$$\frac{\partial \mathcal{O}}{\partial Y_c} = (1-\sigma(inf(v,c)))\cdot X_v$$
$$\frac{\partial \mathcal{O}}{\partial Y_{u^k}} = \left(-\sigma(inf(v,u^k))\right)\cdot X_v \frac{\partial \mathcal{O}}{\partial b_v} =$$
$$(1-\sigma(inf(v,c))) + \sum_{k=0}^{K}\left(\sigma(-inf(v,u^k))\right)$$
$$\frac{\partial \mathcal{O}}{\partial b_c'} = (1-\sigma(inf(v,c)))$$
$$\frac{\partial \mathcal{O}}{\partial b_{u^k}'} = \left(-\sigma(inf(v,u^k))\right) \quad (11)$$

Finally, we get two network embedding matrices $\mathcal{X} = [X_1, X_2, \dots, X_N]$ and $\mathcal{Y} = [Y_1, Y_2, \dots, Y_N]$, which represent the characteristics of information disseminators and information receivers of each user node, respectively, and two bias vectors $\boldsymbol{b} = [b_1, b_2, \dots, b_n]$ and $\boldsymbol{b}' = [b_1', b_2', \dots, b_n']$, which represent the two biases of each user, respectively.

Suppose it is assumed that node u is affected by the cumulative influence of other activated nodes in the network, such as inf(→u). In that case, the probability of node u being started is:

$$p_u = f(inf(\to u)) \quad (12)$$

Among them, f(·) is a function that converts the influence strength into the influence probability. The higher the cumulative influence strength inf☐ inf(→u)☐ of u, the greater the likelihood of being activated pu.This chapter selects the sigmoid function as f(·).

2.3 User Influence Expansion Calculation and High Influence User Identification

For the network embedding method, the length of the co-occurrence window can be set to δ=L. Two embedding matrices $\mathcal{X} = [X_1, X_2, \dots, X_N]$ and $\mathcal{Y} = [Y_1, Y_2, \dots, Y_N]$ and two bias vectors $\boldsymbol{b} = [b_1, b_2, \dots, b_n]$ and $\boldsymbol{b}' = [b_1', b_2', \dots, b_n']$ can be obtained, then the influence strength of node v on node u is:

$$inf(v,u) = X_v \cdot Y_u + b_v + b_u' \quad (13)$$

$\mathcal{N}(v)$ is the set of adjacent reachable nodes of node v, then the influence expansion degree of node v in the whole network can be approximated as:

$$\sigma(v) = \sum_{c\in\mathcal{N}(v)} \frac{1}{1+e^{-X_v\cdot Y_c - b_v - b_c'}} \quad (14)$$

For a set of seed nodes S, $\mathcal{N}(S)$ is the union of the adjacent reachable nodes of all nodes in S ($\mathcal{N}(S)$ does not include any node in S):

$$\mathcal{N}(S) = \cup_{g\in S}\mathcal{N}(g) - S \quad (15)$$

For any node u in $\mathcal{N}(S)$, the influence strength of the entire set S on u can be approximated as:

$$inf(S,u) = \sum_{g\in S}\left(X_g \cdot Y_u + b_g + b_u'\right) \quad (16)$$

Then, the influence expansion degree of the set S can be approximated as:

$$\sigma(S) = \sum_{c\in\mathcal{N}(S)} \frac{1}{1+e^{-\sum_{g\in S}(X_g\cdot Y_c + b_g + b_c')}} \quad (17)$$

For a seed set S, the marginal influence expansion of a node $v(v \notin S)$ is:

$$margin(v) = \sigma(S \cup \{v\}) - \sigma(S) \tag{18}$$

When the co-occurrence window length is set to $\delta = 2$, the two embedding matrices learned by the information dissemination network are $\mathcal{X}^{(1)} = \left[X_1^{(1)}, X_2^{(1)}, \ldots, X_N^{(1)}\right]$ and $\mathcal{Y}^{(1)} = \left[Y_1^{(1)}, Y_2^{(1)}, \ldots, Y_N^{(1)}\right]$, and the two bias vectors are $\boldsymbol{b}^{(1)} = \left[b_1^{(1)}, b_2^{(1)}, \ldots, b_n^{(1)}\right]$ and $\boldsymbol{b}^{(1)} = \left[b_1^{(1)}, b_2^{(1)}, \ldots, b_n^{(1)}\right]$. Therefore, for any two nodes i and j in network $G = (V, E)$, the probability that node i propagates information directly affects node j is:

$$p_{ij} = \begin{cases} f\left(X_i^{(1)} \cdot Y_j^{(1)} + b_i^{(1)} + b_j^{(1)}\right), & \text{if } (i,j) \in E \\ 0, & \text{if } (i,j) \notin E \end{cases} \tag{19}$$

In this chapter, the sigmoid function is selected as $f(\cdot)$, then there are:

$$p_{ij} = \begin{cases} \dfrac{1}{1+e^{-X_i^{(i)} \cdot \gamma_j^{(1)} - b_i^{(1)} - b_j^{(1)}}} & \text{if } (i,j) \in E \\ 0 & , \text{if } (i,j) \notin E \end{cases} \tag{20}$$

The influence expansion degree of nodes in the IC and its extension models can be calculated on this basis.

3 EXPERIMENTAL RESULTS AND ANALYSIS

3.1 Analysis of the Features of Information Dissemination Network

This paper analyzes the nature of information dissemination networks on social media and studies some of the characteristics of high-influence users. All nodes are mapped into a 3-dimensional vector space, and the network is visualized according to the coordinates of each node. The visualization results are shown in Figure 3. We generate two classical complex network models with similar scales, scale-free and small-world network models, to compare the feature differences between forwarding relational networks and other networks. Moreover, they are embedded according to the same method, and the visualization results are shown in Figure 4.

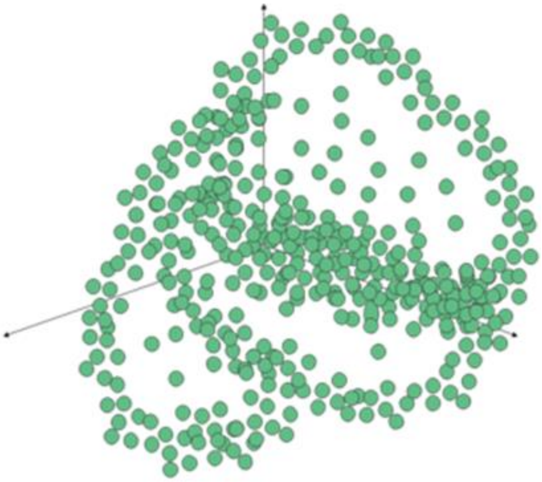
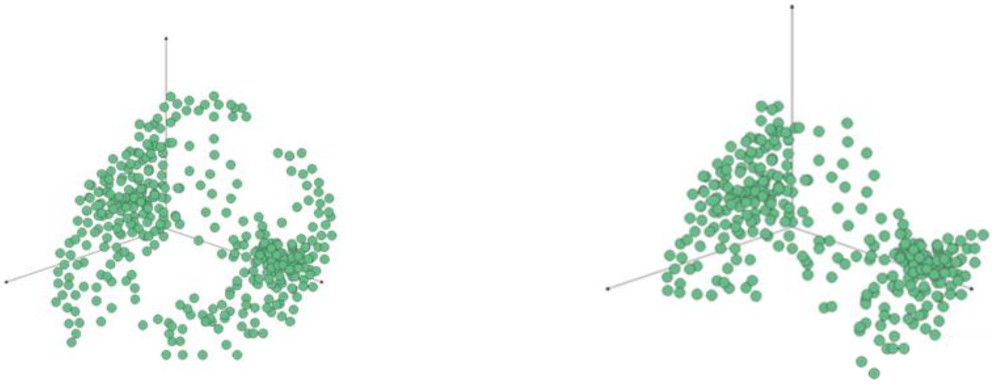


Figure 3: Embedding results of twitter forwarding relationship network.



(a) (b)

Figure 4: Embedding results of classical complex network model. (a) Scale-free network; (b) Small-world network.

3.2 Impact Maximization Experimental Data

CI: The CI (Collective Influence) method believes that the nodes with high influence in the network should also have higher importance in structure. The joint influence expansion degree of such a group of nodes in the network should also be relatively high. For node i, the CI method uses the CI value of the node to estimate its influence in the network, and the CI value of the user the following formula calculated:

$$CI(i) = (k_i - 1)\sum_{j\in \widehat{Ball}(i,l)}(k_j - 1) \tag{21}$$

Among them, k_i represents the degree of node i, and $\partial Ball(i,l)$ refers to all other nodes within the l radius with node i as the center. Like the SingleDiscount method, the CI method selects a node with the highest CI value each time to add it to the seed node-set, removes the node and the corresponding edge from the network, and recalculates the CI value of the remaining nodes. Here, we take the radius length as l=3.

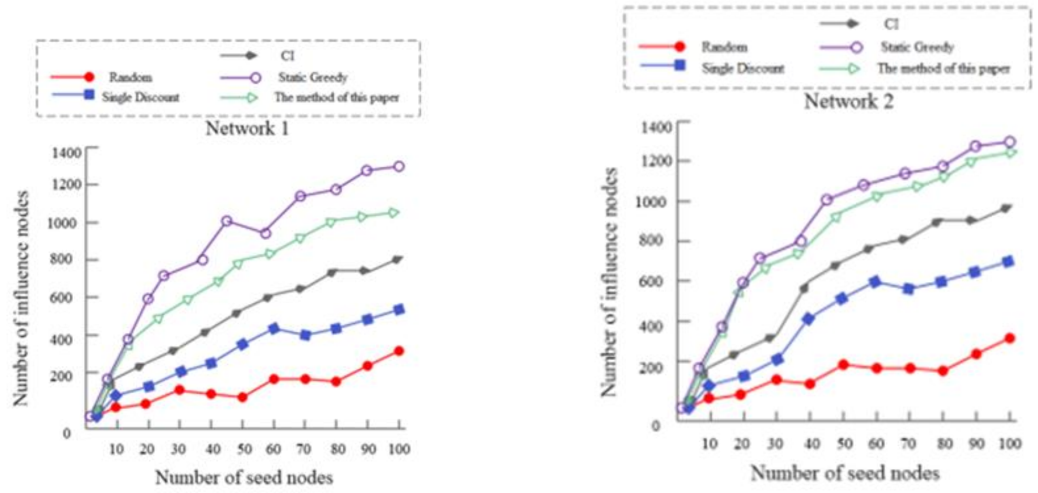
The proposed method and the benchmark above algorithm each select k high-influence users from social media as seed users. The average number of affected users in 1000 experiments measures the influence expansion of each group of seed nodes. The number of seed users selected by several methods and each seed user's average number of influence nodes are compared and counted.

3.3 Marketing Analysis of Community Agricultural Products Based on the Psychological Needs of Consumers' Nutrition and Health

In this paper, the algorithm model proposed above is applied to the psychological needs of consumers for nutrition and health and to the analysis of the marketing effect of community agricultural products; the experimental results are counted separately, and the effect is evaluated through intelligent simulation methods.

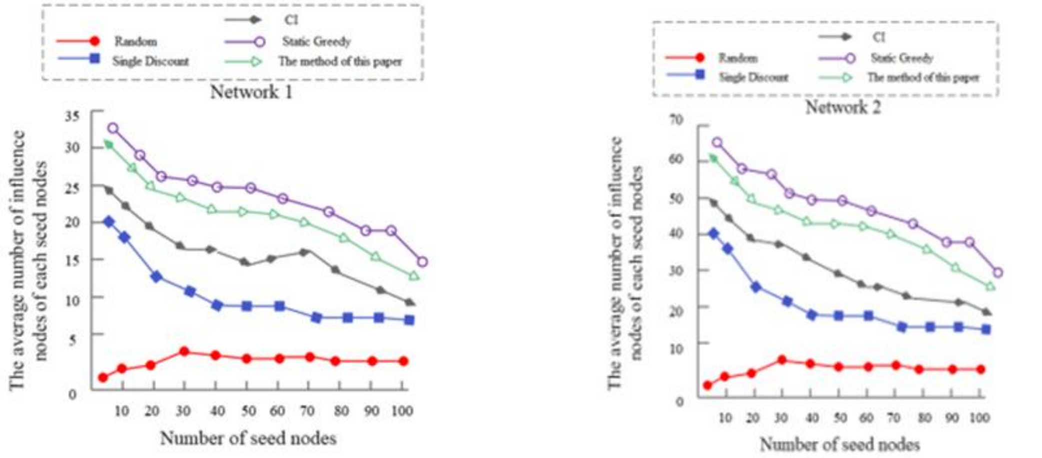
4 RESULTS

Figures 5 and 6 compare the number of influence nodes selected by several methods with each seed user's average number of influence nodes.



(a) (b)

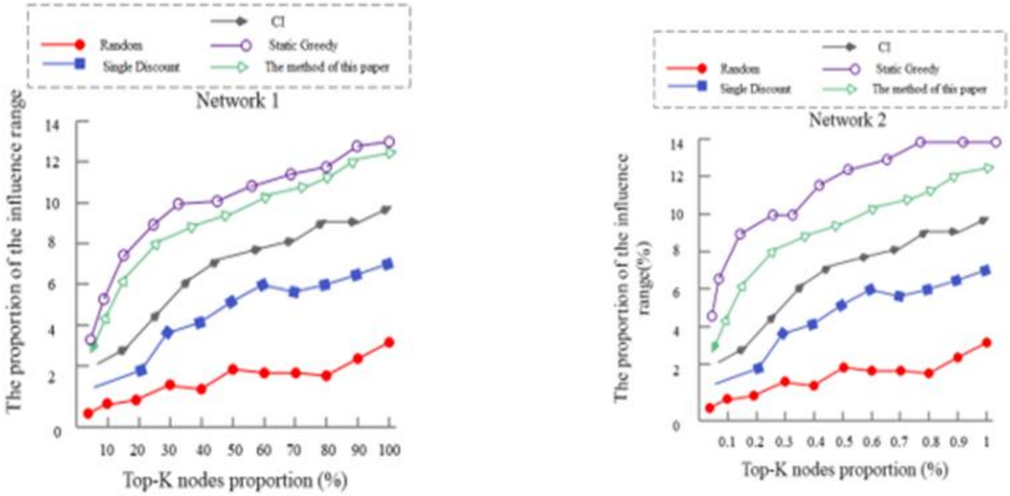
Figure 5: Comparison of the number of influence nodes of seed users selected by several methods. (a) network 1; (b) network 2.



(a) (b)

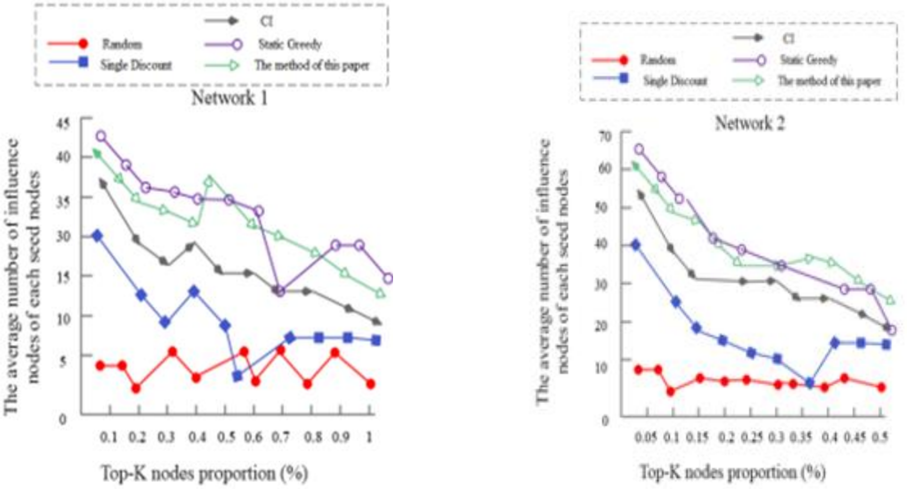
Figure 6: Comparison of the average number of influence nodes per seed user. (a) network 1; (b) network 2.

Figure 7 shows the relationship between the proportion of the total number of nodes in the seed network and the proportion of the number of affected nodes in the total number of nodes in the network. Figure 8 shows the relationship between the proportion of seed nodes and the marginal influence expansion degree of the last selected new seed nodes in the Top-k nodes.



(a) (b)

Figure 7: The relationship between the proportion of seed nodes and the proportion of affected nodes. (a) network 1; (b) network 2.



(a) (b)

Figure 8: The relationship between the proportion of seed nodes and the expansion of marginal influence of new seed nodes. (a) network 1; (b) network 2.

Figure 9 compares the time several methods took to select k=50 users in networks 1 and 2. Tables 1 and 2 below show the analysis results of consumer nutrition and psychological health needs and the study of the marketing effect of community agricultural products, respectively.

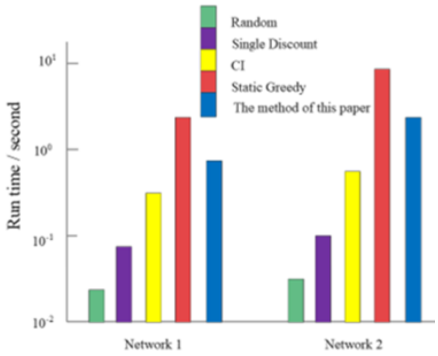


Figure 9: Time-consuming comparison of several methods to select seed users.

Number	*Health Analysis of Consumer Psychological Demand*	*Number*	*Health Analysis of Consumer Psychological Demand*	*Number*	*Health Analysis of Consumer Psychological Demand*
1	*80.80*	*8*	*81.76*	*15*	*81.66*
2	*74.07*	*9*	*72.14*	*16*	*80.67*
3	*77.67*	*10*	*75.24*	*17*	*81.40*
4	*72.24*	*11*	*80.54*	*18*	*79.65*
5	*76.26*	*12*	*72.02*	*19*	*79.09*
6	*69.09*	*13*	*71.94*	*20*	*82.00*
7	*68.40*	*14*	*70.98*	*21*	*77.08*

Table 1: The effect of analysis on the psychological needs of consumers' nutritional health.

Number	*Agricultural Marketing Analysis*	*Number*	*Agricultural Marketing Analysis*	*Number*	*Agricultural Marketing Analysis*
1	*75.05*	*8*	*67.63*	*15*	*63.52*
2	*74.70*	*9*	*63.81*	*16*	*70.43*
3	*66.97*	*10*	*65.47*	*17*	*72.80*
4	*75.95*	*11*	*73.39*	*18*	*72.98*
5	*64.02*	*12*	*64.94*	*19*	*65.21*
6	*71.05*	*13*	*63.19*	*20*	*69.05*
7	*70.37*	*14*	*67.31*	*21*	*67.44*

Table 2: Analysis of the effect of community agricultural product marketing.

5 DISCUSSION

From Figure 5 and Figure 6, it can be seen that the influence maximization algorithm selects k seed nodes with the highest joint influence expansion degree from the network, and these k nodes can also be called Top-k influence nodes in the network.

Figures 7 and 8 show that in iteratively selecting seed nodes, the marginal influence expansion degree of the chosen new seed nodes usually gets smaller and smaller. After about 0.5% of the seed nodes have been selected, the marginal influence expansion of the new seed nodes is already meager. Only a minimal number of nodes in the network have extremely high influence. According to the marginal influence expansion of newly added seed nodes, decision-makers can select an appropriate number of seed nodes.

From Figure 9, the Random method randomly selects nodes, which takes almost no time. SingleDiscount and CI algorithms are heuristic algorithms, and their calculation speed is also breakneck. They only consider the network structure when identifying high-influence users and are unaffected by the propagation model. This also makes them unable to obtain approximate solutions to the influence maximization problem. However, the StaticGreedy algorithm and the method proposed in this paper, as greedy algorithms, ensure the accuracy of the influence maximization solution, and the running time will be higher than the heuristic algorithm. Among them, the computational efficiency of the method proposed in this paper is significantly higher than that of the StaticGreedy algorithm.

From Table 1 and Table 2, the algorithm and model proposed in this paper can play a specific role in analyzing the marketing strategy of community agricultural products based on consumers' psychological needs for nutrition and health.

6 CONCLUSIONS

This paper improves the marketing algorithm based on the actual needs of modern agricultural product community marketing and enhances the information dissemination effect of intelligent community agrarian product marketing. Moreover, this paper uses social networks to process community data and combines agricultural product marketing and consumer nutrition to establish psychological needs for algorithm improvement. Through algorithm improvement and simulation research, it can be seen that the StaticGreedy algorithm and the method proposed in this paper, as greedy algorithms, ensure the accuracy of the solution to maximize the influence, and the running time will be higher than the heuristic algorithm. Among them, the computational efficiency of the method proposed in this paper is significantly higher than that of the StaticGreedy algorithm. The data simulation study shows that the algorithm and model presented in this paper can play a specific role in analyzing the marketing strategy of community agricultural products based on the psychological needs of consumers' nutrition and health.

7 RECOMMENDATIONS

When implementing the new model of farmer-community-connected sales, the community should pay more attention to this model to provide a suitable environment for the sale of agricultural products. In addition, the cooperation of rural cooperatives should be strengthened to provide fresh and high-quality vegetables to effectively enhance the connection between the two, promote the development of urban and rural areas, and provide urban residents with fresh vegetables at favorable prices. Integrating medical research into marketing strategies for community agricultural products holds promise for promoting healthier choices while supporting local agriculture. Ethical communication, accurate information dissemination, and a deep understanding of consumer needs will be vital in harnessing the potential of this approach for the benefit of both consumers and local agricultural communities.

Wei Tao, https://orcid.org/0009-0007-1467-6713

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