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Research on Node Optimization and Propagation Path Calculation in Traditional Chinese Medicine Culture Propagation Networks

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ABSTRACT
In the era of digital media, with the help of media empowerment, Chinese medicine culture dissemination completes the innovation from the two dimensions of disseminators and media channels, which brings new opportunities to Chinese medicine culture dissemination. Aiming at the problem of large time overhead of traditional greedy algorithm in the optimization of nodes of TCM culture dissemination network, NPG algorithm is used to optimize the influence of starting nodes, computational efficiency and selection strategy. On the basis of optimization, the propagation probability is calculated to determine that time, content and social relationship can be used as the basis for judging the propagation path, and the path coefficients are analyzed with the help of structural equations. The path coefficient of social relationship→time→Chinese medicine culture dissemination is 0.173, i.e., under the role of time, there is a significant direct effect between social relationship and Chinese medicine culture dissemination, and time plays the role of mediating effect in the reconstruction of dissemination path. The research in this paper promotes the sustainable development of Chinese medicine culture through the improvement of Chinese medicine culture communication network.

Keywords: Chinese medicine culture, dissemination network, node optimization, traditional greedy algorithm, NPG algorithm, dissemination path calculation

1. Introduction

Chinese medicine culture has a long history, is an important part of traditional Chinese culture, through a variety of channels of dissemination, in order to go to the public and the world. Therefore, efficient dissemination of cultural recognition, inheritance and innovation is an important factor in the continued development of Chinese medicine culture [1]. Cultural export issues, cross-cultural communication issues and the spread of TCM culture are closely related [2]. As China's international

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status continues to rise, the country's image is increasingly emphasized. The spread of culture is the soft power of the country, so we should establish a good image of Chinese medicine culture. At the same time, under the concept of globalization and universal construction of health, the knowledge of Chinese medicine is no longer understood and used by a minority group, and its application in the fields of medical clinic, rehabilitation, and recreation has gradually climbed up, and the culture of Chinese medicine has been repeatedly referred to, especially after the new coronary pneumonia [3-6]. However, the depth of its dissemination shows regional differences, and its acceptance in Southeast Asia is significantly higher than that in developed regions of Europe and the United States, where the latter's acceptance is even lower than 50%, and the environment for dissemination is grim [7]. Possibly, Chinese medicine is built on the basis of the natural materialistic view, constantly recognizing the evolution of pathology in the human body, and its generation, connotation, and core are all based on the perception of nature, and the inherent irreconcilable conflictability with the modern communication environment makes the dissemination of Chinese medicine culture difficult [8].

Traditional Chinese culture is characterized by macro, discursive, abstract and ambiguous, while Western cultural forms are structured, logical, scientific and empirical, so they can adapt to the communication environment [9-10]. This hegemony of cultural transmission makes the recipients in the society distrust traditional Chinese culture and hinders the spread of traditional Chinese medicine culture. Moreover, for its own reasons. First, the modern popular language system cannot help people understand the terms in TCM, and the translated semantics are difficult to effectively express the original meaning of TCM terms, such as "go to oil" and "earthworm head" in TCM, and the public is ignorant of the terms in TCM [11-13]. Secondly, the communication in traditional communication paths and Internet communication paths is boring, the specialized knowledge points are obscure and difficult to understand, and lack of innovation, which leads to the lack of knowledge of Chinese medicine culture and even prejudice of many young people nowadays, making it difficult for Chinese medicine to penetrate into this group [14-16]. Thirdly, due to the government departments, medical institutions, pharmaceutical companies and other communication nodes on their own lack of awareness of the main body of Chinese medicine culture, trust, identity, in the face of Western culture, regardless of the merits and demerits, blind learning, no critical inheritance, this yielding and pandering to the loss of Chinese medicine culture of the right to speak [17-19]. Although the state has introduced policies to improve the situation of TCM and TCM culture, the strength is not enough compared to Western medicine, and the dissemination of TCM culture is slow. Therefore, optimizing the network nodes and designing the communication paths of TCM culture is a necessary way to solve the communication dilemma.

In this project, the marginal gain and greedy algorithm in the traditional greedy thought are first systematically formulated, and the greedy algorithm is found to have limitations in the process of node optimization of TCM culture dissemination network. Accordingly, the node optimization of communication network based on NPG algorithm is proposed, which mainly improves the node influence, node selection strategy and computational efficiency. Under this premise, the influence factors of the propagation path are determined by calculating the probability of TCM culture propagation. Finally, by using structural equation modeling to calculate the path coefficients of each influencing factor and the propagation of Chinese medicine culture, in order to realize the reconstruction of the propagation path, so as to make the Chinese medicine culture propagation network better serve the user groups, and have a good role in promoting the inheritance and exchange of traditional culture.

2. Exploring the optimization of nodes in the dissemination network of Chinese medicine culture

The node influence maximization problem is one of the hot issues in the study of information dissemination in TCM culture dissemination network. The influence maximization problem can be regarded as an extension of the sorting problem, which adopts a completely different independent cascade model and linear threshold model because the maximization problem is a multi-infectious source problem, we expect to get a collection of seed nodes, and use the collection of seed nodes as the source of information to maximize the final influence range. The traditional greedy algorithm is not suitable for large-scale social networks because of its high time overhead, and its practice of selecting the node with the most current influence to join the seed set in each round only guarantees the local optimum. The NPG algorithm (new optimization algorithm) proposes a better "potential node selection strategy in the heuristic stage, which fully considers the neighborhood information of the nodes, takes into account the strength of the connection between the nodes in the network and the differences in the nodes' propagation ability, and has better results. In the greedy phase, the NPG algorithm obtains the current activation set by propagating the current seed set in advance in each round, avoiding the calculation of marginal gains for the nodes in the set, which greatly reduces the amount of repetitive calculations and improves the efficiency of the greedy phase. The details are as follows:

2.1. Traditional Greedy Ideology

2.1.1. Marginal gains. The marginal gain of a node is commonly used in node influence maximization problems to evaluate the current influence size of a node in the network. The marginal gain of a node represents the incremental value of the influence range brought about by a node joining a set, which is a submodular function, so the marginal gain function conforms to the submodular properties, i.e., the gain function is non-negative, monotonic as well as satisfies the natural diminishing returns property. For any node v in the network, the marginal gain of adding v to set S_i is defined as:

$$m(v \mid S_i) = \mid I(S_i \cup \{v\}) \mid - \mid I(S_i) \mid \tag{1}$$

Calculating node marginal gain requires a propagation model through the network, and different propagation models will have different gain values. When selecting seed nodes to calculate the marginal gain, the general practice is to add all the inactive nodes in the network to the seed set in turn, and use the set as the propagation source to calculate the propagation range, and the value added of this range to the propagation range of the original seed set is the value of the marginal gain of the joined nodes.

2.1.2. Greedy Algorithm. The greedy algorithm has the problem of large time overhead, in each round of selection of seed nodes need to calculate the marginal gain value of all non-seeded set nodes in the network, select the maximum marginal gain node as the seed node of this round, and add it to the seed set [20]. The state of the network nodes will change after one round of selection, so the marginal revenue values of all non-seeded set nodes need to be recalculated during the next round of selection [21]. For a network node size of n, edge size of m, and a seed set of k, the time complexity of the greedy algorithm is $O(k \times m \times n)$. The greedy algorithm has too high a time overhead and is not applicable in the network environment of TCM culture dissemination [22].

2.2. NPG Algorithm

2.2.1. Improvements in node influence. The NPG algorithm thus improves the method of evaluating the influence between nodes, and for any node in the network, the neighbor-joining graph is first formed with that node as the central node. Here we assume that there is a node v in the network, and in evaluating the value of node v "feeling" the influence of its incoming neighbors on itself, we first form an adjacency relationship centered on node v, with all of v incoming neighboring nodes, and all of the edges of the relationship between these nodes. The influence of each incoming edge neighbor u on node v is defined as:

$$NG(v) = G^{'}(V^{'}, E^{'}), V^{'} = \{v\} \cup N(v) \tag{2}$$

$$E^{'} = \{(x, y) \mid x, y \in V, (x, y) \in E\} \tag{3}$$

$$b_{uv} = \frac{outDegree(u)}{\sum_{w \in N(v)} outDegree(w)} \tag{4}$$

Where $N(v)$ is the node v adjacency neighbor, i.e., the incoming edge neighbor: $outDegree(u)$ is the out-degree of node u in the adjacency graph. The influence of node u on node v is the ratio of the out-degree of node u in the adjacency graph to the sum of the out-degree of all adjacency neighbors in the adjacency graph.

2.2.2. Selection of “potential” nodes. The NPG algorithm proposes a new seed node selection strategy, i.e., the selection of “potential” nodes before the greedy method. Choosing the appropriate index to represent the “potential” of a node is very important, which is related to the influence range of the final seed set. The hybrid algorithm uses the following approach to evaluate the “potential” of nodes:

$$\inf(u) = \sum_{v \in \bar{M}(u), v \in \bar{A}(u)} b_{uv} \tag{5}$$

$$PI(u) = outDegree(u) + (1 - e^{-\inf(u)}) \tag{6}$$

Where $\bar{N}(u)$ is a collection of nodes, the element nodes in it are the outgoing neighbor nodes of node u, $\bar{A}(u)$ is the collection of nodes in the activation state of node $\bar{N}(u)$, and $outDegree(u)$ is the outgoing degree of node u. PI value is an indicator for evaluating the node's “potential”, which is determined by the value of node's inf and the outgoing degree of node. The inf of a node represents the sum of the influence of the node on all the out-of-edge inactive nodes, and the larger the value, the greater the influence potential of the node on the surrounding area.

2.2.3. Improvement of the “potential” node selection strategy. At the same time, the unactivated neighbor of a node in the network is a high-propagation node, which does not mean that the influence "potential" of the node is large. If the influence value of the high-propagation neighbor node is far less than its activation threshold, it means that the influence of the node on the neighbor is small, and obviously the influence "potential" will not be large. Thus, through the above observations, we arrive at a novel “potential” node selection strategy, where we evaluate the “potential” of a node by taking into account the connection strength of the directed edges and the variability of the outgoing neighbors.

Specifically, in directed networks, we consider that there exists a connection strength of directed edges between nodes, the size of which is affected by the influence value of the node and the activation threshold of the affected node, and the connection strength, which represents the influence strength between nodes, is 0.3 for node v for all three nodes, but due to the different activation thresholds for each of the outgoing edge neighbors, which results in different connection strengths for node v for them as well. We define the connection strength between nodes as S. Then there are two nodes u and v in the network and the connection strength of u to v is defined as S_w:

$$S_{uv} = \begin{cases} \dfrac{b_{uv}}{att(v)} & b_{uv} < att(v) \\ 1 & b_{uv} \geq att(v) \end{cases} \tag{7}$$

Where b_{av} is the influence value of node u on node v, and $att(v)$ represents the activation network value of node v, the connection strengths of node v and node a,b,c are 1, 1/3 and 1/2, respectively. A high "potential" node not only has a high connection strength to the outgoing neighbor, but also has a high propagation ability of the outgoing neighbor, so the evaluation formula for the "potential" node is obtained, and for any inactive node u in the directed network, its "potential" value $PI(u)$ is defined as:

$$PI(u)=\sum_{v\in N(u),v\in\bar{A}(u)} S_{uv}*|C_v| \tag{8}$$

where $N(u)$ is the set of outgoing neighbors of node u, $\bar{A}(u)$ is the set of activated outgoing neighbors of node u, C_v is the set of outgoing neighbors within two hops of node v, and $|C_v|$ represents the size of the set. In the heuristic phase of the node influence maximization problem, we use the new node "potential" assessment method of Eq. (8) to evaluate the potential influence of nodes.

2.2.4. Improvement of computational efficiency in the greedy phase. The greedy phase uses a locally optimal greedy strategy based on the seed nodes selected in the heuristic phase, and the node with the current maximum marginal gain is selected at each step and added to the seed set until the set size reaches a predefined value. Selecting the maximum marginal gain node at each step requires calculating the marginal gains of all non-seed nodes in the network, which has a very large computational overhead. When the network size is n, in the t nd step of the algorithm, the size of the seed set is $t-1$, and the selection of the largest marginal gain node needs to calculate the marginal gain value of $n-t+1$ nodes, which is optimized as follows in this paper to reduce the unnecessary calculations.

In this paper, based on the property that the propagation structure of the linear threshold model remains unchanged when the propagation source is unchanged, we find that when a node is able to be activated under the current seed node set as the propagation source, the current marginal gain value of this node must be 0, that is to say, the node that can be activated by the current seed set has no marginal gain. In this way, when the network size is n and the seed collection size is k, we can propagate the seed collection of size k based on the linear threshold model before selecting the $k+1$ rd seed node, and get the activated node collection A, whose size size is recorded as a. The node in the collection A will definitely not be the $k+1$ th seed node because the marginal gain at this time is 0. Therefore, this paper only needs to compute the largest marginal gain when selecting the node with the largest marginal gain, so this paper only needs to calculate the marginal gain of $n-k-a$ nodes when selecting the node with the largest marginal gain. Through experiments this paper finds that with the gradual increase in the size of the seed set, the size a of set A will increase dramatically, and in the data set taken in this paper's experiments a will soon reach more than 70% of the size of the entire network, avoiding the calculation of the marginal gain of the nodes in set A, greatly reducing the computational overhead of the greedy phase.

3. Exploration of methods for calculating the path of dissemination of Chinese medicine culture

Although the node optimization method of Chinese culture dissemination network given above can effectively improve the dissemination efficiency and influence, but the users failed to accept the dissemination path of Chinese medicine culture, only the users accept its dissemination path, so that each user becomes a new disseminator, which has a facilitating effect on Chinese medicine culture from the source to the future. It can be understood that node optimization is a sufficient condition for propagation path computation, while propagation path computation is a sufficient condition for TCM culture transmission. In this regard, this chapter will discuss the dissemination path computation of TCM culture. The details are as follows:

3.1. Calculation of the impact of different factors on the propagation paths

In this paper, we study the method of calculating the communication path of Chinese medicine culture, and the network structure is the basis of social network, and the network structure can be measured by social relationship, so the paper mainly considers the three influencing factors, which are social relationship, content and time.

3.1.1. Social Relationships. A social network, a social structure consisting of a collection of social individuals and the social connectivity relationships between them, manifests itself as a combination of directed relationships between individuals, and the value of such directed relationships is the relationship between followers and fans.

As the underlying platform of social networks, social relationships are an essential consideration for conducting communication analysis. In the study of this paper, such social relationships are categorized into two types according to the strength of the connection: one refers to the directly identified connections - the users' followers and fans H_1. The other is the users' historical retweeting relationships H_2, which should be more explicitly referred to as historical interaction relationships. The representation formula is as follows:

$$H_1(v,u)=\begin{cases}1 & v \text{ is a fan of } u\\ 0 & \text{Or else}\end{cases} \tag{9}$$

$$H_2(v,u)=\frac{\sum(R(v,u))}{\sum(R(v))} \tag{10}$$

In the above equation, $R(v,u)$ represents how many pieces of content from user u have been forwarded by user v within a period of time. $R(v)$ denotes the total number of content forwarded by user v during this period of time. $H_2(v,u)$ represents the historical forwarding rate of user v to user u, i.e., the frequency of forwarding from user u among all the forwardings of user v (used as a measure of probability).

3.1.2. Content. Content plays an important role in information dissemination, thus it is of great significance to first cluster information into specific topics before conducting dissemination research. This paper applies content as a factor influencing the dissemination in addition to considering this influence, but more importantly, it is to consider the content evolution, i.e., the content of the text may change, in the process of TCM culture dissemination. Users may be influenced by the original microblogs and express their own opinions, or slightly remodel the original microblog content and republish it out, all of which can be measured by the text similarity. Therefore measuring according to text similarity is an important part of path reconstruction. The text similarity is calculated as follows:

$$Sim(A,B)=\frac{\sum_{i=1}^{q}(w_{di}*d_i)}{\sum_{i=1}^{r}(w_{ci}*c_i)} \tag{11}$$

3.1.3. Time. Most of the applications of time in TCM culture communication focus on topic evolution, interest recommendation and hotspot prediction. Studying the periodicity of topic evolution, or inferring users' interests based on historical topic information in time and pushing new similar topic information to users in the existing time, or predicting future hotness based on the individual values of the observed variables at different points in time, are applicable to web content with complex patterns of hotness evolution.

The same is true for user behavior in TCM culture communication networks; when faced with a large amount of new information, most users will only browse the most recent part of the pushed information. Therefore, this paper argues that the probability of a user being able to read a particular blog post is related to the positional alignment of this blog post when it is pushed to the user, and the total number of blog posts that the user is used to reading at a time, and a Gaussian distribution is used to represent this correlation, and the probability distribution function is constructed as follows:

$$T(v,u) = \exp(-\lambda \frac{(t_v - t_u)^2}{2\sigma^2(v,t)}), t_v \geq t_u \quad (12)$$

Where $T(v,u)$ is the probability that the user v receives a message from the user u, and $\sigma(v,t)$ is a parameter for the interval of time at which the user v can read the message at most, the interval of time using the interval of time between the most recent message of the user and the furthest message that the user can read, which varies in value for different users.

3.2. Calculation of time- and content-based propagation probability

To spread Chinese medicine culture through some behaviors of users' reading, commenting, forwarding and liking, in which the forwarding behaviors are some communication paths that can be directly measured, while the reading and un-forwarded comments can only affect the users themselves, and the sources of users' information are difficult to be measured. This paper is based on the above NPG algorithm to construct the dissemination node of TCM culture in the network. First of all, assuming that the sources of TCM culture of users are all networks, on the basis of node optimization, according to whether the user publishes information related to TCM culture, to determine whether the user accepts TCM culture (infected). Then, it is for these infected users in the network (who have accepted a specific TCM culture), to find the node of their information source for each user and determine the propagation path.

Based on the three influencing factors obtained from the research in the previous section, this paper measures the propagation probability through the combination of text similarity, time, and social relationship, and the propagation probability function is as follows:

$$P(v,u) = \frac{1}{n} * \sum_{i=1}^{n} (a * T(v_i, u_1) + b * Sim(v_i, u_1)) + c * H_2(v, u_1) \quad (13)$$

where $P(v,u)$ denotes the topic propagation probability from user u to user v. n denotes the number of posts made by user u before user v. v_i denotes the number of messages published by user u before user v, and v_i denotes the number of messages published by user v who initially followed this particular content. The three parameters a,b,c are the weight parameters regulating the three indicators and $a+b+c=1$, and the initial values are set to 1/3. The value spaces of the three measurement factors T (as in Eqs. 9~10), Sim (as in Eq. 11), and H_2 (as in Eq. 12) are regularized to the value interval [0, 1], respectively. This calculation of propagation probability is used to determine the influencing factors that may generate propagation paths and provide a theoretical basis for the following research work.

3.3. Reconstruction of communication paths

The dissemination path of Chinese medicine culture refers to the dissemination path of Chinese medicine culture on the network. On the basis of optimization, the dissemination probability calculation formula based on time and content is used to determine the influencing factors that may produce the dissemination path, and its path coefficient is calculated with the help of structural equations to realize the reconstruction of the dissemination path. For the propagation path of single forwarding Chinese medicine culture, because the propagation network has its own propagation characteristics (such as forwarding rules, mentioning rules, etc.) for the design expression of the text content, and the information source nodes can be directly accessed according to these characteristics, the propagation path of this Chinese medicine culture can be constructed conveniently. As for some text content will not show or label the topic source, it is impossible to obtain the information source node, so the propagation path can not be obtained directly, so it is necessary to calculate the path coefficients of the network propagation of Chinese medicine culture, and this paper refers to this type of path as the implicit propagation path. Reconstructing the propagation path is of great significance, which can show the propagation of Chinese medicine culture well and play a guiding role in the inheritance and protection of traditional culture.

4. Node optimization and propagation path exploration and analysis

4.1. Optimization analysis of nodes in TCM cultural communication network

4.1.1. Experimental dataset and experimental environment. The experimental dataset used in this paper is from two TCM culture dissemination networks, A and B. Crawling techniques were used to randomly obtain user public data and analyze overlapping user information to determine users across the two social networks, in addition to tweet data from the networks. The experimental environment is Windows 10 operating system, Intel CoreTM i7-7500U 2.9GHz CPU processor, 8 GB RAM, and the programming tool is Anaconda 2. The Python language is used to write the code and conduct related experiments.

4.1.2. Experimental results and analysis:
1) Algorithm performance comparison. In order to verify the effectiveness of NPG algorithm in node optimization, three benchmark algorithms (Greedy-IMaN, Degree-IMaN, and Random-IMaN) are compared with it and the comparison of algorithms' influence ranges are shown in Fig. 1.The difference in the size of the influence ranges obtained by the NPG algorithm and Greedy-IMaN algorithm is small, and it is always superior to the other two algorithms.The NPG algorithm influence range is slightly higher than the Greedy-IMaN algorithm, this is because the NPG algorithm screens the set of candidate nodes with higher potential influence PI in the screening phase, but this strategy cannot avoid that some nodes with high influence are deprived of the possibility of being selected as a node, so the algorithm of this paper can still serve as a node optimization within a certain budget.

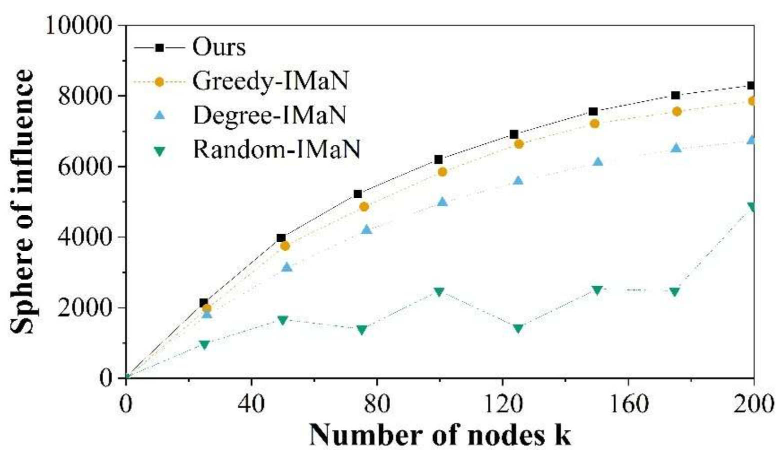

Fig. 1. Comparison of algorithm influence range

2) Runtime Comparison. The running time comparison is shown in Figure 2, where the horizontal axis is the number of nodes in the network and the vertical axis is the running time. In summary, compared with other algorithms, the running time of this paper's algorithm is the lowest, indicating that the NPG algorithm can significantly reduce the running time while maintaining almost the same influence range as the greedy algorithm, which verifies the improvement of the computational efficiency of the greedy phase.

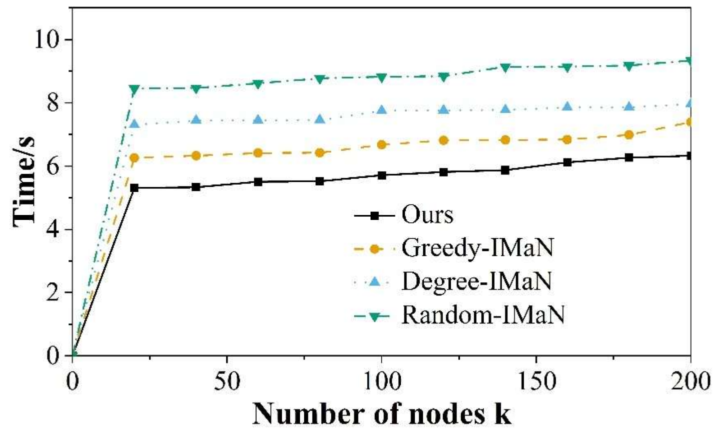

Fig. 2. Run time comparison

3) Effect of parameter p setting on algorithm performance. The effect of parameter p on the influence range is shown in Fig. 3, when k takes a small value, the change of p value has a small effect on the influence range of the algorithm, this is due to the fact that the nodes with the highest influence are almost always selected as candidate nodes, and very few high-influence nodes are omitted, which provides a guarantee that high-quality nodes are mined in the greedy phase. When the value of k increases to a certain value (k=100 in this group of comparison experiments), the influence of p value on the algorithm gradually becomes larger. p value is smaller resulting in a smaller set of candidate nodes selected in the heuristic phase, which inevitably excludes some high-influence nodes, and the algorithm's accuracy decreases.

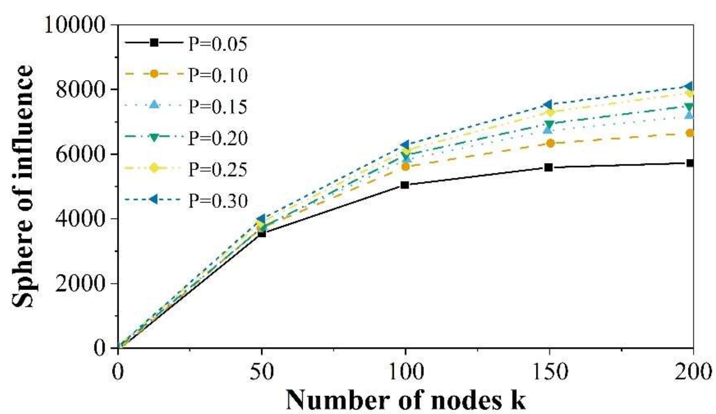

Fig. 3. The influence of parameter p on the influence range

A comparison of the effect of p-value on the running time of the algorithm is shown in Fig. 4, which shows that with the increase of p-value, starting from p=0.25, the influence range of the NPG algorithm is comparable to the results of the Greedy-IMaN algorithm, but instead, as the p-value continues to increase, its running time increases greatly Finding a reasonable balance between the influence range and the time efficiency is the goal of the algorithm, and in the experiments of the present dataset, the influence range of the NPG algorithm is comparable to the results of the Greedy-IMaN algorithm, starting from p= 0.25, the range of influence of the NPG algorithm is comparable to the results of the Greedy-IMaN algorithm, but instead its running time increases greatly as the p value continues to increase.

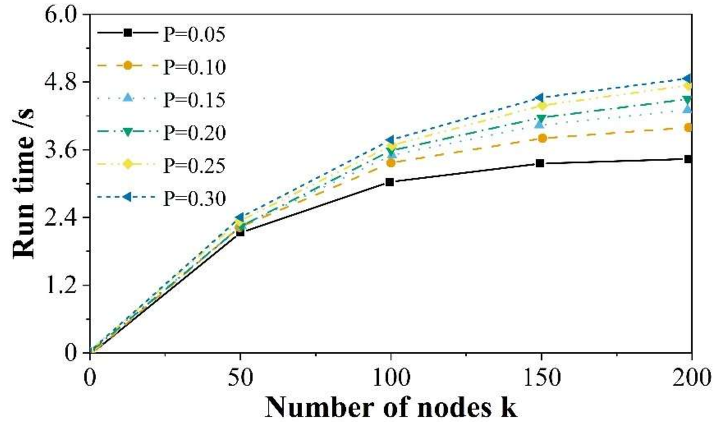

Fig. 4. Comparison of the influence of p value on algorithm running time

4) Node optimization effectiveness. This paper compares how far the influence can be spread by each of the network nodes mined in a TCM culture dissemination network versus separately in multiple independent networks without considering time efficiency. The range of influence in this set of comparison experiments is quantified by the number of nodes that are ultimately optimized, and the number of seed nodes required for the same size range of influence is shown in Figure 5. It can be seen that comparing the other two algorithms, the NPG algorithm is able to spread its influence to a large number of nodes in both networks using an average of about 1/5 of the number of nodes (30), i.e., the NPG algorithm optimizes nodes of a higher quality, and is capable of designing a more comprehensive network that meets the users' needs for the dissemination of Chinese medicine culture.

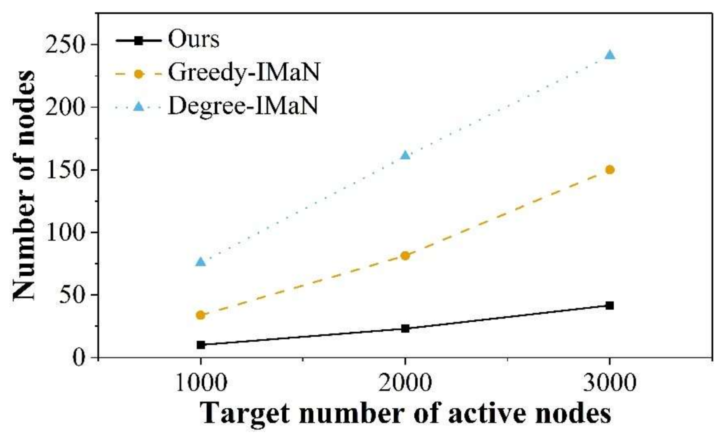

Fig. 5. The number of seed nodes required by the same scale influence range

4.2. Calculation and Analysis of Communication Paths in TCM Cultural Communication Networks

4.2.1. Analysis of the results of the calculation of the probability of transmission. According to the definition of the relevant parameter variables above, the probability of the spread of Chinese medicine culture consists of the forwarding rate of social relations $H_2(v,u_1)$, the text similarity $Sim(v_i,u_1)$, and the probability distribution within a certain period of time $T(v,u)$, and the initial data of the relevant parameters come from academic research websites, which makes the research data more persuasive, and the data does not have the problems of null value and duplicate value, so it can be used directly after crawling, and the data of the relevant parameters can be substituted into the corresponding formula for calculations. Carry out the calculation can be derived from the probability of the spread of Chinese medicine culture $P(v,u)$, the calculation results of the probability of the spread of Chinese medicine culture is analyzed as shown in Table 1. Through the node optimization exploration and analysis in Figure 5, it is determined that the number of node optimization is 30, and the propagation probability of 30 nodes in the TCM culture propagation network is 0.797, which indicates that after the optimization of the nodes in the NPG algorithm, the set text content, time, and social relations can be used in the TCM culture propagation path, and also enrich the TCM culture propagation means, and provide guidance and references to the digital protection and inheritance of traditional culture. It also enriches the means of TCM culture communication and provides guidance and reference for the digital protection and inheritance of traditional culture.

Table 1. Traditional Chinese medicine culture transmission probability

N	$H_2(v,u_1)$	$Sim(v_i,u_1)$	$T(v,u)$	$P(v,u)$
1	0.722	0.713	0.745	0.797
2	0.717	0.818	0.849	
3	0.846	0.775	0.891	
4	0.77	0.761	0.815	
5	0.777	0.734	0.823	
6	0.854	0.73	0.876	
7	0.896	0.835	0.845	
8	0.701	0.809	0.794	
9	0.734	0.774	0.882	
10	0.804	0.754	0.859	
11	0.862	0.719	0.862	
12	0.871	0.724	0.781	
13	0.785	0.78	0.84	
14	0.823	0.803	0.893	
15	0.827	0.783	0.752	
16	0.703	0.844	0.747	
17	0.769	0.886	0.74	
18	0.857	0.802	0.837	
19	0.811	0.755	0.705	
20	0.72	0.868	0.727	
21	0.75	0.791	0.724	
22	0.854	0.893	0.785	
23	0.71	0.764	0.803	
24	0.77	0.881	0.824	
25	0.714	0.855	0.718	
26	0.79	0.842	0.871	
27	0.746	0.849	0.847	
28	0.837	0.785	0.847	
29	0.756	0.735	0.864	
30	0.706	0.875	0.814	

4.2.2. Reconstruction analysis of communication paths. According to the above analysis, it is known that the probability of TCM culture dissemination, also refracts that time, social relationship, and depth of text content influence the TCM culture dissemination path and quality. This subsection realizes the quantitative analysis of communication paths by using structural equations to analyze the path coefficients in the process of communication path reconstruction. Using AMOS24.0 software for 5000 times sample reset sampling and mediation effect test for the model at 95% confidence interval, the results of communication path reconstruction analysis are shown in Table 2. The indirect effect of social relationship factor in the relationship between time factor, content factor and TCM culture dissemination respectively is significant (the confidence interval does not contain 0), which indicates that the indirect effect exists, meanwhile, the direct effect of time factor and content factor on TCM culture dissemination is significant (the confidence interval does not contain 0), which indicates that the social relationship factor plays a mediating role in the relationship between time factor, content factor and TCM culture dissemination respectively. The indirect effect of the time factor in the relationship between the content factor, the social relationship factor and the dissemination of Chinese medicine culture is significant (the confidence interval does not contain 0), indicating the existence of the indirect effect, at the same time, the direct effect of the content factor and the social relationship factor on the dissemination of Chinese medicine culture is significant (the confidence interval does not contain 0), indicating that the time factor plays a partly intermediary role in the process of the dissemination of the content factor, the social relationship factor and the dissemination of Chinese medicine culture respectively The time factor plays a partial mediating role in the process of content factor, social relationship factor and TCM culture dissemination. By analyzing the path coefficients between time, social relationship, text content and the process of TCM culture dissemination, the reconstruction of the dissemination path is successfully realized, so that the TCM culture dissemination network can better serve the audience groups and ensure that the knowledge of TCM culture can flow for a long time.

Table 2. Propagation path reconstruction analysis

Path	Estimate	SE	Lower	P
Social connections→Traditional Chinese medicine culture communication	0.194	0.079	0.056	**
Time→Traditional Chinese medicine culture communication	0.128	0.052	0.034	**
Content→Traditional Chinese medicine culture communication	0.211	0.066	0.078	**
Social connections→Content→Traditional Chinese medicine culture communication	0.164	0.064	0.047	**
Social connections→Time→Traditional Chinese medicine culture communication	0.173	0.026	0.005	*
Time→Content→Traditional Chinese medicine culture communication	0.188	0.016	0.006	*

5. Conclusion

In this paper, facing the problem of maximizing the influence of nodes in the dissemination process of Chinese medicine culture, the node optimization model based on the NPG algorithm is designed under the guidance of the traditional greedy thought, with a view to improving the computational efficiency and influence of nodes. After completing this optimization work, the propagation path calculation method needs to be further discussed, and the linkage between node optimization and propagation path calculation is a sufficiently necessary condition. On the basis of optimization, the formula for calculating the propagation probability based on time and content is determined, and the path coefficients are calculated with the help of structural equations to realize the reconstruction of the propagation path. Combining the above algorithms, node optimization and propagation path are explored and analyzed. Compared with the other two algorithms, the algorithm in this paper only needs about 0.2 nodes to maximize the influence of node propagation, indicating that the nodes optimized by the NPG algorithm are of higher quality, so that its TCM culture propagation network meets the users' needs. On the basis of determining the number of node optimization as 30, the propagation probability is calculated, and it is concluded that the propagation probability after optimization is 0.797, indicating that after optimization, the time, social relationship, and textual content can be used as the basis for judging the reconstruction of the propagation path, and the coefficient of the path of social relationship→content→Chinese medicine culture dissemination is 0.164, where the content plays the role of intermediary role. This paper not only strengthens the communication network construction of Chinese medicine culture, but also promotes the digital development and inheritance of Chinese medicine culture.

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