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An Optimization Method of Knowledge Mapping Relationship Based on Improved Ant Colony Algorithm

Shi-Fu Xu[1,2], Ya-Nan Jiang[1*]

[1] Faculty of Mechanical Engineering and Automation, College of Science and Technology of Ningbo University, Ningbo, China
xushifu@nbu.edu.cn, jiangyanan1202@163.com
[2] Faculty of Mechanical Engineering & Automation, Zhejiang Sci-Tech University, Hangzhou, China
xushifu@nbu.edu.cn

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Abstract. The current knowledge mapping relationship optimization methods cannot obtain high-precision information. An optimization method of knowledge mapping relationship based on improved ant colony algorithm is proposed. The high-precision information of the network is obtained by using the cyclic network. The SGP problem is used to replace the optimization problem of the knowledge map relationship. The optimization objective function of the knowledge map relationship is constructed and solved by the improved ant colony algorithm. The optimization of the knowledge map relationship is realized. Experimental results show that the proposed method has high average accuracy, high knowledge accuracy and high knowledge coverage.

Keywords: knowledge mapping relationship, ant colony algorithm, optimization method, SGP

1 Introduction

Knowledge map is a kind of knowledge system, which can store many kinds of information structurally [1]. With the maturity of emerging technologies related to artificial intelligence and the rapid development of information age, knowledge mapping, as an important part of infrastructure construction, has been widely concerned [2-3], and widely used in search engine, recommendation system and question answering system [4]. For the construction of knowledge map, people have invested a lot of research energy, but the quality of existing knowledge map is generally low, so it is necessary to optimize the relationship of knowledge map [5].

The neural network model optimized based on the empirical knowledge genetic algorithm realizes the time reversal channel prediction method. The empirical knowledge is integrated into the genetic algorithm, and the artificial neural network model is optimized to realize the rapid modeling of the time reversal electromagnetic channel. By extracting the propagation parameters of the time inversion signal and using it as the empirical knowledge for the fitness function of the genetic algorithm, the weights and thresholds of the neural network model are optimized. Under the condition that the number of training samples remains unchanged, compared to directly using neural network modeling, the accuracy of modeling is improved.

An optimization method of knowledge mapping based on weighted ternary closure was proposed [6]. On the basis of weighted ternary closure, the method optimizes the parameter setting to realize the optimization of knowledge map relationship. However, the accuracy of knowledge map information obtained by this method is low, resulting in low average accuracy. The optimization method of knowledge mapping relationship based on 2-mode co-occurrence matrix was put forward [7]. By calculating the similarity between keywords, this method further processes the homogeneous network tomography, realizes the clustering of heterogeneous networks on the basis of 2-mode co-occurrence matrix, and optimizes the relationship of knowledge map by setting different thresholds. However, the network information obtained by this method has errors and the accuracy of knowledge is low. An optimization method of knowledge mapping based on comment semantic analysis was proposed [8].

This article uses the recurrent network to obtain high-precision information of the network. The SGP problem is used to replace the optimization problem of the knowledge graph relationship. The optimized objective function of the knowledge graph relationship is constructed by the improved ant colony algorithm and solved. The optimization of the knowledge graph relationship is realized.

Based on the framework semantic theory, this method constructs a semantic role analysis model and a fine-

* Corresponding Author

grained classification dictionary, and optimizes the knowledge mapping relationship by online comments on semantic annotation. However, the information obtained by this method is incomplete and has the problem of low knowledge coverage.

To sum up, an improved ant colony algorithm based knowledge mapping optimization method is proposed

(1) Information is extracted by cyclic network.

(2) The obtained information is used to construct the knowledge mapping relationship and optimize the objective function.

(3) The improved ant colony algorithm is used to solve the optimization objective function of knowledge mapping relationship to realize the optimization of knowledge mapping relationship.

(4) Experiments and discussions show the effectiveness of the method based on the improved ant colony algorithm through average accuracy, knowledge accuracy and knowledge coverage.

(5) Conclusion.

2 Information Extraction Algorithm Based on Cyclic Network

Let l be the total number of web pages, and each page is divided into n blocks. The maximum length of the content in the block is m. According to the mapping function from (l, n, m) to (l, n, 1), the information of people in the webpage is extracted, and the result function G is used to describe it. The continuous sequence vectors are input into the neural network through the cyclic neural network to realize the in-depth analysis of the correlation effect between the input vectors [9-10]. LSTM can increase the number of layers by setting memory gate in the recurrent neural network without gradient vanishing problem. In the first layer network processing block, the text sequence vector is calculated and (l, n, m) is used instead of (l, n, k). In the second layer network, the vector between the sequence blocks is calculated, and the relationship between the information in the block can be judged by the output (l, n, 1).

Fig. 1 shows the network structure using RNN to deal with the sequence prediction question. Let (x_1, …, x_n) represent the prediction vector to be input, where $x_i < IR^k$. In the same RNN unit, the prediction vector is input from x_1 in sequence. Since there is no preamble input, the prediction vector x_1 belongs to the direct input zero vector [11], and the output results of Y_1 to Y_n can be obtained through RNN. Through the above analysis, both x_i and $Y_{i\text{-}1}$ will affect the output Y_i of x_i.

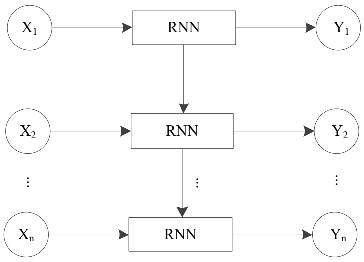

Fig. 1. RNN network structure

The internal structure of LSTM is shown in Fig. 2.

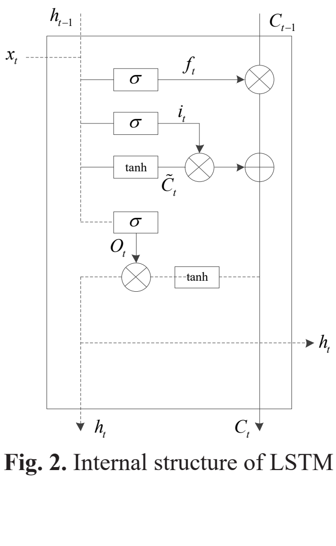

Fig. 2. Internal structure of LSTM

The memory ability of LSTM can be reflected by the implementation part, so LSTM is better than other RNN structures in sequence prediction problem of multiple deep learning [12-13]. Both C_{t-1} and h_{t-1} in the figure represent the output of the preorder calculation and exist in the calculation unit of LSTM. x_t represents the t-th input vector. When the value of t is 1, C_0 and h_0 are both zero vectors. tanh represents the arccosine function and the corresponding output is [-1,1]; *sigmoid* represents the activation function and the corresponding output is [0,1]. The internal memory part of LSTM is the implementation part of correlation analysis of different memory layers C_{t-1} and C_t. h_t is the input vector corresponding to node x_{t+1} and the output vector of current vector x_t. The following process is the basic calculation process of LSTM:

(1) The new vector x'_t is obtained from the current input vector x_t and the output vector h_{t-1} corresponding to the previous node. The expression is as follows:

$$x'_t = [h_{t-1}, x_t] \tag{1}$$

The output f is calculated by the *sigmoid* function. The *sigmoid* function usually takes value in the interval [0,1], and the output f_t can be regarded as the threshold value. In LSTM, part of its structure is adjusted by the input x'_t [14-15].

(2) Input x'_t is processed by *sigmoid* function and tanh function to generate i_t and C'_t. The extent of C'$_t$ added to the memory layer can be controlled by i_t, and the output of memory layer can be calculated by C'_t and $C_{t-1} \times C_{t-1} \times f_t$ [16].

(3) The output h_t is usually transformed by the activation layer, and the corresponding degree of the output of O_t to h_t is controlled by C_t.

$$f_t = \sigma[W_f \times [h_{t-1}, x_t] + b_f] \tag{2}$$

$$i_t = \sigma[W_i \times [h_{t-1}, x_t] + b_i] \tag{3}$$

$$\tilde{C}_t = tanh\ [W_c \times [h_{t-1}, x_t] + b_c] \tag{4}$$

In the formula, W_* and b_* can be optimized through the training process and are the parameters of the activation function. i_t can control the value retained in memory; f_t can control the degree of memory retention; i_t and f_t will affect C_t. LSTM can store the memory memory in a long sequence through C_t. The calculation formula of C_t is as follows:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{5}$$

h_t is calculated by using tanh activation function of C_t and controlled by O_t. O_t can be obtained by *sigmoid* function as follows:

$$O_t = \sigma[W_o \times [h_{t-1}, x_t] + b_o] \tag{6}$$

$$h_t = O_t * tanh(C_t) \tag{7}$$

The network calculation diagram of information extraction is shown in Fig. 3, which mainly includes output layer, word vector layer, bidirectional LSTM layer and sentence meaning layer [17-18].

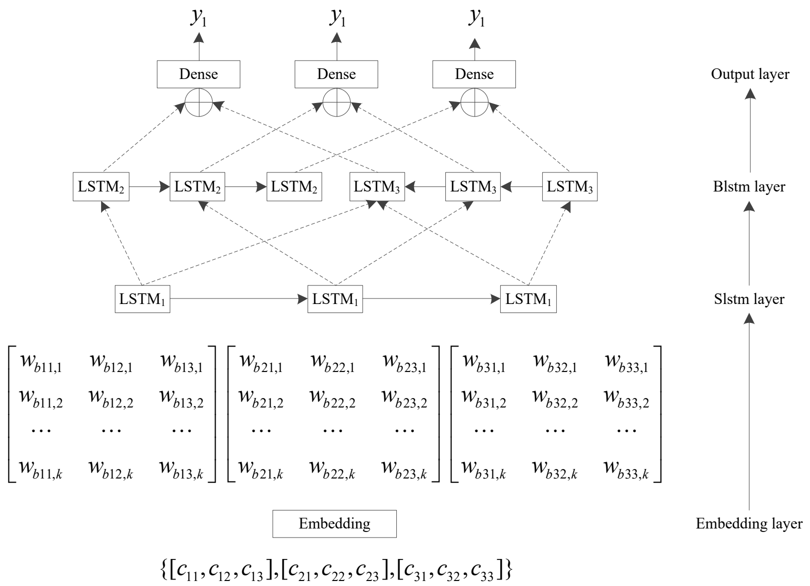

Fig. 3. Network calculation diagram of information extraction

3 Optimization Method of Knowledge Mapping Relationship

3.1 Constructing Optimization Model of Knowledge Mapping Relationship

In this paper, the obtained user information is encoded as constraint equation, and SGP question is used to replace the optimization question of knowledge mapping relationship. Generally, SGP consists of two parts: constraint equation and objective function [19].

Let $x_{i,j}$ represent the weight value of the edge between node i and node j, and the corresponding edge weight value $w(i,j)$ of the edge before optimization in the knowledge map is the initialization value of the variable $x_{i,j}$.

Let v_{a*} represent the best answer node; v_q represent other answer nodes, and the similarity value between them should be higher than that of other answers in the answer sequence and question node [20]. The expression of the constraint equation is as follows:

$$s.t.\begin{cases} S(v_q, v_{a*}) > S(v_q, v_{a_1}) \\ S(v_q, v_{a*}) > S(v_q, v_{a_2}) \\ \vdots \\ S(v_q, v_{a*}) > S(v_q, v_{a_{k-1}}) \end{cases} \tag{8}$$

The standard form of SGP question is used to describe the inequality in the constraint equation as follows:

$$s.t.\begin{cases} \sum_{z:v_q \to v_{a_1}} P[z]c(1-c)^{|z|} - \sum_{z:v_q \to v_{a*}} P[z]c(1-c)^{|z|} < 0 \\ \cdots \\ \sum_{z:v_q \to v_{a_{k-1}}} P[z]c(1-c)^{|z|} - \sum_{z:v_q \to v_{a*}} P[z]c(1-c)^{|z|} < 0 \end{cases} \tag{9}$$

In this paper, the objective function of SGP question is replaced by the total variable of minimizing edge weight.

The total change amount corresponding to the edge weight describes the Euclidean distance between the changed weights in the optimized change set X^* and the original variable set X, which is $d(X, X^*)$ [21]. The weights of entity node i and entity node j in set X and set X^* are defined as $x_{i,j}$ and $x^*_{i,j}$ respectively. The Euclidean distance $d(X, X^*)$ can be calculated as follows:

$$d(X,X^*) = \sum\nolimits_{x_{i,j}\in X, x^*_{i,j}\in X^*} (x^*_{i,j} - x_{i,j})^2 \quad \textbf{(10)}$$

Let $A_k^{'}$ represent the reordered answer sequence, which exists in the positive user feedback, and the best answer v_{a1} remains in the first place in the answer sequence [22]. Through the above analysis, the constraint equation of encoding is set as follows:

$$s.t.\begin{cases} \sum\nolimits_{z:v_q\to v_{a2}} P[z]c(1-c)^{|z|} - \sum\nolimits_{z:v_q\to v_{a1}} P[z]c(1-c)^{|z|} < 0 \\ \sum\nolimits_{z:v_q\to v_{a_{k-1}}} P[z]c(1-c)^{|z|} - \sum\nolimits_{z:v_q\to v_{a1}} P[z]c(1-c)^{|z|} < 0 \end{cases} \quad \textbf{(11)}$$

Let $t_p \in T_p$ represent positive user feedback; $t_n \in T_n$ represent negative feedback; $v_{q_{t_n}}$ and $v_{q_{t_p}}$ represent positive and negative correlation coefficients of t_p and t_n respectively. The comprehensive constraint equation is obtained as follows:

$$\begin{cases} \forall t_n \in T_n, \forall v_{a_n} \in \{\dfrac{A(v_{q_{t_n}})}{a^*_{v_{q_{t_n}}}}\} \\ \forall t_p \in T_p, \forall v_{a_p} \in \{\dfrac{A(v_{q_{t_n}})}{a_{1_{q_{t_n}}}}\} \\ s.t.\begin{cases} S(v_{q_{t_n}}, a^*_{v_{q_{t_n}}}) > S(v_{q_{t_n}}, v_{a_n}) \\ S(v_{q_{t_n}}, a_{1_{q_{t_p}}}) > S(v_{q_{t_p}}, v_{a_p}) \end{cases} \end{cases} \quad \textbf{(12)}$$

In the formula, $A(v_{q_{t_n}})$ represents the k optimal answers returned for $v_{q_{t_n}}$ and $v_{q_{t_p}}$, and is also an ordered queue generated by the system; $a^*_{v_{q_{t_n}}}$ represents the best answer corresponding to question $v_{q_{t_n}}$; $a_{1_{q_{t_n}}}$ represents the best answer corresponding to question $v_{q_{t_p}}$.

Inspired by multi-objective optimization and goal programming, the deviation variable is introduced into the original constraint equation of SGP question as follows:

$$\begin{cases} \forall t_n \in T_n, \forall v_{a_n} \in \{\dfrac{A(v_{q_{t_n}})}{a^*_{v_{q_{t_n}}}}\} \\ \forall t_p \in T_p, \forall v_{a_p} \in \{\dfrac{A(v_{q_{t_n}})}{a_{1_{q_{t_n}}}}\} \\ s.t.\begin{cases} S(v_{q_{t_n}}, v_{a_n}) - S(v_{q_{t_n}}, a^*_{v_{q_{t_n}}}) - d_{x_n} < 0 \\ S(v_{q_{t_n}}, v_{a_p}) - S(v_{q_{t_p}}, a_{1_{q_{t_n}}}) - d_{x_p} < 0 \end{cases} \end{cases} \quad \textbf{(13)}$$

Where d_{x_n} and d_{x_p} represent the deviation variables in the constraint equation.

The concept of step function $F(d_{x_i})$ is introduced to model information as follows:

$$F(d_{x_i})=\begin{cases}1 & d_{x_i}>0\\ 0 & d_{x_i}\le 0\end{cases} \tag{14}$$

In this paper, the *Sigmoid* function is used to approximate the step function $F(d_{x_i})$.

$$L(d_{x_i})=\frac{1}{1+e^{-wd_{x_i}}} \tag{15}$$

Redefine the objective function as follows:

$$\sum\nolimits_{d_{x_i}\in D}\left(\frac{1}{1+e^{-wd_{x_i}}}\right) \tag{16}$$

By fusing the above two objective functions, the objective function F of knowledge mapping relationship optimization is obtained as follows:

$$F=\lambda_1\times\sum_{x_{i,j}\in X,x_{i,j}^*\in X^*}(x_{i,j}^*-x_{i,j})^2+\lambda_2\times\sum\nolimits_{d_{x_i}\in D}\left(\frac{1}{1+e^{-wd_{x_i}}}\right) \tag{17}$$

3.2 Optimization of Knowledge Map Relationship based on Improved Ant Colony Algorithm

In this paper, the improved ant colony algorithm is used to solve the optimization objective function to realize the optimization of knowledge mapping relationship.

Path construction

The strategy of combining random selection and deterministic selection is adopted: ant k introduces a new constant $q_0 \in [0,1]$ before choosing the path, and ant k selects the path j by the following formula:

$$j=\begin{cases}\arg\max\limits_{j\in allowed,k}[\tau_{ij}^{\alpha}(t)\times\eta_{ij}^{\beta}(t)], q<q_0\\ p_{ij}^k=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\times\eta_{ij}^{\beta}(t)}{\sum_{s\in allowed_k}\tau_{is}^{\alpha}(t)\times\eta_{is}^{\beta}(t)} & j\in allowed_k\\ 0 & otherwise\end{cases}, q\ge q_0\end{cases} \tag{18}$$

Pheromone update

a. Global information update

After the ants complete the traversal, the complete path is established, and only the optimal ants are allowed to release pheromones [23]. The rules of global information update are as follows:

$$\tau_{ij}=(1-\rho)\tau_{ij}+\rho\Delta\tau_{ij}^{gb},(i,j)\in T^{gb} \tag{19}$$

$$\Delta\tau_{ij}=\frac{Q}{L_{gb}} \tag{20}$$

Where ρ is the Volatilization Coefficient of pheromone, L_{gb} is the length of the optimal path T^{gb}, and Q is a constant.

b. Dynamic local information update

According to the local update rule of the following formula, the edge is updated when the ant moves from *i* to *j*.

$$\tau_{ij} = (1-\rho)\tau_{ij} + \rho\Delta\tau_{ij} \quad \textbf{(21)}$$

$$\Delta\tau_{ij} = \frac{Q'}{L_{tot}} \quad \textbf{(22)}$$

$$L_{tot} = \sum_{l=1}^{w} d_l^1 + \sum_{l=1}^{w} d_l^2 + \cdots + \sum_{l=1}^{w} d_l^m \quad \textbf{(23)}$$

$$d_l \in \{d_{ij}\}, l = 1,2,\cdots,w;\ i,j = 1,2,\cdots,n \quad \textbf{(24)}$$

Where d_l^k represents the length of the edge that ant *k* has passed; *w* represents the number of edges that ant *k* has visited in this iteration; and L_{tot} represents the sum of the lengths of edges that all ants have passed in this iteration.

The implementation process of knowledge mapping relationship optimization method based on improved ant colony algorithm is as follows:

1) Initialize and set the initial parameters.

2) Place *m* ants randomly in each node, and record the position in the corresponding tabu table $tabu_k$.

3) Determine the next access node *j* of ant *k* by formula (18) and record it in the tabu table $tabu_k$. The local pheromone is updated by the following formula:

$$\tau(i,j) \leftarrow (1-\zeta)\times\tau(i,j) + \zeta\times\tau_0 \quad \textbf{(25)}$$

When the ant *k* forms a loop, it stops updating the local pheromone [24].

4) Calculate the length L_k of the path and record the current optimal value in *L_best*.

5) Carry out coding, crossover and mutation to process part of the sub optimal solution and optimal solution, and update the path.

6) Set the number of iterations *Ncmax*. If the number of iterations is satisfied, enter step 8), if not, enter step 7) [25].

7) The global pheromone matrix is updated by the following formula:

$$\Delta\tau(i,j) = \begin{cases} (L_{gb})^{-1} \\ 0 \end{cases} \quad \textbf{(26)}$$

8) Output the optimal solution.

The process of using improved ant colony algorithm to solve the optimization objective function of knowledge mapping relationship is as Fig. 4.

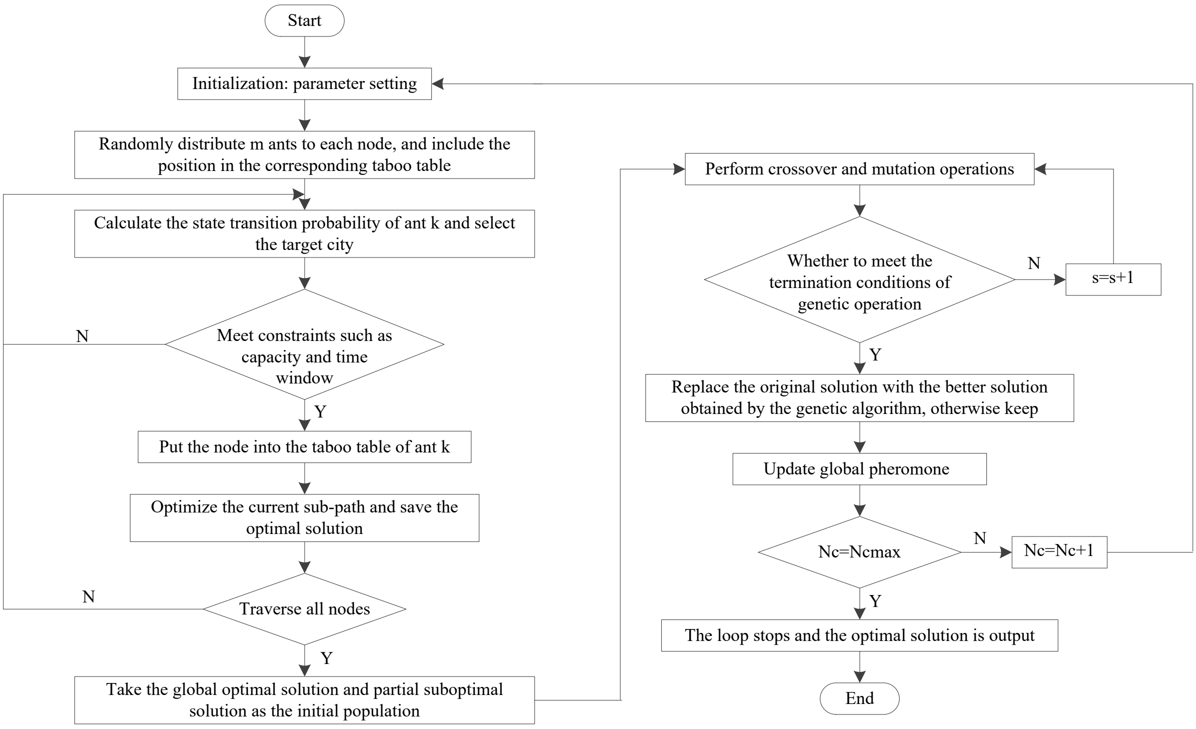

Fig. 4. Solution flow of objective function

4 Experiment and Discussion

In order to verify the effectiveness of the method of knowledge mapping relationship optimization based on the improved ant colony algorithm, it needs to carry out experimental test, and the operating system of this test is Windows 10. Taking the average accuracy, knowledge accuracy and knowledge coverage as test indexes, the knowledge mapping relationship optimization method based on improved ant colony algorithm (Method 1), the knowledge mapping relationship optimization method based on weighted ternary closure (Method 2), the knowledge mapping relationship optimization method based on 2-mode co-occurrence matrix (Method 3) and the knowledge mapping relationship optimization method based on comment semantic analysis are used respectively to test.

(1) Average accuracy

The average accuracy *AP* is used to evaluate the optimization effect of knowledge mapping relationship, and the calculation formula is as follows:

$$AP = \frac{1}{|\Omega_u|} \sum_{i \in \Omega_u} \frac{\sum_{j \in \Omega_u} h(p_{uj} < p_{ui}) + 1}{p_{ui}} \quad \textbf{(27)}$$

Where Ω_u is the result set; $h(p_{uj} < p_{ui})$ is the number of p_{uj} before p_{ui} in the sorted list; p_{ui} is the position of a result in the sorted list. The mean value of average precision *AP* is in the interval [0,10]. The higher the average accuracy *AP* is, the better the optimization effect of the method is.

The average accuracy *AP* of Method 1, Method 2, Method 3 and Method 4 is as Fig. 5.

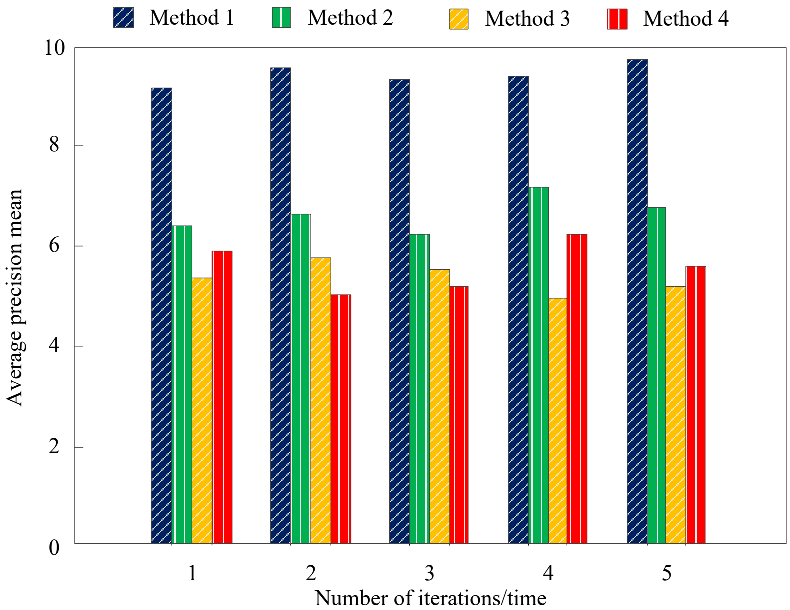

Fig. 5. Average accuracy of different methods

By analyzing the data in Fig. 5, it can be seen that the average accuracy of Method 1 is higher than that of Method 2, Method 3 and Method 4 in multiple iterations, because the method in this paper obtains high-precision information through the cyclic network, optimizes the knowledge mapping relationship by using the high-precision information, and improves the average accuracy mean value of the method, so it has good optimization effect.

(2) Knowledge accuracy

The comparison results of knowledge accuracy of the four methods are as Fig. 6.

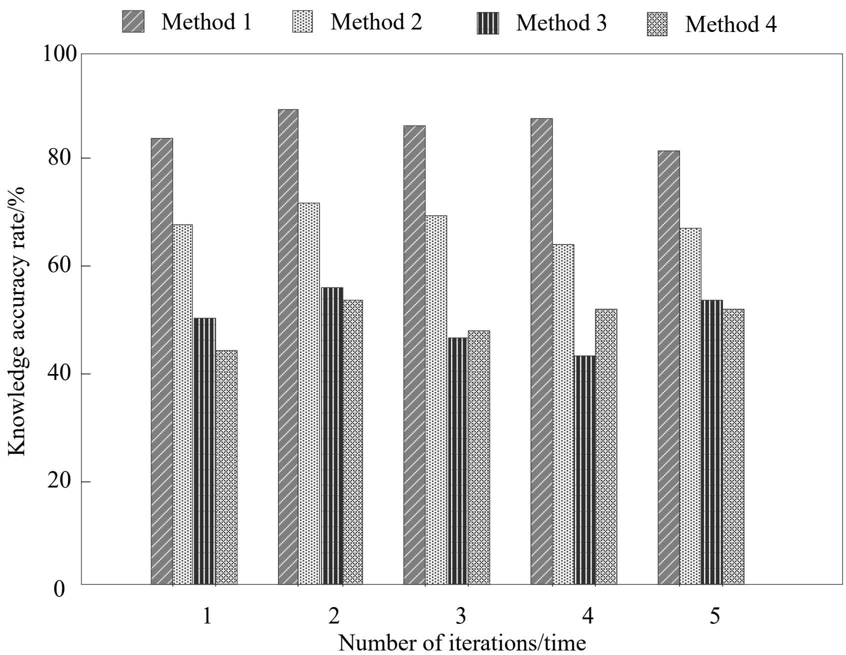

Fig. 6. Knowledge accuracy of different methods

It can be seen from Fig. 6 that the accuracy of knowledge obtained in multiple iterations of Method 1 is higher than that of Method 2, Method 3 and Method 4, because the deviation variable is introduced into the original constraint equation of SGP question to improve the knowledge accuracy.

(3) Knowledge coverage

The comparison results of the four methods are as Fig. 7.

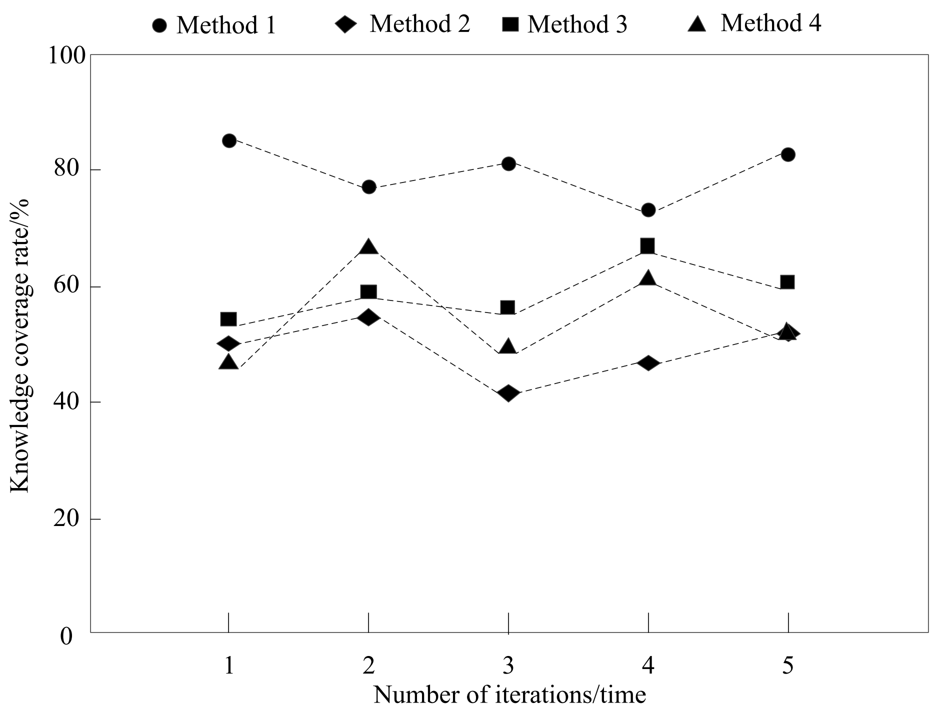

Fig. 7. Knowledge coverage of different methods

Analysis of the data in Fig. 7 shows that the knowledge coverage rate of Method 1 is higher than that of Method 2, Method 3 and Method 4, because the method in this paper obtains high-precision information through cyclic network, uses the obtained information to construct the optimization objective function of knowledge mapping relationship, and uses the improved genetic algorithm to solve the optimization objective function of knowledge mapping relationship, so as to improve the knowledge coverage rate.

5 Conclusions

In recent years, knowledge mapping plays a very important role in many fields, and it is of great significance to optimize the relationship between knowledge maps. In order to solve the problems of low average accuracy, low knowledge accuracy and low knowledge coverage in current knowledge mapping optimization methods, an optimization method of knowledge mapping relationship based on improved ant colony algorithm is proposed. High precision data are obtained through the circular network, and the optimization model of knowledge mapping relationship is constructed. Through solving the model, the optimization of knowledge mapping relationship is realized. The effectiveness of the method is verified by experiments, which can lay a solid foundation for the application and development of knowledge mapping.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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