Representation and Construction of Discipline Knowledge Systems Based on Cognitive Sequence Relationship

https://doi.org/10.3991/ijet.v17i24.35947

Xiaokun Xiong(✉)
Department of Economics and Trade, Shijiazhuang University of Applied Technology, Shijiazhuang, China
2005010213@sjzpt.edu.cn

Abstract—For students, it's an important but difficult thing to form a discipline knowledge system based on the sequence of cognition, and they would need teachers' assistance for that. Therefore, how to arrange the scattered knowledge points in a sequence that conforms to the law of cognition, construct a complete discipline knowledge system, and help students attain, familiarize, absorb, and internalize the new knowledge in a scientific way are urgent issues to be solved for educationalists. To attempt to solve these questions, in a research background that the smart education has been applied and promoted widely, this paper took the finance discipline as an example to study the representation and construction of discipline knowledge system based on cognitive sequence. At first, this paper took a Back Propagation Neural Network (BPNN) based on complex rules as the Cognitive Sequence Relationship (CSR) construction algorithm for correcting contradictions in the CSR of knowledge points in the finance discipline knowledge system, gave the structure of the model for inferring the CSR of knowledge points in the finance discipline knowledge system, and adjusted the existing logical inference rules. Then, when building the CSR for the target discipline, this paper introduced a momentum factor σ into the network model to solve problems such as network oscillation and slow convergence. After that, the established finance discipline knowledge system was corrected to ensure that the old and new knowledge in the system could keep balance, and a fragment in the finance discipline knowledge dataset was introduced as an example. At last, the effectiveness of the proposed algorithm was verified by the experimental results.

Keywords—cognitive sequence relationship (CSR), discipline knowledge system, logic inference, back propagation neural network (BPNN)

1 Introduction

Compared with the teaching method of introducing the knowledge according to a linear sequence based on textbooks, designing the teaching process according to the laws of the knowledge points is more scientific [1–3]. The teaching process refers to the procedures of helping students to build and update their knowledge structure, namely to connect new knowledge to old knowledge and the transfer between the two [4, 5]. Storing knowledge points as fragments and building discipline knowledge system based on the CSR of knowledge can help students better absorb and master the knowledge, thereby learning in an efficient and truly meaningful way.

As smart education has been widely applied and promoted in recent years, students are free from the restrictions of the learning time and learning space, fundamental changes have occurred to the original experience and knowledge structure contained in the selectable learning resources and their transmission patterns, also, the knowledge content tends to be more and more complicated [6–11]. In this context, for students, it's an important but difficult thing to form a discipline knowledge system based on the sequence of cognition, and they would need teachers' assistance for that. Therefore, how to arrange the scattered knowledge points in a sequence that conforms to the law of cognition, construct a complete discipline knowledge system, and help students attain, familiarize, absorb, and internalize the new knowledge in a scientific way are urgent issues to be solved for educationalists [12–22].

Dhuieb et al. [23] gave a comprehensive explanation to an approach regarding knowledge extraction and structuring in the factories; the paper introduced the research background and explained different constraints that need to be considered during the process of modeling. Chen [24] proposed that knowledge system is a new theoretical research field in the humanities and social sciences, the author analyzed the influence of Western knowledge and its knowledge system on China, discussed the evolution of knowledge concept in the history of thought and the anxiety consciousness of literature and art research, and proposed a strategy of value reconstruction in knowledge production and literature knowledge construction. Schoeller et al. [25] successfully replicated a study on aesthetic emotions in different socio-cultural environment, in the paper, the authors reviewed literatures about both positive and negative psychogenic shivering and related this phenomenon to the instinct of knowledge, and they gave a plausible explanation for the relation between temperature and cognition in humans.

After carefully reviewing the related literatures, we found that current studies on the cognitive sequence of knowledge generally ignore to combine with the specific disciplines. Establishing discipline knowledge systems based on cognitive sequence is to complete the construction of an individualized knowledge structure for students based on their knowledge cognition features and the course knowledge structure of each discipline. However, few of these studies have concerned about the teaching activities for students of different cognition features and levels, and it'll be of great research value to build discipline knowledge systems based on cognitive sequence. To this end, this paper took the finance discipline as the target discipline to study the representation and construction of discipline knowledge system based on cognitive sequence. In the second chapter, this paper took a BPNN based on complex rules as the CSR construction algorithm for correcting contradictions in the CSR of knowledge points in the finance discipline knowledge system, gave the structure of the model for inferring the CSR of knowledge points in the finance discipline knowledge system, and adjusted the existing logical inference rules. In the third chapter, this paper built CSR for knowledge points of the target discipline, and introduced a momentum factor σ into the network model to solve problems such as network oscillation and slow convergence. In the fourth chapter, the established finance discipline knowledge system was corrected to ensure that the old and new knowledge in the system could keep balance, and a fragment in the finance discipline knowledge dataset was introduced as an example. At last, the effectiveness of the proposed algorithm was verified by the experimental results.

2 Proposal of the CSR construction algorithm

To improve the efficiency of building CSR for the knowledge structure of the target discipline, this paper chose to use a cognition calculation-based CSR construction method, and defined an operator for correcting the contradictions in the CSR of knowledge points in the finance discipline knowledge system, that is, the result of CSR construction was taken as the correction target of the finance discipline knowledge system to optimize the connection form of nodes and edges in the knowledge system. Figure 1 gives the flow of correcting contradictions in the CSR of knowledge points.

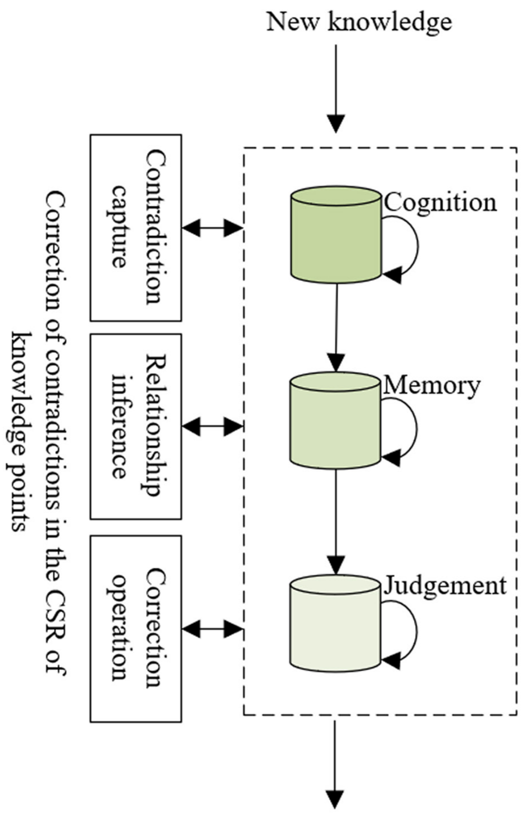

Fig. 1. Flow of correcting contradictions in the CSR of knowledge points

As the correction target of contradictions in the CSR of knowledge points in the knowledge system of the financial discipline, the construction of CSR requires corresponding relationship construction rules. This paper selected a BPNN based on complex rules as the algorithm for constructing CSR in the CSR contradiction correction of knowledge points in the finance discipline knowledge system, and it is a CSR construction method based on cognition calculation.

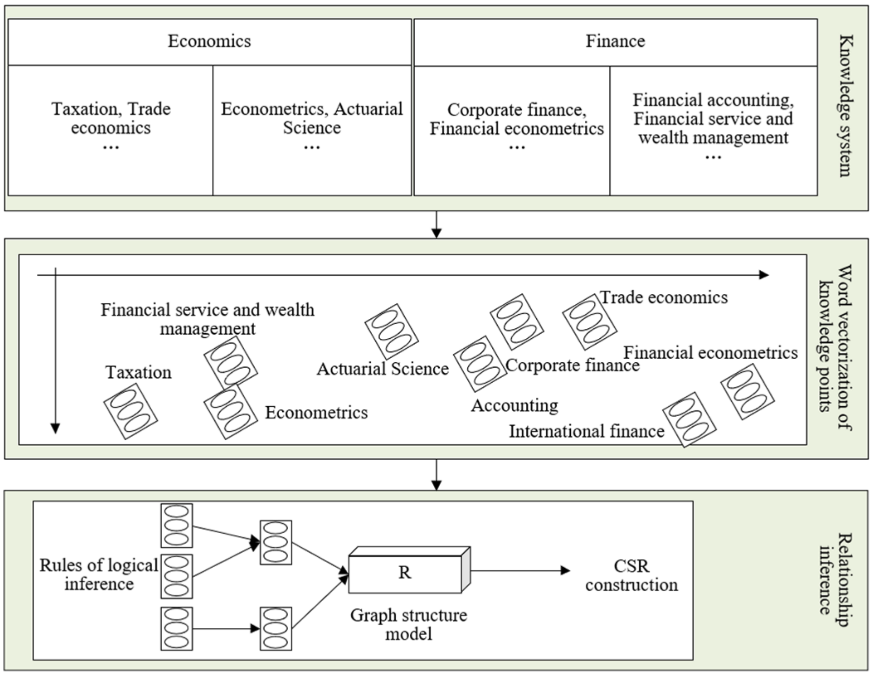

Fig. 2. Structure of the CSR inference model for knowledge points in the finance discipline knowledge system

Figure 2 shows the structure of the CSR inference model for knowledge points in the finance discipline knowledge system. The BPNN-based CSR construction algorithm can build CSR with highly accurate humanoid thinking, at first, it maps the logical inference rules of CSR into a neural network, and then builds the neural network and the CSR of the knowledge; after that, based on the logic inference rules and the mapping relationship of the neural network, the initial structure of the proposed BPNN could be determined (Figure 3).

In the logic inference rules of CSR construction, the intermediate nodes corresponding to intermediate conclusions satisfy a certain causal relationship, and their number determines the number of hidden layers in the neural network. The construction of the structure of the neural network requires that the lengths of the paths that constrain the nodes should be the same. If the path lengths of nodes are different, intermediate nodes need to be added. For this reason, this paper adjusted the existing logic inference rules as follows:

Rule 1: *If* $A \cap B$, *then* C; *if* $A \cup B$, *then* C; *if* $\neg A$, *then* C.

Based on Rule 1, map the three basic logic relationships of AND, OR, and NO into the neural network.

Rule 2: $X \cap Y \cap Z \cap O \cap P \cap Q \cap CCO \cap S \rightarrow B$.

If multiple logical relationships in Rule 2 co-exist, then intermediate conclusions need to be added for decomposition. The same below.

Rule 3: $X \cap Y \rightarrow X_1$, $Z \cap O \rightarrow Z_1$, $P \cap Q \rightarrow P_1$, $CCO \cap S \rightarrow CCO_1$.

Rule 4: $X_1 \cap Z_1 \cap P_1 \cap CCO_1 \rightarrow B$.
Rule 5: $X_1 \cap Z_1 \rightarrow c$, $P_1 \cap CCO_1 \rightarrow a$.
Rule 6: $C \cap A \rightarrow B$.

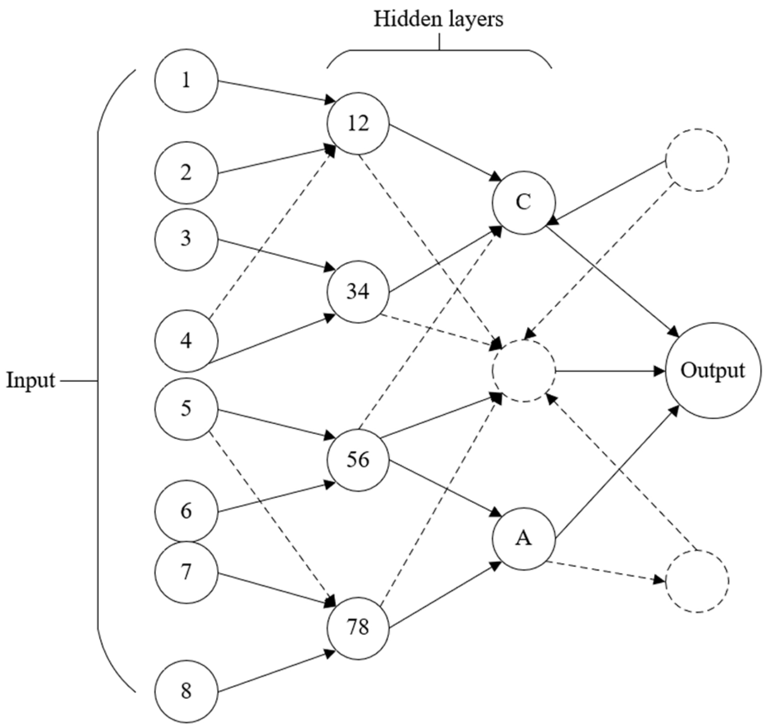

Fig. 3. The mapping neural network of logical inference rules

3 Training of the CSR construction model

If the BPNN algorithm based on complex rules is trained by the gradient descent method, it'll cause network oscillation, resulting in slow convergence. Therefore, when constructing the CSR of knowledge points in the finance discipline knowledge system, this paper introduced a momentum factor σ into the network model to solve these problems.

Before training the constructed network model, the notional words of knowledge points in the finance discipline knowledge system were subject to vectorization and weight assignment. For the vectorization of notional words of knowledge points, the *CBOW* strategy in *woCCOd2vec* was adopted, after the vectorization operation, the attained vector of each knowledge point in the finance discipline knowledge system was represented by $A = (A_1, A_2, A_3, \ldots, A_m)$.

Assuming: $b_e(l)$ represents the output value of output node *1*; $c_e(l)$ represents the expected value of output node *1*; *t* represents the dimensionality of the output variable; *n* represents the number of training samples, that is, *n* is the number of facts ($U_i > U_j$) and

(U_i>U_w); then, the CSRs between nodes U_i, U_j, and U_w were inferred, and a global error function shown as the formula below could be defined:

$$QW\{(U_i > U_j) \mid (U_i > U_w)\} = \frac{1}{2n}\sum_{l=1}^{n}\sum_{e=1}^{t}(c_e(l) - b_e(l))^2 \tag{1}$$

During the construction of CSR, due to the complicated relationships between knowledge points in the finance discipline knowledge system, the structure of the network model may be inconsistent. The training process of the model is elaborated below:

At first, the network model was initialized, namely the mapping between the logic inference rules and the network model was completed. Among the initialized parameters, m represents the number of input layer nodes; i represents the number of hidden layer nodes; n represents the number of output layer nodes; ξ_{if} represents the connection weight between input layer and hidden layer; ξ_{fe} represents the connection weight between hidden layer and output layer; φ_f represents the threshold value of each neuron in the hidden layer; φ_e represents the threshold value of each neuron in the output layer.

Assuming: $A'(l)$ represents the input vector of the l-th input sample; ΔQ_1 represents the weight adjustment coefficient, then based on the following formula, the weight value of the input vector of the input layer of the network model could be adjusted:

$$A'(l) = \Delta Q_1(A_1(l), \Delta Q_2 A_2(l), \Delta Q_3 A_3(l), \ldots, \Delta Q_m A_m(l)) \tag{2}$$

Assuming: f_{if} represents the input value of the hidden layer; f_{ef} represents the output value of the hidden layer; g represents the activation function; then the following formula calculates f_{if} and f_{ef}:

$$f_{if}(l) = \sum_{i=1}^{m}\xi_{if}a_i(l) - \phi_f,\ f = 1,2,\ldots,t \tag{3}$$

$$f_{ef}(l) = g(f_{if}(l)), f = 1,2,\ldots,t \tag{4}$$

Assuming: $\xi_e(l)$ represents the partial derivative of each neuron in the output layer; $\xi_f(l)$ represents the partial derivative of each neuron in the hidden layer; then, $\xi_e(l)$ could be calculated based on the actual output value and the expected value of the constructed network model; $\xi_f(l)$ could be calculated based on $\xi_e(l)$, ξ_{fe}, and f_e; and ξ_{if} and ξ_{fe} could be calculated based on $\xi_f(l)$ and $\xi_e(l)$.

$$\begin{cases} \Delta\xi_{if}(l) = -\lambda \dfrac{\partial o}{\partial \xi_{if}(l)} = -\lambda \dfrac{\partial o}{\partial \xi_{if}(l)} \dfrac{\partial \xi_{if}(l)}{\partial \xi_{if}} = \xi_f(l)a_i(l) \\ \xi_{if}^{M+1} = \xi_{if}^{M} + \sigma\xi_f(l)a_i(l) \end{cases} \tag{5}$$

$$\begin{cases} \Delta\xi_{fe}(l) = -\lambda \dfrac{\partial o}{\partial \xi_{fe}(l)} = -\lambda \dfrac{\partial o}{\partial \xi_{fe}(l)} \dfrac{\partial \xi_{fe}(l)}{\partial \xi_{fe}} = \xi_f(l)a_i(l) \\ \xi_{fe}^{M+1} = \xi_{fe}^{M} + \varepsilon\xi_f(l)a_i(l) \end{cases} \tag{6}$$

When the network error reaches the preset value or the number of network iterations reaches the maximum, the algorithm terminates, and the model outputs the correct CSR among U_i, U_j, and U_w.

4 Correction of the finance discipline knowledge system

For the CSR of knowledge points in the finance discipline knowledge system, the contradiction correction mainly includes the correction rules, the correction operator, and the correction form.

The correction of the finance discipline knowledge system is to ensure the balance between the new and the old knowledge in the system, this paper corrected the contradictions in the CSR of knowledge points in the system based on the graph model, which made it possible to quantify the contradiction correction process. The following are the constraints that the knowledge system of the finance discipline needs to meet before and after the contradiction correction:

(1) Assuming: *LH* represents the finance discipline knowledge system; *Z* represents the new knowledge points; if $LH*Z$ does not meet the node connectivity, then there is $Z \in Pf(LH*Z)$.
(2) If *LH* is coordinated, then $LH*Z$ is coordinated as well.
(3) Minimize the original information of *LH* and the correct the structure.

Assuming: → represents the deducing operation; ∩ represents the operation of taking the intersection; ψ represents the new knowledge set; *x* and *y* represent elements in the knowledge set; * represents the correction symbol. Then, based on the above constraints, it can be summarized that the contradiction correction operators of the CSR of knowledge points in the system need to meet these assumptions:

a) *If* $x \rightarrow y \| y \rightarrow z$, *then* $x \rightarrow z$;
b) *If* $x \rightarrow y$, *then* $x > y$;
c) For $\forall x$ and y, there are $x < x \cap y$, $y < x \cap y$;
d) $\psi \in LH*\psi$;
e) $LH*\psi \subseteq LH+\psi$;
f) If $\neg\psi \notin LH$, then $LH*\psi \subseteq LH+\psi$;
g) $LH*\psi$ is consistent unless ψ is contradictory.

The function of the correction operator is to correct the contradictory information in the CSR of the knowledge points based on the graph structure. Since a student' cognition of an unknown discipline is limited, the correctness of the correction of the finance discipline knowledge system has the local feature, so when the corrected graph structure is in an ideal balanced state, it's considered that the correction operation is successful.

Define: * represents the contradiction correction symbol in the knowledge system $LH = (Z, S, G)$; *h* represents the notional word attribute; $h::p$ represents that *h* is an attribute of notional word *p*; $lh = (z, s, g)$ represents the graph structure after correction; $g = (f, s, p)$ represents the notional word relationship in the graph structure after correction; $lh*Z$ represents the result after contradiction correction, then the specific correction operators can be defined as follows:

$CCO1$: If it satisfies $Z=p\notin f$ and $p\in f\subseteq lh$, then $lh*Z=lh-p\in f$;
$CCO2$: If it satisfies $Z=p\in f$ and $p_1\in P$ that makes $p_1\in p$ and $p_1\in f\subseteq lh$, then $lh*Z=lh+Z-p_1\in f$;
$CCO3$: If it satisfies $Z=p\in f$ and $f_1\in F$ that makes $p\in f_1$ and $f\in f_1\subseteq lh$, then $lh*Z=lh+Z-p\in f_1$;
$CCO4$: If it satisfies $Z=p\in f$ and $f_1\in P$ that makes $p_1\in p$ and $f\in p_1\subseteq lh$, then $lh*Z=lh+Z-f\in p_1$;
$CCO5$: If it satisfies $Z=p\in f$ and $f_1\in F$ that makes $f_1\in f$ and $p\in f_1\subseteq lh$, then $lh*Z=lh+Z-p\in f$;
$CCO6$: If it satisfies $Z=-(h::f)$ and $h::f\subseteq lh$, then $lh*Z=lh-h::l$;
$CCO7$: If it satisfies $Z=\neg(h::f)$ and $h::p\subseteq lh$, then $lh*Z=lh-h::p$;
$CCO8$: If it satisfies $Z=h::f$ and $p\in P$ that makes $h::p$ and $p\in f\subseteq lh$, then $lh*Z=lh+Z-h::p$;
$CCO9$: If it satisfies $Z=h::f$ and $f_1\in F$ that makes $h::p$ and $f\in f_1\subseteq lh$, then $lh*Z=lh+Z-h::f_1$;
$CCO10$: If it satisfies $p\in f$ and $Z=h::f$ that makes $p\notin f\subseteq lh$, then $lh*Z=lh+Z-p\in f$;
$CCO11$: If it satisfies $p\in f$ and $Z=h::f$ that makes $f\in p\subseteq lh$, then $lh*Z=lh+Z-p\in f$;
$CCO12$: If it satisfies $p\in f$, $h::f$, and $Z=h_1::f$ that makes $p\notin f\subseteq lh$, then $lh*Z=lh+Z-p\in f$;
$CCO13$: If it satisfies $p\in f$, $h::p$, and $Z=h_1::p$ that makes $p\notin f\subseteq lh$, then $lh*Z=lh+Z-p\in f$;
$CCO14$: If it satisfies $p\in f$, $h::f$, and $Z=h_1::f$ that makes $\neg(h::f)\subseteq lh$, then $lh*Z=lh+Z-p\in f$;
$CCO15$: If it satisfies $p\in f$, $h::p$, and $Z=h_1::p$ that makes $\neg(h::p)\subseteq lh$, then $lh*Z=lh+Z-p\in f$;
$CCO16$: If it satisfies $Z=c[f\leftarrow p]$ and $\psi=c[f\rightarrow p_1]$, $\lambda=c[\textit{the maximum num}\leftarrow 1]$, $p_1\neq p$, and ψ, $\lambda\subseteq lh$, then $lh*Z=lh+Z-\psi$;
$CCO17$: Assuming DN_{max} represents the maximum number of measurements, if it satisfies $Z=c[f\leftarrow p]$ and $\psi=c[f\leftarrow\{p_1, p_2, \ldots, p_m\}]$, $c[DN_{max}\leftarrow l]$, $p_1\neq p$, and ψ, $\lambda\subseteq lh$, then $lh*Z=lh+Z-\psi-\lambda+c[DN_{max}\leftarrow m+1]$.
$CCO18$: Assuming M_{max} represents the maximum amount, if it satisfies $Z=c[f\leftarrow p]$ and $\psi=c[M_{max}\leftarrow l]$, $p>l$, and $\psi\subseteq lh$, then $lh*Z=lh+Z-\psi+c[M_{max}\leftarrow p]$.
$CCO19$: If it satisfies $Z=c[f*p]$ and $\psi=c[M_{ma}\leftarrow l]$, $p<l$ and $\psi\subseteq lh$, then $lh*Z=lh+Z-\psi+c[M_{ma}\leftarrow p]$.
$CCO20$: Assuming RA represents the rang, if it satisfies $Z=c[f*p]$ and $\psi=c[RA\leftarrow l]$, $p\notin l$ and $\psi\subseteq lh$, then $lh*Z=lh$.

This paper took a fragment in the knowledge dataset of the finance discipline as an example to introduce the constructed 20 correction operators. Assuming: a certain knowledge point *Mid* in the dataset is */y/*11***hgus***, wherein the fact FA = (*/y/*11***hgus***, *Finance Act*, *Glass-Steagall Act*), then the logical inference rules in the dataset were mapped into the BPNN with a three-layer structure, after the CSR of the knowledge points was subject to the inference of the network model, then this certain fact in the knowledge system could be attained as:

$$FA_1 = (/y/11\boldsymbol{hgus}, \textit{Finance Act}, \textit{Dodd of Finance Act}) \tag{7}$$

According to above formula, FA_1 and FA were different. The fact C_1FA_1 might be inferred from facts (/*y*/11*hgus*, *Financial Regulations*, *Administrative measures for Payment services of non-financial institutions*) and (*Administrative measures for Payment services of non-financial institutions*, *Online Finance*, *Glass-Steagall Act*). The contradiction that the attribute "Financial Technology" of the notional word "/y/11hgus" is satisfied may be due to the satisfaction of the fact $FA2$ = (Transactions, *Financial Technology*, *Internet*) and the fact (*Transactions*, *Finance Act*, *Glass-Steagall Act*). Therefore, when correcting the knowledge system of the finance discipline, according to the constraints that the finance discipline knowledge system needs to meet before and after contradiction correction, the contradiction was corrected based on $CCO1$, and in the corrected graph structure, FA_2 should be added and FA_1 should be deleted.

In this paper, the finance discipline knowledge system could be regarded as a graph structure model constituted by nodes and edges, therefore it is significantly extensible. When there're changes in the CSR of students due to individual difference, then the possible cost should be minimized when correcting and updating the finance discipline knowledge system. The five changes conforming to the correction constraints were summarized as follows:

(1) When it's decided to add a new node to the finance discipline knowledge system, at first, a relationship should be formed between the new node and a known node in the knowledge system that has a certain correlation to it. The relationship between the new node and the known node can be obtained by the CSR construction method given in Chapter 2.
(2) When it's decided to delete an old node from the finance discipline knowledge system, at first, the edges connecting to this node should be sorted out, the deleting operation needs to delete the node and all the edges connecting to it at the same time.
(3) When it's decided to add a new relationship between two nodes in the finance discipline knowledge system, the serial numbers of the nodes should be retrieved at first and then connecting edge is added.
(4) When it's decided to correct an erroneous relationship between two nodes in the finance discipline knowledge system, at first, the edge between the two nodes should be found by retrieving the serial numbers of the nodes, and then the error edge is deleted.
(5) When it's decided to correct the attribute of the relationship between two nodes in the finance discipline knowledge system, at first, the edge between the two nodes should be found by retrieving the serial numbers of the nodes, and then the attribute of the connecting edge is corrected.

5 Experimental results and analysis

By identifying the notional words of the names of core course in the finance discipline knowledge system and constructing the CSR, a simple knowledge system could be preliminarily constructed.

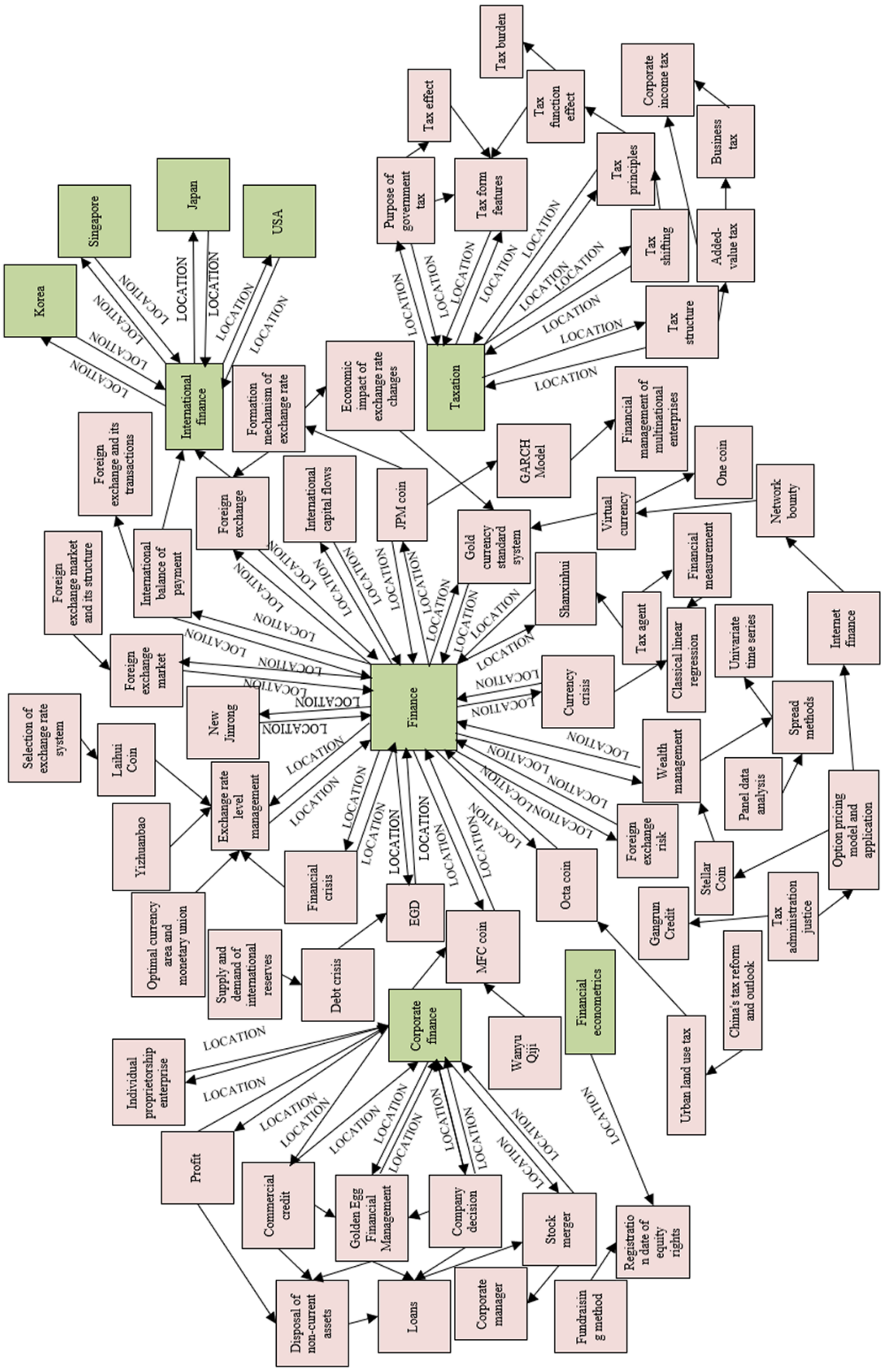

Fig. 4. An example of CSR extraction of knowledge points

Figure 4 gives an example of extracting the CSR of knowledge points. The notional words of courses including corporate finance, financial econometrics, taxation, and international finance and the relationships among related knowledge points were extracted, the relationships can be divided into two types: one-to-one and one-to-many, specifically, it includes the inclusion relationship of currency, wealth management, foreign exchange, and tax system, etc., as well as the information of their specific positions, for example, the inclusion relationship of international finance contains position notional words such as Korea, Singapore, Japan, and USA, etc.

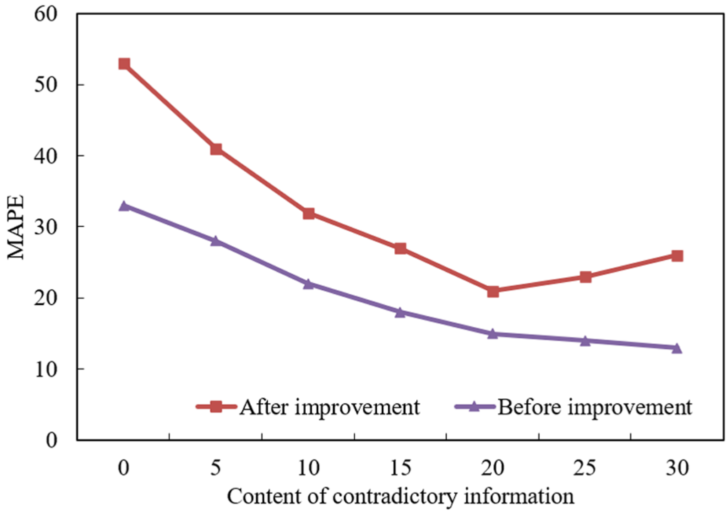

Fig. 5. Comparison of CSR inference errors of knowledge points

To verify the effectiveness of using the complex rules-based BPNN algorithm in constructing the CSR of knowledge points in the knowledge system of finance discipline. Figure 5 compares the CSR inference errors of knowledge points before and after improved by the conventional neural network. As can be seen from the figure, when the contents of the contradictory information in the CSR of knowledge points in the finance discipline knowledge system were the same, before and after the improvement of neural network, the difference of MAPE was within [8.5%, 12.7%], indicating that the effect of the BPNN algorithm in constructing the CSR of knowledge points in the knowledge system of finance discipline was stable. For this complex rules-based BPNN, with the increase of the content of contradictory information in the CSR of knowledge points, its MAPE was lower than the conventional BPNN, which had verified that the proposed algorithm performed better in terms of constructing the CSR of knowledge points.

For graph structure models, a greater depth means more nodes, therefore, when correcting the contradictions in the CSR of knowledge points in the finance discipline knowledge system, the algorithm's efficiency and performance were largely affected by the depth of the graph structure model. Figure 6 shows the system correction precision under the conditions of different depths of graph structure models. As can be seen from the figure, with the increase of model depth and contradictory information content, the CSR correction precision showed an improvement.

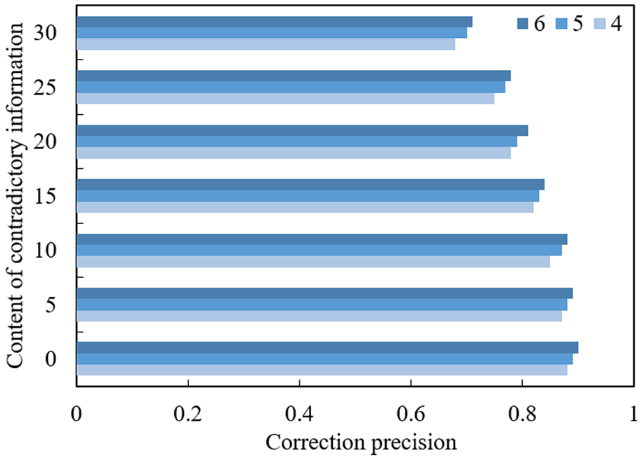

Fig. 6. System correction precision of graph structure models with different depths

The ultimate purpose of this paper is to verify the effectiveness of the proposed BPNN and its precision in correcting the contradictions in the CSR of knowledge points in the finance discipline knowledge system. The three reference models adopted for comparison were *NTN*, *R-GCN* and *IRN*, and the results of three evaluation indicators of precision, recall rate, and *F1* value suggested that the proposed algorithm exhibited better performance, comparison results of the contradiction correction precision are given in Table 1.

Table 1. Comparison results of contradiction correction precision

	Pre	***Recall***	***F1***
NTN	75.29%	75.26%	75.42%
R-GCN	81.35%	71.49%	82.63%
IRN	86.29%	82.35%	81.52%
The proposed model	84.51%	86.93%	87.38%

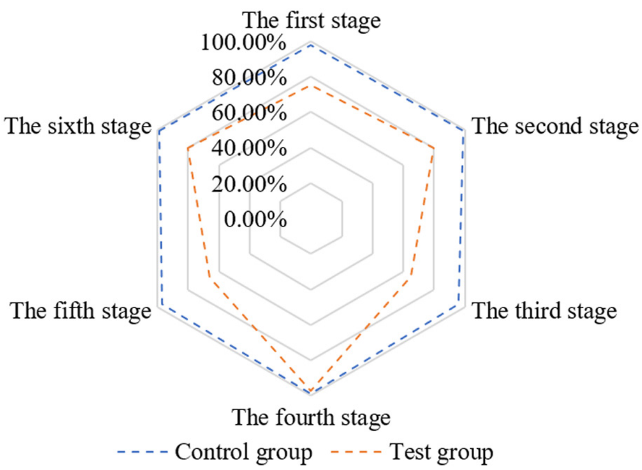

Fig. 7. Comparison of cognition efficiency

To verify the positive influence of the CSR of discipline knowledge system on students' cognition efficiency and learning effect, this study set a comparative experiment, and the finance major students participated in the experiment were divided into a control group and a test group, during the experiment period, a learning cycle was divided into 6 learning stages. Figure 7 gives the comparison of cognition efficiency. As can be seen from the figure, there're certain differences in the cognition efficiency of students in the control group and the test group, and the evaluation values of the cognition efficiency of test group students were higher than those of control group students. Table 2 gives the statistical results of the learning effect of the test group and the control group. According to the figure, there're certain differences in the test scores between control group students and test group students, and the test scores of test group students were higher than those of control group students.

Table 2. Statistical results of learning effect of test and control group students

		n	*Min*	*Max*	*M*	*SD*
Pre-test	Test group	45	15	78	42.69	13.629
	Control group	41	22	72	49.05	11.547
Two-side independent T-test			*F*	*P*	*t*	P_2
		3	2.147	0.162	–0.749	0.414
		1			–0.753	0.469
		n	*Min*	*Max*	*M*	*SD*
Post-test	Test group	49	26	69	41.59	11.205
	Control group	43	20	72	48.16	16.529
Two-side independent T-test			*F*	*P*	*t*	P_2
		2	1.629	0.247	0.685	0.547
		4			0.629	0.502

6 Conclusion

This paper took the finance discipline as the example to study the presentation and construction of CSR for discipline knowledge systems. In the paper, at first, a BPNN based on complex rules was taken as the CSR construction algorithm in the CSR contradiction correction of knowledge points in the finance discipline knowledge system, then, it gave the structure of the model for inferring CSR of knowledge points in the finance discipline knowledge system, and adjusted the existing logical inference rules. When building the CSR of knowledge points in the finance discipline knowledge system, this paper introduced a momentum factor σ into the network model to solve the problems of network oscillation and slow convergence. It corrected the finance discipline knowledge system to ensure the balance between the new and the old knowledge, and gave an example in the finance discipline knowledge dataset.

Combining with experiment, this paper gave an example of knowledge point CSR extraction and compared the CSR inference errors before and after improved by conventional neural network. The effectiveness of the proposed BPNN algorithm based on complex rules in constructing CSR of knowledge points in the finance discipline knowledge system was verified. The system correction precision of graph structure models with different depths was given. It can be known that, with the increase of the graph structure model depth and the content of contradictory information, the correction precision of CSR was improved. This paper gave the comparison results of the contradiction correction precision, proved that the proposed algorithm had better performance, compared the cognition efficiency and learning effect of students, and verified that the discipline knowledge systems constructed based on CSR has a positive influence on students' cognition efficiency and learning effect.

7 References

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8 Author

Xiaokun Xiong, graduated from Hebei Normal University in 2005. Then she taught in Shijiazhuang University of Applied Technology. Her research interests include economic and management.

Article submitted 2022-10-01. Resubmitted 2022-10-25. Final acceptance 2022-10-26. Final version published as submitted by the authors.