Use of a Knowledge Network for Management and Sharing of Teaching Resources for Building Construction Simulations

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Abstract—A Knowledge network can well describe the knowledge development progress during teaching process and the relations of teaching resources. Managing the virtual simulation teaching resources based on knowledge network technology and arranging the scattered resources around each teaching point are very important for teachers to form a complete teaching system. However, there are many problems pending for solutions in research fields such as the construction of Chinese knowledge network and the text management based on knowledge network technology. For this reason, this paper aims to study the management and sharing of building construction virtual simulation teaching resources based on knowledge network analysis. At first, this paper elaborated on the construction process of the knowledge network of teaching resources, and introduced in detail a few steps during the construction process, including the entity/attribute extraction, coreference resolution, and relation extraction, etc. Then, this paper proposed an improved spectral clustering algorithm for the management and sharing of the said teaching resources, and realized the resource management and sharing works on a platform. At last, experimental results verified the validity of the proposed algorithm and the constructed model.

Keywords—knowledge network, building construction, teaching resource, virtual simulation, spectral clustering algorithm

1 Introduction

As virtual simulation has been introduced into education field and been promoted constantly ever since, the data volume of virtual simulation of teaching resource management platforms is increasing dramatically, and merely relying on current relational databases can hardly realize the comprehensive management and sharing of resources [1–8]. In terms of the selection and utilization of resources for virtual simulation teaching, teachers need to manually manage the knowledge they about to teach and the acquired learning resources, and they are not able to form sound teaching ideas or a complete teaching system through the relation between the knowledge of information tools and the learning resources [9–15]. It is not difficult to discover the cause of above problems, the root lies in the lack of a universal model of virtual simulation teaching resource management and sharing for organizing teaching resources involved in the teaching content [16–25]. Knowledge network can well describe the knowledge development progress during teaching process and the relations of teaching resources. Therefore, managing the virtual simulation teaching resources based on knowledge network technology and arranging the scattered resources around each teaching point are very important for teachers to form a complete teaching system [26–28].

Zhang [29] pointed out that in conventional English teaching, teachers have to spend a lot of time and energy to develop English courseware and other teaching materials, the author investigated how to use a ubiquitous learning resource sharing platform and a neural network to analyze the method of English major education resource sharing, took advantages of the BP neural network's good classification and prediction performance and applied the algorithm to information classification and prediction in the sharing of English major teaching resources. To enhance the effect of intelligent processing of physical education (PE) resources, Li et al. [30] integrated Genetic Algorithm (GA) with unsupervised learning to study the processing of PE videos and images, the authors designed an intelligent PE resource processing approach based on GA and unsupervised learning and built system function modules. Abd El-Haleem et al. [31] noticed that recently the demand for remote laboratories is increasing as the education system is shifting from face-to-face education to online education, the authors designed a novel laboratory learning system and proposed to minimize the number of blocked time slots per acquiring student by optimizing the association between the reserving students and the available resources at different time slots, and this has reflected the maximization of resources utilization. Simulation results suggest that, comparing with the resource association schemes of other students, the proposed matching game-based framework is significative in minimizing the number of blocked time slots per acquiring student and maximizing the resources utilization efficiency. Zhu [32] argues that as the Internet develops rapidly, an extensive teaching resource sharing phenomenon appears in the field of education, in the paper, the author discussed the sharing and management of school English teaching resources, and designed a English teaching resources information management system based on artificial intelligence, which is necessary for realizing information-based education and recommending teaching resources that can increase students' learning interest and improving the quality of teaching. Shi and Yang [33] developed a personalized matching system for the management of teaching resources based on collaborative filtering (CF) algorithm in their work. At first, they built a user interest model, designed the flow and algorithm for personalized matching, and improved the similarity calculation method. Then a personalized recommendation algorithm was developed based on CF, and a personalized matching engine was constructed with the help of Apache Mahout. The research results shed a new light on personalized recommendation of teaching resources, opening up a new way to information-based education.

At present, there are many problems pending for solutions in research fields such as the construction of Chinese knowledge network and the text management based on knowledge network technology. For this reason, this paper took the virtual simulation teaching of building construction as subject to explore ways of teaching resource management and sharing based on knowledge network analysis. In the second chapter, this paper elaborated on the construction process of the knowledge network of teaching resources, and introduced in detail a few steps during the construction process, including the entity/attribute extraction, coreference resolution, and relation extraction, etc. In the third chapter, this paper proposed an improved spectral clustering algorithm for the management and sharing of the said teaching resources, and realized the resource management and sharing works on a platform. At last, experimental results verified the validity of the proposed algorithm and the constructed model.

2 Construction of knowledge network based on data of teaching resources

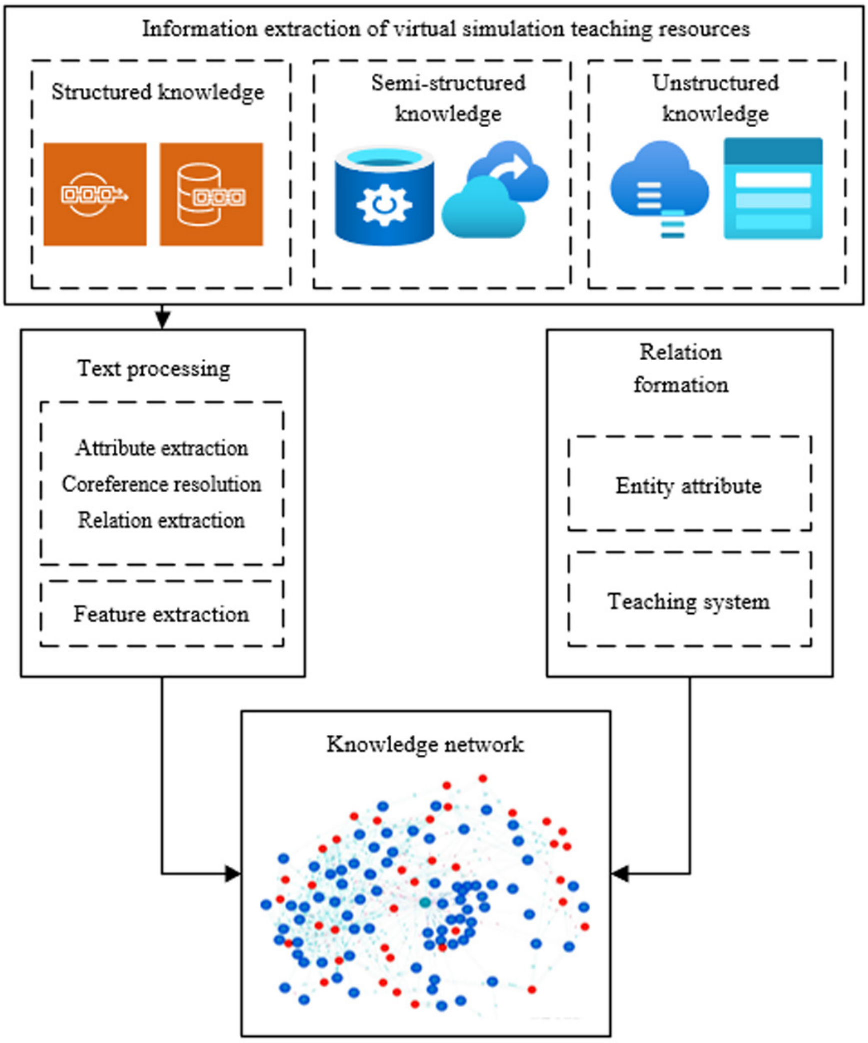


Fig. 1. Knowledge network construction process

Building a knowledge network manually would cost too much and the development of Chinese language processing technology and computer technology has made the task of building a text data knowledge network of teaching resources possible. The automatic construction of the said knowledge network is essentially to extract effective elements such as entities, relations, and attributes from the text data of teaching resources and generate triples of "entity-relation-attribute", which then are imported into graph database to complete the construction of the said knowledge network. Figure 1 gives a diagram showing the process of knowledge network construction. Detailed steps including entity/attribute extraction, coreference resolution, and relation extraction are given below.

Attribute extraction is to extract words that can describe entity attributes from text data of teaching resources. Detailed steps include two aspects: word segmentation and word extraction. In this paper, the Hidden Markov algorithm Model (HMM) was adopted for word segmentation of the text data of teaching resources. The structure of HMM is shown in Figure 2. HMM contains two state sequences: a hidden state sequence and an observable state sequence, and the model has two basic hypotheses, it assumes that the state of any time moment o is independent of other observations and states, and is determined by the state of the previous time moment.

$$E(a_o \mid a_{o-1}, a_{o-2}, ..., a_1, b_{o-1}, b_{o-2}, ..., b_1) = E(a_o \mid a_{o-1}) \tag{1}$$

It is assumed that the observed value of any time moment o is independent of other observations and states, and is determined by the state of the Markov chain at that time moment.

$$E(b_o \mid a_o, a_{o-1}, a_{o-2}, ..., a_1, b_{o-1}, b_{o-2}, ..., b_1) = E(b_o \mid a_o) \tag{2}$$

According to the principle of HMM, during the word segmentation of text data of teaching resources, it can be considered that each word in the text has a state corresponding to it. Assuming: Y represents the start of a word, N represents the middle of the word, and P represents the end of the word, R represents the word formed by a single character, $H = \{Y, N, P, R\}$ represents the state set. In this way, we can perform word segmentation on sentences based on the state sequence of the text data of teaching resources. Here, the terminology set of building construction teaching was imported to improve the accuracy of word segmentation.

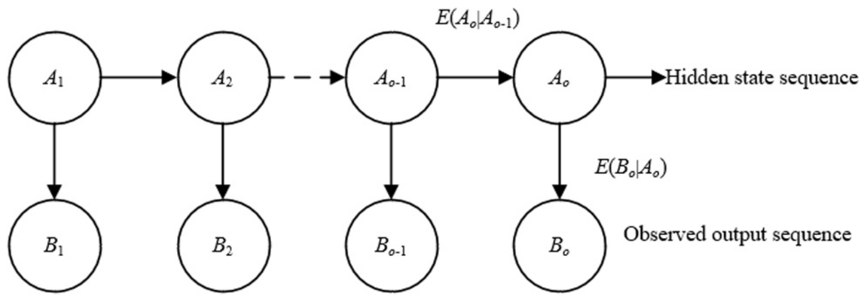


Fig. 2. Structure of HMM

The word extraction of text data of teaching resources is to match the results of word segmentation with the terminology set of building construction one by one, once a match is found, then the word is taken as the entity node, attribute name, and attribute value of the constructed knowledge network of teaching resource text data.

The text data of teaching resources are stored in the form of natural languages, they are usually recorded according to the preferences of providers, the management platform hasn't formed a unified specification yet, so it's necessary to perform coreference resolution on the extracted entity attributes. This paper performed coreference resolution on the text data of teaching resources based on the word training model CBOW and the word embedding algorithm Wonl2vec, structure of the model is shown in Figure 3. The training of the CBOW model is essentially to get two weight matrices through calculations, namely the initialized shared weight matrix and the output weight matrix. In order to speed up the training, this paper adopted the method of stochastic gradient decline to update the training parameters of the model. Assuming: q represents the feature word in teaching resource text, $CO(q)$ represents the context of q, c^{qj} represents the Huffman code corresponding to the j-th node in word q, ω_{j-1}^{q} represents the vector corresponding to the j-1-th non-leaf node in path e^q, e^q represents the path of the Huffman tree from the root node to the leaf node corresponding to word q, A_q^O represents the transposed matrix of the summation matrix of input word vectors. Specifically, for each sample of the teaching resource text ($CO(q)$, q), a round of updates was made to parameters in the objective function shown below:

$$\delta(q,j) = (1-c_j^q)\log[\xi(a_q^O\omega_{j-1}^q)] + c_j^q \log[1-\xi(a_q^T\omega_{j-1}^q)] \tag{3}$$

For the objective function, the gradient of these vectors was calculated, at first, the gradient of $\delta(q, j)$ with respect to ω_{j-1}^{q} was calculated:

$$\begin{aligned}\frac{\partial\delta(q,j)}{\partial\omega_{j-1}^q} &= \{(1-c_j^q)\log[\xi(a_q^O\omega_{j-1}^q)] + c_j^q \log[1-\xi(a_q^T\omega_{j-1}^q)]\} \\ &= [1-c_j^q - \varepsilon a_q^T\omega_{j-1}^q]a_q\end{aligned} \tag{4}$$

Assuming: ψ represents the learning rate, then the update formula of ω_{j-1}^{q} is:

$$\omega_{j-1}^q := \omega_{j-1}^q + \psi[1-c_j^q - \varepsilon(a_q^T\omega_{j-1}^q)]a_q \tag{5}$$

Then, the gradient of $\delta(q, j)$ with respect to a_q was calculated, in $\delta(q, j)$, since variables a_q and ω_{j-1}^{q} are symmetric, so we only need to exchange the positions of a_q and ω_{j-1}^{q} based on $\partial\delta(q,j)/\partial\omega_{j-1}^q$ to get the corresponding gradient $\partial\delta(q, j)/\partial a_q$, that is:

$$\frac{\partial\delta(q,j)}{\partial a_q} = [1-c_j^q - \varepsilon(a_q^T\omega_{j-1}^q)]\omega_{j-1}^q \tag{6}$$

Relation extraction is to determine whether there is a relation between entities in the text data of teaching resources and what is the type of this relation. Since the teaching of building construction is a special and professional education field, the number of relation types of text of teaching resources is limited, this paper performed relation extraction on the text data of teaching resources based on the BERT model, and the flow of relation extraction is shown in Figure 4.

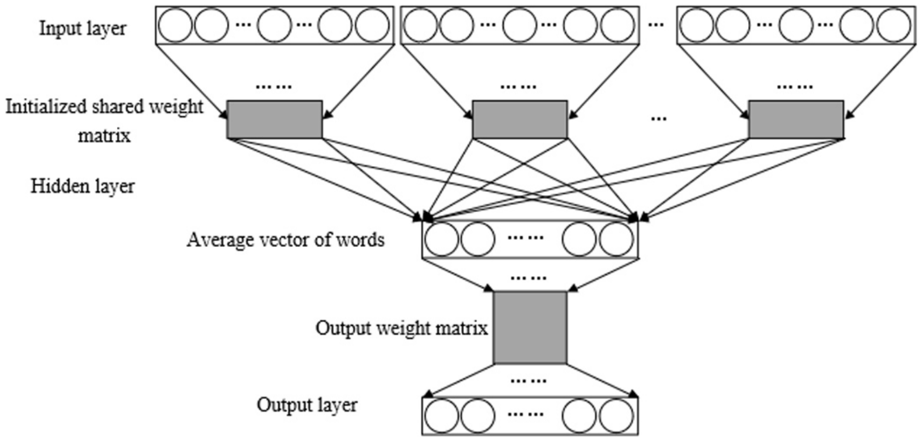


Fig. 3. Structure of the CBOW model

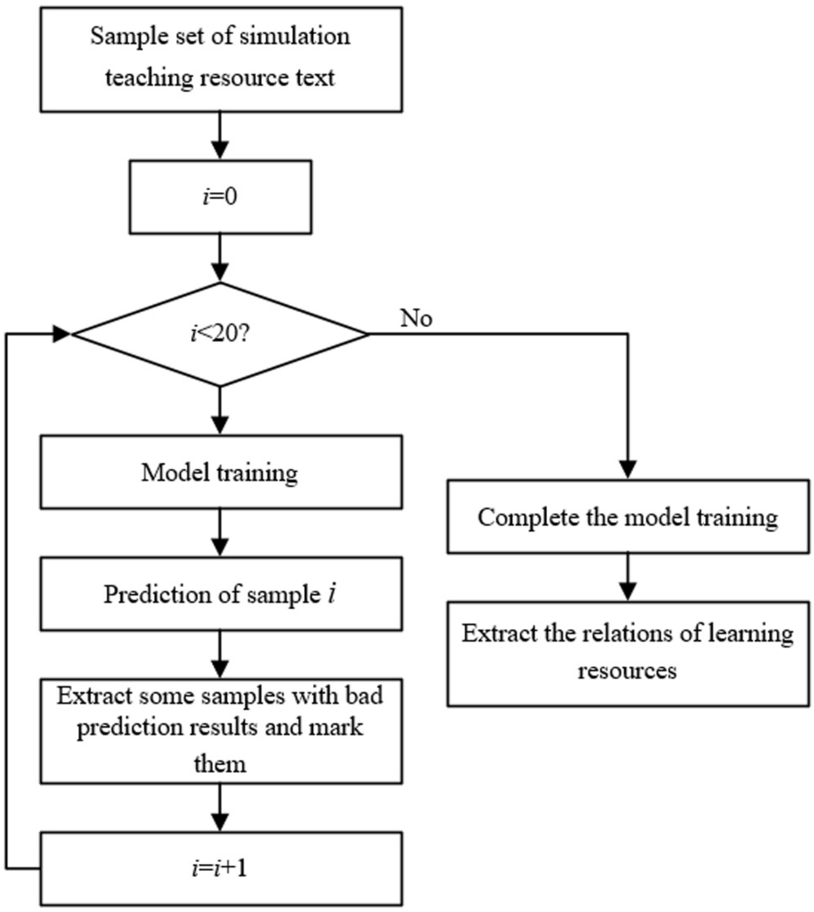


Fig. 4. Relation extraction based on BERT model

Assuming: F represents the final hidden state output from the BERT model, F_0 represents the hidden state vector at the beginning of sentences in the teaching resource text; F_i–F_j represents the hidden state vector of *Entity*1; F_l–F_n represents the hidden state vector of *Entity*2. Through averaging operation the processing of the tanh activation function, the vector of each teaching resource text target could be attained. For each vector, after processed by the fully connected layer of the model, features of the beginning of the sentences of teaching resource text and the entities *Entity*1 and *Entity*2 were attained, the mathematical expression of the calculation process is:

$$F_0 = Q_0(\tanh(F_0)) + \pi_0 \tag{7}$$

$$F_1' = Q_1\left[\tanh\left(\frac{1}{j-i+1}\sum_{p=i}^{j} F_p\right)\right] + \pi_1 \tag{8}$$

$$F_2' = Q_2\left[\tanh\left(\frac{1}{n-l+1}\sum_{p=l}^{n} F_p\right)\right] + \pi_2 \tag{9}$$

Assuming: Q_0, Q_1, and Q_2 represent matrices with a same dimension; c represents the size of hidden layer state in BERT model, then there is Q_0, Q_1, $Q_2 \in R^{c\times c}$. After the three features of sentence beginning, *Entity*1, and *Entity*2 were attained, they were spliced and the spliced results were subjected to relation classification processing of the fully connected layer and the *soft* max function. Assuming K represents the number of relation types and it satisfies $Q_3 \in R^{K\times 3c}$; e represents the output probability; π_0, π_1, π_2, π_3 represent bias vectors, then the mathematical expression of the specific calculation processes is:

$$f'' = Q_3[concat(F_0', F_1', F_2')] + \pi_3 \tag{10}$$

$$e = soft\max(f'') \tag{11}$$

3 Management and sharing of teaching resources based on spectral clustering

In order to realize the management and sharing of virtual simulation teaching resources of building construction, it is very important to cluster the constructed knowledge network of teaching resources during the process of classifying the relations and analyzing the attributes of teaching resources. The clustering effect will directly affect the accuracy of learning resources acquired by teachers. The clustering performance of existing analysis tools in dealing with text-type knowledge networks is not satisfactory enough. For the problem of management and sharing of virtual simulation teaching resources of building construction, this paper proposed an improved spectral clustering algorithm to facilitate the platform's management and sharing of the virtual simulation teaching resources. Figure 5 gives the flow of teaching resource management and sharing.

For spectral clustering, one thing needs to be considered is the selection of similarity of different sample sets. Euclidean distance is a commonly-used clustering indicator, it can describe the local consistency of text clusters but its ability to describe global consistency is not that good, so this paper introduced the density sensitivity to measure the similarity of teaching resource samples during the process of spectral clustering.

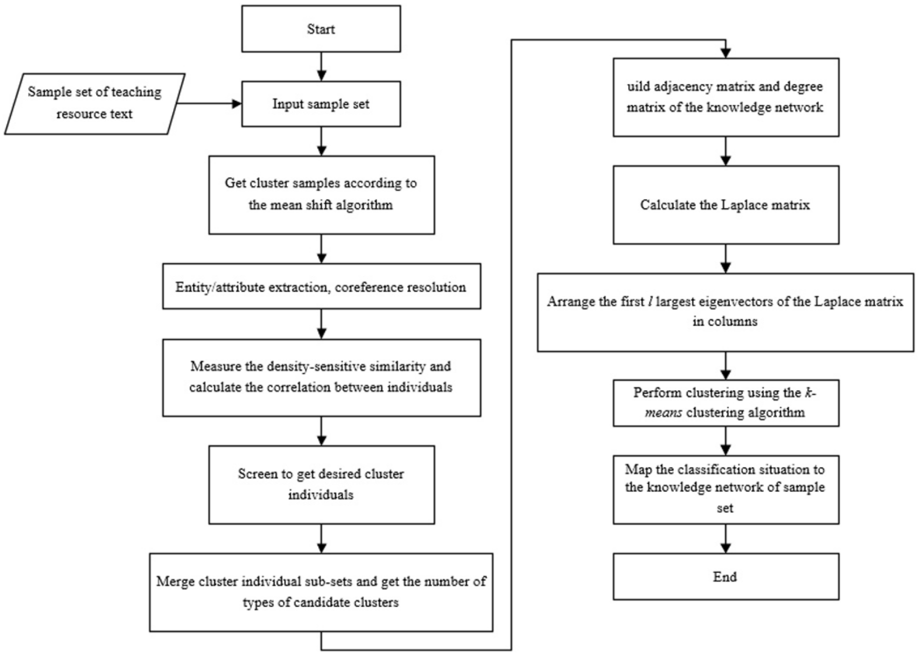


Fig. 5. Flow of teaching resource management and sharing

Different from Euclidean distance, the idea of similarity measurement based on density sensitivity is to increase the distance of different-type teaching resource text data points and decrease the distance of same-type teaching resource text data points. If two data points are highly similar, then it's considered that there is a path passing through same-type regions that can connect the two data points.

Assuming: *DIS*(*a*, *b*) represents the Euclidean distance between two element points *a* and *b*, σ ($\sigma > 1$) represents the stretch factor, then the following formula gives the definition of line segment length of adjustable density:

$$K(a,b) = \sigma^{DIS(a,b)} - 1 \tag{12}$$

The definition given by above formula can solve the Euclidean distance's poor ability in describing global consistency, that is, to use the σ value of stretch factor to adjust the distance between two data points of teaching resources.

Next, the distance of density sensitivity was defined. At first, all data points of teaching resources in the knowledge network and the relations between them were represented by the knowledge network *H*(*U*, *P*), *U* represents the set of vertices in the knowledge network and P represents the set of connecting edges of the similarity between points; $\sigma = \{\sigma_{1\to}\sigma_2\to\cdots\to\sigma_k\} \in U^k$ represents the path between data points σ_1 and σ_k in H; k represents the number of vertices in the path; every edge $(\sigma_{m\to}\sigma_n)$ in the path is contained in set P; e_{ij} represents the set of all paths between any two points e_l and e_{l+1} in H and there are $1 \le i$ and $j \le m$. The length of line segment of adjustable density between two points a_i and a_j is represented by $K(e_l, e_{l+1})$, then the formula for calculating the density sensitivity distance between e_l and e_{l+1} is:

$$C_{ij} = \min_{\sigma \in e_{i,j}} \sum_{l=1}^{k-1} K(e_l, e_{l+1}) \tag{13}$$

By combining the above two formulas, we have:

$$C_{ij} = \min_{\sigma \in e_{i,j}} \sum_{l=1}^{k-1} \left[\sigma^{dist(e_l, e_{l+1})} - 1\right] \tag{14}$$

Based on above definition, the weight value q between data points of teaching resources can be calculated, and an adjacency matrix $Q \in R^{n\times m}$ shown in the following formula was constructed:

$$Q_{ij} = \frac{1}{C_{ij} = \min_{\sigma \in e_{i,j}} \sum_{l=1}^{k-1} (\sigma^{dist(e_l, e_{l+1})} - 1)}, Q_{ii} = 0 \tag{15}$$

After the density-sensitive similarity was introduced, the distance between data points in teaching resource clusters with a same high density could be shortened by reducing the σ value of stretch factor, for data points in teaching resources clusters with a high density, the distance between data points can be increased by increasing the σ value of stretch factor, so the distance problem between types in the constructed teaching resource knowledge network can be solved by introducing the density sensitivity similarity mentioned above.

This paper proposed an algorithm for the management and sharing of virtual simulation teaching resources of building construction based on spectral clustering, at first, sample set of the virtual simulation teaching resources of building construction was regarded as the node set U of the knowledge network, the similarity between text data points was taken as the weight value of the connecting edges of nodes, the density sensitivity similarity between all text data points constituted the edge set P. Then, the sample set of the virtual simulation teaching resources of building construction can form a knowledge network represented by $H = (U, P)$, Q represents the adjacency matrix corresponding to H, then the degree matrix of knowledge network can be constructed based on the sum of elements in each column of Q, and the sum values of each column were the diagonal of the matrix.

$$c_i = \sum_{j=1}^{m} q_{i,j} \tag{16}$$

$$Let\ K = C - Q \tag{17}$$

The Laplace matrix K can be calculated based on Formula 17. However, if the data volume of the sample set of teaching resource text is huge, the efficiency of algorithm execution will be lower. Based on formula derivation, the transformation formula $K = C^{1/2}QC^{1/2}$ used for solving Laplace matrix could be attained. Further, the Laplace matrix K can be calculated and normalized. By arranging the first l largest eigenvectors of K attained through calculation in columns, matrix $A = [u_1,u_2,...,u_l]$ was formed. Then A was normalized and the newly generated matrix was processed by the *k-means* clustering algorithm in rows. At last, by corresponding the classification results to the classification of nodes in the knowledge network of the sample set of virtual simulation teaching text, the management and sharing of virtual simulation teaching resources of building construction could be realized easily.

4 Experimental results and analysis

The terminology set of building construction teaching was introduced in our experiment. Since the frequency of some professional terms is high, these high-frequency terms can describe the necessity and importance of the objects of teaching resource management and sharing to a certain extent. This paper took terminology frequency as the statistical standard of teaching resource management. Table 1 gives the distribution of terminologies with a frequency higher than 50.

Terminologies used in teaching resource management and sharing were classified and explained according to their entity attributes, then, this paper analyzed several selected mutated terminologies in a visualization software. Table 2 gives the distribution of these mutated terminologies in the field of building construction teaching since 2015, as can be known from the table, for some high-frequency terminologies in the said field in recent years, although some have a small centrality, since their frequency is high, they can still describe the necessity and importance of the objects of teaching resource management and sharing to a certain extent.

To verify the validity of the proposed entity attribute extraction method, 500 pieces of teaching resource text provided by the sample sets were experimented, and the performance of three word segmentation methods was compared, namely the forward maximum matching algorithm, the n-gram algorithm, and the algorithm proposed in this paper, the comparison results are shown in Figure 6. According to the figure, in terms of three indicators, accuracy, coverage rate, and F1, the proposed algorithm showed significant advantages.

Experiments of the *CLARANS* algorithm, the hierarchical clustering algorithm and the proposed algorithm were run on 5 sample sets of teaching resources respectively, the normalized mutual information and clustering error rate corresponding to each sample set were recorded, and the records are listed in Table 3. Analysis shows that, compared with the proposed algorithm which measures similarity based on density sensitivity distance, the *CLARANS* algorithm and the hierarchical clustering algorithm that measure similarity based on the Euclidean distance have a higher clustering error rate, and the normalized mutual information indicator of the proposed algorithm is significantly higher than that of the *CLARANS* algorithm and the hierarchical clustering algorithm, therefore, the clustering idea of the proposed algorithm is more suitable for the scenario of teaching resource management and sharing.

Table 1. Distribution of terminologies with a frequency higher than 50

Frequency	Centrality	First Appearance (Year)	Terminology	Frequency	Centrality	First Appearance (Year)	Terminology
610	0.26	1996	Engineering Construction	94	0.05	1992	Subcontract plan
317	0.06	1999	Building	91	0.03	2001	Labor use
263	0.07	1999	Construction	88	0.02	2004	Material supply
175	0.06	1998	Design drawing	76	0.03	2001	Project management
150	0.19	1995	Foundation project	70	0.03	2004	Earth excavation process
126	0.15	1996	Main structure construction	65	0.03	2004	Constructor
122	0.07	1996	Roofing project	65	0.02	2001	Collapse
122	0.13	1993	Decoration project	65	0.02	1995	Enclosure
109	0.04	2001	Construction work	62	0.04	2002	Safety precautions
106	0.11	1999	Construction flow	53	0	2002	Seasonal construction
104	0.07	1993	Construction sequence	51	0	2001	Construction standardization
103	0.14	1998	Construction machinery	50	0	1992	Quality project
94	0.1	2000	Safe construction design				

Table 2. Distribution of mutated terminologies in the field of building construction teaching since 2015

<table>
<tr><th>Term (Frequency)</th><th>Term (Frequency)</th><th>Term (Frequency)</th></tr>
<tr><td rowspan="3">2015, 2016
Steel structure
Accident safety
Pile foundation construction
Corporate finance
Dust control</td><td>2017
Construction cost management
Leak-proof construction</td><td rowspan="3">2020~2023
Fabricated building
Delicacy management
Intelligent device management
Green building construction</td></tr>
<tr><td>2018
High-rise building construction</td></tr>
<tr><td>2019
BIM technology
Construction cost</td></tr>
</table>

To further verify the superiority of knowledge network of teaching resource text data in teaching resource management and sharing, this paper used three performance indicators of accuracy, recall rate and query time to verify the proposed method. The greater the values of accuracy and recall rate, the better the effect of teaching resource management and sharing. With 7 teaching resource cases as samples, the experimental results of the teaching resource management objects are given in Figure 7.

Table 3. Performance comparison of different clustering algorithms

Sample Set No.	Indicator	*CLARANS* Algorithm	Hierarchical Clustering Algorithm	The Proposed Algorithm
1	Normalized mutual information	0.2506	0.3304	0.4259
	Clustering error rate	0.3175	0.2832	0.1802
2	Normalized mutual information	0.5816	0.6869	0.7753
	Clustering error rate	0.4492	0.3506	0.2335
3	Normalized mutual information	0.4587	0.5827	0.6801
	Clustering error rate	0.4223	0.4975	0.2167
4	Normalized mutual information	0.5627	0.6881	0.7695
	Clustering error rate	0.3825	0.2176	0.1852
5	Normalized mutual information	0.4408	0.5445	0.5751
	Clustering error rate	0.3892	0.2321	0.2216

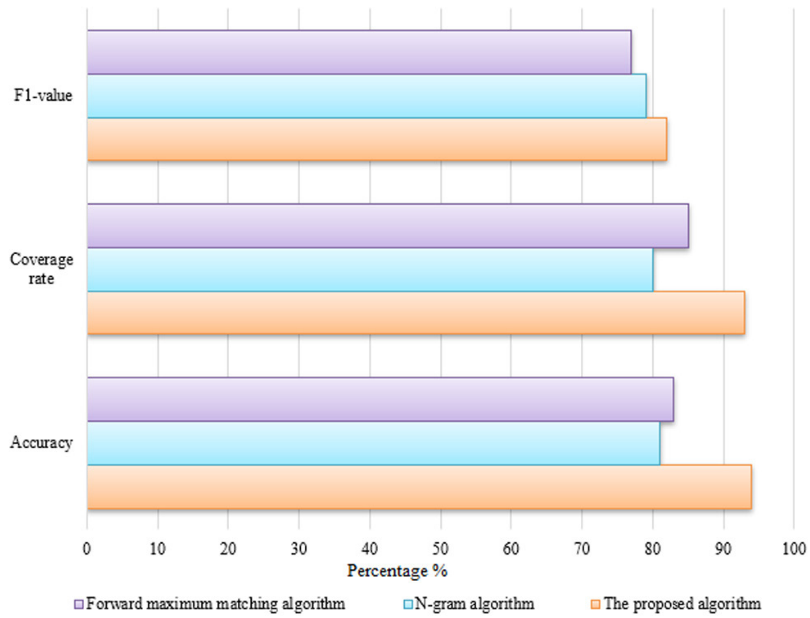
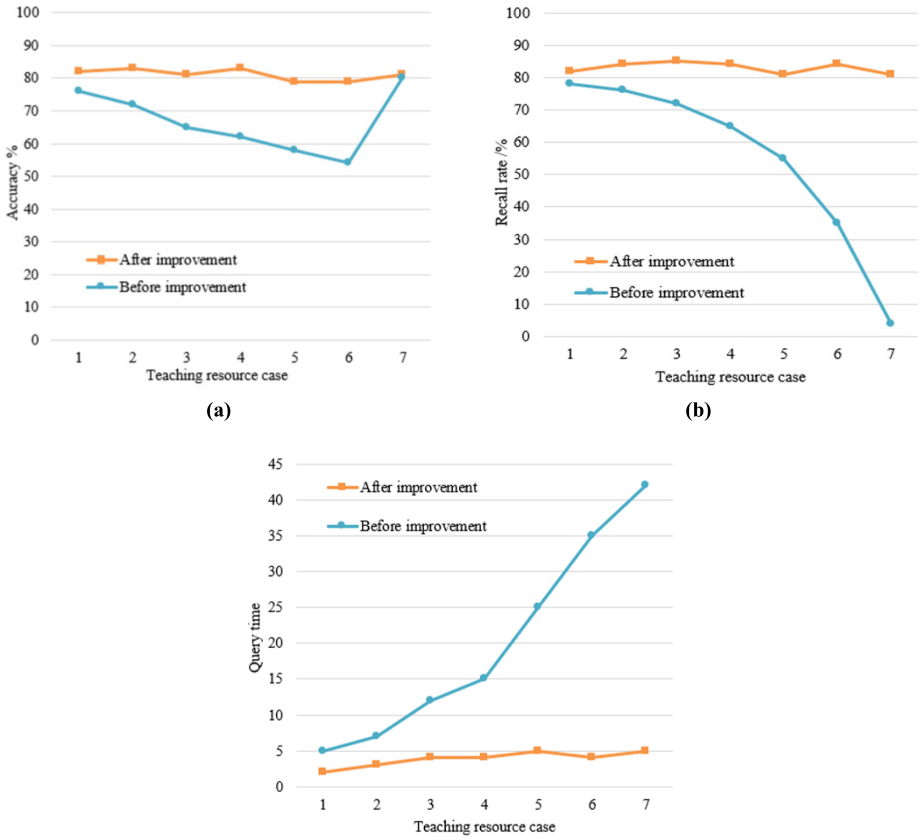


Fig. 6. Comparison of different word segmentation algorithms



(a) (b) (c)

Fig. 7. Verification results

According to Figure 7, the improved algorithm outperformed the previous algorithm in terms of accuracy, recall rate, and query time. Compared with the conventional clustering management methods, the effect of the teaching resource management and sharing method based on knowledge network is better, and the main reason is that the proposed method has fewer limitations on the 6 teaching resource cases and the constructed knowledge network provides more relevant information of educational resources that is convenient for teaching resource management and sharing, so the success rate of management and sharing has been greatly increased, and the management efficiency is higher. This has verified that the knowledge network has obvious advantages in assisting teaching resource management and sharing.

5 Conclusion

This paper studied the management and sharing of virtual simulation teaching resources of building construction based on knowledge network analysis. At first, the paper elaborated on the construction process of the knowledge network of teaching resources, and introduced in detail a few steps during the construction process, including the entity/attribute extraction, coreference resolution, and relation extraction, etc. Then, this paper proposed an improved spectral clustering algorithm for the management and sharing of the said teaching resources, and realized the resource management and sharing works on a platform. Combining with experiment, this paper gave the distribution of terminologies with a frequency higher than 50, and the distribution of mutated terminologies in the field of building construction teaching since 2015; then the performance of three word segmentation methods, namely the forward maximum matching algorithm, the n-gram algorithm, and the algorithm proposed in this paper, was compared, and the results verified the validity of the proposed entity attribute extraction method. Moreover, the performance of different clustering algorithms was compared, and the results proved that the proposed algorithm has a higher normalized mutual information indicator and its clustering error rate is lower. At last, three performance indicators of accuracy, recall rate and query time were selected to verify the proposed teaching resource management and sharing method, and the results demonstrated the superiority of the constructed knowledge network of teaching resource text data in teaching resource management and sharing.

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