A New Learning Resource Retrieval Method Based on Multi-knowledge Association Mining

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Abstract—Ever since the human society has entered the era of big data, the quantity and type of digital learning resources on the Internet are increasing exponentially, and the requirement of students for learning resource retrieval is on the rise. However, the existing methods of learning resource retrieval generally overlook the overall knowledge systems that the students have already possessed, so it's impossible for them to predict the students' learning path or perform deviation adjustment. In view of these issues, this paper aims to study a new learning resource retrieval method based on multi-knowledge association mining. At first, the paper introduces the application of the Knowledge Graph Embedding (KGE) technology in learning resource retrieval, proposes the problem of learning resource retrieval, and points out the goal of learning resource retrieval. Then, a breadth-first soft-matching search algorithm is introduced to attain the multiple association paths between students and learning resources, and a retrieval module is constructed based on association path to further learn the association paths between students and learning resources within the framework of feature learning, and to predict the probability of interactions between students and learning resources. At last, this paper evaluates the association paths and uses experimental results to verify the validity of the proposed learning resource retrieval method.

Keywords—multiple Knowledge Graph Embedding (KGE), learning resource retrieval, association path mining, knowledge association

1 Introduction

Ever since the human society has entered the era of big data, the quantity and type of digital learning resources on the Internet are increasing exponentially [1–5]. In front of such massive amount of learning resources, inevitably, students might get lost in the sea of knowledge or drift from the main topic from time to time, so the requirement of students for learning resource retrieval is growing and changing [6–14]. When a student has just get started with a certain course or come into contact with the knowledge of a certain field, he or she does not have the ability to analyze the relevance between the professional knowledge and the learning resources, so it's impossible for the student to accurately describe the learning resources in need [15–17]. Out of these concerns, now world field scholars are paying more attention to the problems of how to derive the true retrieval intentions of students from the fuzzy keywords given by them, and how to solve the data sparseness, cold start and scalability problems of the learning resource retrieval systems.

Pardi et al. [18] introduced a methodological approach for capturing and analyzing the processing and utilization of text, images, and video content during the learning process based on web search. The authors asked 108 college students to search a natural science topic on the web and recorded their eye movements and navigation behaviour while they were doing so, then the software "reading protocol" was used to automatically map the students' fixations to text, images, and video content that they had fixated upon on any information resource retrieved. Ciloglugil and Inceoglu [19] proposed an e-learning model based on Agents and Artifacts (A&A) Meta model and used it to search for learning resources from multiple sources. The proposed model focuses on environment modeling in multi-agent system design and models entities in the environment as artifacts, that are first class entities like agents. Viewing from the angle of e-learning systems developed based on multi-agent design, the authors pointed out that learning resources are main components in the environment that agents interact with, then they discussed the limitations of the proposed method and its future direction. Sawadogo et al. [20] proposed an approach that can provide users with new ways to interpret the resource search results, in the paper, they also invented a method for adaptive visual representation of these results based on the context of use and the user profile. The proposed approach uses an adaptive tf-idf scoring and adaptive visual representation to achieve the selection of relevant digital resources. Valiente et al. [21] reported an exploratory study based on the availability and suitability of keywords and classifications in metadata-based educational resources to improve collaborative learning between teachers and students through the search and analysis of learning resources from a large sample obtained from the Global Learning Objects Brokered Exchange (GLOBE). Segura et al. [22] proposed an expansion of queries based on formal domain ontology in case of the search for learning resources in repositories. The expansion process uses the relation types that are represented in these models; common ontological relations, and ontological relations specific to domain and traditional terminology relations, typical of thesauri. Authors performed tests using Gene ontology as the knowledge base and MERLOT as the test repository. Results of the case study suggest that, at similar levels of precision, expanded queries improve levels of novelty and coverage compared to the original query (without expansion), that is, the expanded queries allow the user to retrieve relevant objects, which might not be attained without expansion.

After reviewing existing research results, it's found that the existing retrieval methods give targeted resource retrieval results based on the different learning styles of students, but they generally overlook the overall knowledge systems that the students have already possessed, so it's impossible for them to predict the students' learning path or perform deviation adjustment. Therefore, as the learning process continues, the knowledge learnt by students can not be connected effectively, and it's hard for them to build a complete knowledge system. For this reason, this paper studies a new learning resource retrieval method based on multi-knowledge association mining. In the second chapter, the paper introduces the application of the KGE technology in learning resource retrieval, the third chapter proposes the problem of learning resource retrieval, and points out the goal of learning resource retrieval; then in the fourth chapter, a breadth-first soft-matching search algorithm is introduced to attain the multiple association paths between students and learning resources; the fifth chapter constructs the retrieval module based on association path to further learn the said association paths within the framework of feature learning, and to predict the probability of interactions between students and learning resources. At last, this paper evaluates the association paths and uses experimental results to verify the validity of the proposed learning resources retrieval method.

2 About the KGE

To perform KGE on the course knowledge learnt by students is to map the high-dimensional information of course knowledge into a lower-dimension space, in this way, low-dimensional embedded vectors of the associations between each knowledge entity could be mined based on the premise that the original structure of the course knowledge system and the semantic information of knowledge points are fully retained. In terms of learning resource retrieval, KGE has the following merits: it can supplement the missing information in the existing knowledge systems of students, it can facilitate the calculation of similarity of learning resources and the merge of multi-type information of learning resources, and it can effectively utilize different-type learning resources, therefore, it can exert a great influence in aspects such as the construction, inferring, and application of knowledge graphs.

KGE can be divided into two types: the distance-based translation model, and the semantics-based matching model. For the research objective of this paper, in the distance-based translation model, elements o_f, o_p, and s in the triplet (o_f, o_p, s) are associated with a corresponding c-dimensional knowledge vector, the model uses the distance between head entity vector f and tail entity vector p to represent the knowledge association vector s, namely $o_f+s\approx o_p$. Assuming: R represents the correct triplet, R' represents the error triplet, then the score minimization function is:

$$K=\sum_{(o_f+s-o_p)\in R}\ \sum_{(o'_f+s'-o'_p)\in R'}\left(\left\|o_f+s-o_p\right\|_2^2+\alpha-\left\|o'_f+s'-o'_p\right\|_2^2\right) \tag{1}$$

For the research objective of this paper, the semantics-based matching model can associate knowledge entities with a c-dimension vector, and associate the knowledge association relationship with a c-order matrix, when triplet (o_f, o_p, s) holds, it can attain credible matches of knowledge semantics and scoring function, and the optimized scoring function is given by the following formula:

$$K=\sum_{(o_f+s-o_p)\in R}\ \sum_{(o'_f+s'-o'_p)\in R'}\left(o_f^T\cdot s\cdot o_p^T+\alpha-o'^T_f\cdot s'\cdot o'^T_p\right) \tag{2}$$

By fully considering the multi-hop relationships between knowledge entities and adding additional information of association paths into the KGE model, a model based on knowledge association path could be constructed. Here, the knowledge association path is the sequence of association relationships between two nodes o_f and o_p in the knowledge graph of courses learnt by students, and it's written as $s_1 \rightarrow \ldots \rightarrow s_k$. Assuming: t represents the semantics combination of knowledge association embedding, then the semantic expression of t can be attained based on the multiply operation of the association relationship matrix in the association path, that is:

$$\text{Semantic expression:} t = s_1 \circ \cdots \circ s_k \tag{3}$$

3 Description and goal of the learning resource retrieval problem

The objective of learning resource retrieval is to search for learning resources, and present and interpret the results for students. This paper focuses on the high performance and interpretability of learning resource retrieval methods, namely to find learning resources that are most likely to be adopted by student, and create a complete natural language sentence for each retrieved learning resource to explain why the student needs to learn it. This paper combines with the semantic information in the knowledge graph of courses to build a learning resource retrieval model, which can improve the performance of learning resource retrieval model and provide retrieval results and interpretations to students. Figure 1 shows the flow of the proposed learning resource retrieval method.

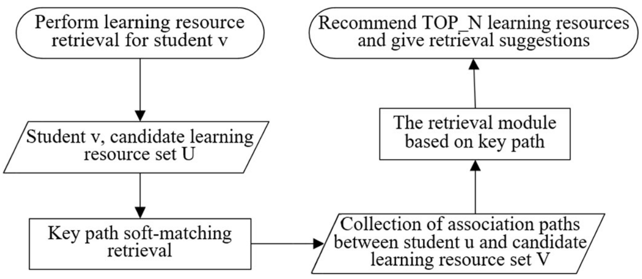

Fig. 1. Flow of the learning resource retrieval method

At first, the learning resource retrieval problem is described. Students' feedback about learning resources is the primary part for establishing the learning resource retrieval model. Such feedback implicitly reflects students' preference for learning resources. The feedback information can be automatically collected by the learning resource retrieval system, including the retrieval records, learning records, and learning scores, etc. In the learning resource retrieval model constructed based on knowledge graph of courses, this paper uses implicit feedback to describe the learning resource retrieval problem. Assuming: there are n students and m learning resources; $V=\{v_1, v_2, \ldots, v_n\}$ and $U=\{u_1, u_2, \ldots, u_n\}$ respectively represent the student set and learning resource set, wherein each student individual v and each learning resource u both belong to entity node O; $b_{vu}=1$ represents there are implicit interactions between student v and learning resource u, such as the click, watch, browse, and other operations performed by the student on the learning resource; based on student's implicit feedback of retrieval results, the student-resource implicit matrix can be defined as $B=\{b_{vu}|v\in V, U\in U\}$, and there is:

$$b_{vu}=\begin{cases}1,\text{If }(v,u)\text{ have interactions}\\0,\text{If }(v,u)\text{ do not have any interaction}\end{cases}\tag{4}$$

The essence of the implicit-feedback learning resource retrieval problem is to predict the possibility of interactions between students and learning resources in matrix b_{vu}.

The first sub-goal of the learning resource retrieval method is to predict whether student v has a potential learning interest in learning resource u which he/she hasn't interacted with in history; assuming: ω represents the given model parameter, then this sub-goal can be considered as to learn the predicted probability $b^*_{vu}=G(v, u, \omega)$ of student v and learning resource u.

The second sub-goal of the learning resource retrieval method is to give students reasonable retrieval suggestions. These suggestions are inferred by the retrieval method after learning the association paths between student v and learning resource u. The knowledge association path of course knowledge graph can be defined by the l-step path between two nodes. The following formula gives the collection of the l-step association paths from entity o_0 to entity o_l:

$$t_l(o_0,o_l)=\left\{o_0\overset{s_1}{\leftrightarrow}o_1\overset{s_2}{\leftrightarrow}\ldots\overset{s_o}{\leftrightarrow}o_l\right\}\tag{5}$$

According to above formula: o_0 connects to $l+1$ entities through l association relationships until reaches the sequence set of o_l. Assuming: LH represents the knowledge graph, then $o_{i-1}\leftrightarrow^{s1}o_i$ can be used to represent $(o_{i-1}, s_i, o_i)\in LH$ or $(o_i, s_i, o_{i-1})\in LH$. The *1*-step association path between student v and learning resource u that contains rich structural and semantic information of knowledge graph can give natural language explanations between v and u, and it gives the learning resource retrieval model sufficient interpretation ability.

4 Association path soft-matching retrieval

To attain the multiple association paths between students and learning resources, this paper introduces a breadth-first soft-matching search algorithm. The idea of this algorithm is to take student and learning resource as initial node and target node based on the principle of taking breadth as the priority, then searches for shorter paths from the initial node to the target node, and gives multiple possible choices between the initial node and the target node.

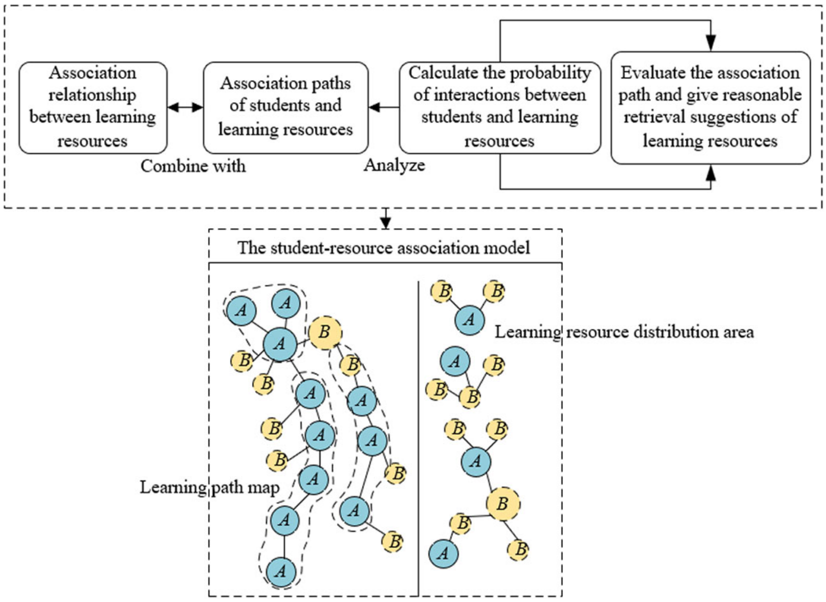

Fig. 2. Construction process of the student-resource association model

Figure 2 gives the construction flow of the student-resource association model. In the figure, the yellow nodes are learning resources nodes (B) that haven't been visited by the student, and the blue nodes are learning resource nodes (A) that have already been visited by the student. In the knowledge graph network, two nodes with more common neighbors have a higher similarity. Assuming: $\Pi(a)$ represents the set of neighbor nodes of node a, $l(a)=|\Pi(a)|$ represents the degree of node u, then the following formula gives the expression of the *Salton* indicator which is used to measure the similarity of nodes:

$$SA(a,b)=\frac{|\Pi(a)\cap\Pi(b)|}{\sqrt{l(a)l(b)}} \tag{6}$$

To get reasonable search direction, this paper emphasizes the association relationship between the search access node that is closer to the target short-distance path and the nodes connected to it, and assigns a higher access priority to this search access node. Nodes with higher priority have a greater probability of being visited. Assuming: $\Pi(u)$

represents the set of neighbor nodes of node u; $l(u)=|\Pi(u)|$ represents the degree of node u, the following formula gives the definition of access probability $GR(u_a|b_l, u)$:

$$GR(u_a \mid u_a, v) = \frac{|\Pi(u_a) \cap \Pi(u_b)|}{\sqrt{l(u_a)l(u_b)}} + \frac{|\Pi(u_a) \cap \Pi(u)|}{\sqrt{l(u_a)l(u)}} \tag{7}$$

Execution steps of this breadth-first soft-matching search algorithm are detailed below: 1) Pre-set the search depth l and width χ of the algorithm; 2) Starting from initial node u_0, traverse the access probability $GR(u_a|b_l, u)$ of all unvisited nodes that are connected with u_0 until all nodes in l layers are traversed, and describe all traversed nodes and the association relationships between them based on association path; 3) If the attained association paths contain the association paths departing from or arriving at the target node, then the search is stopped, otherwise return to step 2 until all l-layer nodes are traversed; 4) Output χ association paths between initial node and target node. Figure 3 shows the process of attaining association path based on the breadth-first soft-matching search algorithm.

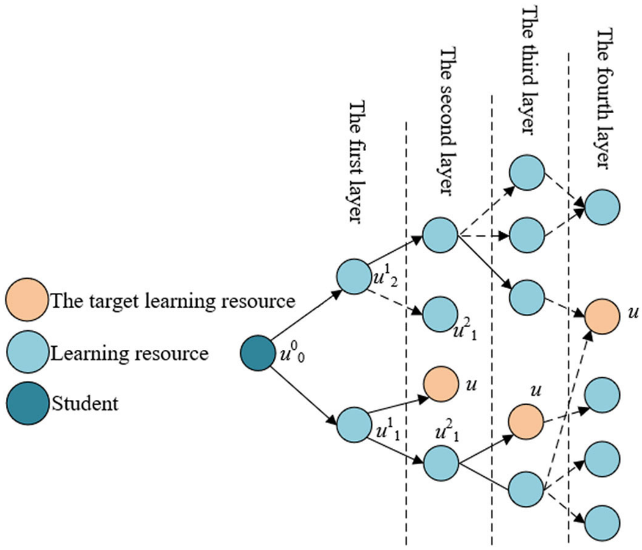

Fig. 3. The process of attaining association path

5 Result output of learning resource retrieval based on knowledge association

Based on the model input of known students and learning resources, after processed by the algorithm, the set of association paths between students and learning resources could be output, and these association paths contain the information of learning resources that students have interests in the past in the knowledge graph of courses and the information of the attributes of learning resources that have potential associations. To build the retrieval module based on association path, in this paper, the association paths between students and learning resources are learnt further within the framework of feature learning, then the probability of interactions between students and learning resources is predicted, after that the association paths are evaluated and reasonable retrieval suggestions will be recommended to students. Figure 4 shows the framework of feature learning.

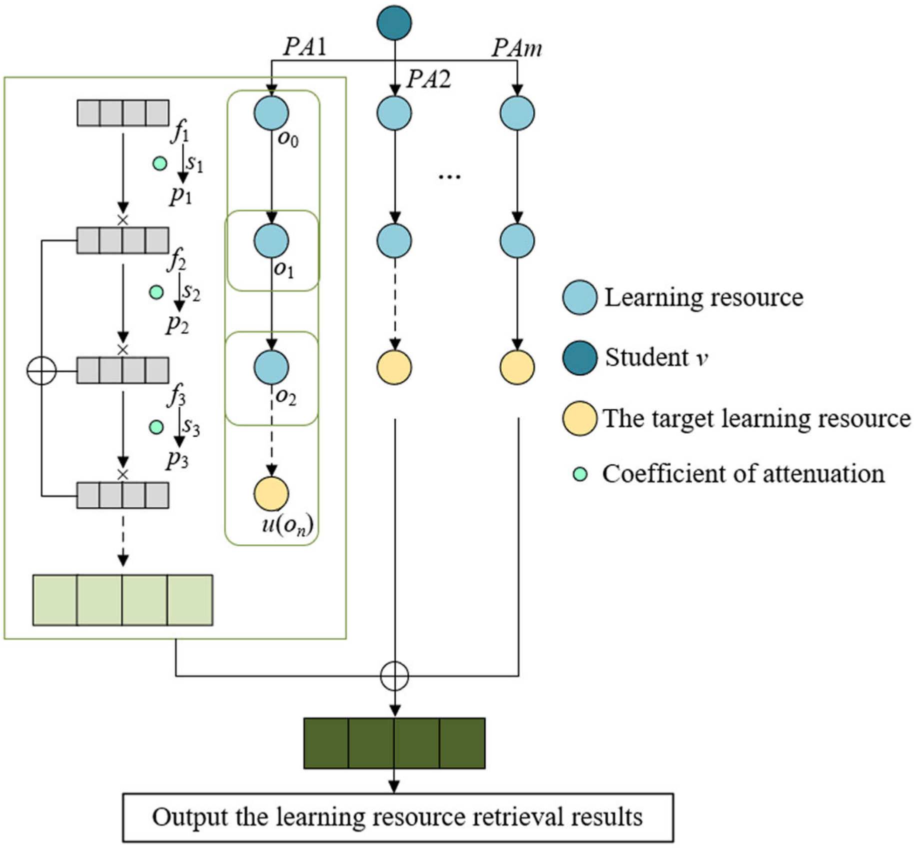

Fig. 4. Framework of feature learning

Under the guidance of different association paths of learning resources, there will be some differences in the student's preference for learning resources. During the formation process of the paths, nodes in each layer are traversed, and the student's interest in the target learning resource will decrease gradually, and the attenuation loss mainly comes from two aspects: node deviation and relationship deviation.

By default, there are multiple association paths between student v and learning resource u. Starting from the history learning resource o_0 which student u has learnt before, the learning resource retrieval method respectively passes through nodes o_1 and o_2 through s_1, s_2, s_3 and other association relationships, and chooses learning resource $v(e_h)$ after traversing several layers. Assuming: PA represents the path vector fitted by known association relationships, and C_ϕ represents the KL distance, then the following formula gives the method for calculating the attenuation coefficient β of each step:

$$\beta_i = \frac{1}{C_\varphi(u \mid o_i) + C_\varphi(o_i \mid PA_{HO_i})} \tag{8}$$

The calculation formula of PA is:

$$PA_i = o_0 s_1 \cdots s_i \tag{9}$$

The calculation formula of C_ϕ is:

$$C_\varphi(t \mid w) = \sum_{i=1}^{c} t(i) \log \frac{t(i)}{w(i)} \tag{10}$$

Specifically, $C_\phi(u|o_i)$ describes the degree of deviation between o_i and u, $C_\phi(o_i|PA_i)$ describes the deviation degree between o_i and PA_i. The greater the value of C_ϕ, the greater the attenuation degree of student's interest in the target learning resource. Along the association path PA_1 of student v, the student's learning preference is transmitted to the target learning resource u. Based on other associated nodes and the attenuation coefficient β of student-resource paths, the preference vector $t^1_{v,u}$ shown in Formula 11 could be attained, which is the preference of student v for selecting retrieval path PA_1:

$$t^1_{v,u} = \sum_{i=1}^{3} \beta_i o_i \tag{11}$$

Through above processing, the multiple retrieval paths between student v and learning resource u can measure the preference of student v for learning resource u from different dimensions of association path, that is, it measures the possibility of student v choosing learning resource u. Based on m association paths, the embedding vector of the preference of student v for learning resource u can be calculated by the following formula:

$$v = t^1_{v,u} + t^2_{v,u} + \cdots + t^m_{v,u} \tag{12}$$

Assuming: $\varepsilon(a)$=1/1+$exp(-a)$ is the *sigmoid* function, then based on the embedding vector of student and the embedding vector of target learning resource, the probability that the student will choose the target learning resource could be calculated:

$$\hat{b}_{vu} = \varepsilon(v^T u) \tag{13}$$

At last, the association path with the largest preference value is selected to generate the reason for outputting the learning resource retrieval results.

$$Path^* = \max\left(\varepsilon\left((t^i_{v,u})^T u\right)\right), i = 1, 2, \ldots, m \tag{14}$$

The basic principle for the proposed method to achieve learning resource retrieval is to ensure that the retrieval probability of student for the learning resource he/she is interested in is the highest, and the retrieval probability of the learning resource he/she is not interested is the lowest. Assuming: b_{vu} represents the binary value indicating whether student v chooses learning resource u; O and S respectively represent the embedding matrices of entities and relationships in the knowledge graph, $I_{f,s,j}$ represents the indicator function, in order to realize the learning of model parameter ω, the embedding vector of student, and the embedding vector of target learning resource, this paper sets a loss function as follows:

$$\begin{aligned} \min LO &= -\log\left(GR(B \mid \omega, LH) * GR(LH \mid \omega) * GR(\omega)\right) \\ &= \sum_{(v,u)\in B} -\left(b_{vu} \log \hat{b}_{vu} + (1-b_{vu})\log(1-\hat{b}_{vu})\right) \\ &\quad + \mu_1 \sum_{s\in R} \left\| I_s - O^T S O \right\|_2^2 + \mu_2 \left(\left\|O\right\|_2^2 + \left\|S\right\|_2^2 \right) \end{aligned} \tag{15}$$

In above formula, when (f, s, p) belongs to a knowledge graph LH, $I_{f,s,p}$=1, otherwise, $I_{f,s,p}$=0. According to this formula, the first term on the right side of the equation is a binary cross-entropy loss function between the predicted value and the real value of <v, u>, the second term on the right side of the equation characterizes the degree of fit between the model parameter and the knowledge graph LH, the third term on the right side of the equation is a regular term to prevent the algorithm from over-fitting.

6 Experimental results and analysis

The proposed learning resource retrieval method constructed based on association path is realized by the Java programming language, combining with the learning resource features of economics and management related courses, 1780 learning resources were subjected to knowledge tag extraction and knowledge association analysis. Table 1 gives the knowledge types of the learning resources adopted in the experiment.

Table 1. Knowledge types of the learning resources

Type	Quantity	Type	Quantity	Type	Quantity	Type	Quantity
Economic prediction	23	Economic profit	125	Market operation	85	Cross elasticity	66
Economic decision making	296	Normal profit	63	Demand curve	42	Production function	314
Marginal analysis	45	Explicit cost	274	Supply curve	2	Returns to scale	185
Opportunity cost	22	Implicit cost	55	Price elasticity	528	Cost function	162
Accounting profit	114	Market supply and demand	869	Revenue elasticity	74		

Then the student-resource association paths were sorted out and screened, and the experimental results are shown in Figure 5. According to the figure, the proposed learning resource retrieval algorithm can output learning resource sets according to the different learning preferences of students, then the learning paths will be updated and adjusted further to instruct students to learn in a coherent manner, so the proposed learning resource retrieval method can output satisfactory retrieval results.

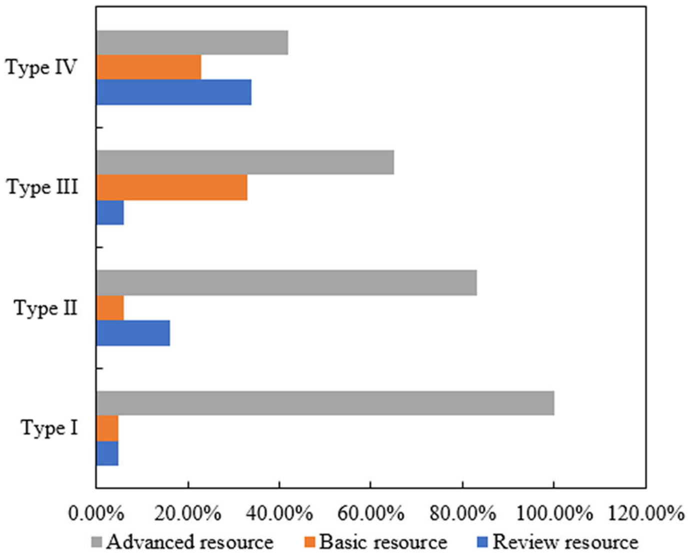

Fig. 5. Experimental results of learning resource retrieval based on association path

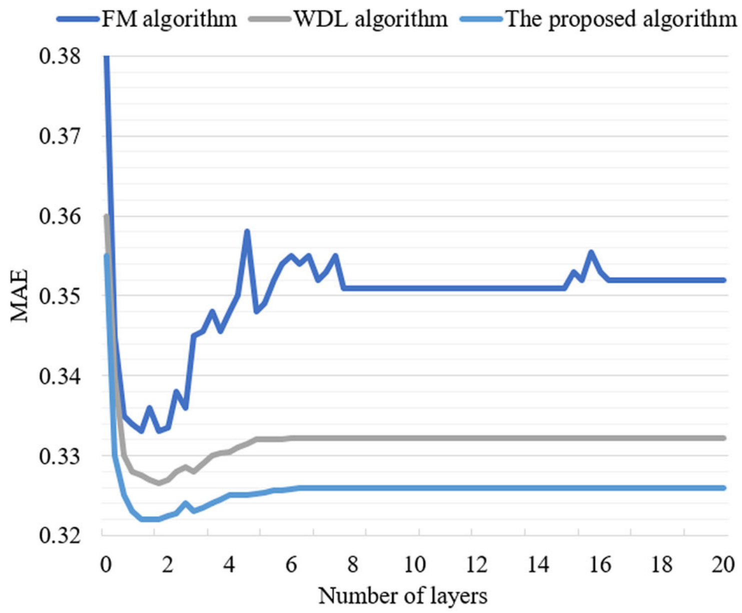

Fig. 6. Comparison of MAE values of different algorithms under the condition of different numbers of association relationship layers

To verify whether the proposed learning resource retrieval algorithm has a better effect than other algorithms when applied to economics and management related courses, in this paper, MAE and RMSE were taken as indicators for evaluating the errors of the retrieval algorithms, and three algorithms were tested on a same learning resource sample set. Figures 6 and 7 compare the MAE and RMSE of these algorithms under the condition of different numbers of association relationship layers. At first, the algorithm proposed in this paper created a knowledge graph based on the learning resource sample set, then it learnt the association paths between students and learning resources in the knowledge graph within the framework of feature learning, so it attained better retrieval results than other algorithms; moreover, after the search depth exceeded 10 layers, the recommendation errors of reference algorithms FM and WDL basically stabilized, after the proposed algorithm was stabilized, its MAE and RMSE values were lower, indicating that the introduction of association paths between students and learning resources has a positive effect on improving the retrieval performance of the retrieval system.

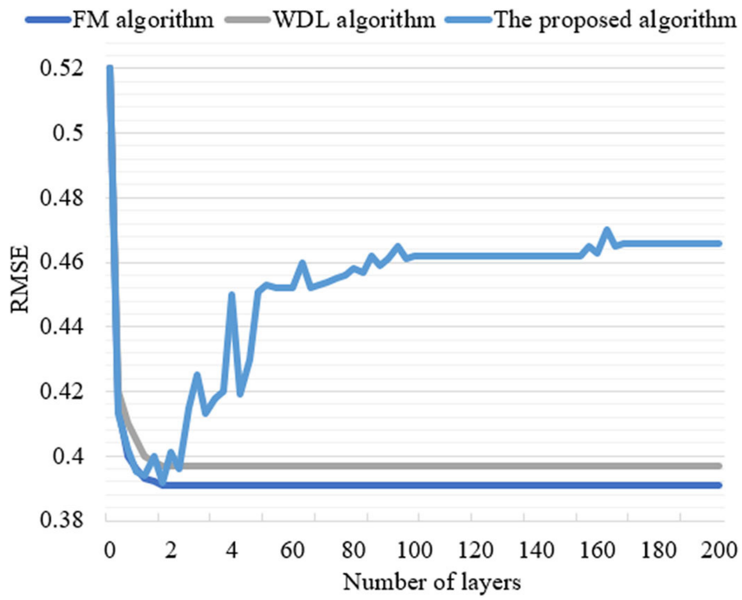

Fig. 7. Comparison of RMSE values of different algorithms under the condition of different numbers of association relationship layers

Table 2. Comparison of output results of different algorithms

Methods	**Indicator**			
	recall@5	***recall@10***	***NDCG@10***	***MRR@10***
The proposed algorithm	0.3929	0.5152	0.3417	0.3857
The proposed algorithm (without KGE)	0.3741	0.4968	0.2693	0.2639
The proposed algorithm (without association path soft-matching retrieval)	0.3850	0.4285	0.2685	0.2181
Content-based retrieval	0.3714	0.4362	0.2035	0.2856
Collaborative filtering retrieval	0.2639	0.3847	0.2859	0.1742
Rule-based retrieval	0.2528	0.3014	0.2653	0.1629
Utility-based retrieval	0.2416	0.4352	0.2369	0.142
Knowledge-based retrieval	0.3629	0.4857	0.2274	0.263
Algorithm combination 1	0.4362	0.4692	0.3104	0.3748
Algorithm combination 2	0.1958	-0.1636	0.3968	0.5296

Table 2 compares the output results of different algorithms, as can be seen in the table, in terms of the four indicators related to *Recall*, *NDCG* and *MRR*, the retrieval performance of the proposed algorithm is obviously better than that of other algorithms. Specifically, in case that 10 retrieval results of learning resources have been recommended to each student, compared with the algorithm combination that integrates content-based retrieval and utility-based retrieval, the proposed algorithm respectively improved the indicators of *Recall*@10, *NDCG*@10, and *MRR*@10 by 9.34%, 31.24%, and 50.27%. Compared with the proposed algorithm without KGE and without association path soft-matching retrieval, the indicators *Recall*@10, *NDCG*@10, and *MRR*@10 had been improved by 5.21%, 15.61%, and 23.03%, respectively. Overall speaking, the created knowledge graph contains rich heterogeneous information about the association paths between students and learning resources, the multi-hop association relationships between students and learning resources could be captured, and the KGE and association path soft-matching retrieval can greatly improve the retrieval performance of the proposed algorithm.

7 Conclusion

This paper studied a learning resource retrieval method based on the mining of multi-knowledge association. At first, the paper introduced the application of KGE in learning resource retrieval, described the problem of learning resource retrieval, and pointed out the goal of learning resource retrieval. Then, the paper introduced a breadth-first soft-matching search algorithm to attain the multiple association paths between students and learning resources, built a retrieval module based on association path, and learnt the association paths within the framework of feature learning. After that, the probability of interactions between students and learning resources was predicted, and the association paths were evaluated. After experimented on the learning resource retrieval based on association path, the MAE and RMSE errors of different algorithms under the condition of different numbers of association relationship layers were compared, and the comparison results indicate that the application effect of the proposed algorithm in economics and management related courses is better than other algorithms. At last, the output results of different algorithms were also compared, and the results demonstrated that KGE and association path soft-matching retrieval can greatly improve the retrieval performance of the proposed algorithm.

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