Path Planning for the Fragmented Learning of College Students Based on Artificial Intelligence

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Xia Li(✉)
Faculty of Culture and Education, Henan Institute of Economics and Trade, Zhengzhou, China
hnjmlixia@henetc.edu.cn

Abstract—Most education platforms attempt to plan reasonable learning paths for college student users, but they have generally ignored differences in their learning time distribution preferences, learning habits, and learning requirements, and haven't taken the dynamic development trends of their learning states into consideration. To make up for these shortcomings, this paper aims to study the learning path planning for the fragmented learning of college students based on artificial intelligence. At first, this paper proposed a fragmented learning path planning model for college students, and introduced a fragmented knowledge concept map method to mine the recommended fragmented knowledge structure and the association between concepts, so as to fragment knowledge concept into small knowledge pieces and realize fragmented knowledge recommendation. Then, this paper introduced the regularization constraints, and adopted the sparse auto-encoder to predict the missing values in the interaction matrix, so as to solve the problem of data sparsity. After that, hybrid recommendation of fragmented knowledge was made based on the multi-layer perception network model, and the accuracy of the personalized recommendation of fragmented knowledge had been effectively improved. At last, experimental results verified the effectiveness of the proposed recommendation model.

Keywords—neural network, college students, fragmented learning, learning path, planning, artificial intelligence

1 Introduction

Information age has brought dramatic changes to the learning method and environment of college students. With their advantages of rich content and ease-of-use, online education platforms and mobile education platforms have broken through the limits of conventional education mode in terms of fixed positions, fixed teaching environment, fixed teaching content, and fixed teachers [1–7]. At the same time, students' learning requirements are developing toward the direction of searching for services of personalized learning and fragmented learning [8–15]. Most education platforms attempt to plan reasonable learning paths for college student users, but they have generally ignored differences in their learning time distribution preferences, learning habits, and learning requirements, and haven't taken the dynamic development trends of their learning states into consideration. Moreover, the generated learning path often does not conform to the cognition sequence of college students, and is not easily accepted or recognized by them, sometimes it can even lead to problems such as cognitive overload, disorientation, and learning efficiency in them [16–24]. Therefore, rationally planning the learning path for the personalized and fragmented learning of college students is a very meaningful and practical work.

Online learning platforms are prone to information overload because of the massive resources contained. To solve this problem, field scholars generally put their emphases on the personalized recommendation of learning resources, in terms of the prediction of online learning path, the performance of existing studies is not ideal, and they failed to clarify the associations between students' overall knowledge systems and the knowledge contained in the learning resources. Jia et al. [25] discussed the collaborative filtering recommendation of online learning resources based on a knowledge association model, the authors extracted knowledge units from the semantic information of online learning resources to establish the said knowledge association model, and designed a collaborative filtering recommendation algorithm combining semantic adjacency and learning interest and applied it to the quantification of the semantic similarity of online learning resources, and the effectiveness of the proposed algorithm was verified via experiment. The connotation of fragmented learning is to make full use of fragmented time slices to learn and accumulate fragmented knowledge pieces. The present mobile learning applications haven't fully considered the preferences, requirements, and adaptability of their users, so the content and difficulty of resources recommended often fail to match with the characteristics of users. Scholar Xu [26] discussed the problem of personalized recommendation of online learning resources based on mobile devices. At first, the paper developed a system structure for an adaptive recommendation model of online learning resources and modelled the learners and the scattered learning resources; then, it built a personalized recommendation model of online learning resources, introduced the flow of the recommendation engine in detail, and calculated the matching degree of the recommended resources; at last, the effectiveness of the proposed model was verified by experiment. Most of the present personalized recommendation methods of learning resources function based on learners' basic information and learning behavior without considering the logical relationships among the learning resources. Wei and Yao [27] used knowledge graphs to build class models, proposed a high-efficient personalized recommendation algorithm based on interest similarity and knowledge association, and designed a recommendation system, the correctness and effectiveness of the recommendation algorithm were verified via experiment based on discrete mathematics. Liu [28] took human resource recommendation as example to study the personalized resource recommendation algorithm and model based on deep learning. Yang and Tan [29] proposed an accurate recommendation model of learning resources based on knowledge graph and deep learning, the constructed deep learning-based recommendation system consists of a learner knowledge representation model and a learning resource knowledge representation model; the recommendation engine uses learner basic information, learning resource information, and other data to calculate the target learner's score and generate a recommendation list for the learner according to the learner knowledge representation and the learning resource knowledge representation, the experimental results show that, compared with conventional systems, the proposed recommender system could attain better results.

After carefully reviewing the existing literatures on personalized learning path recommendation, it's found that the present models haven't taken college students' features into consideration, they cannot handle the diversity of college students, the degree of personalization is too low to satisfy their requirements of using fragmented time for learning, and the fragmented knowledge recommendation problem hasn't been solved yet. For these reasons, this paper studied the planning of learning path for the fragmented learning of college students based on artificial intelligence. The second chapter gave the fragmented learning path planning model for college students, and introduced the fragmented knowledge concept map to mine the recommended fragmented knowledge structure and the association between concepts, so as to fragment knowledge concept into small knowledge pieces and realize fragmented knowledge recommendation. The third chapter introduced the regularization constraints, and adopted the sparse auto-encoder to predict the missing values in the interaction matrix, so as to solve the problem of data sparsity; then the hybrid recommendation of fragmented knowledge was made based on the multilayer perceptron network model, which effectively improved the accuracy of the personalized recommendation of fragmented knowledge. In the end, the experimental results verified the effectiveness of the proposed recommendation model.

2 Fragmented knowledge association and feature representation

In order to fragment knowledge concept into small knowledge pieces and realize fragmented knowledge recommendation, when mobile education platforms plan the learning path for college students' fragmented learning, they need to mine the association between the recommended fragmented knowledge structure and concepts. Taking the analysis results of learning behavior features as reference information for the recommendation of fragmented knowledge can effectively optimize the recommendation effect.

Figure 1 shows a diagram of the fragmented learning path planning model for college students. This paper has introduced the representation method of fragmented knowledge concept map, that is, the relationship of knowledge nodes in the fragmented knowledge concept map was mapped to a low-dimensional vector space based on the knowledge embedding network technology. Then, the features of the learning behavior were analyzed, specifically, it included the identification of learning habit types, the setting of cognition basis, and the calculation of learning time distribution preferences, etc.

The fragmented knowledge concept map is represented by multiple node triples (head, relation, tail). Under the condition of different semantics, the distances between knowledge nodes in the fragmented knowledge concept map are different. Assuming: f and o respectively represent the knowledge node vectors at the head position and at the tail position; this paper used the relation matrix to map f and o to the relation vector space to complete the representation of knowledge vectors. If the distance between f and o in the relation vector space is smaller than the original distance, then it can be considered that the association formed between two knowledge nodes is established, and vice versa:

$$f_{\perp} = K_s f, o_{\perp} = K_s o \tag{1}$$

Assuming: Ko represents the projection matrix of mapping f and o to the relation vector space; $f_{\perp}$ and $o_{\perp}$ represent mapped f and o; the difference between relation s and the relation between $f_{\perp}$ and $o_{\perp}$ is defined as the scoring function, which is used to measure the degree to which the node triple is truly established, that is:

$$g_s(f,o) = -\left\| f_{\perp} + s - o_{\perp} \right\|_2^2 \tag{2}$$

The relation matrix can also be used to represent the latent semantic relationship between f and o, the bilinear transformation of the relationship between f and o can be defined as a scoring function to measure the degree to which the node triple is truly established. Figure 2 shows the calculation process of the scoring function based on the relation matrix. Assuming: K_s represents the bilinear transformation matrix of relation s, then there is:

$$g_s(f,o) = \sum\sum\left[K_s\right]_{ij} \cdot \left[f\right]_i \cdot \left[o\right]_j \tag{3}$$

Neural networks can also be applied to the learning of the latent semantics of knowledge nodes to achieve relationship matching between different knowledge nodes. Figure 3 gives the calculation process of the scoring function based on neural networks. The initialized node triple vector is represented by f_0, s_0, and o_0, then, by inputting into the corresponding parameter matrix, the representation of the embedded vector of f, s, and o could be attained:

$$f = Q_f f_0 \;\; s = Q_s s_0 \;\; o = Q_o o_0 \tag{4}$$

Next, embed f and s into vector c_0=[f:s], and input c_0 into the constructed fragmented knowledge embedding network. Assuming: K^n and y^n represent the weight matrix and bias vector of the n-th layer; x^n and c^n represent the input and output of the n-th layer, then the following formulas calculate the input and output of each layer in the network:

$$x^n = K^n c^{n-1} + y^n, n = 1,2,...,N \quad c^n = ReLU\,(x^n), n = 1,2,...,N \tag{5}$$

The result attained based on the dot product of c and o can also be defined as a scoring function to measure the degree to which the node triple is truly established, that is:

$$g_s(f,o) = o^O c^N \tag{6}$$

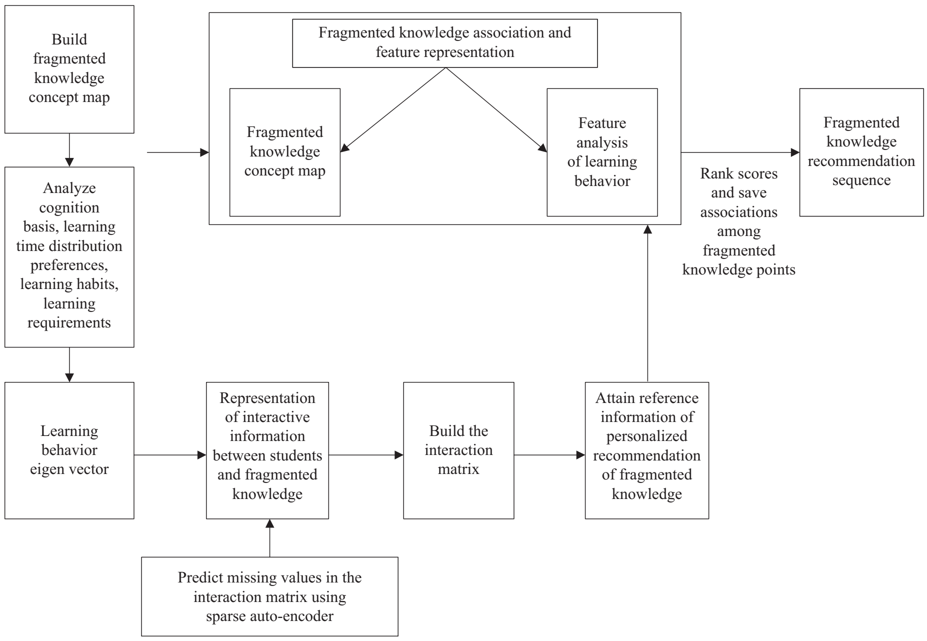

Fig. 1. Fragmented learning path planning model for college students

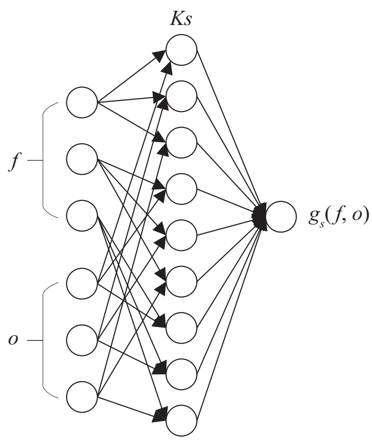

Fig. 2. Calculation process of the scoring function based on relation matrix

The specific training steps of the constructed model are:

(1) Randomly initialize node triples (f, s, o) and matrix K_s.
(2) Randomly select from all node triples to form a mini-batch triple set R for model training.

(3) Traverse all triples (f, s, o) in R, and randomly replace f and o in triples to construct negative samples, and add the constructed negative samples into R to form a new model training set R'.
(4) Build the loss function of the model and perform gradient calculation, then adjust and update the parameters of the vector, matrix and network through backpropagation.
(5) Train the model until it meets the training accuracy, f, s, and o represent the attained accurate knowledge node relationship vector.

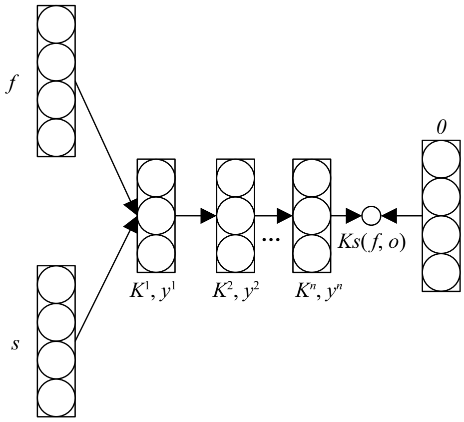

Fig. 3. Calculation process of scoring function based on neural network

The adopted logistic regression loss function is given by:

$$\min_{\Psi} \sum_{s \in E^+ \cup E^-} log\left(1 + exp\left(-b_H \cdot g_s\left(f, o\right)\right)\right) \tag{7}$$

Set E^+ and set E^- in the loss function respectively store the real positive facts and unobserved negative facts. Assuming: O=(f, s, o) is a training example in $E^+ \cup E^-$, when $\rho \in E^+$, b_H=1; when $\rho \in E^-$, b_H=–1. But if the values of b_H of all events in E^- are set to –1, there must be certain errors. Assuming: α represents the distance constant between positive and negative samples, the pairwise loss function introduced in this paper was adopted to optimize the above formula:

$$\min_{\Psi} \sum_{\rho^+ \in E^-} \sum_{\rho^- \in E^-} max(0, \alpha - g_s(f, o) + g_{s'}(f', o')) \tag{8}$$

Next, analyze the features of learning behavior. Assuming: $Z_1, Z_2, \ldots, Z_m$ represent multiple learning behavior patterns generated by college students during fragmented learning, then the learning behavior features of each set are jointly determined by $Z_1, Z_2, \ldots, Z_m$. In the calculation process, at first, compare the description values of $Z_1, Z_2, \ldots, Z_m$ with the threshold value to realize value assignment; if the description value of any pattern Z_i is higher than the upper limit of the threshold value, then Z_i=1 and $Z_i \in F$. If the description value of Z_i is lower than the lower limit of the threshold value, then Z_i=–1 and $Z_i \in N$.

If the description value of Z_i is lower than the upper threshold and higher than the lower threshold, then Z_i=1 and $Z_i \in N$. The following formula gives the constraints on the value of the fragmented learning behavior pattern Z^j_i of student j:

$$U_j(D) = \begin{cases} 1, if \quad Z_i^j \in F \\ 0, if \quad Z_i^j \in K \\ -1, if \quad Z_i^j \in N \end{cases} \tag{9}$$

Based on the value of the fragmented learning behavior pattern Z^j_i of college students, the value $U_j(D)$ of the learning behavior feature D of student j can be calculated based on the following formula. If $U_j(D) \in [1/3,1]$, it means that student j has the learning behavior feature on the left. If $U_j(D) \in [-1,-1/3]$, it means that student j has the learning behavior feature on the right. If $U_j(D) \in [-1/3,1/3]$, it means that student j has the balanced-type learning behavior feature.

$$U_j(D) = \frac{\sum_{i=1}^{l} Z_i^j}{l} \tag{10}$$

3 Hybrid recommendation of fragmented knowledge

The existing recommendation mechanisms in the field of education cannot deal with the diversity of college students, the degree of personalization is too low to satisfy students' requirements, and the effect of recommendation is limited. To solve this problem, combining with the fragmented knowledge structure, learning behavior feature and other information attained in the previous section, this paper made hybrid recommendation of fragmented knowledge based on the multi-layer perception network model, which effectively improved the accuracy of the personalized recommendation of fragmented knowledge.

In order to attain the middle dense vector that can accurately represent the interactive information between students and fragmented knowledge, this paper introduced the auto-encoder, and the auto-encoder network consists of three parts: the input layer, the hidden layer, and the output layer. Assuming: Q_1, y_1, and ε_p represent the weight matrix, bias vector, and activation function in the encoding process; Q_2, y_2, and ε_e represent the weight matrix, bias vector, and activation function in the decoding process, then for the auto-encoder, the encoding process between the input layer and the hidden layer and the decoding process between the hidden layer and the output layer are given by the following formulas:

$$f = \varepsilon_p(Q_1 a + y_1) \tag{11}$$

$$b = \varepsilon e_p(Q_2 a + y_2) \tag{12}$$

The loss function of the auto-encoder network could be expressed as:

$$DR(Q,y)=\sum\left(SU\left(a,b\right)\right)=\sum\left\|b-a\right\|^{2} \tag{13}$$

For the overfitting problem of the conventional auto-encoder which is easy to occur during the reconstruction process, this paper built an interaction matrix to describe the interactive information between students and fragmented knowledge, introduced the regularization constraints, and used the sparse auto-encoder to predict the missing values in the interaction matrix to solve the problem of data sparsity.

Assuming: k represents the number of students, l represents number of fragmented knowledge pieces, then the interaction matrix of students and fragmented knowledge can be written as $S\in S^{k\times l}$. For each student $v\in V=\{1,...,k\}$, the interaction with fragmented knowledge can be represented by the vector $s^v=\{S_{v1},...,S_{vl})\in S^l$. Similarly, for each fragmented knowledge piece $i\in I=\{1,...l\}$, the interaction with students can be represented by the vector $s^i=(S_{1i},...,S_{ki})\in S^k$. Assuming S_{ki} represents the interaction between student v and fragmented knowledge piece i, then 1 represents valid interaction, 0 represents invalid interaction, and –1 represents no interaction.

Input the interaction matrix information into the sparse auto-encoder network, assuming $s\in S^e$ represents the input vector, after encoder reconstruction, the output vector $f(s;\omega)$ could be attained as follows:

$$f(s;\omega)=g\left(h\left(Us+\lambda\right)+y\right) \tag{14}$$

Assuming $g(\cdot)$ and $h(\cdot)$ represent activation functions; $\omega=(Q,U,\lambda,y)$, $Q\in S^{e\times m}$, $U\in S^{m\times e}$, $s\in S^m$, and $y\in S^e$ are network parameters; m represents the dimension of middle layers; $\|\ \|^2_0$ represents observable score; $\|Q\|^2_G+\|U\|^2_G$ represent regular terms of the loss function, then the loss function of the sparse auto-encoder can be expressed as:

$$\min_{\omega}\sum_{i=1}^{m}\left\|s^{(i)}-f\left(s^{(i)};\omega\right)\right\|_{o}^{2}+\frac{\mu}{2}\cdot\left(\left\|Q\right\|_{G}^{2}+\left\|U\right\|_{G}^{2}\right) \tag{15}$$

Assuming: $x\in S^l$ represents the dense vector of the middle layer; during iterations, network parameters update constantly, and $f(s;\omega)$ gradually approaches input vector s, then x can well describe the features of the hidden layer, and there is:

$$x=h(Us+\lambda) \tag{16}$$

According to the auto-encoder network constructed based on the input student interaction vector $s^v\in S^l$ the auto-encoder network constructed based on the input fragmented knowledge interaction vector $s^i\in S^k$, it's attained that $x^i\in S^m$ and $x^v\in S^m$, and taking x^i as the reference information of the personalized recommendation of fragmented knowledge can improve the recommendation effect.

In this paper, the personalized hybrid recommendation model of fragmented knowledge was built based on the multi-layer perception neural network, and the model consists of three parts: the input layer, the hidden layer, and the output layer, as shown in Figure 4. Assuming: Q_a, y_a, and ξ_a respectively represent the weight matrix, bias vector, and activation function of the n-th layer, c represents the input vector, then the layer-by-layer transmission process of the neural network can be expressed as:

$$\begin{aligned} &\psi_1(c_0) = \xi_1(Q_1^O c_0 + y_1) \\ &\cdots \\ &\psi_N(c_{N-1}) = \xi_N(Q_N^O c_{N-1} + y_1) \end{aligned} \tag{17}$$

Assuming: f represents the weight matrix; ε represents the activation function, then the predicted score b'_{ki} can be obtained from f and ε:

$$b'_{vi} = \varepsilon(f^T c_N) \tag{18}$$

The constructed recommendation model integrated the interaction information between students and fragmented knowledge attained by auto-encoder with the multi-dimensional analysis results such as fragmented knowledge structure and learning behavior features, it also has the advantages of collaborative filtering recommendation of fragmented knowledge and content recommendation in line with the cognition order of students.

Dense vectors $x^{(v)}$ and $x^{(i)}$ are represented by the embedded vector p_x, which can be attained by the product operation of elements:

$$p_x = x^{(v)} \otimes x^{(i)} \tag{19}$$

Assuming: p_v represents the attribute vector of student learning behavior features; p_i and p_{mk} respectively represent the attribute vector of fragmented knowledge features and the embedded vector; in order to integrate multi-granularity information such as the fragmented knowledge structure, the student learning behavior features, and the interaction between students and fragmented knowledge, the above feature attribute vectors were embedded, and the generated long vector is represented by $P_1[p_x; p_v; p_i; p_{mk}]$, then the vector ψ^* attained by embedding them into the recommendation model could be expressed as:

$$\psi^* = x_N\left(Q_N^O\left(x_{N-1}\left(\cdots x_2\left(Q_2^O P_1 + y_2\right)\cdots\right)\right) + y_N\right) \tag{20}$$

The score b'_{vi} given by student v to fragmented knowledge i can be calculated by the following formula:

$$b'_{vi} = \varepsilon(f^O \psi^*) \tag{21}$$

According to the level of b'_{vi}, accurate personalized recommendation of fragmented knowledge could be achieved. The formula below gives the loss function adopted by the recommendation model:

$$N = -\sum_{(v,i)\in b} log\hat{b}_{vi} - \sum_{(v,i)\in b} log(1-\hat{b}_{vi}) = -\sum_{(v,i)\in b\cup b^-} b_{vi} log\hat{b}_{vi} + (1-\hat{b}_{vi}) log(1-\hat{b}_{vi}) \tag{22}$$

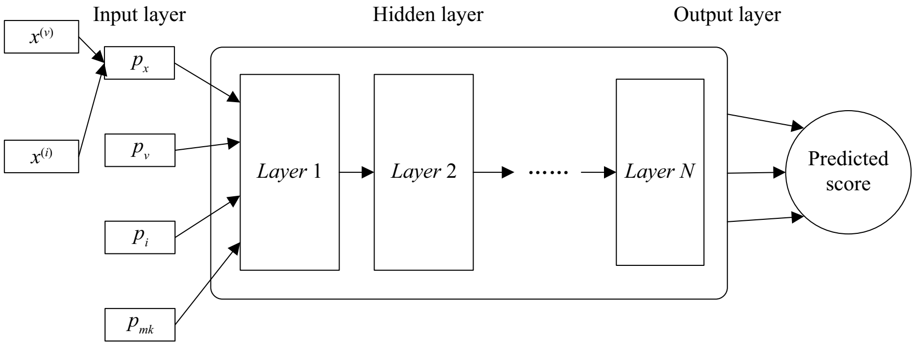

Fig. 4. Structure of the personalized hybrid recommendation model of fragmented knowledge

4 Experimental results and analysis

This chapter verified the effectiveness of the proposed recommendation model. At first, for the sparse auto-encoder, the effectiveness of data sparsity optimization was verified. Hit rate and Normalized Discounted Cumulative Gain (NDCG) were selected as two verification indicators, and the adopted reference models have three kinds of classic collaborative filtering algorithms: the conventional auto-encoder, the noise-reduction auto-encoder, and the stacked noise-reduction auto-encoder. The changes of the two indicators with the k-value recommended by Top-k are given by Figures 5 and 6, respectively.

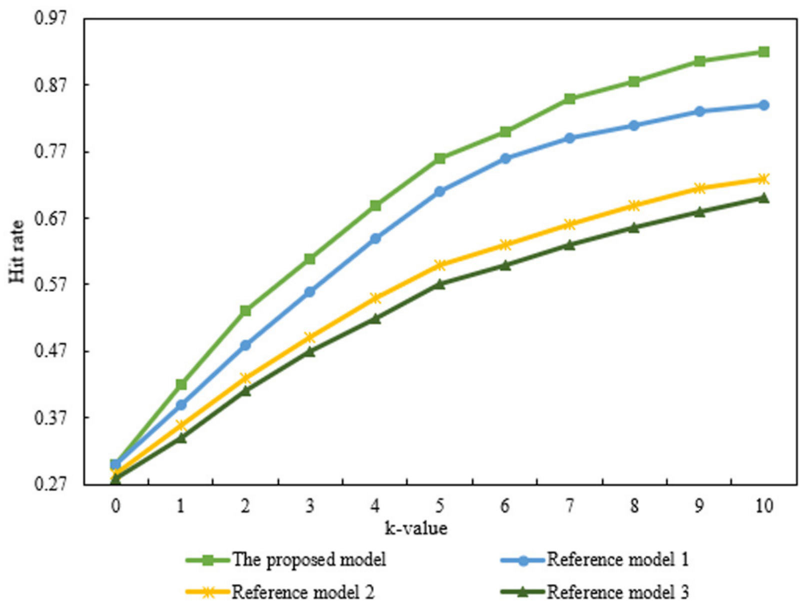

Fig. 5. The hit rate in case of different k-values

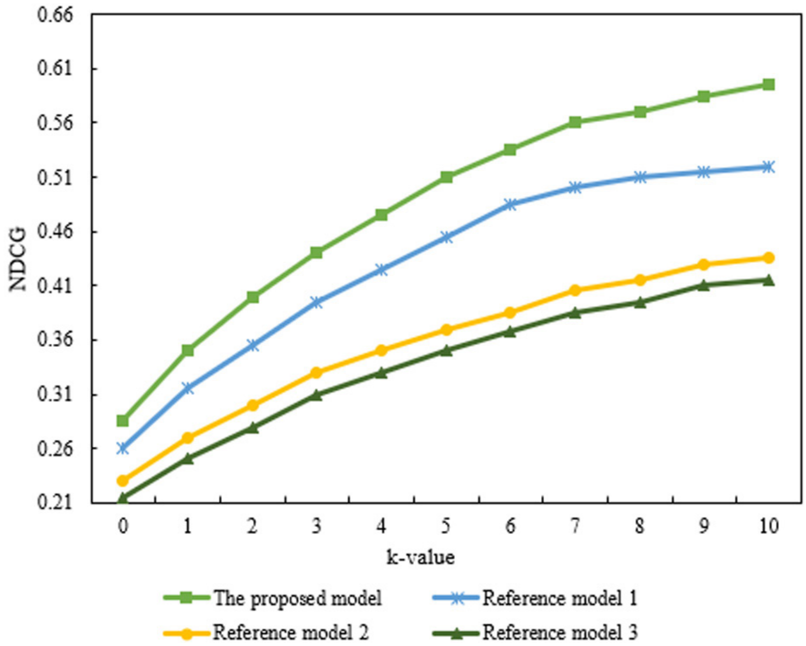

Fig. 6. The NDCG in case of different k-values

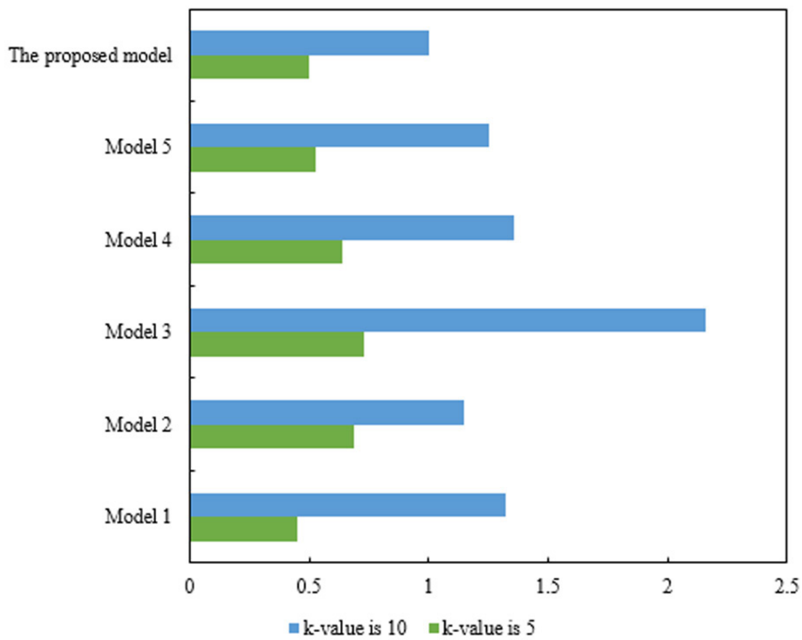

Fig. 7. Comparison of MAE of different models

According to Figures 5 and 6, after the three kinds of auto-encoders and the sparse auto-encoder adopted in this paper completed the data sparse optimization, the hit rate and NDCG of the proposed recommendation model both increased with the increase of the k-value recommended by Top-k. When the k-value reached 10, the values of the indicators tended to be stable and reached the maximum values. The performance of the stacked noise-reduction auto-encoder was better than that of the noise-reduction auto-encoder; and the noise-reduction auto-encoder was obviously better than the conventional auto-encoder. The performance of the sparse auto-encoder adopted in this paper was better than that of the stacked noise-reduction auto-encoder, and the performance improvement was significant.

In this paper, five models including the naive Bayes model, the restricted Boltzmann machine, the Markov model, the latent semantic model, and the support vector regression model were selected to compared with the recommendation model proposed in this paper, and the comparison results are shown in Figures 7 and 8. In the comparative experiment, the MAE value and MSE value of the proposed recommendation model were both lower than those of other classic recommendation models, which had verified that the recommendation effect of the proposed model had basically met the requirements of personalized recommendation of fragmented knowledge for college students. Table 1 lists the recommendation errors of different models in case of different samples, and the data had further verified the effectiveness of the proposed model.

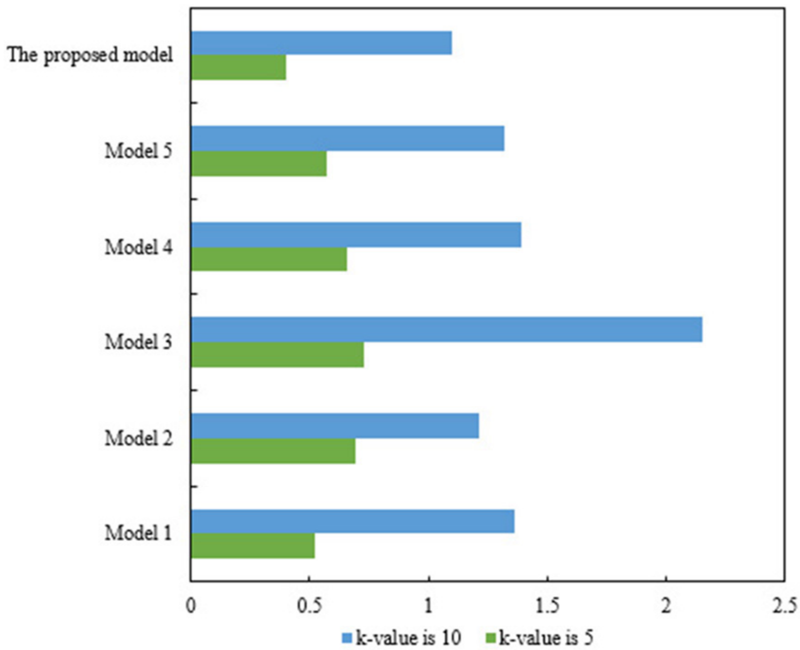

Fig. 8. Comparison of MSE of different models

Table 1. Recommendation errors of different models in case of different samples

Model		Model 1	Model 2	Model 3	Model 4	Model 5	Proposed Model
Sample 1	MAE	1.528	1.263	1.427	1.425	1.928	1.302
	MSE	3.513	3.697	5.284	3.629	3.526	3.174
Sample 2	MAE	1.629	1.352	1.475	1.296	1.205	1.318
	MSE	3.528	3.101	5.263	3.314	3.529	3.624
Sample 3	MAE	1.225	1.367	1.628	1.937	1.695	1.172
	MSE	3.418	3.692	5.347	3.629	3.518	3.326
Sample 4	MAE	1.925	1.531	1.512	1.695	1.371	1.469
	MSE	3.627	3.615	5.629	3.907	3.162	3.025

5 Conclusion

This paper researched the planning of learning path for the fragmented learning of college students based on artificial intelligence. At first, this paper proposed a fragmented learning path planning model for college students, and introduced a fragmented knowledge concept map method to mine the recommended fragmented knowledge structure and the association between concepts, so as to fragment knowledge concept into small knowledge pieces and realize fragmented knowledge recommendation. Then, this paper introduced the regularization constraints, and adopted the sparse auto-encoder to predict the missing values in the interaction matrix, so as to solve the problem of data sparsity. After that, hybrid recommendation of fragmented knowledge was made based on the multi-layer perception network model, and the accuracy of the personalized recommendation of fragmented knowledge had been effectively improved. Combining with experiment, this paper verified the effectiveness of the data sparsity optimization of the sparse auto-encoder, chose hit rate and NDCG as two verification indicators, and gave the changes of the two indicators with the k-value recommended by Top-k. The experimental results verified that the sparse auto-encoder adopted in this paper outperformed the others. Moreover, the MAE and MSE values of different algorithms were compared, and MAE and MSE values of the proposed model were lower than those of other recommendation models, which had verified that the proposed model had basically met the requirements of personalized recommendation of fragmented knowledge for college students.

6 References

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7 Author

Xia Li, received a master's degree in civil and commercial law from Zhongnan University of Economics and Law in 2008, and now works as associate professor at Henan Institute of Economics and Trade. Her research directions include economic law, and civil and commercial law. She has published 19 papers and edited 7 textbooks. Email: hnjmlixia@henetc.edu.cn.

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