Retrieval and Recommendation of English Learning Resources Based on Knowledge Correlation

https://doi.org/10.3991/ijet.v17i16.33763

Fangfang Li
School of Foreign Studies, Henan Polytechnic University, Jiaozuo, China
lff@hpu.edu.cn

Abstract—The design of retrieval and recommendation method of personalized learning resources based on students' cognition level of professional knowledge and the correlation degree of the knowledge is of certain practical significance. In reality, students' learning preferences and needs will change with the passing of time and the upgrading of learning stages, so giving learning resource recommendations without considering the time series features of students' needs for learning resources cannot guarantee students' learning efficiency or the effect of personal knowledge system perfection. To solve this problem, this paper took online English learning as an example to study the retrieval and recommendation of English learning resources based on knowledge correlation. At first, the paper gave the relationship between the knowledge points of English learning resources, and gave judgements on students' mastery degree of knowledge points. Then, the influence of the semantics and relationships of knowledge points involved in English learning was fully considered, and the closeness degree of the correlation of learning resources was calculated. At last, this paper introduced a hybrid attention mechanism into the learning resource recommendation model, and gave the process for calculating the weight of hybrid attention. The effectiveness of the constructed model was verified by the experimental results.

Keywords—knowledge correlation, online learning, learning resource, retrieval, recommendation, English learning

1 Introduction

Newly emerged technologies such as Internet+ and cloud computing are changing people's every life aspect subtly, in terms of education, they have greatly promoted the development of smart education and online education [1-6]. However, the existing learning resource search engines provided by current smart education platforms couldn't meet students' needs of retrieving personalized learning resources based on fuzzy learning objectives, as a result, personalized teaching and accurate application of the competency-based instructing system couldn't be realized, especially for students with large structural differences in their professional knowledge cognition level and knowledge system, more attention needs to be paid to their learning preferences and personality traits when recommending personalized learning resources for them [7-10]. In this context, it is of certain practical meaning to design personalized learning resource retrieval and recommendation methods based on students' cognition level of professional knowledge and the correlation degree of the knowledge with smart teaching assistance system as the reference framework [11-14].

The objective of fragmented learning is to make full use of learners' fragmented time slices to learn and accumulate knowledge piece by piece. At present, existing mobile and online learning apps haven't fully considered the preferences, needs, and adaptability of their users, usually, the content and difficulty of resources recommended by these apps couldn't match well with user functions. Xu [15] discussed the problem of personalized online learning resource recommendation based on mobile devices and developed a system structure for adaptive online learning resource recommendation models; in the paper, the authors modeled the learners and the scattered learning resources, built a personalized online learning resource recommendation model, introduced the work flow of recommendation engine in detail, and calculated the recommendation degree and matching degree of the resources. Yu et al. [16] proposed a collective POI (point of interest) recommendation framework leveraging latent individual preferences and contextual information; in the text, the authors built a rating prediction model for recommended POIs, and the influence of similarity, popularity, and location of POIs had been taken into consideration in the model. Zhu [17] provided a recommendation model of news media textbooks based on user model which can capture changes in user interests and describe and integrate the short-term and long-term preferences. Some existing personalized network resource recommendation systems do not have clear personalized classification standards of user history information, which has resulted in a low matching degree between the recommendation results given by the system and the actual interests of users. Thus, in order to improve the accuracy of recommendation results, Qiu and Cheng [18] designed a personalized recommendation system of network resources based on the collaborative filtering algorithm; in the hardware design, the authors devised the overall circuit module, configured the bus sequence, and accelerated the running speed of system hardware; in the software design, the authors calculated the time weight function, established an implicit scoring matrix of users, calculated the measured scores and actual scores of each scoring item, and constructed the said model. Discovering valuable learning paths and patterns from learners' online learning data can provide useful references for subsequent learners and improve their learning experience and learning effects, Diao et al. [19] put forward a personalized learning path recommendation method based on weak concept mining, which can use clustering and association rule mining algorithms to generate concept maps for different type learners according to their history mastery degree of the concepts.

By reviewing and summarizing existing research results, we found that current learning resource recommendation systems generally default that the students' learning preferences are static, however, in reality, their learning preferences and needs will change with the passing of time and the upgrading of learning stages, so giving recommendations without considering the time series features of students' needs for learning resources cannot guarantee learning efficiency or learning effect. To solve this problem, this paper took online English learning as an example to study the retrieval and recommendation of English learning resources based on knowledge correlation. In the second chapter, this paper gave the relationship between the knowledge points of English learning resources, and judged the situation of students' mastery of knowledge points; in the third chapter, this paper discussed the influence of the semantics and relationships of knowledge points involved in English learning, and calculated the closeness degree of the correlation of learning resources; in the fourth chapter, this paper introduced a hybrid attention mechanism into the learning resource recommendation model, and gave the process for calculating the weight of hybrid attention; at the last part, the effectiveness of the constructed model was verified by the experimental results.

2 Judgement of cognition level of English knowledge

Before retrieving and recommending English learning resources, this paper made judgements about students' mastery of knowledge points, attained the knowledge correlation of students' current cognition level of English knowledge points, and generated the recommendation results of English learning resources. In this paper, the said cognition level (of students for English knowledge points) was calculated based on two steps: the diagnosis of initial cognition and the diagnosis of current cognition. The initial cognition represents the cognition level of English knowledge possessed by students before entering the smart education platform for learning, and its data could be attained by the DINA (Deterministic Input Noisy output AND gate) optimization model.

Figure 1 shows the relationship between knowledge points of English learning resources. Assuming: $T=\{T_1,T_2,...,T_m\}$ represents the set of students; $I=\{I_1, I_2,...,I_u\}$ represents the set of English learning resources; $R=\{R_1,R_2,...,R_l\}$ represents the set of knowledge points; $C=[c]_{V\times U}$ represents the learning effect score matrix of English learning resources, it describes the learning effect of V students for U items of English learning resources, wherein $c_{vu}=1$ means that item I_u has a learning effect on student T_v; and $c_{vu}=0$ means that item I_u has no learning effect on student T_v; $W=[w]_{U\times L}$ represents the knowledge point matrix of English learning resources, which describes the situation of students' mastery of the knowledge points of English learning resources, wherein $w_{ul}=1$ means that item I_u involves knowledge point R_l; and $w_{ul}=0$ means that item I_u does not involve knowledge point R_l; $\beta_v=\{\beta_{v1},\beta_{v2},...,\beta_{vl}\}$ represents the vector of the mastery degree of student T_v of all knowledge points; $\beta_{vl}=1$ represents that student T_v has mastered knowledge point R_l; $\beta_{vl}=0$ represents that student T_v hasn't mastered knowledge point R_l.

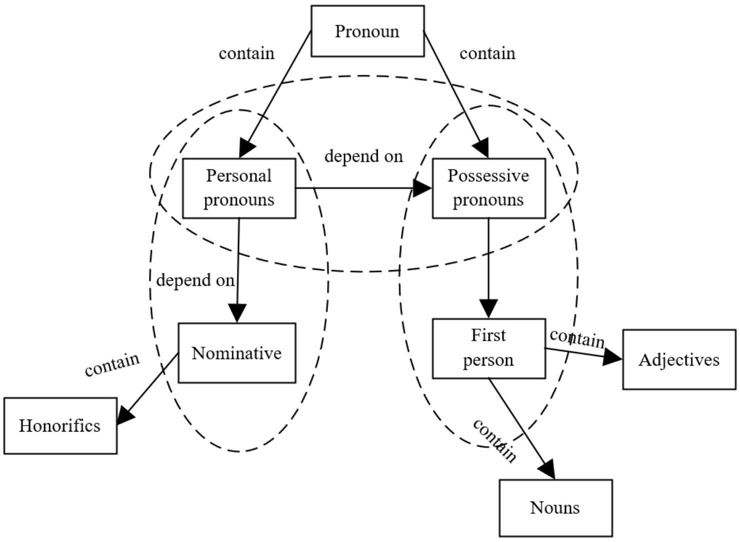

Fig. 1. Relationship between knowledge points of English learning resources

Assuming: the vector of the mastery degree of student T_v of knowledge points x_m and the knowledge point matrix of English learning resources are known, $f(\beta_v,w_u)$ represents the exponentiation that raises each element of β to w_{ul} power, then the following formula gives the quantification of student's potential learning situation of the unlearned item I_j:

$$\delta_{vu} = \prod_{l=1}^{L} {\beta_{vl}}^{w_{ul}} = f\left(\beta_m, w_u\right) \tag{1}$$

Assuming: h_u represents the probability that the student T_v has learned item I_u but has not fully mastered all the knowledge points involved, then its value can be calculated by the following formula:

$$GD\left(C_{vu} = 1 \middle| \delta_{vu} = 0\right) = h_u \tag{2}$$

Assuming: r_u represents the probability that the student T_v hasn't learned item I_u yet but has already fully mastered all the knowledge points involved, then its value can be calculated by the following formula:

$$GD\left(C_{vu} = 0 \middle| \delta_{vu} = 1\right) = r_u \tag{3}$$

δ_{vu}=1 represents that the student has the learning condition of item I_u; δ_{vu}=0 represents that the student doesn't have the learning condition of item I_u.

In *DINA* model, in order to simulate the online learning status of students for English learning resources under actual conditions, based on the above two formulas, the probability that the English learning resources do have learning effects for students can be calculated as:

$$GD_u\left(\beta_v\right)=GD\left(C_{qv}=1\mid\beta_v\right)=h_u^{1-\delta_{vu}}\left(1-r_u\right)^{\delta_{vu}} \tag{4}$$

This paper adopted the EM algorithm to search for optimal solution through parameter iteration so as to attain the marginal maximum likelihood estimation, and the estimated values are denoted as $\{r^*_1,r^*_2,\ldots,r^*_U\}$and $\{h^*_1,h^*_2,\ldots,h^*_U\}$. The following formula gives the expression of dynamic prior distribution attained based on the parameter estimation of the previous iteration and the students' learning effect of English learning resources, the attained results could be used for the parameter estimation of the next iteration.

$$GD\left(\beta\right)=\frac{\sum_{v=1}^{J}GD\left(\beta_{va}\mid h^*,r^*,S_v\right)}{J} \tag{5}$$

After learning the English learning resources, the binary vector β^*_v of students' mastery of knowledge points could be calculated by the following formula:

$$\begin{aligned}\beta_v^*\left(C_v\right)&=\underset{\beta}{argmax}\,G\left(\beta\middle|C_v\right)=\underset{\beta}{argmax}\,G\left(C_v\middle|\beta,r_u^*,h_u^*\right)GD\left(\beta\right)\\&=\underset{\beta}{argmax}\,G\left(C_v\middle|\beta,r_u^*,h_u^*\right)GD\left(\beta\right)=\underset{\beta}{argmax}\prod_{u=1}^{U}G\left(C_v\middle|\beta,r_u^*,h_u^*\right)GD\left(\beta\right)\end{aligned} \tag{6}$$

β^*_v=0 means that the student hasn't mastered the knowledge points after learning the English learning resources; β^*_v=0 means the student has mastered the knowledge points after learning the English learning resources.

To normalize the values of the mastery degree of students into the range of [0,1], assuming: L represents the number of knowledge points contained in all English learning resources; 2^L represents all possible presentation forms of the knowledge points; $GD(x_a)$ represents the prior distribution of students' mastery of knowledge after learning, then, Formula 7 gives the expression of the vector of estimated knowledge point mastery degree β'_v:

$$\tilde{\beta}_{vl} = GD\left(\beta_{vl} = 1 \middle| C_v\right) = \frac{\sum\limits_{\beta_{vl}=1} GD\left(\beta_a \middle| C_v\right)}{\sum\limits_{a=1}^{2^K} GD\left(\beta_a \middle| C_v\right)} = \frac{\sum\limits_{\beta_{vl}=1} G\left(C_v \middle| \beta_a, \hat{r}_u, \hat{h}_u\right) GD\left(\beta_a\right)}{\sum\limits_{x=1}^{2^L} GD\left(\beta_a \middle| C_v\right)}$$
$$= \frac{\sum\limits_{\beta_{vl}=1} \prod\limits_{u=1}^{U} G\left(C_{qv} \middle| \beta_a, \hat{r}_u, \hat{h}_u\right) GD\left(\beta_a\right)}{\sum\limits_{a=1}^{2^L} GD\left(\beta_a \middle| C_v\right)} \tag{7}$$

After students entering the smart education platform, with the progress of online learning, they absorbed the recommended learning resources and completed the knowledge transfer. In this paper, the ratio of knowledge amount absorbed by students through the learning of recommended learning resources is defined as the knowledge transfer probability, its value determines the change degree of students' cognition level after they completed the learning of English learning resources for one time, and it has four influencing factors: learning interest, learning motivation, knowledge matching degree, and knowledge presentation form. In this paper, multiple linear regression was adopted to calculate the value of knowledge transfer probability, assuming: A_h, A_e, A_d, and A_x represent the four influencing factors; ω_1, ω_2, ω_3, and ω_4 represent the regression coefficients; and σ_1, σ_2, σ_3, σ_4, and σ_5 represent the coefficients of the nested linear regression, then there is:

$$SF\left(A_h, A_e, A_d, A_x\right) = \omega_1 A_h + \omega_2 \left(\frac{1}{1 + A_e}\right) + \omega_3 A_d$$
$$+\omega_4 \left[A_x\left(a_{x1}, a_{x2}, a_{x3}, a_{x4}, a_{x5}\right) * \left(\sigma_1, \sigma_2, \sigma_3, \sigma_4, \sigma_5\right)^{\rho} \Big/ 10 \right] \tag{8}$$

Assuming: $SF(K_d)$ represents the current cognition level; $SF(K_o)$ represents the initial cognition level, then the normalization of the calculated value of the knowledge representation form could be expressed as:

$$SF\left(K_d\right) = SF\left(K_o\right) + \left(1 - SF\left(K_o\right)\right) * SF\left(A_h, A_e, A_d, A_x\right) \tag{9}$$

3 Calculation of the closeness degree of knowledge correlation

When facing the large amounts of English learning resources, it is impossible to use only the direct correlation to distinguish the differences in the closeness degree of knowledge correlation of other English learning resources that have the same type of correlation as the retrieval target of knowledge points. This paper built a relationship network based on the relationship of all English learning resources. The indirect relationship of learning resources can be defined as the relationship between two learning resources that are directly related to a certain learning resource.

In order to attain objective and accurate calculation values of the closeness degree of the correlation of learning resources, it's necessary to fully consider the influence of the semantics and relationships of knowledge points involved in English learning. Before calculating the correlation closeness degree, at first, the *TransR* model was used to describe the vector of knowledge points involved in the learning resources, wherein TE_h represents the retrieval target of knowledge points; h represents the serial number of learning resources corresponding to the knowledge points.

$$TE_h = \left(o_{1i}, o_{2i}, \ldots, o_{vh}\right)^{\rho} \tag{10}$$

Then, the knowledge points involved in the learning resources were embedded into a m-dimensional vector, the value corresponding to the j-th dimension is represented by o_{jh}, then the similarity of knowledge points involved in learning resources can be calculated based on the following formula:

$$\xi\left(TE_h, TE_s\right) = \sqrt{\sum_{j=1}^{m}\left(o_{jh} - o_{js}\right)^2} \tag{11}$$

Assuming: L_h and L_s represent knowledge points involved in two correlated learning resources, then the similarity of the two learning resources can be performed based on the following formula:

$$sim_{rh}\left(TE_h, TE_s\right) = \frac{1}{1 + \xi\left(TE_h, TE_s\right)} \tag{12}$$

The direct relationship $r_v(TE_h, TE_s)$ between two English learning resources is unique, while the indirect relationship S may not be unique, which can be written as:

$$S = \left(s_1, s_2, \ldots, s_7\right) = \left(1, 0, \ldots, 1\right) \tag{13}$$

S=0 means that there is no indirect relationship between two English learning resources, and S=1 means that there is an indirect relationship between two English learning resources. Assuming: TE_s represents English learning resources directly related to the retrieval target of knowledge points; R represents the vector of correlation closeness degree values; λ represents the weight (namely the importance degree) of knowledge points in the relationship network, then the calculation formula of the closeness degree of the correlation of learning resources is given by Formula 14:

$$sim\left(TE_h, TE_s\right) = \begin{cases} \dfrac{1}{1 + \sqrt{\sum_{j=1}^{m}\left(o_{jh} - o_{js}\right)^2}}\left[\lambda r_v\left(TE_h, TE_s\right) + \lambda^2 S \bullet R^{\rho}\right], r_v\left(TE_h, TE_s\right) \neq 0 \\ 0, r_v\left(TE_h, TE_s\right) = 0 \end{cases} \tag{14}$$

4 The learning resource recommendation method

For the large amounts of knowledge correlation information involved in the English learning resources, the features of knowledge points involved in the English learning resources R could be attained through learning resource embedding and the grouping convolution and pooling processing of the recommendation model, this paper introduced the hybrid attention mechanism into the learning resource recommendation model, and the model results are shown in Figure 2.

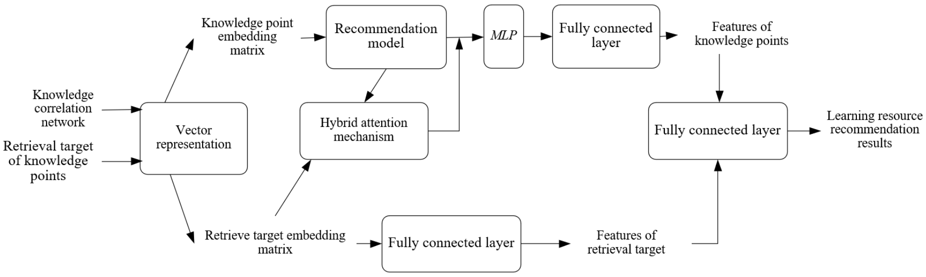

Fig. 2. Structure of the learning resource recommendation model

In the previous calculation process of the closeness degree of the correlation of learning resources, the knowledge point embedding matrix and the learning resource features were input into the hybrid attention model. Assuming: $\oplus$ represents matrix stitching; R represents the merge results of the features of knowledge points involved in the learning resources; $\Gamma(*)$ represents the *matmul* function; $\Omega(*)$ represents the *softmax* function; then the weight of attention β_P can be attained from the following formula:

$$R = R_1 \oplus R_2 \oplus R_3 \cdots R_m \tag{15}$$

$$\beta_P = \Omega\left(\sum_v \Gamma\left(P_v, R\right)\right) = \frac{exp\left(\sum_v \Gamma\left(P_v, R\right)\right)}{\sum_n exp\left(\sum_v \Gamma\left(P_v, R\right)\right)} \tag{16}$$

The weight attained from above formulas represents the student's preference for English learning resources, which was then used in the construction of the features of knowledge points involved in learning resources. The following formula can calculate the self-attention weight β_O:

$$\beta_O = \Omega\left(\Gamma\left(R_s, R\right)\right) = \frac{exp\left(\Gamma\left(R_s, R\right)\right)}{\sum_n exp\left(\Gamma\left(R_s, R\right)\right)} \tag{17}$$

The weights represent the different emphases of knowledge points involved in a learning resource itself. Finally, by combining β_P with β_O, the hybrid attention weight could be attained, after subjected to the fully connected layer of the recommendation model, the final features of knowledge points involved in the learning resources could be attained. Figure 3 shows the calculation flow of the two weights, and Figure 4 gives the calculation flow of the hybrid attention weight. Assuming: the *tanh* function is chosen as the activation function of the fully connected layer; Q and φ represent the weight and bias of the fully connected layer of the recommended model, then there are:

$$Q = matmul\left(\beta_P, \beta_O\right) \tag{18}$$

$$Z' = tanh\left(QZ + \phi\right) \tag{19}$$

The retrieval target of knowledge points, and the features of knowledge points involved in learning resources were input into the fully connected layer, then the model output the recommendation results of learning resources.

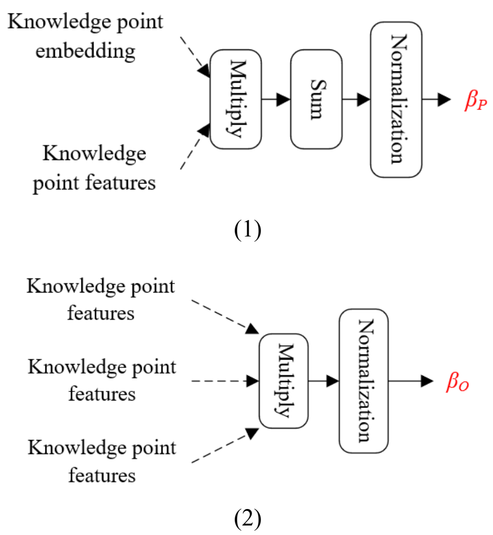

Fig. 3. Calculation flow of β_P and β_O

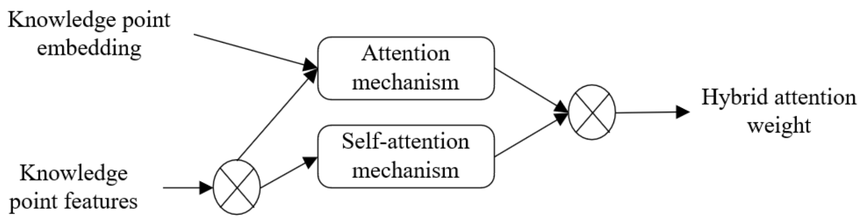

Fig. 4. Calculation flow of hybrid attention weight

5 Experimental results and discussion

Based on the 500 participant learners of a smart English education platform, 20 learning resources in the pronoun module in English grammar were measured and evaluated. 10 knowledge points are involved in the learning resources, and the distribution of these knowledge points is shown in Figure 5.

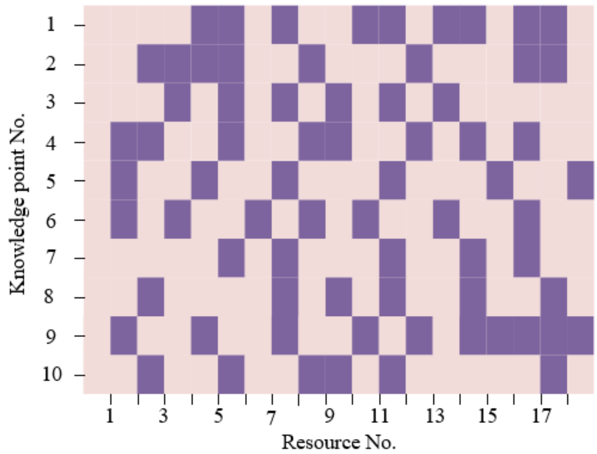

Fig. 5. The situation of knowledge points involved in learning resources

Table 1. Calculation results of the initial cognition level of students

Knowledge point No.	T_1	T_2	T_3	T_4	T_5	T_6	T_7	T_8	T_9	T_{10}
1	0.82	0.63	0.35	0.04	1.25	0.42	0.95	0.03	0.97	0.37
2	0.71	0.15	0.62	1.03	0.95	0.88	0.52	1.58	0.62	0.95
3	0.91	0.96	0.27	0.01	0.92	0.98	1.26	0.42	0.96	1.32
4	0.27	0.05	0.01	0.96	0.94	0.91	0.57	1.15	0.02	0.08
5	0.92	0.67	0.43	0.95	1.14	0.96	0.94	1.39	0.96	0.94
6	0.77	0.83	0.34	0.98	0.03	0.07	0.92	1.27	0.92	0.31
7	0.64	0.52	0.58	0.96	0.91	0.97	0.52	0.96	0.51	0.53
8	0.71	0.82	0.41	0.95	1.24	0.92	0.04	0.92	0.67	0.96
9	0.37	0.33	0.81	0.91	0.74	0.31	0.91	1.05	0.42	0.38
10	0.62	0.47	0.32	0.55	1.21	0.86	0.34	0.89	0.76	0.34

Based on the algorithm proposed in this paper, the initial English knowledge cognition level of students participating in online English learning was attained, and Figure 1 gives the calculation results. Figure 6 gives the radar map of some students' initial English knowledge cognition level.

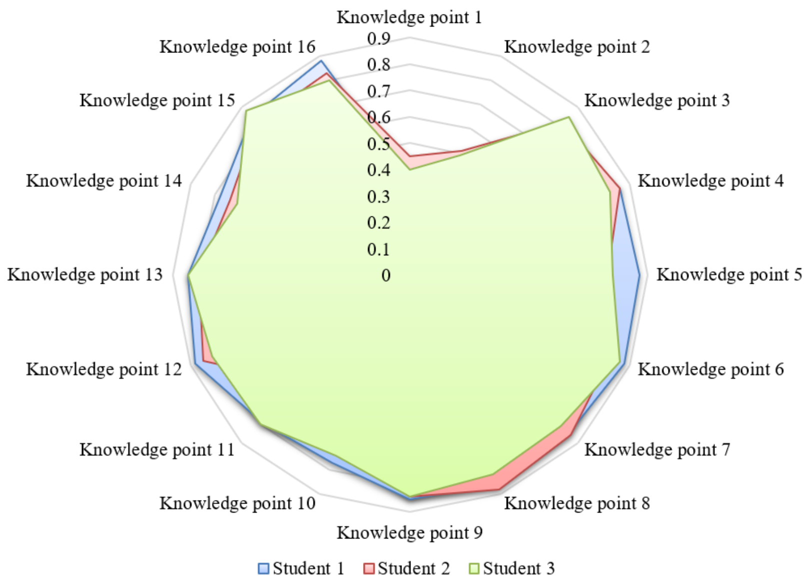

Fig. 6. Radar map of the initial English knowledge cognition level of different students

To verify the performance of the learning resource recommendation model constructed in this paper, comparative experiment was performed to examine the recommendation effect of the proposed method and other resource recommendation models on the real dataset of resource recommendation of the smart English education platform. Table 2 shows the experimental results.

Table 2. Experimental results of the learning resource recommendation model

Model		***KG-GAT***	***DeepFM***	***KHA-CNN***	***Wipe&Deep***	***NCF***	***KCNN+***	**The proposed model**
Freshman	*MAE*	0.6012	0.6925	0.6295	0.6481	0.6184	0.6295	0.5327
	MSE	0.7583	0.7958	0.7514	0.6253	0.7485	0.6592	0.6152
	AUC	0.6258	0.6748	0.6953	0.6529	0.6748	0.7253	0.4362
Sophomore	*MAE*	0.4748	0.4362	0.4125	0.3925	0.4857	0.3629	0.3341
	MSE	0.4712	0.4362	0.4718	0.3925	0.4571	0.4623	0.3415
	AUC	0.4958	0.5623	0.5748	0.5625	0.5932	0.5473	0.5169

According to the data shown in the table, the proposed model achieved better experimental results in terms of three performance evaluation indicators *MAE*, *MSE*, and *AUC*, which had verified the effectiveness of introducing the hybrid attention mechanism into the proposed model. The main reason is that the attention mechanism in the introduced hybrid attention mechanism has effectively reflected the influence of students' learning preferences on the learning resources, meanwhile the self-attention mechanism in the hybrid attention mechanism has well reflected the different emphasis of the knowledge points involved in the learning resource itself. This paper has integrated these two mechanisms, and innovatively constructed a recommendation model which has the function of retaining both the information of resource recommendation target and the information of resources to be recommended, this ensures that the extracted learning resource features are more accurate and comprehensive, and the recommendation effect of learning resource could be better.

Figure 7 gives the experimental results of different application methods of the model target information and the information to be recommended. According to the figure, the retrieval target of knowledge points and the features of knowledge points involved in the learning resources were taken as the input of the constructed recommendation model, the features of knowledge points involved in the learning resources were weighted based on the calculated hybrid attention weight, and good recommendation effect has been achieved in the end. Because the retrieval target of knowledge points and the features of knowledge points involved in the learning resources are the most valuable information of students' learning needs and learning resources, calculating the hybrid attention weight based on the information of the corresponding retrieval and recommendation target and the information to be recommended, and introducing it into the features of knowledge points involved in the learning resources not only takes the influence of students' preferences for learning resources into consideration, but also describes the different emphases of knowledge points involved in the learning resource itself; moreover, it reduces the complexity of the model, and achieves the best learning resource recommendation effect.

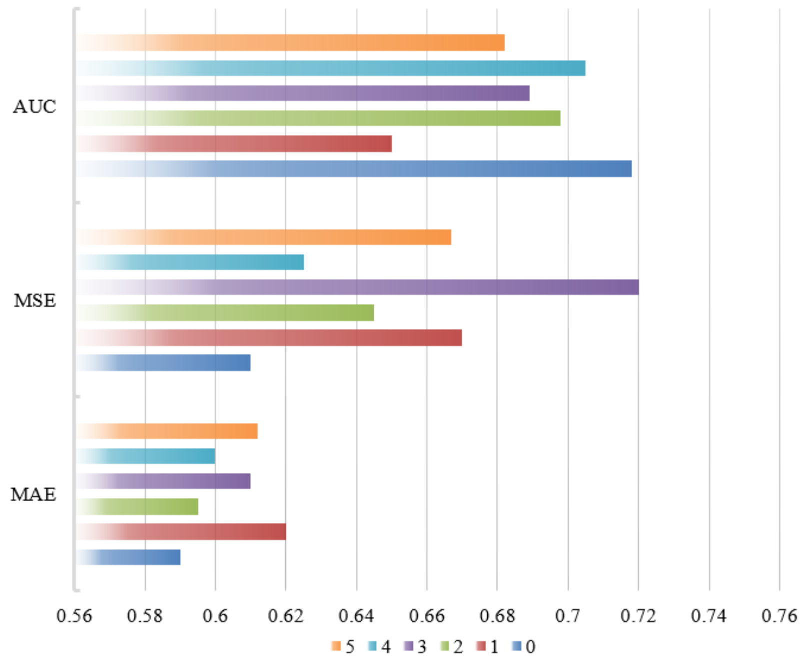

Fig. 7. Experimental results of different application mods of model target information and information to be recommended

6 Conclusion

This paper took online English learning as an example to study the retrieval and recommendation of English learning resources based on knowledge correlation. At first, this paper gave the relationship between the knowledge points of English learning resources, and judged the situation of students' mastery of knowledge points; then, it discussed the influence of the semantics and relationships of knowledge points involved in English learning, and calculated the closeness degree of the correlation of learning resources; after that, the paper introduced a hybrid attention mechanism into the learning resource recommendation model, and gave the process for calculating the weight of hybrid attention; in the experimental part, this paper gave the distribution of knowledge points involved in the learning resources, measured the initial cognition level of students, and plotted the radar map of some students' initial English knowledge cognition level. On a real dataset of resource recommendation of the smart English education platform, the recommendation effect of the proposed model and other resource recommendation models was tested and compared, and the results proved the effectiveness and advantages of the proposed model.

7 References

[1] Shraim, K.Y. (2020). Quality Standards in Online Education: The ISO/IEC 40180 Framework, International Journal of Emerging Technologies in Learning, 15(19): 22-36. https://doi.org/10.3991/ijet.v15i19.15065
[2] Wei, F. (2022). Connotation and construction assumption of wisdom education in the era of artificial intelligence. Innovative Computing, pp. 1219-1225. https://doi.org/10.1007/978-981-16-4258-6_149
[3] Chen, X., Xia, E.Y., Jia, W. (2020). Utilisation Status and User Satisfaction of Online Education Platforms, International Journal of Emerging Technologies in Learning, 15(19): 154-170. https://doi.org/10.3991/ijet.v15i19.17415
[4] As'ari, R., Rohmat, D., Maryani, E., Ningrum, E. (2019). Management of water resource based on local wisdom: a development study of Kampung Naga as field laboratory of Geography Education in Tasikmalaya, West Java. IOP Conference Series: Earth and Environmental Science, 243(1): 012002. https://doi.org/10.1088/1755-1315/243/1/012002
[5] Wen, J., Wei, X.C., He, T., Zhang, S.S. (2020). Regression analysis on the influencing factors of the acceptance of online education platform among college students. Ingénierie des Systèmes d'Information, 25(5): 595-600. https://doi.org/10.18280/isi.250506
[6] Wang, S.Y. (2021). Online learning behavior analysis based on image emotion recognition. Traitement du Signal, 38(3): 865-873. https://doi.org/10.18280/ts.380333
[7] Yu, Y., Chen, X., Zhang, L., Gao, R., & Gao, H. (2020). Neural Graph for Personalized Tag Recommendation. IEEE Intelligent Systems, 37(1): 51-59. https://doi.org/10.1109/MIS.2020.3040046
[8] Wang, J. (2021). Personalized recommendation system based on vocal characteristics. In International Conference on Machine Learning and Big Data Analytics for IoT Security and Privacy, Shanghai, China, pp. 1051-1057. https://doi.org/10.1007/978-3-030-89508-2_136

[9] Zhang, Q., Liu, Y., Liu, L., Lu, S., Feng, Y.X., Yu, X. (2021). Location identification and personalized recommendation of tourist attractions based on image processing. Traitement du Signal, 38(1): 197-205. https://doi.org/10.18280/ts.380121
[10] Wang, C., Yang, Y., Suo, K., Wang, P. (2022). MulSetRank: Multiple set ranking for personalized recommendation from implicit feedback. Knowledge-Based Systems, 249: 108946. https://doi.org/10.1016/j.knosys.2022.108946
[11] Guo, S., Zhu, X., Liu, Y., Han, J. (2022). Personalized recommendation method of entrepreneurial service information based on blockchain. Journal of Interconnection Networks, 22(3): 2145010. https://doi.org/10.1142/S0219265921450109
[12] Kumar, S.G., Sridhar, S.S., Hussain, A., Manikanthan, S.V., Padmapriya, T. (2022). Personalized web service recommendation through mishmash technique and deep learning model. Multimedia Tools and Applications, 81(7): 9091-9109. https://doi.org/10.1007/s11042-021-11452-4
[13] Liu, Y., Li, J., Ren, Z., Li, J. (2022). Research on personalized recommendation of higher education resources based on multidimensional association rules. Wireless Communications and Mobile Computing, 2022: 2922091. https://doi.org/10.1155/2022/2922091
[14] Zhang, Q. (2022). Personalized hybrid recommendation for tourist users based on matrix cluster apriori mining algorithm. Mathematical Problems in Engineering, 2022: 8299761. https://doi.org/10.1155/2022/8299761
[15] Xu, S. (2022). Recommendation of online learning resources for personalized fragmented learning based on mobile devices. International Journal of Emerging Technologies in Learning (iJET), 17(3): 34-49. https://doi.org/10.3991/ijet.v17i03.29427
[16] Yu, D., Yu, T., Wu, Y., Liu, C. (2022). Personalized recommendation of collective points-of-interest with preference and context awareness. Pattern Recognition Letters, 153: 16-23. https://doi.org/10.1016/j.patrec.2021.11.018
[17] Zhu, S. (2022). User model-based personalized recommendation algorithm for news media education resources. Mathematical Problems in Engineering, 2022: 7431948. https://doi.org/10.1155/2022/7431948
[18] Qiu, G., Cheng, J. (2021). Network resource personalized recommendation system based on collaborative filtering algorithm. In International Conference on Advanced Hybrid Information Processing, Sydney, Australia, pp. 645-655. https://doi.org/10.1007/978-3-030-94551-0_50
[19] Diao, X., Zeng, Q., Li, L., Duan, H., Zhao, H., Song, Z. (2022). Personalized learning path recommendation based on weak concept mining. Mobile Information Systems, 2022: 2944268. https://doi.org/10.1155/2022/2944268

8 Author

Fangfang Li, got the bachelor's degree in Shannxi Normal University and gained the master's degree in Henan Normal University. She has been working in School of Foreign Studies, Henan Polytechnic University since 2004. Her research interests include English literature, English teaching, translation, and cultural studies (e-mail: lff@hpu.edu.cn).

Article submitted 2022-06-02. Resubmitted 2022-07-15. Final acceptance 2022-07-25. Final version published as submitted by the author.