A New Resource Recommendation Method for Experiential Leaching Based on the Completion Degree of Online Learning Tasks

https://doi.org/10.3991/ijet.v18i01.37129

Ligang Jia(✉)
Shandong University (Weihai) Art College, Weihai, China
201999800028@stu.edu.cn

Abstract—Experiential Learning (ExL) is an effective way to consolidate theoretical knowledge and deepen understandings, and the recommendation of ExL resources needs to also take the effect of students' theoretical learning into consideration. However, existing studies generally ignore the stage-by-stage assessment of students' completion of online learning tasks, and the recommendation performance of existing resource recommendation models for ExL is not satisfactory enough. Therefore, the recommendation method needs to be innovated, and the interpretability of recommendation results is facing challenges. To respond to these issues, this paper studied a new resource recommendation method for ExL based on the completion degree of online learning tasks. At first, the paper gave the principle of recommending ExL resources based on the completion degree of online learning tasks, and built an online learning task completion degree prediction model. Then, this paper adopted a bi-directional GRU network model based on attention mechanism to analyze the recent online learning behavior sequence of students and attain the completion degree of students' short term learning tasks. After that, a knowledge map representing ExL resources and the correlation of knowledge attributes was drawn; by combining the completion degree of both the short-term and long-term learning tasks, the ExL resources suitable for students were recommended to them. At last, experimental results verified the effectiveness of the constructed model.

Keywords—online learning, task completion degree, Experiential Learning (ExL), learning resource recommendation

1 Introduction

With the advent of Internet and big data, the sharp increase in data volume and the continuous optimization of information collection and sharing methods have resulted in the problem of information overload, and online learning platforms have to develop learning resource recommendation systems to deal with this problem [1–6]. The learning resource recommendation systems can analyze students' learning behavior, mine the personalized learning requirements of students based on their completion degree of online learning tasks, and help them find learning resources that are suitable for their learning level and might attract their interests [7–11].

Experiential Learning (ExL) is an effective way to consolidate theoretical knowledge and deepen understandings. To assist students to enhance their hands-on ability and get good learning effect, the recommendation of ExL resources should be able to connect theory with practice and it must take the effect of students' theoretical learning into consideration [12–21]. Therefore, the recommendation method needs to be innovated, and the interpretability of recommendation results is facing challenges.

Zhang et al. [23] pointed out that as smart education is being extensively applied in higher education, now the recommendation of personalized learning resources has become an important research field of smart learning. The authors proposed a Q-LRDP-D (Learning Resource Difficulty Prediction and Dijkstra based on Q matrix) algorithm. At first, the learning resources were modeled based on the Q matrix theory, and the students' learning difficulty was predicted by the long short-term memory (LSTM) algorithm of the learning resource difficulty prediction module; then, according to the requirements of the teaching units, the knowledge points to be learnt were combined for cyclic prediction so as to form a directed path map of learning resources; at last, the shortest path algorithm was used to recommend the minimum learning resources suitable for students' learning level to complete the learning tasks. Dien et al. [24] constructed a deep matrix decomposition model which is an extension from standard matrix decomposition, and used it to recommend learning resources based on the capabilities and requirements of learners. The authors tested the model on two sets of experimental data, one dataset was a college student's learning results of recommended courses, another dataset was the learning resource data of five users; at last, the authors gave a few useful suggestions for the learners. In terms of ExL, Zhang and Guan [25] researched the assessment background, characteristics, contents, and methods of ExL and gave a few application examples. Cardona Zapata and López Ríos [26] introduced the potential of a heuristic V diagram designed as a theoretical-methodological tool that can increase the potential of data acquisition system in ExL, aiming to solve the shortage in teaching resources for experimental scenarios.

After reviewing relevant literatures, we found that field scholars in the world have conducted a lot of research on the influence of students' online learning preferences on their learning effect, but there're differences in the determination of factors affecting students' completion of online learning tasks, and few of them have given stage-by-stage assessments on students' completion degree of online learning tasks, or built resource recommendation model for ExL. To fill in this research blank, this paper aims to develop a new resource recommendation method for ExL based on the completion degree of online learning tasks. In the second chapter, this paper gave the principle of recommending ExL resources based on the completion degree of online learning tasks, and built an online learning task completion degree prediction model. In the third chapter, this paper adopted a bi-directional GRU network model based on attention mechanism to analyze the recent online learning behavior sequence of students and attain the completion degree of students' short term learning tasks, and a knowledge map representing ExL resources and the correlation of knowledge attributes was drawn. In the fourth chapter, the paper combined the completion degree of both the short-term and long-term learning tasks, and generated suitable ExL resources for students and made recommendations. At last, experimental results verified the effectiveness of the constructed model.

2 Prediction model based on completion degree of online learning tasks

Figure 1 shows the principle of recommending learning resources for ExL based on online learning. At first, the learning resource recommendation algorithm analyzes the target student's online learning behavior based on texts; then, it calculates the potential correlation between the target student and the ExL resources, searches for ExL resources that fit the student's completion degree of online learning tasks, and screens them; at last, recommendations are made for the target student.

In order to assess students' completion of online learning tasks stage by stage, this paper collected the data of students' online learning task scores, the number of teaching videos watched, the watching frequency of teaching videos, and the average watching time of each teaching video. These data can reflect the differences in the knowledge structure of students formed by their learning styles and theoretical knowledge review states before the learning of ExL resources in the online learning environment.

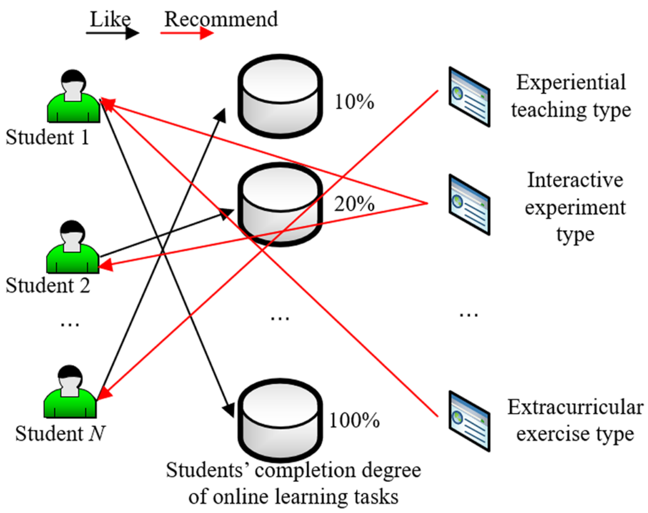

Fig. 1. Principle of recommending ExL resources based on completion degree of online learning tasks

When building the prediction model, at first, this paper assumed that the final scores of the online learning tasks reflect the comprehensive completion degree of students for the learning tasks of each theoretical learning topic, it can be considered that for students with different completion degrees of online learning tasks, their final scores might be the same. The formula below gives the full probability formula of the online learning task completion degree prediction model, which describes the probability of the completion degree of primary task constituted by the completion degrees of sub-tasks.

$$GU'_p = \sum_{i=1}^{n} GU(r_i) \cdot GU(p|r_i) \tag{1}$$

Assuming: GU represents the probability that a student has completed a certain learning task; p represents an online learning unit task; GU_p represents the probability that the student has fully grasped the learning topic corresponding to task p; r_i represents the quiz sub-task corresponding to task p; n represents the number of quizzes. When p represents the task in the class, then it can be considered that GU_p is the probability of the student getting full score in the online learning task.

At this time, the prediction model hadn't involved the collected data of the online learning behavior of students. In this paper, a 5-dimensional vector q was set, and the function g about the online learning behavior of students was equivalent to $GU(p|r_i)$, which satisfies $GU(p|r_i)=g(U)$ and its value range is [0,1]; let $U=<U_s,U_m,U_g,U_p,K_o>$, then the expression of function g is:

$$g(U) = sigmoid(U \cdot q') \tag{2}$$

Combining the above two formulas, we can get the formula for calculating the expected completion degree of learning tasks:

$$GU'_p = \sum_{i=1}^{n} GU(r_i) \cdot sig(U \cdot q'_i) \tag{3}$$

Assuming: q'_i represents the weight coefficient of learning task topic i; $Q = \left[q'_1, q'_2, \ldots . q'_n\right]$ represents the weight coefficients of all learning task topics. Then, Q was trained with the minimization of the variance of the difference between GU_p and $P'_e GU'_p$ as the objective, and the formula below gives the expression of the optimization training process:

$$\min \left\| GU_p - GU'_p \right\|^2 \tag{4}$$

By combining Formula 1, Formula 2, and the above Formula, we have:

$$\min \left\| GU_p - GU \cdot G \right\|^2 \tag{5}$$

Assuming: $GU=[GU(r_1), GU(r_2),\ldots GU(r_n)]$, $G = \left[sig(U \cdot q'_1), sig(U \cdot q'_2) \ldots sig(U \cdot q'_n)\right]^{-1}$, the constraint of the optimization training process is:

$$\sum_{i=1}^{n} sig(U \cdot q'_i) = 1 \tag{6}$$

As important independent variables for predicting the completion degree of learning tasks, the tags of the data collected from four aspects are multidimensional. To increase the accuracy of prediction results, after the collected data were pre-processed, this paper adopted the multivariate linear regression to fit the prediction model. Assuming: S represents the total number of visits of the videos of all sub-tasks under a certain learning task topic; M represents the total number of visits of the videos of all sub-tasks under the learning task topic within a fixed time period; U represents the average watching time of the videos of all sub-tasks under the learning task topic within the fixed time period; E represents the average score of all sub-tasks under the learning task topic, then the expression of the regression model is:

$$GU_p = 59.447 - 0.521 * S + 0.635 * M + 3.215 * U - 6.074 * P \tag{7}$$

3 Knowledge map of ExL resources

To capture students' completion degree of recent online learning tasks, this paper built a bi-directional GRU network model based on attention mechanism to analyze the recent online learning behavior sequence of students and attain the completion degree of students' short term learning tasks. The completion degrees of both the short-term and long-term learning tasks were combined to recommend suitable ExL resources to students. To enrich the correlation between the ExL resources, this paper plotted a knowledge map to show the ExL resources and the correlation between the attributes of the knowledge in the ExL resources, and attained the knowledge vector of ExL resources that contain the information of the knowledge attributes of ExL resources, at last, based on the attained vector, the recommendations were made.

Assuming: $V=\{v_1,v_2,...\}$ represents the set of students; $U=\{u_1,u_2,...\}$ represents the set of ExL resources, the formula below gives the definition of $B=\{b_{vu}|v\in V,u\in U\}$, the interaction matrix of ExL resources based on students' implicit feedback:

$$b_{vu} = \begin{cases} 1, if \ \text{int} ER \ (v,u) \ is \ OB \\ 0, otherwise \end{cases} \tag{8}$$

If the value of b_{vu} is 1, then it indicates that there is a possibility of clicking, browsing, watching, or other types of interactions between student v and ExL resource u. Assuming: triplet (f,t,r) represents the entity-relation tuple in knowledge map H; σ and T are the set of entities and the set of relations in H. In this paper, the purpose of establishing the ExL resource recommendation model is to predict the possibility of potential interactions between student v and the unknown ExL resource u. Assuming: b'_{vu} represents the probability that student v would visit ExL resource u, Ψ represents the relevant function parameter, then the prediction function can be represented by $b'_{vu} = G(v,u;\Psi)$.

The completion degree of online learning tasks is often affected by short-term factors. To improve the recommendation performance, the ExL resource recommendation model constructed in this paper not only can fully consider the completion degree of short-term online learning tasks, but also can extract the correlations between students, ExL resources, and knowledge attributes in the knowledge map through the *RippleNet* algorithm, then it could apply the constructed knowledge map and the extracted correlations to the ExL resource recommendation tasks.

Assuming: *B* represents the interaction matrix; the formula below defines the set of first *l* ExL resources recommended by the *RippleNet* algorithm to student *v*:

$$\sigma_v^l = \left\{ r \mid (f,t,r) \in H \ and \ f \in \sigma_v^{l-1} \right\}, l = 1,2,...,F \tag{9}$$

Student *v*'s *TupleSet* is defined as:

$$\xi_v^l = \left\{ (f,t,r) \mid (f,t,r) \in H \ and \ f \in \sigma_v^{l-1} \right\}, l = 1,2,...,F \tag{10}$$

Student *v*'s *RippleSet* is defined as:

$$O_v = \left\{ (v,l,p) \mid (f,t,r) \in \xi_v^l \ and \ p \in \left\{ f,r \right\} \right\}, l = 1,2,...,F \tag{11}$$

Assuming: *c* represents the dimension of eigenvectors *u* and *f* corresponding to the ExL resources and the knowledge attributes; for resource *u* and the knowledge attribute *f* corresponding to *u* in the knowledge map, at first, a cross matrix $D \in R^{c \times c}$ was built as:

$$D = uf^T = \begin{bmatrix} u^{(1)} f^{(1)} & \cdots & u^{(1)} f^{(c)} \\ \cdots & & \cdots \\ u^{(c)} f^{(1)} & \cdots & u^{(c)} f^{(c)} \end{bmatrix} \tag{12}$$

Figure 2 gives a diagram showing the cross-compressed units. Assuming: $q \in R^c$ represents the weight of the cross-compressed unit; $\tau \in R^c$ represents the bias parameter, then the formula below gives the expression of the output of the cross-compressed unit:

$$\begin{aligned} u_{out} &= Dq^{UU} + D^T q^{FU} + \tau^U = uf^T q^{UU} + fu^T q^{FU} + \tau^U \\ f_{out} &= Dq^{UF} + D^T q^{FF} + \tau^F = uf^T q^{UF} + fu^T q^{FF} + \tau^F \end{aligned} \tag{13}$$

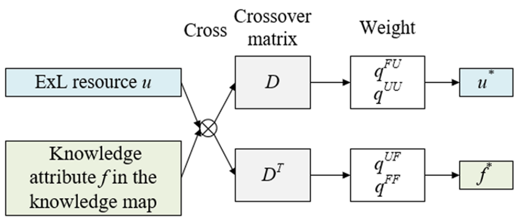

Fig. 2. Diagram of cross-compressed unit

By adjusting parameters *q* and *τ*, the two steps of the semantic matching of knowledge attributes in the knowledge map and the recommending of ExL resources could be completed at the same time. At first, this paper processed (*f*), (*t*), and (*r*) via the deep semantic matching mechanism, then *f* and *t* were spliced, and the dimension was reduced to *c* to attain the predicted *r*, denoted as $\dot{r}$; assuming DD_u represents the cross-compressed unit, DGJ represents the multilayer perceptron and it satisfies $DGJ(a)=\varepsilon(Qa+\tau)$, then there are:

$$f = DD_u(u, f)[f] \tag{14}$$

$$r = DGJ(r) \tag{15}$$

$$\dot{r} = DGJ\left(DGJ\left(\begin{bmatrix} f \\ t \end{bmatrix}\right)\right) \tag{16}$$

Assuming: ε represents the nonlinear activation function the *sigmoid* function; at last, the similarity function g_{lh} was used to evaluate the prediction results:

$$SIM(r, \dot{r}) = g_{lh}(r, \dot{r}) = -\varepsilon(r^T \dot{r}) \tag{17}$$

4 ExL resource recommendation model

In the ExL resource recommendation module, the students' completion degree of short-term learning tasks in the recent online learning behavior sequence was learnt based on the cyclic neural network, the attention mechanism was introduced into the bi-directional cyclic neural network to optimize the ability of the network model to learn the completion degree of short-term learning tasks, and the structure of the model is shown in Figure 3.

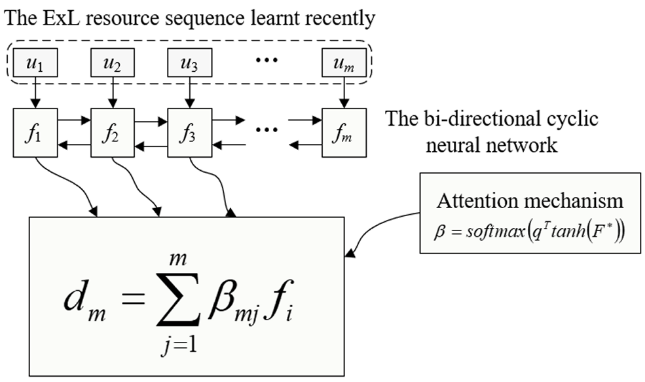

Fig. 3. Bi-directional cyclic neural network with attention mechanism introduced

Inputs of the ExL resource recommendation model were the first m learnt ExL resource sequences in the recent online learning behavior sequences, denoted as $u^m{}_{LR}$; assuming: a_r represents the input vector of the r-th time step; f_{r-1} represents the information of the previous time step r–1; Z and V represent parameter matrixes; then when the time step is r, the calculation formulas of the update door and reset door are:

$$c_r = \varepsilon(Q^c a_r + V^c f_{r-1}) \tag{18}$$

$$s_r = \varepsilon(Q^s a_r + V^s f_{r-1}) \tag{19}$$

Assuming: ⊗ represents the Hadamard product; f_{r-1} represents the hidden layer of the previous moment; then the calculation formulas of $\dot{f}_r$ (the hidden layout output of the cyclic neural network at the current moment) and f_r (the final output of the hidden layer) are:

$$\dot{f}_r = tanh(Q^f a_r + V^f (f_{r-1} \otimes a_r)) \tag{20}$$

$$f_r = (1 - c_r) \otimes f_{r-1} + c_r \otimes \dot{f}_r \tag{21}$$

For the final output f_r, the amount of information that needs to be forgotten by f_{r-1}, and the amount of $\dot{f}_r$ that needs to be added were both controlled by c_r. Assuming: F^* represents the hidden layer output of the cyclic neural network; q^T represents the parameter matrix; s represents the cyclic neural network with weight taken into consideration; then the formula below gives the expression of the introduced attention mechanism:

$$\beta = softmax(q^T tanh(F^*)) \tag{22}$$

$$s = F^* \beta^T \tag{23}$$

After that, through the multilayer perceptron, the completion degree of short-term learning tasks with weight taken into consideration was attained, and the process of attaining the completion degree could be written in a simple form as:

$$FR = DGJ(u^m_{LR}) \tag{24}$$

Because the inputs of the ExL resource recommendation model constructed in this paper were eigenvectors v and u that describe the student and the ExL resource and the sequence $u^m{}_{LR}$ of ExL resources that recently learnt by the student, if the eigenvector of student v is known, then the eigenvector of student v^* after subjected to cross-compression and processed by the multilayer perceptron is:

$$v_{dd} = DD_v(v, f)[v] \tag{25}$$

$$v^* = DGJ(DGJ(\ldots DGJ(v_{dd}))) \tag{26}$$

Similarly, the processed u^* could be attained through the following steps:

$$u_{dd} = DD_u(u, f)[u] \tag{27}$$

$$u^* = DGJ(DGJ(\ldots DGJ(u_{dd}))) \tag{28}$$

Assuming: μ_1 represents the weight of the completion degree of short-term learning tasks; $FR(u^m_{LR})$ represents the student's completion degree of short-term learning tasks, then the following formula gives the comprehensive recommendation of ExL resources:

$$\dot{b}_{vu} = (1-\mu_1)\cdot v^* u^{*T} + \mu_1 \cdot FR(u_{LR}{}^m)u^{*T} \tag{29}$$

Assuming: ψ represents the cross-entropy loss function; WQ_{TO} represents the loss value of the ExL resource recommendation model; WQ_{LHv} and WQ_{LHu} represent the loss values of the fitting degree of the "student – relation – ExL resource knowledge attribute" triple and the "ExL resource – relation – ExL resource knowledge attribute" triple; $||Q||_2{}^2$ represents the regularization term; μ_2 represents the coefficient of the regularization term, then the loss function of the constructed recommended model is:

$$\begin{aligned} WQ &= WQ_{TO} + WQ_{TO_v} + WQ_{LH_u} \\ &= \sum_{v\in V, u\in U} \psi(\hat{b}_{vu}, b_{vu}) + \sum_{(f,t,r)\in H} SI_v(r,\hat{r}) + \sum_{(f,t,r)\in H} SI_u(r,\hat{r}) + \mu_2 \|Q\|_2^2 \end{aligned} \tag{30}$$

5 Experimental results and analysis

Figure 4 shows the fitting results of four types of data: the score of online learning tasks, the number of watched teaching videos, the watching frequency of teaching videos, and the average watching time of teaching videos. The results showed that the effect of the model designed in this paper is significant. Next, comparative experiment was designed to compare the performance of the logistic regression model and the model proposed in this paper in predicting the completion degree of online learning tasks. Table 1 lists the prediction accuracy of different models. The fitting degree and prediction accuracy of the proposed model are both higher, indicating that it is feasible to predict the students' completion of online learning tasks based on the four types of data mentioned above. This is because after a student has finished all online learning tasks, the prediction of his/her completion degree of online learning tasks depends on the differentiated online learning behavior of the student. That is to say, the summative assessment and prediction of the completion degree of online learning tasks wouldn't affect the learning process of this student.

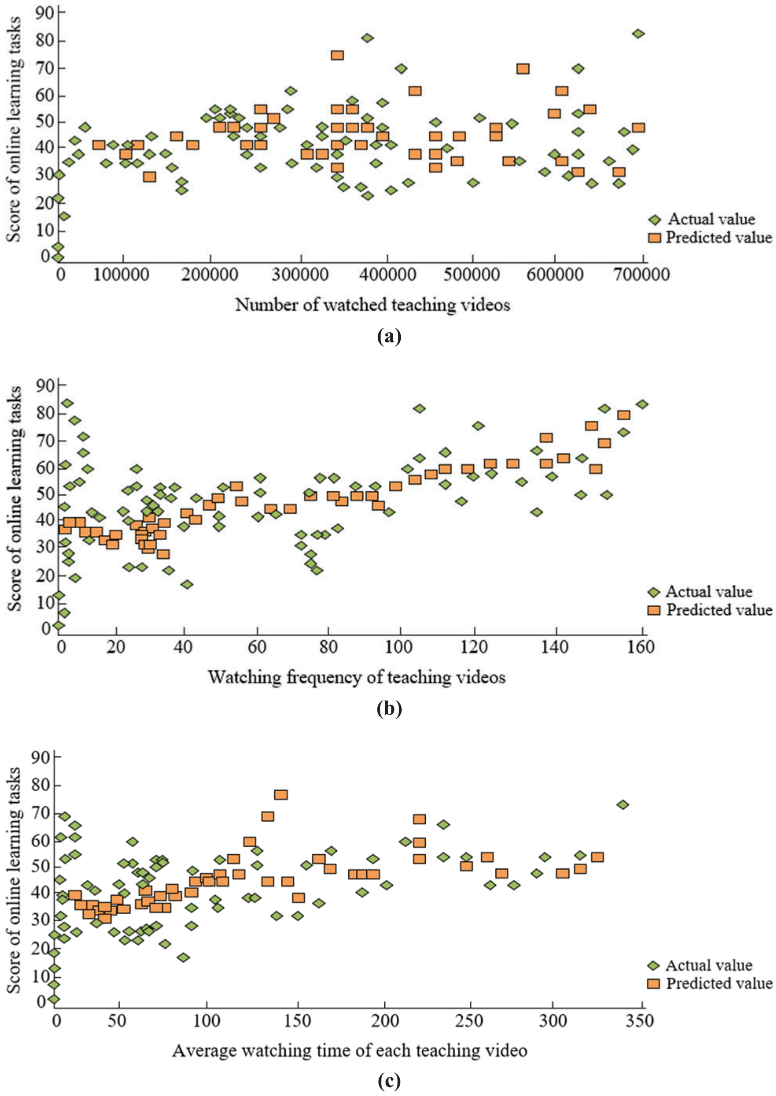

Fig. 4. Fitting effect of each type of collected data

Table 1. Prediction accuracy of different models

	Training Accuracy		Prediction Accuracy	
	Avg	*s.d.*	*Avg*	*s.d.*
The proposed model	0.528	0.069	0.536	0.058
Logistic regression model	0.41	0.47	0.43	0.041

Table 2. Model prediction accuracy for different learning topics

Learning Topic	Model Accuracy	
	Logistic Regression Model	The Proposed Model
*Topic*1	0.48	0.56
*Topic*2	0.49	0.59
*Topic*3	0.43	0.57
*Topic*4	0.47	0.59
*Topic*5	0.41	0.57
*Topic*6	0.49	0.63

Table 3. Experimental results of different models in recommending ExL resources

Model	Dataset 1		Dataset 2	
	AUC	*ACC*	*AUC*	*ACC*
SVD++	0.8152	0.8032	0.625	0.7152
CNN+K-Means	0.8695	0.8159	0.6392	0.7485
CNN+FP Tree	0.8325	0.8362	0.6147	0.7362
GBDT	0.8471	0.8171	0.6853	0.7481
LDA	0.8269	0.8629	0.6295	0.7596
The proposed model	0.8326	0.8361	0.6847	0.7158

Table 2 shows the model prediction accuracy for different learning topics. Based on the 4 types of data collected after the student finished the learning tasks of Topic 3, the proposed model attained a prediction rate close to 60%, while the prediction rate of the logistic regression model was lower than 50%; when the student began the learning tasks of Topic 4, the prediction rate of the completion degree of the proposed model far exceeded that of the logistic regression model, in other words, regardless of the collected data is all or part of the learning behavior data, the proposed model can attain better prediction effect of the completion degree of online learning tasks, and this makes it possible for the ExL resource recommendation system to predict students' basic level of theoretical learning in advance and provide corresponding intervention measures.

Table 3 gives the experimental results of different models in recommending ExL resources. Specifically, the results include the recommendation AUC and accuracy of different models attained in the same experimental environment on the training set. These models are: *SVD++* (reference algorithm 1), *CNN+K-Means* (reference algorithm 2), *CNN+FP Tree* (reference algorithm 3), *GBDT* (reference algorithm 4), *LDA* (reference algorithm 5), and the proposed algorithm. According to the table, compared with other recommendation algorithms, the proposed model attained the best results in terms of both performance indicators. On dataset 1 (for science and engineering students), compared with other models, the proposed model showed a 1.75% improvement in terms of AUC, and a 1.18% improvement in terms of accuracy. On dataset 2 (for liberal arts students), compared with other models, the proposed model obtained a 1.92% improvement in AUC and a 1.31% improvement in accuracy, indicating that the introduction of knowledge map can improve the recommendation performance of the ExL resource recommendation model, and this has proved the superiority of the proposed model.

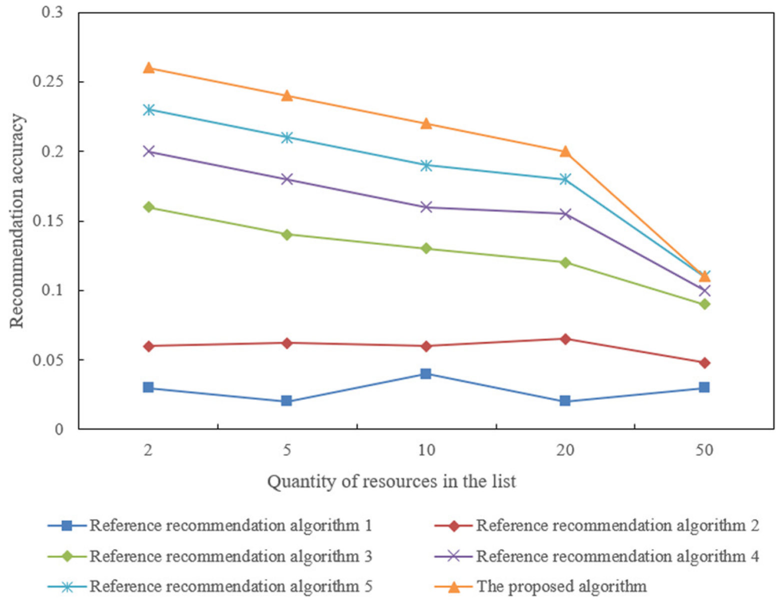

Fig. 5. Accuracy of different models in recommending ExL resources

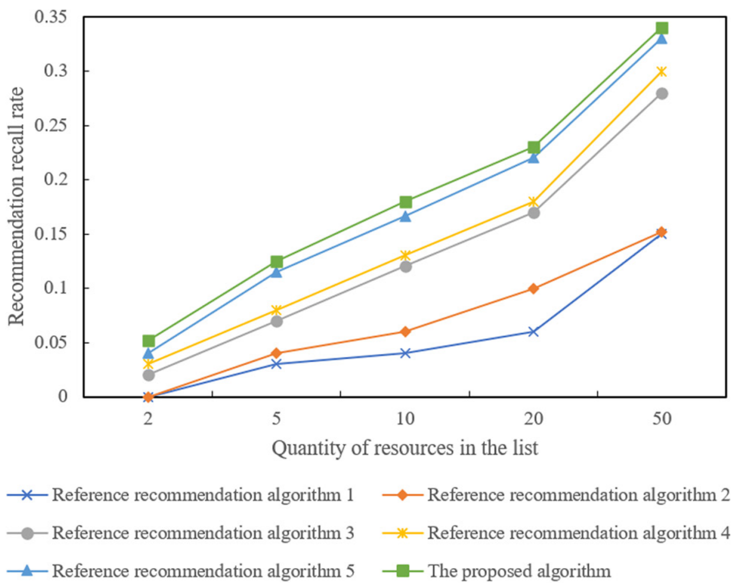

Fig. 6. Recall rate of different models in recommending ExL resources

After experiment, the accuracy and recall rate of different models in recommending ExL resources are shown in Figure 6. As can be seen from the figure, compared with other recommendation models, the proposed model showed great improvements in both indicators, wherein when the list resource quantity is 10, the improvement in accuracy of the proposed model is 10.5% compared with other models, and the improvement in recall rate is 7.8%, which has further proved the superiority of proposed model in recommending ExL resources.

6 Conclusion

This paper studied a ExL resource recommendation method based on the completion degree of online learning tasks. In the beginning, this paper gave the principle of recommending ExL resources based on the completion degree of online learning tasks, and built an online learning task completion degree prediction model. Then, the paper adopted a bi-directional GRU network model based on attention mechanism to analyze the recent online learning behavior sequence of students and attained the completion degree of students' short term learning tasks, and a knowledge map representing ExL resources and the correlation of knowledge attributes was drawn. After that, this paper combined the completion degrees of both the short-term and long-term learning tasks, and generated suitable ExL resources for students and made recommendations. In the experimental part, the fitting results of four types of data (including the score of online learning tasks, the number of watched teaching videos, the watching frequency of teaching videos, and the average watching time of teaching videos) were given, which verified that the effect of the model designed in this paper is significant. Then, the results of the accuracy of different models verified that the fitting degree and prediction accuracy of the proposed model are both higher; and the results of the model prediction accuracy for different learning topics verified that regardless of the collected data is all or part of the learning behavior data, the proposed model can attain better prediction effect of the completion degree of online learning tasks. Next, the experimental results, accuracy, and recall rate of different models in recommending ExL resources were given, which verified that the introduction of knowledge map can improve the recommendation performance of the ExL resource recommendation model, and this had also proved the superiority of the proposed model.

7 References

[1] Liu, Z.Y., Dong, L.Y., Wu, C.L. (2020). Research on personalized recommendations for students' learning paths based on big data. International Journal of Emerging Technologies in Learning, 15(8): 40–56. https://doi.org/10.3991/ijet.v15i08.12245

[2] Benjelloun, T.Y., Abdelladim, H., Nour-Eddine. E.F., Samir, B. (2020). Intelligent chatbot-LDA recommender system. International Journal of Emerging Technologies in Learning, 15(20): 4–20. https://doi.org/10.3991/ijet.v15i20.15657

[3] Mikić, V., Ilić, M., Kopanja, L., Vesin, B. (2022). Personalisation methods in e-learning-A literature review. Computer Applications in Engineering Education, 30(6): 1931–1958. https://doi.org/10.1002/cae.22566

[4] Rahmania, A., Jesslyn, K., Gui, A., Sari, S.A. (2022). Understanding higher education students continuance intention towards e-learning. In 2022 2nd International Conference on Information Technology and Education (ICIT&E), pp. 196–200. https://doi.org/10.1109/ICITE54466.2022.9759858

[5] Sergeyeva, T., Festeu, D., Bronin, S., Turlakova, N. (2021). Student-training environment interaction: Soft skills development within e-learning. In IT & I, 290–298.

[6] Alamsyah, D.P., Hikmawati, N.K. (2022). Model of expected benefit, e-learning curriculum, and education partners on e-learning. In 2022 International Conference on Information Management and Technology (ICIMTech), pp. 318–322. https://doi.org/10.1109/ICIMTech55957.2022.9915129

[7] Hao, C., Yang, T. (2022). Deep collaborative online learning resource recommendation based on attention mechanism. Scientific Programming, 2022: Article ID: 3199134. https://doi.org/10.1155/2022/3199134

[8] Ming, L. (2022). A deep learning-based framework for human resource recommendation. Wireless Communications and Mobile Computing, 2022: Article ID: 2377143. https://doi.org/10.1155/2022/2377143

[9] Liu, X. (2022). Personalised resource recommendation method for collaborative tagging system based on machine learning. International Journal of Industrial and Systems Engineering, 42(1): 1–19. https://doi.org/10.1504/IJISE.2022.126023

[10] Ahmed, S.T., Kumar, V.V., Singh, K.K., Singh, A., Muthukumaran, V., Gupta, D. (2022). 6G enabled federated learning for secure IoMT resource recommendation and propagation analysis. Computers and Electrical Engineering, 102: 108210. https://doi.org/10.1016/j.compeleceng.2022.108210

[11] Zhou, F. (2022). Research on teaching resource recommendation algorithm based on deep learning and cognitive diagnosis. Journal of Healthcare Engineering, 2022: Article ID: 5776341. https://doi.org/10.1155/2022/5776341

[12] El-Mahdy, D., Alaa, A. (2022). An experimental study of a curved brick wall using robot assembly as a teaching tool in architectural curriculum. In 2022 International Conference on Electrical, Computer and Energy Technologies (ICECET), pp. 1–6. https://doi.org/10.1109/ICECET55527.2022.9872791

[13] Huang, Z.B. (2021). Research on experimental teaching information collection method of visual communication specialty in hybrid universities under intelligent terminal. In International Conference on Advanced Hybrid Information Processing, pp. 601–614. https://doi.org/10.1007/978-3-030-94551-0_47

[14] Wei, X., Zhang, M. (2022). Experimental research and analysis of immersive virtual reality technology on children's language teaching. In 2022 International Symposium on Educational Technology (ISET), pp. 186–188. https://doi.org/10.1109/ISET55194.2022.00047

[15] Wei, S., Liu, Y., Wang, J. (2022). Experimental teaching reform of angle measuring method in digital signal processing course. In 2022 Asia Conference on Algorithms, Computing and Machine Learning (CACML), pp. 379–384. https://doi.org/10.1109/CACML55074.2022.00070

[16] Tao, J., Xia, Q., Liu, Q., She, X. (2022). Design and research of a virtual computer network experimental teaching system. In 2022 11th International Conference on Educational and Information Technology (ICEIT), pp. 16–20. https://doi.org/10.1109/ICEIT54416.2022.9690752

[17] Zhang, X., Zhou, F., Yan, Y. (2022). Multi-collaborative C++ language experimental teaching reformation based on PTA. In Proceedings of the 2022 6th International Conference on E-Education, E-Business and E-Technology, pp. 15–21. https://doi.org/10.1145/3549843.3549846

[18] O'Connell, B. (2022). Work in progress: Teaching MATLAB through authentic data collection and analysis experiences using self-contained, guided experimental setups with a range of disciplinary themes. In 2022 ASEE Annual Conference & Exposition.
[19] Xu, W., Wu, C., Lu, J. (2021). Exploration of experimental teaching reforms on c programming design course. In 2021 International symposium on advances in informatics, Electronics and Education (ISAIEE), pp. 330–333. https://doi.org/10.1109/ISAIEE55071.2021.00086
[20] Deng, X., Lei, J., Chen, M. (2021). Application of VR in the Experimental Teaching of Animation Art. Mobile Information Systems, 2021: Article ID: 4642850. https://doi.org/10.1155/2021/4642850
[21] Song, B., Sun, Y., Guo, J., Zhao, D., Tan, J. (2021). Application of case teaching method and Microteaching Method in experimental teaching based on wechat platform. In Proceedings of the 2021 International Conference on Bioinformatics and Intelligent Computing, pp. 407–411. https://doi.org/10.1145/3448748.3448988
[22] Wang, X. (2021). Construction of intelligent experimental teaching platform based on intelligent control algorithm. In 2021 International Symposium on Advances in Informatics, Electronics and Education (ISAIEE), pp. 228–231. https://doi.org/10.1109/ISAIEE55071.2021.00063
[23] Zhang, L., Zeng, X., Lv, P. (2022). Higher education-oriented recommendation algorithm for personalized learning resource. International Journal of Emerging Technologies in Learning, 17(16): 4–20. https://doi.org/10.3991/ijet.v17i16.33179
[24] Dien, T.T., Thanh-Hai, N., Thai-Nghe, N. (2022). An approach for learning resource recommendation using deep matrix factorization. Journal of Information and Telecommunication, 6(4): 381–398. https://doi.org/10.1080/24751839.2022.2058250
[25] Zhang, F., Guan, S. (2022). Evaluating the effectiveness of teaching experimental design in universities in the context of information technology. Scientific Programming, 2022: Article ID: 9087653. https://doi.org/10.1155/2022/9087653
[26] Cardona Zapata, M.E., López Ríos, S. (2022). Methodological elements for the implementation of data acquisition systems as support for experimental activity in the physics teaching. Technology, Knowledge and Learning, 27(3): 879–890. https://doi.org/10.1007/s10758-021-09517-2

8 Author

Ligang Jia, teacher at Shandong University (Weihai) Art College, Weihai 264209, China, mainly engages in the research of college art education. His email address is 201999800028@stu.edu.cn.

Article submitted 2022-11-01. Resubmitted 2022-12-07. Final acceptance 2022-12-11. Final version published as submitted by the authors.