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Research Article

Recommendation of Online Business English Learning Resources Integrating Attention Mechanism and Collaborative Filtering Model

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Faced with massive resources, many learners find it difficult to quickly screen out useful content for themselves. In order to help learners acquire the required network resources quickly and accurately, the birth of a personalized recommendation system solves this problem perfectly. A collaborative filtering algorithm has been widely used in the field of personalized recommendation. However, due to the limitation of the model, the recommendation effect has not been further improved. The single weakness of a collaborative filtering algorithm to recommend learning resources is difficult to meet the needs of learners to acquire personalized resources. This paper proposes a recommendation algorithm for business English online learning resources based on an attention mechanism and collaborative filtering model. The learner vector and learning resource vector are mapped to multispace, and the learner-learning resource interaction is done from multiple angles. The final learner representation vector and learning resource representation vector are aggregated by a two-level attention mechanism to predict scores. Through teaching practice in student associations, it is found that students from different backgrounds have different preferences for business English online learning resources. This method has a positive impact on online learning. This study aims to provide some references for English education resource recommendations. The results at Precision@K and Recall@K prove that the proposed model has better recommendation ability.

1. Introduction

With the rapid development of online education, digital learning resources show the characteristics of massive resources. When learners have many choices, they also inevitably face serious knowledge overload and learning loss [1]. To solve this problem, learners need to rely on personalized learning and adaptive recommendation to navigate [2]. The adaptive recommendation is the core task in the process of personalized learning. Classical recommendation algorithms explore learners' potential interest preferences based on the historical behaviour information and similarity relationship of groups [3]. However, such algorithms only take the interaction information between learners and resources as input, and the sparsity of data makes the recommendation have certain defects.

The goal of the recommendation algorithm is to extract the information that learners are interested in from massive data, and it is one of the effective tools to solve the problem of "information overload." Literature [4] converts learners' learning behaviours into learners' scoring of resources and improves learners' similarity calculation to solve potential data sparsity and cold start problems in the recommendation system. Literature [5] uses learning materials to build an e-learning resource knowledge base based on domain ontology and combines content-based and rule-based methods to provide mixed recommendations for learners. A feature model based on domain ontology and learner attribute information was proposed in literature [6]. Based on the learning feature model, a collaborative filtering recommendation method integrating similarity was designed. The learning resource recommendation algorithm based on behaviour analysis was proposed in literature [7], which is used to mine the behavioural data of learners and format it into collaborative filtering recommendations. In the above literature, in order to overcome the defects of traditional recommendation algorithms and improve recommendation performance, researchers introduced different types of auxiliary information. However, these auxiliary information contain only isolated characteristics of learners or learning resources. In fact, there are abundant connections between learners and learning resources and between learning resources and learning resources.

The reform of English teaching in universities proposes to explore the deep integration of information technology and English education under the background of "Internet + education," so as to bring about changes in education methods and learning methods [8]. Online English learning is a new learning mode under the background of education informatization. It breaks the space-time limit and reconstructs the learning process and teacher-student relationship by relying on mobile devices [9]. Online business English learning in the context of English learning not only can create a real language communication environment with the help of modern information technology so that students can appreciate diverse cultures but also can provide the possibility to change the "teacher-cantered" education [10].

In actual learning, due to the weakened role of teachers as instructors, students lack the correct positioning of learning activities and themselves when facing massive resources independently. They are unable to construct their own knowledge networks and choose appropriate learning methods as needed, resulting in information overload [11]. Many students do not have a deep understanding of "what to learn and how to learn," and cannot become the active acquirer and constructor of knowledge. The Ten-year Development Plan for Education Informatization proposes to "build an intelligent teaching environment and provide personalized learning information environment and services for learners" [12].

With the widespread use of online learning platforms, the number of English online learning resources has also increased rapidly, and it is difficult for learners to quickly locate the resources they need among the huge number of English online learning resources [13]. How to recommend valuable information to interested learners from massive English resources has always been a core issue in online education services [14]. As an important solution to this problem, the educational resource recommendation system has attracted more and more researchers' attention [15]. However, at present, most educational resource recommendation systems are only for college students and are used by their own online systems. However, a wider range of off-campus students and online systems outside universities are unable to obtain educational resource recommendation services, which greatly reduces the utilization rate of English online learning resources [16].

In order to solve the problem of resource rate limitation existing in existing models, this paper introduces the concept of multispace interactive feature extraction and proposes a resource recommendation model for business English online learning based on the attention mechanism and collaborative filtering model, namely Multispace Interactive Collaborative Filtering (MSICF). The proposed model maps the learner vector and the learning resource vector to multiple spaces to extract interactive features for scoring prediction. Multispace can consider the interaction of learners' learning resources from multiple perspectives, and more comprehensive features can better fit the learner-learning resource scoring, thus improving the recommendation ability of the model.

The innovations and contributions of this paper are listed below:

(1) The multispace concept is introduced into the collaborative filtering recommendation system, which enhances the interpretability of recommendations and refines the granularity of learner-learning resource interaction feature extraction.

(2) A novel multispace interactive collaborative filtering recommendation model (MSICF) is proposed, which maps the learner vector and the learning resource vector to multiple spaces and extracts the interactive features of learners and learning resources from multiple perspectives.

(3) For the top-K recommendation task, the top-K learning resources are recommended for learners in the test set, and the performance of the model is evaluated by using Precision@K and Recall@K indicators. The results of the MSICF model are better than other comparison models under multiple evaluation indexes.

This paper consists of four main parts: the first part is the introduction, the second part is methodology, the third part is result analysis and discussion, and the fourth part presents the conclusion.

2. Methodology

Figure 1 shows a recommended example of a learner's access to a business English online learning resource. Figure 1 provides a learner-learning resource interaction matrix G. When the element is 1, it means that learners like the independent learning resource. When the element is 0, it means that the corresponding learners have not visited the corresponding independent learning resource. For example, G11 = 1 means that learners p1 likes the independent learning resource x1. According to the learner-learning resource interaction matrix, learners p3 and p1 both like independent learning resources x2 and x5, and learners p3 and p2 both like independent learning resources x4. According to the traditional collaborative filtering idea, learners p3 and p1 are more similar. It is considered to recommend the independent learning resources favoured by learners p1 to p3, but it is not clear whether p3 prefers x1 or x3. However, learners' access to business English online learning resources can be divided into two situations: (1) interaction occurs from the perspective of types of learning

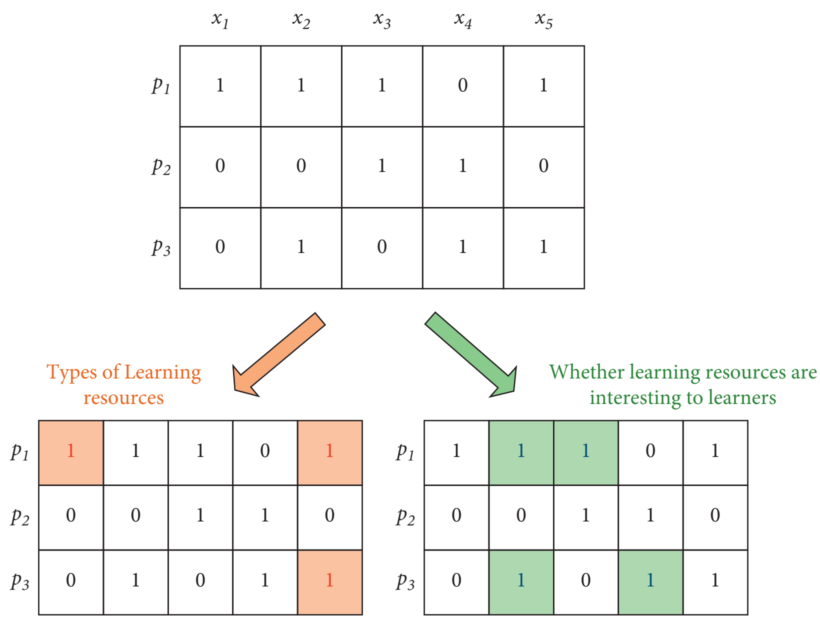

Figure 1: Examples of learner-learning resource interaction from different perspectives.

resources and (2) interaction from the perspective of whether learning resources are interesting to learners. From the perspective of the types of learning resources, learner p1 only likes x1 and x5, and both learners p1 and p3 like x5, so the x1 favoured by learner p1 is recommended to p3. Similarly, from the perspective of whether learning resources cater to learners' interests, learners p1 and p3 like x2 at the same time, so they recommend x3 that learners p1 likes p3. The traditional collaborative filtering model fails to analyze the interaction between learners and learning resources from multiple perspectives, and the recommendation performance is limited. However, feature interaction extraction from different perspectives can discover learners' preferences more effectively.

Learner-learning resource interaction from different perspectives is different, so learner-learning resource interaction from multiple perspectives is described. In this paper, the full connection layer is used to map the learner's embedding vector and learning resource embedding vector to multiple spaces. Due to the difference in the full connection weight, the learner's embedding vector and learning resource embedding vector after mapping also contain different features, indicating learner-learning resource interaction from different perspectives.

The connotation of the recommendation system is to get learners' scores of learning resources through the model. Figure 2 is a frame diagram of the proposed model. This model uses row data and column data of the learner-learning resource interaction matrix as input for the learner module and learning resource module, respectively. After the learner embedding vector and the learning resource embedding vector are mapped to multiple spaces, the learner representation vector and learning resource representation vector are obtained through a multispace interaction module. Then, the learner representation vector and the learning resource representation vector are splicing and sent into the multilayer perceptron (MLP) to obtain the learner's score on the learning resource. The learner part and the learning resource part have similar structures. The learner part and the learning resource part's multispace interaction modules aggregate the learning resource embedding vector and the learner embedding vector, respectively, to generate the learner representation vector and the learning resource representation vector. As the key innovation point of this paper, the multispace interaction module mainly does the following operations:

(1) Through N full connection layers with different weights, the embedded vectors are mapped to N different vector spaces

(2) The magnitude attention mechanism assigns different weights to vectors in a single subspace and aggregates them into a representation vector of learners (or learning resources)

(3) Spatial attention mechanism assigns different weights to different subspace vectors and aggregates them into the final representation vector of learners (or learning resources)

2.1. Input Module. The learner-learning resource interaction matrix G features with original data W and T; the number of rows in the matrix is the number of learners W; and the number of columns is the number of learning resources T. The interaction matrix represents the element value G_{yz} of row y and column z as whether learner y has interaction with learning resource z. The number 1 indicates interaction, and 0 indicates no interaction. For row y, 2, 4, 5, . . ., column data is 1, indicating learning resources 2, 4, 5, ... There was interaction with learner y. A full connection layer is used to embed all learners and learning resources into the low-dimensional and dense vector space to obtain the embedding

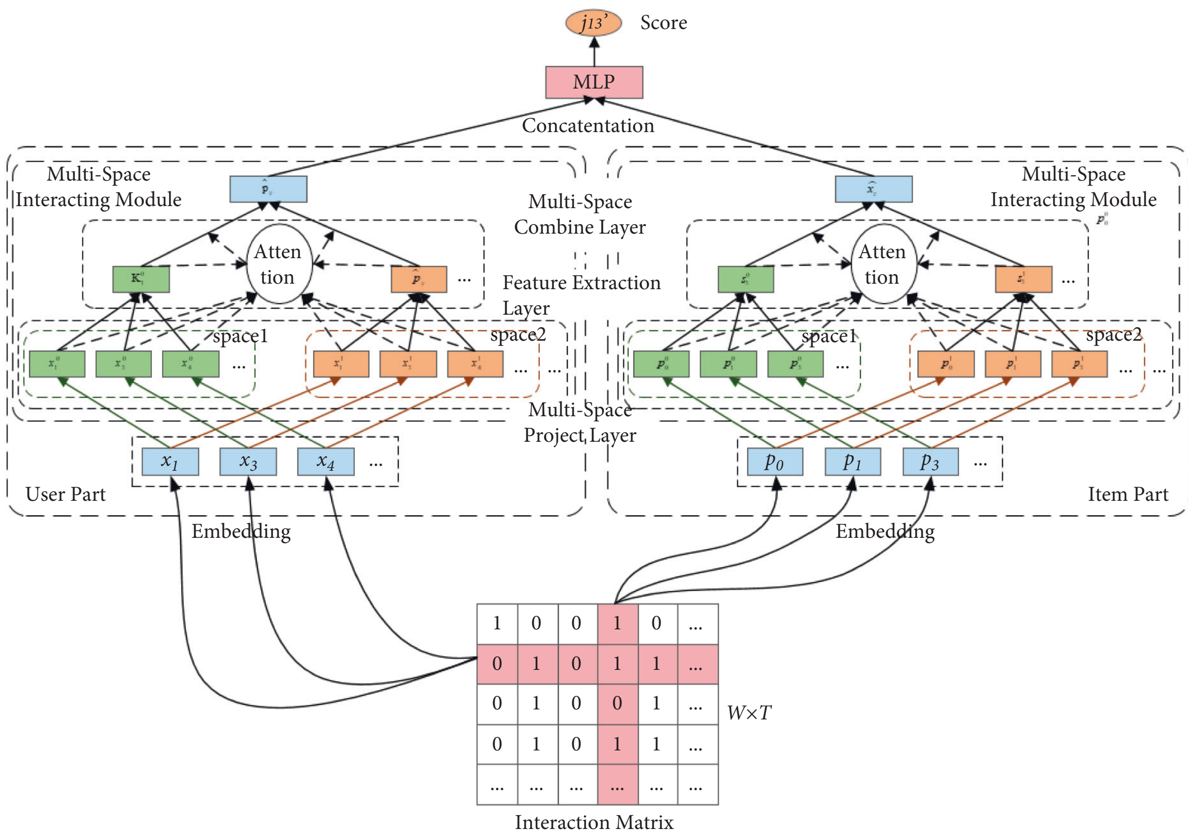

FIGURE 2: Framework of the proposed model.

vectors of all learners and learning resources. And y produced interactive learning resources, as well as corresponding learning resources; vector $\{x_z | z \in x_y\}$ are embedded to learners. Learning resources will work with the same z corresponding to the interaction of learners; vector $\{p_y | y \in p_z\}$ are embedded into the learning resources section as the input of the model.

2.2. Multispace Interaction Module. The learner part and the learning resources part have a similar structure of a multispace interaction module. As to learners, for example, many spatial interaction modules are input to learners' history, interactive learning resources embedded with vector $\{x_z | z \in x_y\}$ the output of the final learners is said by vector $\hat{p}_y$. Specifically, the multispace interaction module consists of three parts: multispace mapping layer, feature extraction layer and multispace combination layer.

In order to extract learner-learning resource interaction features comprehensively from multiple perspectives, this paper introduces the concept of multispace feature extraction. Through n full connection layers, learners and learning resource data are mapped to corresponding n different spaces, and the mapping process of learners y to space n is as follows:

$$p_y^n = \mathrm{Dense}_t(p_y) = U_n p_y, \tag{1}$$

where $U_n \in U = \{U_1, U_2, \ldots, U_N\}$ that is the weight matrix of the full connection layer and p_y^n represents the new embedding vector after the embedding vector of learner y is mapped to space n. Different spatial mappings adopt different weight matrices. After mapping, learner embedding vectors in different spaces contain different elements, which can describe learner characteristics from different perspectives.

For learning resource z, a similar operation is performed to map learning resource to space n.

$$x_z^n = \mathrm{Dense}_n(x_z) = V_n x_z, \tag{2}$$

where $V_n \in V = \{V_1, V_2, \ldots, V_N\}$ that is the weight matrix of the full connection layer and x_z^n represents the new embedding vector after the embedding vector of learning resource z is mapped to space n.

After learning resource vectors are mapped to multiple spaces, learners' preferences can be obtained by aggregating their representation vectors in each space. In the learner part, x_y, a set of learning resources that interact with learner y, is used as a feature to aggregate and generate the representation vector of learner y in a single space. In each space, when learning resource vectors are aggregated to generate learner representation vectors, learners' interest in each learning resource in this space is inconsistent. Therefore, when aggregation generates a learner representation vector, different weight values should be assigned to each learning resource vector. A directional attention mechanism is used in the feature extraction layer to assign different weights to each learning resource vector in a single space.

In space n and j produced interactive learning resources of embedded vector for $\{x_z^n|z \in x_y\}$, in this space, learning resources z's contribution to the learners y vector generated is calculated by the following formulas:

$$\alpha_{yz}^n = \frac{\exp\left(\Psi\left(p_y, x_z^n\right)\right)}{\sum_{z\in X_y}\exp\left(\Psi\left(p_y, x_z^n\right)\right)},$$
$$\Psi\left(p_y, x_z^n\right) = M_{\text{Query}} p_y, M_{\text{Key}} x_z^n, \tag{3}$$

where $\Psi(p_y, x_z^n)$ is the scoring function used to score the learning resource z. It can be defined as a neural network or other similarity calculation function. Because the inner product is simple and efficient, this paper directly uses the inner product to calculate the similarity between the representation vector p_y of learner y and the representation vector x_z^n of learning resource z in space n. M_{Query} and $M_{\text{Key}} \in R^{d\times d}$ are mapping matrices, which map the representation vector p_y of learner y and x_z^n of learning resource Z in space N from R^d to $R^{d'}$.

After obtaining the weights of all learning resource vectors in space n, they are aggregated into the representation vector k_y^n of learner y in space n.

$$k_y^n = \sum_{z\in X_y} \alpha_{yz}^n \left(M_{\text{Value}} x_z^n\right), \tag{4}$$

where $M_{\text{Value}} \in R^{d\times d}$ is the mapping matrix. So, every space layer of feature extraction from input for learners to interactive learning resources is embedded with vector y $\{x_z^n|z \in x_y\}$. In the space of the output of said vector k_y^n polymerization of learners. N spaces can aggregate n learner representation vectors $\left\{k_{\sigma_y}^n\right\}_{n=1}^N$.

The structure of learning resources is similar to that of learners, and the representation vector of learning resources in N is spaces $\{S_z^n\}_{n=1}^N$.

In the learner part, n learner representation vectors $\{k_y^n\}_{n=1}^N$ are synthesized from n different spaces from different angles. When the representation vectors of n learners are aggregated into the final representation vector of learner y because learners have different preferences for different angles, vectors in different spaces should make different contributions to the aggregation. Therefore, a spatial attention mechanism is used to assign different weights to different spaces.

This layer will be the output of all feature extraction layers $\{K_y^n\}_{n=1}^N$ as input; learn different weight values for them.

$$\beta_y^n = \frac{\exp\left(\Phi\left(k_y^n\right)\right)}{\sum_{n=1}^N \exp\left(\Phi\left(k_y^n\right)\right)},$$
$$\Phi\left(k_y^n\right) = \sigma\left(v k_y^n + h\right), \tag{5}$$

where $\Phi(k_y^n)$ is the scoring function, and a layer of the neural network is used to calculate the score of k_y^n. Parameter v is the weight of the neural network. h is the offset. σ is ReLU function, which is the activation function of the neural network.

After obtaining the weight values of all space vectors $\{\beta_y^n\}_{n=1}^N$, the representation vectors of each space are aggregated according to different weights.

$$p_y = \sum_{n=1}^N \beta_y^n \cdot k_y^n. \tag{6}$$

The learner representation vector of the multispace was weighted and aggregated, and the learner representation vector p_y containing multiple feature interaction information was obtained as the output of the multispace combination layer. The learning resource representation vector x_z containing multiple feature interaction information can also be obtained by using the same method.

2.3. Output Module. The output layer splices the learner representation vector p_y obtained by the learner module and the learning resource representation vector x_z obtained by the learning resource module into the Multilayer Perceptron (MLP), so as to obtain the score values of learner y and the learning resource z.

Specifically, the learner representation vector p_y and learning resource representation vector x_z are spliced into a vector.

$$g_0 = \text{Concat}\left(p_y, x_z\right). \tag{7}$$

Then, the splicing vector is sent into the feedforward neural network F with D hidden layers. The d hidden layer of feedforward neural network F is f^d, and its nonlinear function with the previous hidden layer f^{d-1} is expressed as follows:

$$f^d = \sigma\left(M^d f^{d-1} + h^d\right), \tag{8}$$

where M^d and h^d are the parameters of layer d, $f^1(i) = g_0$, and σ Is the nonlinear activation function ReLU. Combining formulas (7) and (8), the following can be obtained:

$$j'_{yz} = f^D\left(\cdots f^2\left(f^1, \left(p_y, x_z\right)\right)\cdots\right), \tag{9}$$

where D is the total number of hidden layers. Finally, the predicted score j_{yz}' of learner y on learning resource z is obtained.

2.4. Model Training. The final output of the MSICF model is learners' rating of learning resources. For the scoring prediction problem, the commonly used objective function is the square loss function.

$$L_r = \sum_{(y,z)\in T} \left(j'_{yz} - j_{yz}\right)^2, \tag{10}$$

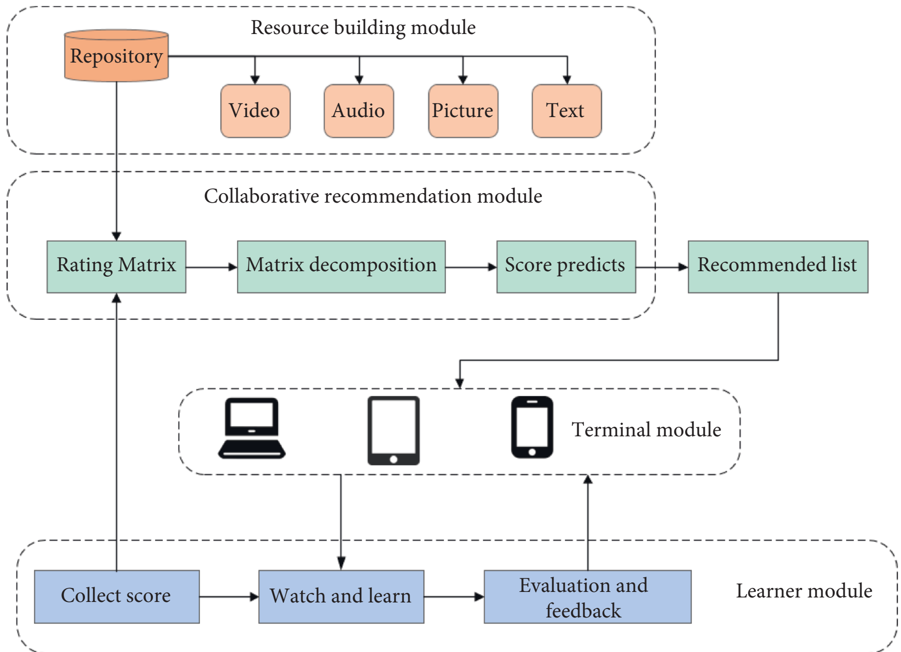

FIGURE 3: Personalized collaborative recommendation framework.

where T is the interactive set of all users and projects and j_{yz} is the real score of learner y on learning resource z.

This paper uses the adaptive gradient algorithm (Adam) to minimize the objective function. Adam algorithm is different from the traditional gradient algorithm. The learning rate in the traditional gradient algorithm is fixed. Adam algorithm can design independent adaptive learning rates for different parameters.

As the number of spaces increases, the model parameters also increase, and the model is more prone to overfitting, which leads to a decrease in the generalization ability of the model. To alleviate the problem of overfitting, dropout and L2 regularization techniques are introduced.

The idea of dropout is to randomly drop connections between neurons during training so that each training model is somewhat different. It has been proved to alleviate the overfitting problem of complex models. The introduction of the L_2 regular term can punish the high-frequency parameters and alleviate the overfitting problem.

After introducing L_2 regularization, the actual objective function used for training is as follows:

$$L = L_r + \lambda \|M\|^2 = \sum_{(y,z)\in 7} \left(j'_{yz} - j_{yz}\right)^2 + \lambda \|M\|^2, \tag{11}$$

where λ is the regularization coefficient, which controls the intensity of regularization, and M is the parameter set of the model.

This research adopts qualitative and quantitative research methods, and the framework is shown in Figure 3, mainly involving four modules.

First is resource construction module. Business English online learning aims to cultivate students' English communication skills in work and social life. In view of the above factors, this study selected four popular English online learning websites in teaching practice according to the characteristics of English online learning scenarios. These online resource sites include Tianya Xiaozhu, Akasuo oral English, One 100 easy multimedia textbook library, and Cocoa English.

TABLE 1: Distribution of learners' scores.

Number of scores	Number of learners	Proportion (%)
[6, 10)	10	33
≥10	14	47
<3	2	6.67
[3, 6)	4	13.33

Second is collaborative recommendation module. Here, we use matrix factorization. R represents the original scoring matrix. P represents the number of learners. X represents the number of resources. Each row in the matrix represents a learner; each column represents a teaching resource; and each element value in the matrix represents the score of the corresponding learner on the corresponding resource.

Third is terminal module. Data will be collected through laptops, mobile phones, Pads, and other terminal devices, and business English online learning resources will be displayed to target learners.

Fourth is learner module. Learn the knowledge reserve and preferences of learners based on the collected data. When collecting data in the teaching practice, the options of each question are set at five levels from "very good," "not bad," "average" to "not very good," and "very bad." The collected scoring data is quantified into a scoring matrix and sent to the collaborative recommendation module. Then, the resources recommended by the system are shown to students for learning. After watching, students give feedback and score as post-test data.

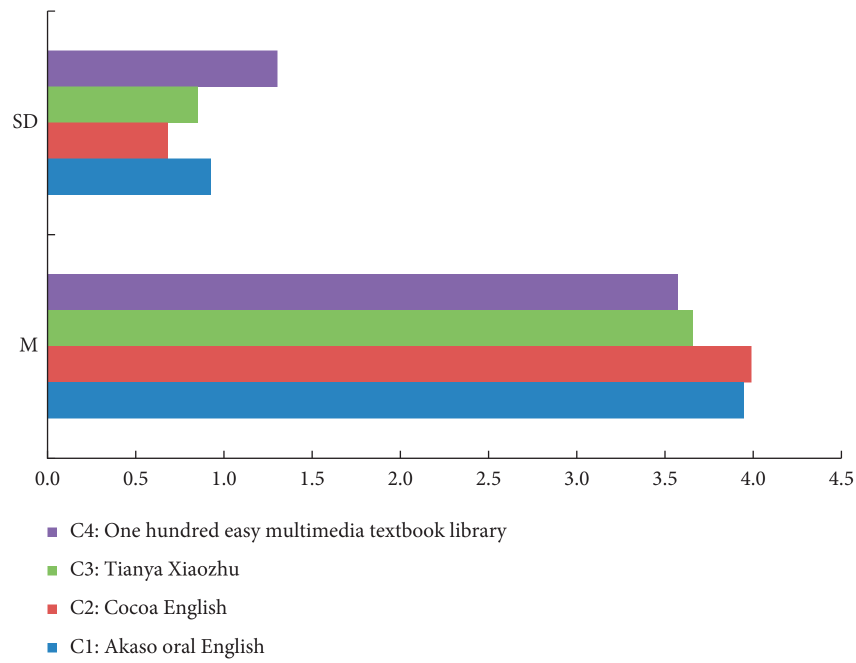

Figure 4: Descriptive analysis of different resource types.

3. Result Analysis and Discussion

The teaching practice was carried out for students in the community, and 30 students had different degrees of understanding of the 4 online business English learning websites provided by the platform, as shown in Table 1. There are 2 people who use Tianya Xiaozhu, 4 people who use One hundred easy multimedia textbook library, 10 people who use Akasuo oral English, and 14 people who use Cocoa English. It can be seen that most students are familiar with the selection of materials, which provides a good foundation for the follow-up implementation of online independent learning. All data with a score of 0 (i.e., "not used") were filtered out, and a total of 260 pieces of rating data were collected. The density of the scoring matrix reaches $260/(30 * 12) \sim 72.22\%$, and the scoring data per capita also reaches 8.6, indicating that the matrix sparsity problem faced in this case is not obvious.

In this study, business English online learning resources are divided into four types: Tianya Xiaozhu, Akasuo oral English, One hundred easy multimedia textbook library, and Cocoa English. First, descriptive analysis is carried out. The mean and standard deviation of scores of different types of resources are shown in Figure 4. As can be seen from Figure 4, the average score of Cocoa English resources is the highest at 3.99. Akasuo followed with an average of 3.95. The average score of Tianya Xiaozhu and One hundred easy multimedia textbook library is relatively low. It can be seen from Table 1 and Figure 4 that in general, the students in this English club are familiar with the networked and information-based learning environment and have much contact with online business English learning resources in daily life. At the same time, the resources are more inclined toward Cocoa English and Akasuo oral English.

Table 2: Analysis of gender differences in business English online learning resources.

Type	Gender	*N*	M	Sd	*t*	Sig.
C1	Female	24	4.23	0.8	2.004	0.067
	Male	6	3.34	1.63		
C2	Female	24	4.07	0.62	3.635	0.012
	Male	6	2.73	1.44		
C3	Female	24	4.08	0.84	−0.233	0.819
	Male	6	4.17	0.73		
C4	Female	24	3.74	1.53	−0.052	0.961
	Male	6	3.78	1.05		

The independent sample t-test was used to analyze the preference differences of students of different genders in different business English online learning resources (see Table 2). As can be seen from Table 2, the significance on C1, C3, and C4 were all greater than 0.05, without a significant gender difference. The significance on C2 was less than 0.05, indicating a significant difference between genders.

Variance analysis was conducted on the preference differences of students of different grades in different business English online learning resources, and the results are shown in Table 3. In this study, there are 18 sophomores, accounting for 60%. There are 6 juniors, accounting for 20%. There are 6 senior students, accounting for 20%. Because the English club requires members to have a certain level of professional English literacy, the club mainly recruits students of sophomore and above grade. As can be seen from Table 3, the significance was less than 0.05 in C1 and C2, indicating that there were significant differences among different grades, while there were no significant differences in C3 and C4.

The post hoc comparison of C1 and C2 is shown in Figure 5. In C1 and C2, the significance of sophomore and

Table 3: Analysis of differences in online learning resources of business English for learners of different grades.

Type	Grade	M	Sd	F	Sig.
	Sophomore	4.08	0.65		
C1	Junior	4.01	0.42	5.23	0.011
	Senior	2.62	1.65		
	Sophomore	3.71	0.41		
C2	Junior	4.34	0.73	8.16	0.001
	Senior	2.35	1.57		
	Sophomore	4.04	0.68		
C3	Junior	3.55	0.42	1.59	0.208
	Senior	3.42	1.04		
	Sophomore	3.66	1.3		
C4	Junior	2.64	1.8	0.838	0.418
	Senior	3.62	1.31		

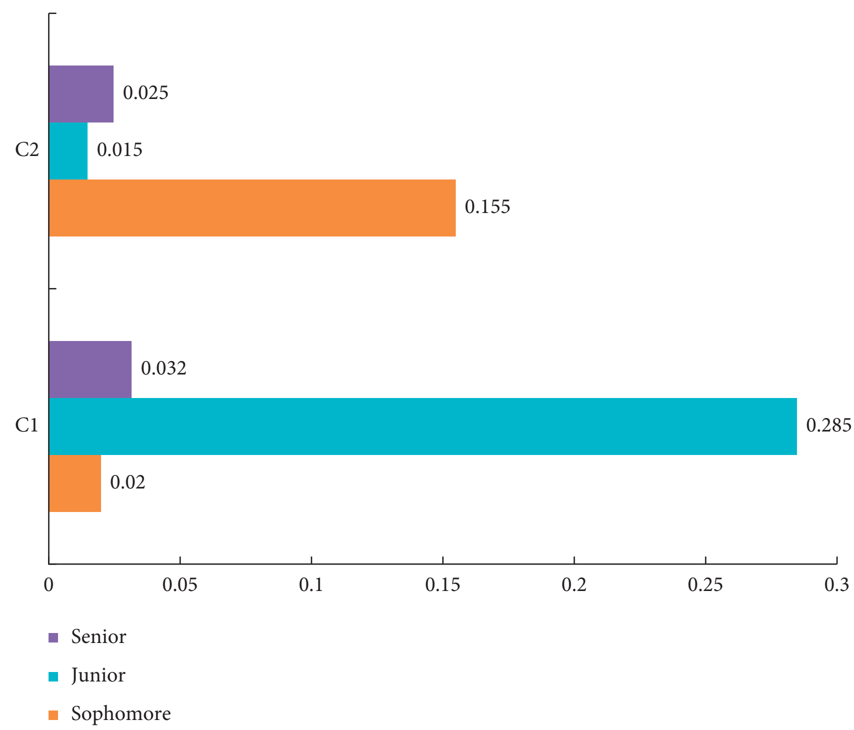

Figure 5: Comparisons of C1 and C2 at grade level.

senior, junior, and senior were all less than 0.05, indicating significant differences. Compared with seniors, sophomores and juniors preferred Akasuo oral English and Cocoa English, indicating that these resources are more attractive to middle- and lower-grade students.

Analyze students' satisfaction with the recommended resources. The collected data is used for collaborative recommendations. Score 0 indicates that the student has not used the resource, and the resource is added to the set of candidate resources to be recommended. When the predicted score reaches more than 3.5, it corresponds to "not bad" and "very good," thinking that the resource is likely to be useful to the learner, so it will be pushed to students. Urge them to watch and learn online and score comprehensively. Click the "Submit" button to indicate the end of this round of learning. The behavioural data of learners were recorded throughout the experiment as the basis for experimental analysis.

Compare the feedback received with the system's predictions, as shown in Figure 6. Blue data indicates that the prediction score recommended by this resource is 4 or 5 points, a total of 46 items. Students' feedback after learning was marked as read data. When the student also scores 4 or 5, the student is considered to have approved the resource recommended by the system. Students rated the resource 3 and below as not resonating with students. Among the 46 recommended data, 33 received positive feedback from learners, with a satisfaction rate of 71.74%.

Based on the above quantitative analysis and teaching practice, it can be concluded that the collaborative filtering recommendation model based on the attention mechanism used in this paper can effectively recommend business English online learning in the context of online learning and meet the needs of students' personalized learning.

In interaction rate prediction, the top-K learning resources were recommended for learners in the test set for the

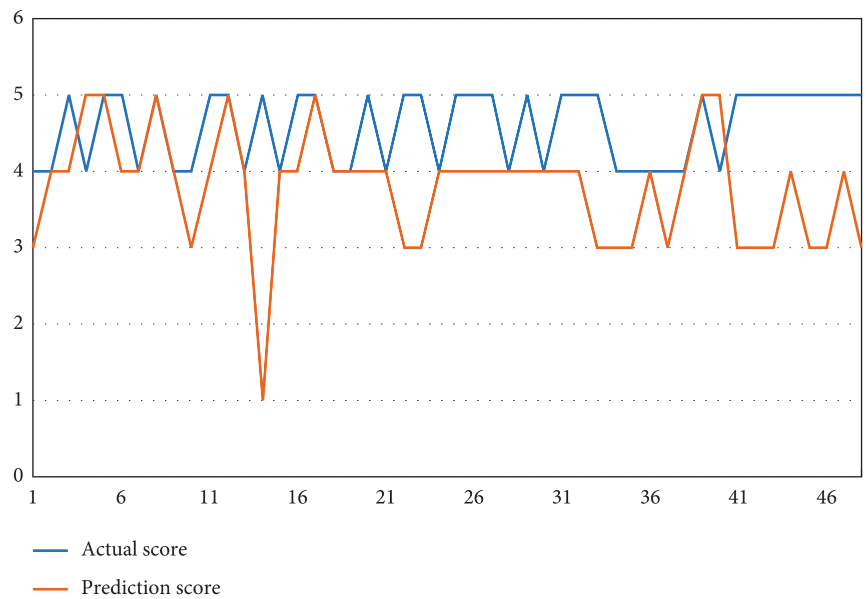

Figure 6: Statistics on the effect of pushing business English online learning resources.

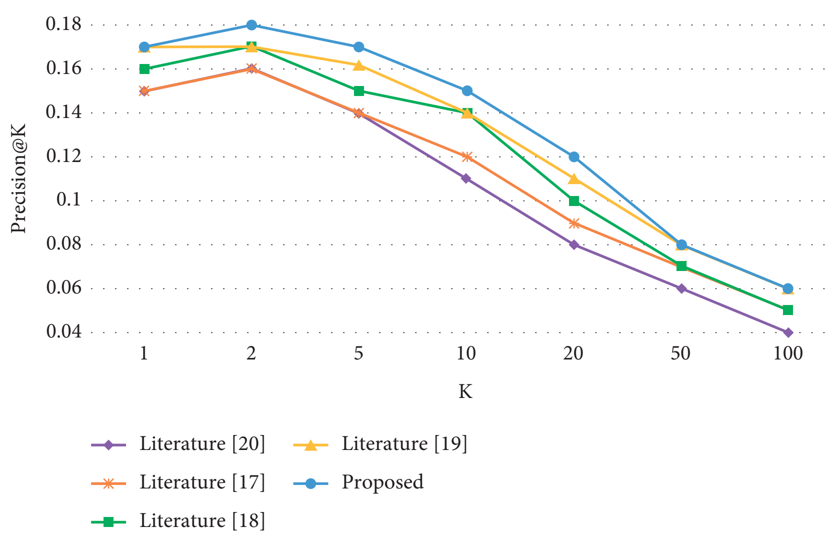

Figure 7: Precision of Top-K.

top-K recommendation task, and the model performance was evaluated by using Precision@K and Recall@K indicators. The algorithm in this paper was compared with recent literature [17–20]. Figures 7 and 8 show the comparison between Precision@K and Recall@K in top-K services.

As can be seen from Figures 7 and 8, when $K = 5$, Precision@K and Recall@K of literature [19] perform best. Compared with literature [19], the proposed model has improved by 8% and 15% in Precision@K and Recall@K. By comparing the experimental data, the analysis shows that the three baseline models referred to in literature [17] are superior to literature [20], indicating that entity and relationship information is conducive to improving recommendation performance after the introduction of attention mechanism. Among them, literature [17], starting from the learner end, uses the entities around learning resources to spread the preference information of learners to calculate the vector representation of learners. Its deficiency lies in that it does not use the attention mechanism to improve the information quality at the learning resource end. Similar to literature [17], literature [18] focuses on the learning resource end, integrates the neighbour nodes of learning resources to obtain its embedded representation, and enriches the learner embedded representation without utilizing the information of the knowledge graph. The advantage of literature [19] is that both the learner end and the learning resource end are taken into account. However, when aggregating information on the learner end, the demographic information of learners is aggregated by constructing learner attribute maps. This results in the lack of knowledge characteristic information on the learner side, which leads to the lack of semantic richness of the learner's embedded

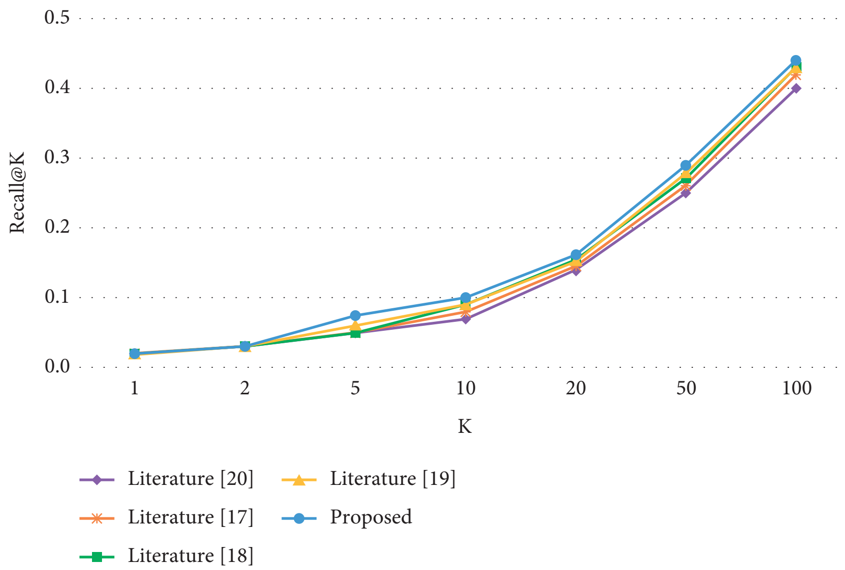

FIGURE 8: Recall of Top@K.

representation. The model proposed in this paper makes full use of the heterogeneous information of attention mechanism at both the learner side and the learning resource side and integrates the entity information between the learner's interactive learning resource and learning target and its neighbour information into the vector embedded representation of the learner, thus resulting in a significant improvement in performance.

4. Conclusion

Most of the existing improvement methods based on the collaborative filtering model introduce representation learning methods to get better representation vectors of learners and learning resources. The recommendation ability is enhanced by improving the learner-learning resource matching function. However, such work is focused on extracting learner-learning resource interaction information from a single interaction. In order to solve the problem of limited feature extraction of existing models, this paper proposes a recommendation algorithm for online business English learning resources based on the attention mechanism and collaborative filtering model. The model maps the learner vector and learning resource vector to multiple spaces to extract interactive features for score prediction. Multispace can consider the interaction of learner-learning resources from multiple perspectives, and more comprehensive features can better fit learner-learning resource scoring. The teaching practice in student associations proves that the model has a good recommendation ability in business English online learning resources recommendation. The data set in this paper is the interaction matrix between learners and learning resources, with only the index of learning-learning resources as the input of the model. In future work, we try to add more contextual information, social network information, and other auxiliary information to enhance the expressive force of the model.

Data Availability

The labeled data sets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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References

[1] W. Wang, L. Guo, and L. He, "Effects of social-interactive engagement on the dropout ratio in online learning: insights from MOOC," *Behaviour & Information Technology*, vol. 38, no. 6, pp. 621–636, 2019.
[2] Y. Xiong and H. K. Suen, "Assessment approaches in massive open online courses: possibilities, challenges and future directions," *International Review of Education*, vol. 64, no. 2, pp. 241–263, 2018.
[3] J. Guo, W. Zhang, W. Fan, and W. Li, "Combining geographical and social influences with deep learning for personalized point-of-interest recommendation," *Journal of*

Management Information Systems, vol. 35, no. 4, pp. 1121–1153, 2018.

[4] J. Jeevamol and V. G. Renumol, "An ontology-based hybrid e-learning content recommender system for alleviating the cold-start problem," *Education and Information Technologies*, vol. 26, no. 4, pp. 4993–5022, 2021.

[5] U. Javed, K. Shaukat, I. A. Hameed, F. Iqbal, T. M. Alam, and S. Luo, "A review of content-based and context-based recommendation systems," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 16, no. 3, pp. 274–306, 2021.

[6] M. K. Najafabadi, A. Mohamed, and C. W. Onn, "An impact of time and item influencer in collaborative filtering recommendations using graph-based model[J]," *Information Processing & Management*, vol. 56, no. 3, pp. 526–540, 2019.

[7] N. A. Albatayneh, K. I. Ghauth, and F. F. Chua, "Utilizing learners' negative ratings in semantic content-based recommender system for e-learning forum," *Journal of Educational Technology & Society*, vol. 21, no. 1, pp. 112–125, 2018.

[8] Z. Sun, M. Anbarasan, and D. Praveen Kumar, "Design of online intelligent English teaching platform based on artificial intelligence techniques," *Computational Intelligence*, vol. 37, no. 3, pp. 1166–1180, 2021.

[9] C. H. Lai, H. W. Lin, R. M. Lin, and P. D. Tho, "Effect of peer interaction among online learning community on learning engagement and achievement," *International Journal of Distance Education Technologies*, vol. 17, no. 1, pp. 66–77, 2019.

[10] A. Tratnik, M. Urh, and E. Jereb, "Student satisfaction with an online and a face-to-face Business English course in a higher education context," *Innovations in Education & Teaching International*, vol. 56, no. 1, pp. 36–45, 2019.

[11] S. D. M. Chethiyar, M. Asad, M. R. U. Kamaluddin, and A. Ali, "Impact of information and communication overload syndrome on the performance of students," *Opción: Revista de Ciencias Humanas y Sociales*, vol. 35, no. 24, pp. 390–405, 2019.

[12] L. Zhou, S. Wu, M. Zhou, and F. Li, "School's out, but class' on', the largest online education in the world today: taking China's practical exploration during the COVID-19 epidemic prevention and control as an example," *Best evid chin edu*, vol. 4, no. 2, pp. 501–519, 2020.

[13] S. Dhawan, "Online learning: a panacea in the time of COVID-19 crisis," *Journal of Educational Technology Systems*, vol. 49, no. 1, pp. 5–22, 2020.

[14] J. K. Tarus, Z. Niu, and G. Mustafa, "Knowledge-based recommendation: a review of ontology-based recommender systems for e-learning," *Artificial Intelligence Review*, vol. 50, no. 1, pp. 21–48, 2018.

[15] J. Xiao, M. Wang, B. Jiang, and J. Li, "A personalized recommendation system with combinational algorithm for online learning[J]," *Journal of Ambient Intelligence and Humanized Computing*, vol. 9, no. 3, pp. 667–677, 2018.

[16] R. R. F. Sinaga and R. Pustika, "Exploring STUDENTS'ATTITUDE towards English online learning using moodle during COVID-19 pandemic at smk yadika bandarlampung," *Journal of English Language Teaching and Learning*, vol. 2, no. 1, pp. 8–15, 2021.

[17] Y. Luo, T. Xu, and Z. Xu, "Recommended method study based on incorporating complex network ripple net[J]," *Journal of Northwestern Polytechnical University*, vol. 39, no. 5, pp. 1070–1076, 2021.

[18] H. Zhang, Y. Wang, C. Chen, and R. Liu, "Enhancing knowledge of propagation-perception-based attention recommender systems," *Electronics*, vol. 11, no. 4, p. 547, 2022.

[19] L. I. Xiang, Y. Xingyao, and Y. U. Jiong, "Double end knowledge graph convolutional networks for recommender systems," *Journal of Frontiers of Computer Science & Technology*, vol. 16, no. 1, p. 176, 2022.

[20] D. Jannach, A. Manzoor, W. Cai, and C. Li, "A survey on conversational recommender systems," *ACM Computing Surveys*, vol. 54, no. 5, pp. 1–36, 2021.