Online Course Learning Resource Recommendation Based on Difficulty Matching

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Abstract—The current methods for online course learning resource recommendation tend to continuously push similar items to students. To make students more satisfied with the overall recommendation service, it is necessary to explore the recommendation methods for online course learning resources based on difficulty matching. Therefore, this paper devises an online course learning resource recommendation method based on difficulty matching. Firstly, an online course learning resource recommendation approach was developed based on the autoencoder, in the light of difficulty matching. The flowchart of learning resource recommendation was presented, and the proposed algorithm was described in details. Then, the authors depicted the flow of the online course learning resource recommendation model, which considers difficulty matching, and proposed to capture the hierarchy of resources by assigning difficulty labels to texts, such that the proposed recommendation model outputs interpretable recommendation results. Finally, the authors designed a model that can discover the influence of the difficulty of learned resources on the difficulty of unlearned learning resources, and recommended online course learning resources considering difficulty matching. The effectiveness of the proposed model is verified through experiments.

Keywords—online course, learning resource recommendation, difficulty labeling, autoencoder

1 Introduction

The extensive application of online courses changes the form and content of online course learning resources. Currently, such learning resources are student-oriented, highlighting students' learning engagement and learning enthusiasm [1–5]. During the development of online course learning resources, putting resource diversity over difficulty makes it impossible to grasp the overall learning situation of students [6–14]. Learning needs and learning preferences are not static. With the improvement of their abilities, students will gradually ask for more difficult learning resources [15–19]. Therefore, the recommendation methods for online course learning resources should not only consider the short-term needs of students, but also take account of the changes of their learning status. This is the only way to effectively explore their potential interests, and assure ideal learning effects [20–23]. The current methods for online course learning resource recommendation tend to continuously push similar items to students. To make students more satisfied with the overall recommendation service, it is necessary to explore the recommendation methods for online course learning resources based on difficulty matching.

In e-learning, most content-based recommendation systems work on the matching rules between learners and learning objects. To improve the adaptability and diversity of recommendation, Wan and Niu [24] incorporated an LO-oriented recommendation mechanism to learner-oriented recommender systems, and proposed an LO self-organization-based recommendation approach (Self). The proposed approach was applied to the actual learning process, and proved highly adaptable, diverse, and personalized through adequate experiments. Chunwijitra et al. [25] presented a new framework that effectively connects open educational resources (OER) and massive open online courses (MOOC) for a life-long e-learning platform for Thai people. They utilized the Fedora Commons repository for an OER back-end, and developed a new front-end to manage OER resources. Without considering the learning context, the existing learning resource recommendation methods cannot effectively solve knowledge navigation loss and learning topic drift. To solve these problems, Li et al. [26] put forward an e-learning resource recommendation method based on learning context. Specifically, the learning context map and "knowledge resource" context association model were constructed, and combined with personalized recommendation technology to it provide learners with learning resources that meet their learning goals, knowledge capabilities and personal preferences. This strategy helps learners master the knowledge system and learning direction, and improve learning efficiency. Based on online learning style, Yan et al. [27] proposed a new learning resource recommendation method, which integrates learning style features into a collaborative filtering algorithm with association rule mining. Experimental results show that the method improves the recommendation accuracy by 25% compared to the method without learner features. Nguyen et al. [28] developed a way to study the relationship between online learning resources. This relationship is a special attribute of online education systems, which supports resource search and recommendation. Specifically, Google's PageRank algorithm was adopted to rank the network learning resources according to their correlations. The ranking was integrated to text matching search engines to optimize search results.

The students' preferences are crucial to successful recommendation of online course learning resources. However, the difficulty matching between learning resources is not considered in common preference acquisition methods, such as differentiating the weights of different historical item by the attention mechanism, and finding the weighted average of the curriculum embedding vectors. To activate students and improve learning effect, it is important to construct a personalized recommendation system for online course learning resources that can match the difficulty of learning resources. Therefore, this paper devises an online course learning resource recommendation method based on difficulty matching. Section 2 develops an online course learning resource recommendation approach based on the autoencoder, in the light of difficulty matching, presents the flowchart of learning resource recommendation, and details the proposed algorithm. Section 3 depicts the flow of the online course learning resource recommendation model, which considers difficulty matching, and proposed to capture the hierarchy of resources by assigning difficulty labels to texts, such that the proposed recommendation model outputs interpretable recommendation results. Section 4 designs a model that can discover the influence of the difficulty of learned resources on the difficulty of unlearned learning resources, and recommends online course learning resources considering difficulty matching. The effectiveness of the proposed model is verified through experiments.

2 Difficulty preference recognition

The purpose of determining the difficulty of online course learning resources is to screen topics, and ensure that difficulty of resources benefits students' online learning. To determine the difficulty, it is important to consider the differences between students' learning ability and learning foundation, and prevent hurting the self-esteem of students with learning difficulties. For online courses with different levels of difficulty, the learning resource recommendation must take account of the impact on the distribution of scores. Sometimes, the skewed normal distribution can stimulate students' interest in learning. This paper devises an online course learning resource recommendation method based on difficulty matching.

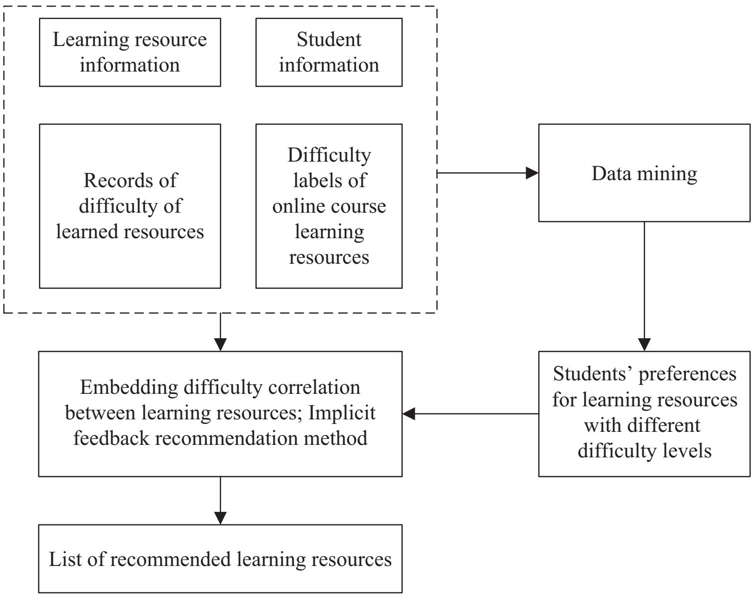

Fig. 1. Flow of learning resource recommendation

At present, data mining has been widely applied in online course learning resource recommendation. Domestic and foreign scholars often treat fine-grained methods that understand students' learning needs and learning preferences as a special type of recommendation approaches. Given the differences in students' learning ability and learning foundation, the relevant factors should be paid attention to in the recommendation method. This paper develops an online course learning resource recommendation approach based on the autoencoder, in the light of difficulty matching. The flow of learning resource recommendation is provided in Figure 1. The proposed algorithm is detailed as follows

The self-attention encoder was constructed through the following procedure. Firstly, the difficulty record of the resources learned by a student is converted into a multi-hot preference vector $A_r \in S^L$. Then, A_r is input to the autoencoder. The students who have completed the learning the resources of this difficulty level are denoted by 1 in A_r, and those who have not are denoted by 0 in A_r. Let $M_r = \{m_1, \ldots, m_l\}$ be the set of difficulty records of learned resources, where m_l is the difficulty index of learning resources. The embedding matrix weight Q_1 for learning resource difficulty, which represents the difficulty of the unlearned resources selected by the student corresponding to the vector of learning resource difficulty can be expressed as:

$$Q_1[M_r] = (Q_1^{m_1}, \ldots, Q_1^{m_l}) \tag{1}$$

where, $Q_1 \in S^{F \times L}$; [ ] is the selection of the corresponding learning resource difficulty by the submatrix of Q_1; Q_1^{ml} is the m_l-th column of the difficulty index of learning resources.

This paper introduces the self-attention mechanism to the autoencoder neural network, aiming to mine the students' preference for learning resources of different difficulties from the difficulty records of learned resources, and easily acquire the internal correlations of the data features between students and learning resource difficulty. The student implicit representation vector b_1^r can be obtained by weighting and processing $Q_1[M_r]$. Let $q_x \in S^F$ be the parameter of the attention layer. Then, $Q_1[M_r]$ is embedded based on the learned resources corresponding to the students. The attention weight can be solved by:

$$x_r = softmax(tanh(Q_x^O Q_1[M_r]) + y_1) \tag{2}$$

The value of b_1^r can be obtained by multiplying and superimposing x_r and $Q_1[M_r]$:

$$b_1^r = \sum_{m_i \in M_r} x_{r,j} \cdot Q_1^{m_i} \tag{3}$$

To capture students' preferences for learning resources of different difficulties from different aspects, it is necessary to set and execute the above formula multiple times with different parameters. This paper uses the importance score matrix Q_x to capture the influence of the multi-dimensional attention on the difficulty of learning resources, i.e., the dimension F_x of the self-attention layer. The importance of learning resources of different difficulties to students is determined by the importance score of each dimension. Let $X_r \in S^{Fx \times F}$ be the importance score matrix; q_x be the self-attention weight; $Q_x \in SS^{Fx \times F}$ be the attention weight matrix. Then, q_x can be extended to $Q_x \in SS^{Fx \times F}$. Then, we have:

$$X_r = softmax(tanh(Q_x Q_1[M_r]) + y_1) \tag{4}$$

For a learning resource of a specific difficulty, the importance vector is represented by a column in matrix X_r; meanwhile, each row of the matrix characterizes the importance of a student to the learning resource difficulty on level l. The activation function *softmax* operates along the second dimension of the input. Let $B_1^r \in S^{Fx \times F}$ be the preference matrix of student r for learning resources on dimension F_x. This matrix can be obtained as the inner product between X_r and $Q_1[M_r]$:

$$B_1^r = X_r \cdot (Q_1[M_r])^O \tag{5}$$

To facilitate the decoding module of the network, this paper sets up a merging layer in the neural network to merge student vectors of different dimensions. Let Q_o, y_o, and g_o be the weight, bias, and activation function in the merging layer, respectively. The merged student vector can be expressed as:

$$b_1^r = g_o(B_1^{rO} q_o + y_o) \tag{6}$$

In addition, it is necessary to reconstruct the captured students' learning preference for unlearned resources during the training of the self-attention encoder. For this purpose, a stack autoencoder network with a bottleneck layer is introduced to deeply mine the complex interaction between students and learning resource difficulties. Let $Q_2 \in S^{Y \times F}$ and $Q_3 \in S^{F \times Y}$ be the relevant parameters in the stack autoencoder network. The relevant calculation is as follows:

$$\begin{cases} b_2^r = g_2(Q_2 b_1^r + y_2) \\ b_3^r = g_3(Q_3 b_2^r + y_3) \end{cases} \tag{7}$$

3 Acquisition of learning resource hierarchy

Figure 2 illustrates the flow of online course learning resource recommendation model considering difficulty matching. Since some online course learning resources have difficulty labels, the proper selection of the resources of proper difficulties calls for consideration of the hierarchy of difficulty in the resource recommendation process. However, it is very challenging to derive the accurate resource hierarchy from the difficulty labels of online course learning resources. Thus, this paper decides to capture the resource hierarchy based on the difficulty label texts, making the results of the proposed recommendation model more interpretable.

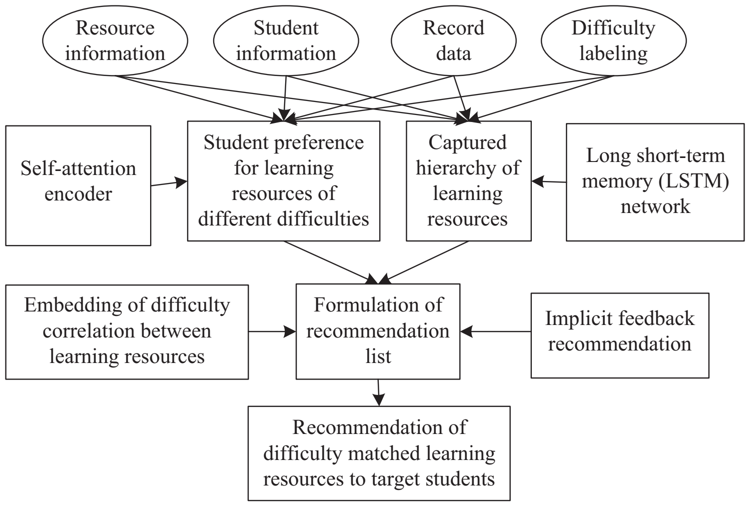

Fig. 2. Flow of online course learning resource recommendation model considering difficulty matching

Firstly, the information of difficult label texts is converted into a word vector. Then, the word vector series are trained by the LSTM. Let a_o be the input at time point o; Q be the weighted matrix from input to hidden state vector; V be the weighted matrix on the hidden state vector at time step o-1; a be the time step size; f_o be the hidden state vector. When the LSTM satisfies $a \in 1, \ldots, o, f_o$ can be updated by:

$$f_o = \varepsilon(Q \cdot f_o + V \cdot f_{o-1}) \tag{8}$$

To better capture the hierarchy of hidden resources in the difficulty label texts of learning resources, an attention mechanism is embedded in the LSTM. Let Q_n and y_n be the weight and bias of the attention layer, respectively. Then, the attention weight x_d corresponding to the hidden state at time t can be expressed as:

$$x_d = softmax(tanh(Q_n \cdot f_o + y_n)) \tag{9}$$

Let f_o be the hidden state at time point o. After weighted summation, the hidden state vector f_i can be calculated by:

$$f_i = \sum_o x_d \cdot f_o \tag{10}$$

Let f_1 and f_2 be the outputs of the last output layer of the left and right twin networks, respectively. The correlation measure between the label text information of the difficulty of the two encoded learning resources can be obtained by:

$$E[M_r] = exp\left(-\left\|f_1 - f_2\right\|\right) \tag{11}$$

4 Realization of learning resource recommendation model

After learning the resource of a certain difficulty, the students are very likely to continue with learning more difficult resources, thus enhancing their learning ability, and consolidating their mastery of the knowledge points in the learned resources. The difficulty correlation between learning resources determines the students' decision on the preferred difficulty of learning resources. The proposed model can detect the influence of the difficulty of learned sources over that of unlearned resources. Let $M_r = \{m_1, \ldots, m_l\}$ be the set of difficulties of learned resources. The influence of the difficulty of a learning resource over that of other resources is represented as a column of $N_r \in S^{L\times l}$, $Q \in S^{L\times F}$. Then, the influence factor of the difficulty of learned resources over that of unlearned resources can be given by:

$$M_r = Q_4 \cdot Q_1[M_r] \tag{12}$$

To integrate the hierarchy of learning resource difficulties, the authors considered the influence of the difficulty correlation between learning resources over the recommendation of learning resources. This paper obtains how the difficulty of learned resources over that of unlearned resources from the difficulty label text of learning resources. Let $\otimes$ be the element product. Then, the matrix integrating the difficulty correlation of learning resources can be expressed as:

$$N_r = (Q_4 \cdot Q_1[M_r]) \otimes E[M_r] \tag{13}$$

To solve the influence of the difficulty of all learning resources over that of unlearned resources, it is assumed that i and j are the index values of rows and columns in N_r, respectively. By summing up each row of matrix N_r, $n_r \in S^L$ can be obtained:

$$n_r = \sum_{i=1}^{L} \sum_{j=1}^{l} N_r^{(i,j)} \tag{14}$$

After embedding the difficulty correlation between learning resources, the output vector $\dot{a}_r$ of the autoencoder is obtained, which integrates the difficulty correlation between learning resources in the reconstructed space. Let $Q_4 \cdot b_3^r$ be the students' preference features for learning resources of different difficulties in Section 2; n_r be the difficulty correlation between learning resources solved by the difficulty correlation encoder; y_4 be the bias. Then, we have:

$$\dot{a}_r = g_4(Q_4 \cdot b_3^r + n_r + y_4) \tag{15}$$

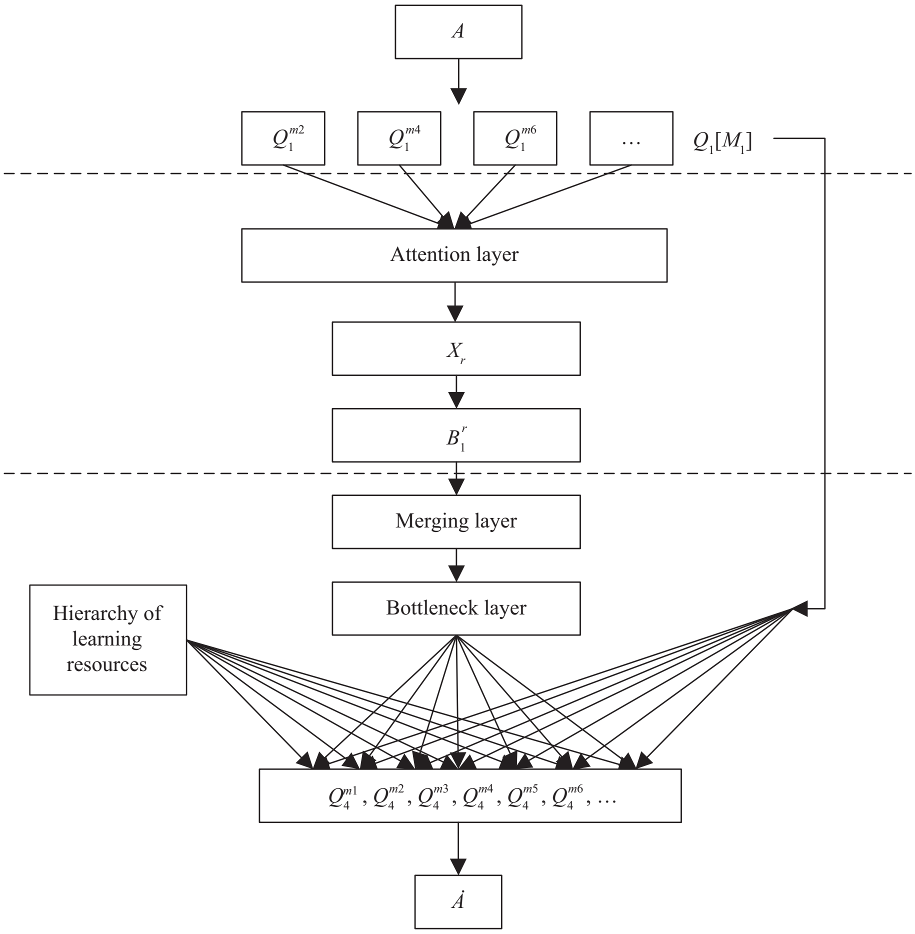

Fig. 3. Framework of recommendation model

Figure 3 shows the framework of our recommendation model. This paper adopts the implicit feedback recommendation of the difficulty data of the learned resources, and studies the data records of the student selections of learning resources difficulty. The primary goal is to obtain the information on the difficulty of the learned resources. If a student gets used to a learning resource of a certain level of difficulty, he/she would be more likely to learn a more difficult resource. To derive students' real preferences from the difficulty data of the learned resources, the weighting method was adopted to differentiate between the difficulty of the learned resources and that of the unlearned resources. When the students learn the resources of a certain difficulty level more frequently, the corresponding weight will grow proportionally. Let β and σ be the confidence weights. Then, the weights of the elements in the confidence matrix D of students' preference for learning resources can be configured by:

$$d_{r,d} = \begin{cases} 1+\beta log(1+g_{r,d}/\rho) \\ 1 \end{cases} \tag{16}$$

If the learning frequency of a resource of a certain difficulty is greater than zero, the weight is indicated by $g_{r,d}$; otherwise, the weight $g_{r,d}$ equals 1. After embedding D, the regularization parameter is denoted by μ; Q_x and Q_o be the learning parameters of the attention layer and merging layer, respectively. Then, the objective function of the model can be expressed as:

$$LO = \sum_{r=1}^{K}\sum_{d=1}^{L}\left\| D \otimes (A_{r,d} - \hat{A}_{r,d}) \right\|_2^2 \tag{17}$$

$$N = LO + \mu(\|Q_i\|_2^2 + \|Q_x\|_2^2 + \|Q_o\|_2^2) \tag{18}$$

5 Experiments and results analysis

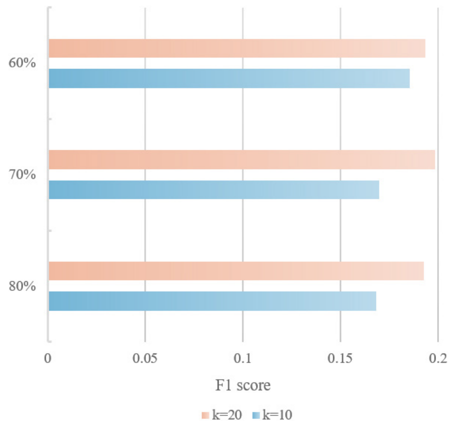

Fig. 4. F1 scores at different division methods and different k values

To recommend learning resources more reasonably, the difficulty records of each student in the training set for the learned resources are regarded as positive cases, and those for unlearned resources as negative cases. To obtain the best recommendation effect, the training parameters were configured as follows: The minimum batch size, 256, the learning rate, 0.001, and the dimensionality of the attention layer, 18.

The recommendation results change with the division methods for the training set and the test set, as well as the number k of recommended learning resources. As shown in Figure 4, when the ratio of the training set to the test set was 7:3, the recommendation model achieved a high training stability, and rarely encountered overfitting. Thus, this paper selects this ratio to carry out subsequent model performance tests. To ensure the effectiveness of the tests, the parameters of the reference models were configured the same as those of our model.

Table 1. Model performance

Model	***IBCF***	***DQN***	***MRLGRec***	***GRU***	**Our Model**
Precision @10	0.1925	0.1396	0.1827	0.1692	0.2748
Precision @20	0.1358	0.0951	0.1625	0.1374	0.1926
Recall @10	0.2947	0.1382	0.1629	0.1362	0.2819
Recall @20	0.3419	0.1284	0.1637	0.2741	0.3624
F1 score @10	0.1625	0.1481	0.1209	0.1574	0.1362
F1 score @20	0.1362	0.1247	0.1525	0.1632	0.1857

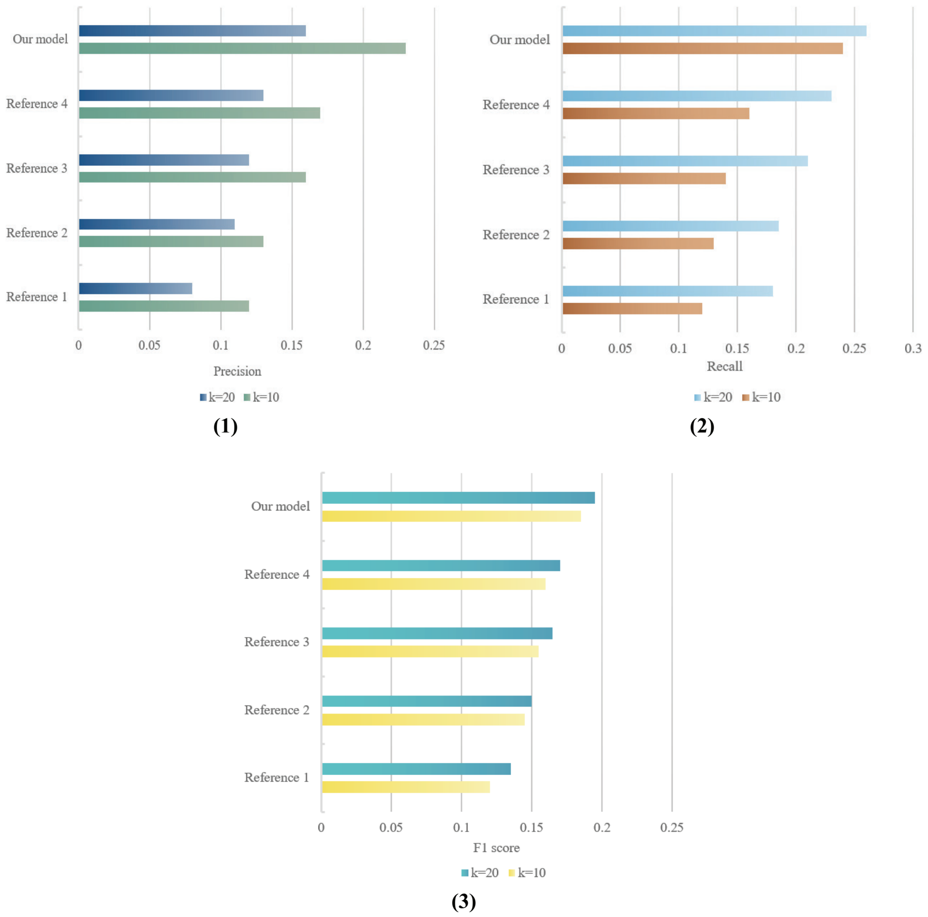

Fig. 5. Performance indices of our model and GRU model

Table 1 compares the test performance of four reference models with our model, including IBCF (model 1), DQN (model 2), MRLRec (model 3), and GRU (model 4). @k refers to the top-k recommended online course learning resources. The results show that our recommendation model outperformed the four reference models. By integrating the hierarchy of learning resource difficulties, the proposed model effectively improves the recommendation effect of learning resources based on difficulty matching. It was also confirmed that the proposed model can effectively handle the hierarchy of learning resource difficulties. In all difficulty matching-based learning resource recommendation tests, our model achieved the most superior performance, and the superiority increased with the changing number of recommended resources.

Figure 5 compares the performance indices of our model and those of GRU model, which were obtained through experiments. The model performance was measured by precision, recall, and F1 score. The results show that our model had better performance than GRU model. In terms of F1 score @ 20, our model was 4–8% better than the other model. It was demonstrated that the embedding of hierarchy correlation between learning resources improves the capturing of learning resource attributes from the label text information of learning resource difficulties, laying a solid basis for difficulty matching-based learning resource recommendation.

To verify the accuracy of difficulty matching-based online course learning resource recommendation, this paper carries out 10 repeated tests on two indices: Cumulative learning effect, and click rate increase. It can be seen from Table 2 that the two indices of all models improved with the growing number of recommended resources. When $k = 10$, our model achieved 8–60% greater cumulative learning effect than the other models; and 13–6% greater click rate increase than the other models. When $k = 20$, the edge widened to 9%~67%, and 9%~54%, respectively. The results show that the learning effect can be maximized, and the click rate can be increased greatly, after adopting the online course learning resource recommendation based on difficulty matching.

Table 2. Comparison of recommendation performance of different models

Model		*IBCF*	*DQN*	*MRLGRec*	*GRU*	*Our Model*
$k = 10$	Cumulative learning effect	15.29	13.85	25.69	21.57	26.77
	Click rate increase	0.43	0.68	0.62	0.78	0.91
$k = 20$	Cumulative learning effect	11.37	21.59	26.37	22.01	28.45
	Click rate increase	0.49	0.62	0.74	0.73	0.81

6 Conclusions

This paper mainly explores the online course learning resource recommendation method based on difficulty matching. Firstly, an online course learning resource recommendation approach was developed based on the autoencoder, in the light of difficulty matching, the flowchart of learning resource recommendation was presented, and the proposed algorithm was described in details. After that, the authors depicted the flow of the online course learning resource recommendation model, which considers difficulty matching, and proposed to capture the hierarchy of resources by assigning difficulty labels to texts, such that the proposed recommendation model outputs interpretable recommendation results. In addition, the authors designed a model that can discover the influence of the difficulty of learned resources on the difficulty of unlearned learning resources, and recommended online course learning resources considering difficulty matching.

Finally, multiple experiments were carried out to verify the performance of our model. In all difficulty matching-based learning resource recommendation tests, our model achieved the most superior performance, and the superiority increased with the changing number of recommended resources. Furthermore, this paper compares the performance indices of our model and those of GRU model, as well as the recommendation performance of different models. The results demonstrate that the embedding of hierarchy correlation between learning resources improves the capturing of learning resource attributes from the label text information of learning resource difficulties, laying a solid basis for difficulty matching-based learning resource recommendation.

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