Personalized Course Resource Recommendation Algorithm Based on Deep Learning in the Intelligent Question Answering Robot Environment

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ABSTRACT

Aiming at the problems of difficult-to-extract effective information and insufficient feature extraction in the existing intelligent question answering robot environment, a personalized course resource recommendation algorithm based on deep learning is proposed. Firstly, the potential preferences of users are obtained through course-related data. Secondly, the authors use one-hot coding and embedding to convert word vectors into low-dimensional, dense real-valued vectors and input them into the CIN-GRU model. Finally, the attention mechanism is used to improve the attention of some words and the accuracy of personalized course recommendation. The experiment shows that when the recommended list is 35, the precision, recall, and F1 value of the proposed personalized course recommendation method are 0.862, 0.851, and 0.857, respectively, which are higher than those of the comparison method. Therefore, the performance of the proposed method in sustainable personalized course resource recommendation is better than that of the comparison method.

KEYWORDS

Attention Mechanism, Big Data, Course Resource Recommendation, Deep Learning, Intelligent Question Answering Robot, Personalized Recommendation, Sustainable

INTRODUCTION

Online education uses a variety of information technology strategies, including big data, multimedia, and artificial intelligence, to carry out distance education on an internet platform (Yang et al., 2010; Bahmani et al., 2012). Some studies have examined how two-tier online community learning and heterogeneous teams influence the knowledge performance of online work community organizations in the presence and absence of leader forgetting (Wu et al., 2021). The development of online education has not only injected new power into traditional education but has also brought movement toward educational reform and development.

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In recent years, various computer-related technologies have been developed, and the internet era has also transformed into a big data era. In particular, the emergence of multimedia has triggered a revolution in education models. Online education has flourished, in general. It breaks the traditional education model and realizes leapfrog teaching on the internet in different periods (Yu et al., 2018; Min, 2022; Wang et al., 2019a; Zhang et al., 2017). There is much useful information on many social networking sites for consumers to compare products. Sentiment analysis is considered suitable for summarizing opinions (Ng et al., 2021). The same user can learn in different places and at different times, and this has gradually become the mainstream means of education.

The number of online education users in China is growing rapidly. The establishment of open universities has enabled millions of adults to continue their education. Simultaneously, the emergence of many learning websites has provided new opportunities for users who want to continue improving themselves (Dwivedi et al., 2018; Lin et al., 2021; Wan & Niu, 2016; Ni & Ni, 2020). Prior studies have proposed dynamic measurements and evaluation frameworks for hotel customer satisfaction through sentiment analysis of online reviews (Gang & Chenglin, 2021). When learning a topic, most of the corresponding learning resources can be found on the internet, and many can be used freely. With the rapid increase in the number of online users and course resources, online education platforms are generating much browsing data every day, which increases the platform load. To enable online users to accurately find the course resources they need, the course recommendation system was created. Course recommendation systems can provide users with course resources that meet both their characteristics and their interests and preferences. Therefore, the course recommendation system has become a new and mainstream form of personalized information service and (Liu et al., 2019).

Internet of Things (IoT) technology solves the limitations of space and distance in traditional education and helps realize the openness and sharing of educational resources (Wang, 2015; Bahmani et al., 2011; Duan, 2019). The high-quality educational resources owned by educational institutions are no longer limited to the scope of their activities but can be widely disseminated around the world through the network. As the storage locations and learning methods of educational resources have changed, learners can freely choose learning content by breaking through the restrictions brought about by time and place through online teaching (Imran et al., 2016). This change in learning style causes learners to change from traditional passive learning to active learning. Learners can choose the learning content and grasp the learning rhythm freely according to their own needs. At the same time, it also makes learners' abilities more diversified (Gan & Zhang, 2020; Li et al., 2022; Xu et al., 2016).

This leads to the personalized course recommendation algorithm, represented by an intelligent question-answering robot environment, developing rapidly. However, owing to learners' lack of accurate judgement and understanding of platform resources, "information overload," "information maze," and other problems have gradually emerged. Learners need to spend significant time and energy to find courses that meet their needs. Moreover, learners' own needs are not clear, leading to an inability to accurately find learning resources and loss of massive resource information (Tavakoli et al., 2022). Finally, with the popularity of online shopping, many studies have begun to focus on the factors influencing consumer information search and evaluation (Lu & Bai, 2021). Therefore, accurate recommendation of sustainable personalized learning resources for target users has become an urgent problem for the platform (Qiao et al., 2014). The remainder of this paper is organized as follows: the Related Works section introduces related work, the Personalized Course Resource Recommendation Method section introduces the personalized course resource recommendation method based on deep learning, the Experiment and Analysis section describes the experiment and analysis, and the Conclusion section concludes the paper.

RELATED WORKS

Deep learning realizes complex function approximation by constructing a nonlinear network structure with multiple hidden layers. At the same time, it uses a large amount of training data to obtain more abstract deep features, which improves the accuracy of the model classification or prediction. Naumov et al. (2019) developed the deep-learning recommendation model (DLMR). The advantage of this model is that it uses model parallelism on embedded tables to reduce memory constraints and uses data parallelism for fully connected layer calculations, which greatly improves performance. The disadvantage is that, owing to the low attention and small scope of application, more experiments are needed to improve the model.

Wang et al. (2019b) proposed a multitask feature learning recommendation (MKR) using a knowledge graph as a supplementary information source. The advantage of this method is the design of a cross-compression unit for correlating the tasks. The unit can automatically learn high-order interactions between items and entity features and perform knowledge transfer between tasks. The disadvantage is that the method currently has fewer usage scenarios and requires more experiments to prove its versatility.

Mohan & Mohan (2019) proposed a hybrid method, whose advantage is that it extends the deep autoencoder with top-k semantic information by establishing a joint optimization function that can accurately capture implicit semantic social information. The disadvantage is that this method has high requirements and needs to be further optimized for deep learning technology.

Guo et al. (2017) proposed a neural network framework, DeepFM, which integrates a decomposition machine (FM) and deep neural network (DNN). The advantage of this method is that it does not require any pretraining and can learn high- and low-order feature interactions. The disadvantage of this method is that the high-order feature interactions must be improved.

Zhang et al. (2017) proposed a personalized recommendation system based on the deep belief network (DBN). The advantage of this method is that it can improve learning efficiency, and the disadvantage is that the course classification needs to be further refined and the performance of the model recommendation is improved.

Ng and Linn (2017) used topic analysis, label analysis, sentiment analysis, and course score prediction to show students' course priorities and rank potential courses according to the results of course analysis. An advantage of this method is its high recommendation efficiency. The disadvantage of this method is that the courses need to be further refined to improve the comprehensive recommendation performance.

Lin et al. (2021) calculated the user's preference for a topic by constructing an latent dirichlet allocation (LDA) user interest model, thus completing the recommendation of personalized learning resources. The advantage of this method is that its recommendation accuracy is high. The disadvantage is that the course refinement needs to be further improved.

Chen et al. (2020) proposed a personalized online course recommendation click-through rate (CTR) model, which has different user characteristics, item characteristics, and cross-features. The advantage is that the recommendation accuracy can be improved by model optimization. The disadvantage is that the amount of data is insufficient, and the model needs to be further optimized.

However, the above methods can only mine shallow information in feature extraction, while a large amount of deeper feature information is difficult to extract, which often results in low course recommendation accuracy. To overcome these problems, this paper proposes a personalized course resource recommendation algorithm based on deep learning in an intelligent question-answering robot environment. The innovation of the proposed method is as follows:

1. Through data, such as course summaries, course review information, and the user's learned courses, we can obtain the user's potential favorite preferences. By using the bidirectional encoder representation from transformers (BERT) pretraining language model to obtain contextualized word vectors, the feature extraction ability of the system was significantly improved.
2. One-hot coding and embedding are used to transform the word vector into a low-dimensional, dense real-value vector and input it into the CIN-gated recurrent unit (GRU) model. The attention mechanism is used to improve the accuracy of course recommendation.

PERSONALIZED COURSE RESOURCE RECOMMENDATION METHOD

Model Framework

Aiming at the actual situation of course recommendations on massive open online courses (MOOC) of Chinese universities, this paper proposes a personalized recommendation model that integrates BERT. In the process of learning, the model adds the BERT text information feature extraction network, which can be used to extract the features of the course summary description information and the review text to obtain their feature vectors. For user Identity document (ID), course ID, and course publishing organization, which are difficult to be directly used as input of the machine learning model, this method first uses one-hot coding and then uses embedding to transform them into a low-dimensional, dense real-value vector and inputs them into the compressed interaction network- gate recurrent unit (CIN-GRU) model. This improves the accuracy of course recommendation through the attention mechanism. Finally, the training model is updated iteratively using the input feature vector and course score given by the user. The network structure of the proposed recommendation model is shown in Figure 1.

CIN

A characteristic of the CIN is that the degree of feature interaction learned is determined by the number of layers of the network, and each hidden layer is connected to the output layer through a pooling layer. At the same time, the structure of the CIN is very similar to that of a recurrent neural network (RNN). The difference is that the parameters of different layers in the CIN are different, but they are the same as in an RNN. Moreover, each additional input data in an RNN is different, while the additional input data in the CIN is fixed, as shown in Figure 2, where x represents the input data and the superscript indicates the number of layers.

GRU

The GRU is a type of RNN. The GRU can solve the problem of long dependence that cannot be solved by a traditional RNN. The network structure is shown in Figure 3.

The GRU is mainly composed of an update gate and reset gate. If the current time is t, the GRU calculation formula is as shown in Equations (1)–(4):

Figure 1.
Network structure of recommendation model

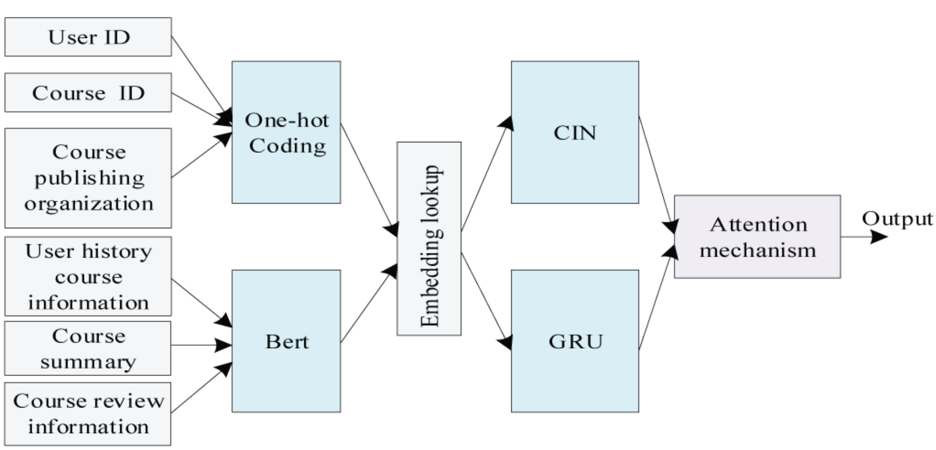


Figure 2.
Schematic diagram of CIN macro framework

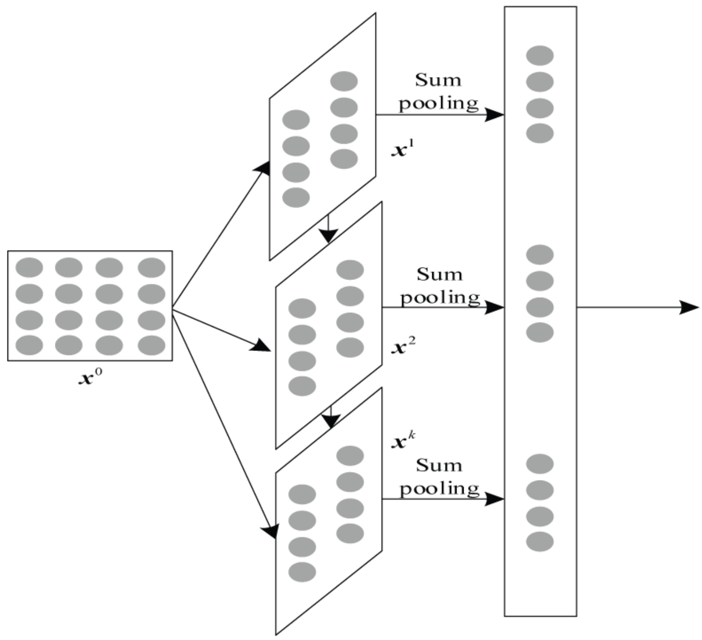
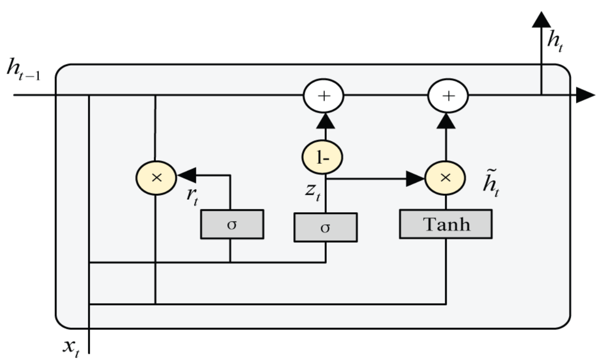


Figure 3.
Schematic diagram of CIN macro framework



$$r_t = \sigma(w_r \cdot [h_{t-1}, W_t] + b_r) \tag{1}$$
$$z_t = \sigma(w_z \cdot [h_{t-1}, W_t] + b_z) \tag{2}$$
$$\tilde{h}_t = \tanh(w_{\tilde{h}} \cdot [r_t * h_{t-1}, W_t] + b_{\tilde{h}}) \tag{3}$$
$$h_t = z_t * h_{t-1} + (1 - z_t) * \tilde{h}_t \tag{4}$$

where w_r, w_z, and $w_{\tilde{h}}$ are weight matrices and b_r, b_z, and $b_{\tilde{h}}$ are offset values. W_t is the input vector at time t, r_t is the reset gate, z_t is the update gate, $\tilde{h}_t$ is the candidate set of the current state, and h_t is the hidden state and final output.

Attention Mechanism Model

The attention mechanism has become an important concept in neural networks and has achieved good results in different research fields. The most common use of the attention mechanism in recommendation systems is to model user behavior data. In general, the attention module includes a query, key, and value, and the output is the weighted sum of the query and key value similarity. The attention mechanism distinguishes the importance of the interactions between different features and assigns different weights. These three components are the same and consist of user-history interaction functions, as shown in Figure 4. The calculation formula is as follows:

$$Attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d}}\right)V \tag{5}$$

where Q is the query matrix, K is the bond matrix, V is a numerical matrix, d is the number of hidden layer nodes, and n is the input length.

Personalized Course Recommendation

After extracting the time-series characteristics of the data, the recommendation results are obtained using the Softmax function. The recommendation system model is illustrated in Figure 5.

EXPERIMENT AND ANALYSIS

Experimental Environment

The Python programming language was used as the coding language for this experiment. The basic code of the experimental model and code related to data processing were written in Python. The 64-bit operating system of Microsoft Windows 10 builds a Python environment using the Windows platform.

Figure 4.
Attention mechanism

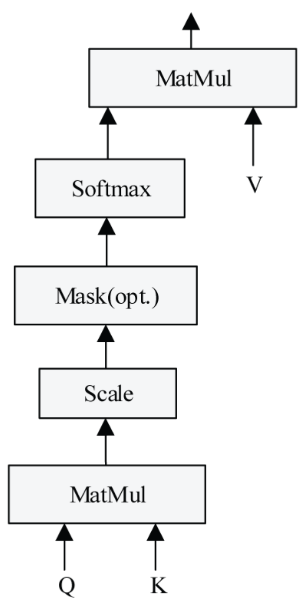
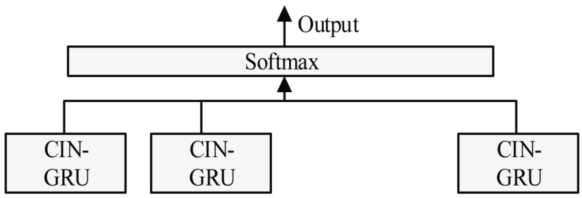


Figure 5.
Course recommendation model



The development software was PyCharm 2018, and the compilation environment was Python 3.6. PyTorch was selected as the training framework in this experiment. PyTorch supports dynamic graphs and provides Python interfaces. The software environment completed the construction of the Python framework using Anaconda. The specifications of the experimental environment are listed in Table 1.

Experimental Data Set

The data set is the MOOC data userlabel08rl of the University of China from 2014 to 2022, crawled online after data cleaning and preprocessing, as shown in Table 2.

Evaluation Metrics

This study used Precision, Recall, and F1 value to evaluate the performance metrics of the proposed method. The calculations of these three metrics are shown in Equations (6)–(8):

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{8}$$

Table 1.
Experimental environment settings

Experimental environment	Specific information
Operating system	Windows
Graphics card	GTX 1080 Ti
Memory	32GB
Language	Python 3.6
Development platform	PyTorch
Development tool	PyCharm

Table 2.
Basic information of data set

Data set	Number of courses	Number of people	Interactive record
userlabel08rl	1,045	4,275	301,476

where *TP* indicates the number of samples that are positive, where the classifier prediction is positive. *TN* indicates the number of samples that are negative, where the classifier prediction is also negative. *FP* represents the number of samples that are negative but predicted by the classifier as positive. *FN* indicates the number of samples that are positive but predicted by the classifier as negative.

Influence of Epochs on the Model

As shown in Figure 6, by migrating the pretraining model on the standard data set to the course recommendation task, the model parameters were fine-tuned, which reduced the training time and improved the training efficiency of the model. The proposed personalized course recommendation model performed well on the course data set. The proposed personalized course recommendation model converges faster and has a better model fitting ability, and its log loss reached 0.051. The results show that the proposed personalized course recommendation model achieved good results in course recommendation tasks.

Effect of Epochs on Accuracy and Loss

The personalized course recommendation model proposed in this paper achieved high accuracy in the experiment. In the experiment, the training and test sets were divided in a 4:1 ratio. The results obtained after 70 training epochs are shown in Figure 7. The loss decreases prove that it is converging, and the accuracy increases prove that its accuracy is improving. The experimental results prove that the proposed model can effectively carry out personalized course recommendations.

Experimental Comparison and Analysis

To prove the effectiveness of the proposed CIN-GRU algorithm, the MOOC data of the userlabel08rl data set of the University of China was used for experimental verification. Existing methods (Lin et al., 2021; Chen et al., 2020) were compared with the proposed method. The experimental results are shown in Figures 8 and 9. It can be seen that on the aforementioned data set, the indicators of the proposed algorithm are optimal for all recommended list lengths. When the recommended list length N is 35, the Precision of the proposed algorithm is 0.862, Recall is 0.851, and F1 value is 0.857. The Precision of the algorithm of Lin et al. (2021) is 0.824, Recall is 0.830, and F1 value is 0.827. The Precision of the algorithm of Chen et al. (2020) is 0.785, Recall is 0.795, and F1 value is 0.789. This is because the proposed algorithm uses one-hot coding and embedding to transform the

Figure 6.
Influence of Epochs on the model

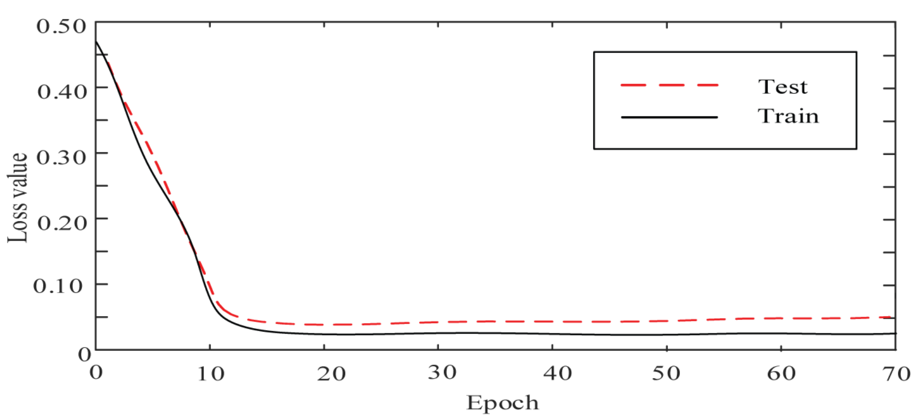
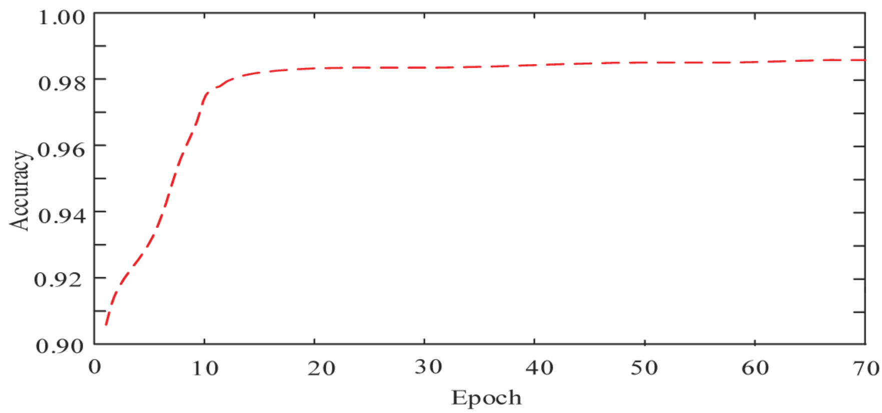
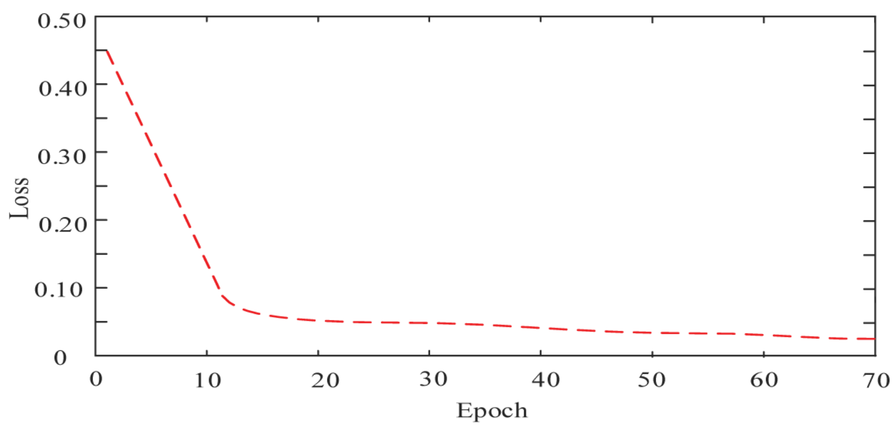


Figure 7.
Effect of Epochs on accuracy and loss



(a) Precision



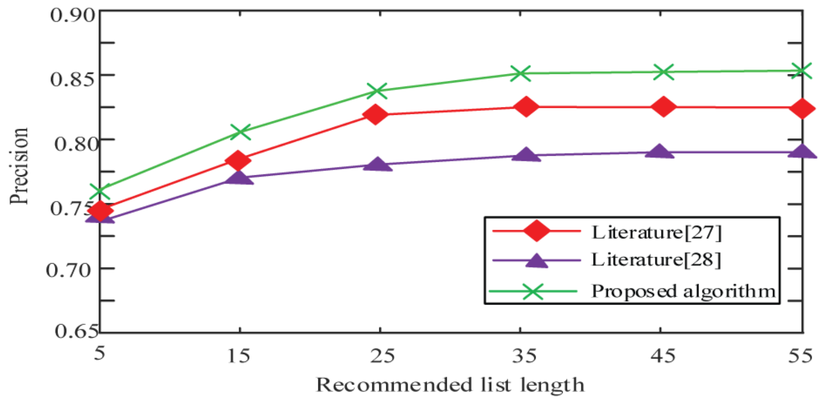
(b) Loss

word vector into a low-dimensional, dense real-value vector and input it into the CIN-GRU model. This improves the attention of some words through the attention mechanism, which improves the accuracy of course recommendation.

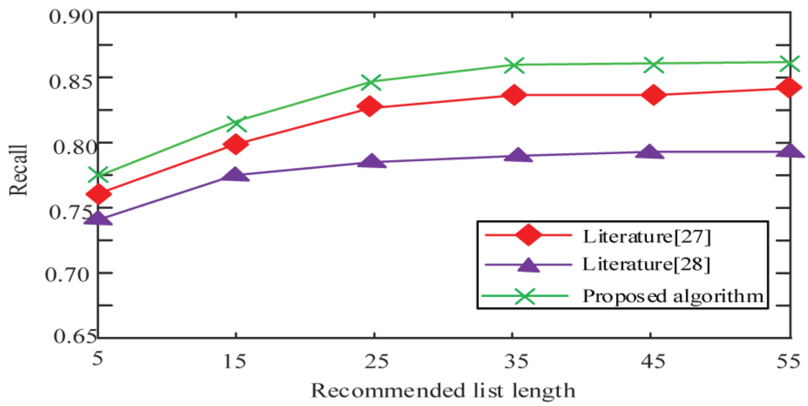
CONCLUSION

Aiming at the problem that existing sustainable personalized course resource recommendation algorithms based on deep learning of an intelligent question-answering robot environment have difficulty extracting effective information and insufficient feature extraction, this paper proposed a personalized course resource recommendation algorithm based on deep learning of intelligent question-

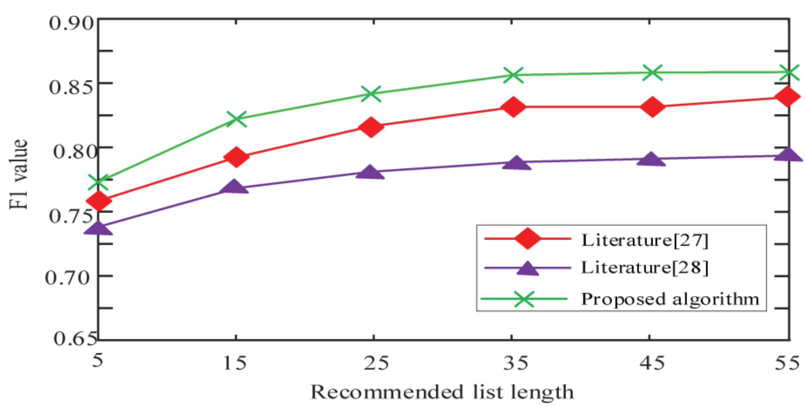
Figure 8.
Precision, recall, and F1 value of different algorithms



(a) Precision

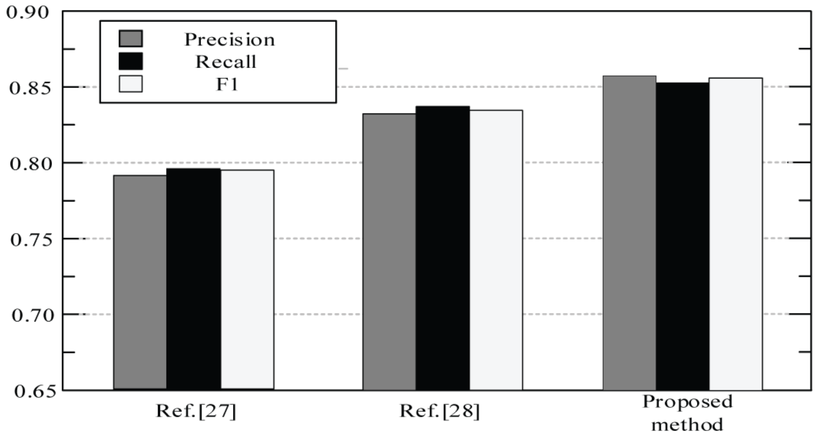


(b) Recall



(c) F1 value

Figure 9.
Comparison of metrics of different recommendation models



answering robot environments. Experimental results show that the proposed method performs better than the comparison methods for personalized course resource recommendation.

The recommendation model proposed in this paper only uses the information of the user's learned courses but not the user's personal information, such as their educational background, school, and research direction, so it can obtain more features. At the same time, there is no time-series feature acquisition for user-learned courses, and users' interests are constantly changing with the growth of experience and cultural levels. Therefore, the proposed method must dynamically track changes in user preferences to respond in advance. In addition, although the system considers the interaction behavior of many users as the basis for analysis, there are other implicit and valuable interaction behaviors between users and the website, such as frequent clicking behavior and the duration of watching courses. The model can also increase the collection and analysis of this behavior, which will be further studied later.

AUTHOR NOTE

The data used to support the findings of this study are included within the article. The author declares that there is no conflict of interest regarding the publication of this paper. This research received no external funding.

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