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Research on Personalized Learning Resource Recommendation Method for Students Supported by Artificial Intelligence

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ABSTRACT

With the rapid development of artificial intelligence technology, the education sector is undergoing unprecedented changes. Personalized learning has become a key method to enhance teaching quality and learning outcomes. This paper aims to explore the application of artificial intelligence technology in personalized learning resource recommendation for students, by constructing user profiles, multidimensional models, and personalized recommendation algorithms, in order to provide precise learning resource recommendations for students. This paper proposes a personalized learning resource recommendation algorithm based on a one-dimensional convolutional neural network (1D-CNN). The algorithm first extracts local features of the sequence through convolutional operations, then uses pooling operations to extract long-term features of the sequence, and combines the two features through weighted addition to obtain the user feature information, which allows for the comprehensive extraction of both local and long-term features. Subsequently, the user feature information is multiplied by the linearly transformed sequence information to introduce temporal information. Additionally, student learning records, class performance, and incorrect question records are collected and integrated as user feature information. These user features are passed through a feedforward network to achieve nonlinear transformation and cross-dimensional interaction enhancement. Finally, the user feature vector and item feature vector are computed to obtain their relevance, which is then used for recommendations. Experimental evaluations validate the effectiveness and feasibility of the proposed method, with the aim of providing valuable insights for educational reform and development.

Keywords: Convolutional Neural Network, Personalized Recommendation, Learning Resources, User Features, Recommendation Algorithm

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1. Introduction

In recent years, with the rapid development of the Internet and intelligent technology, personalized learning has become a hot topic in the field of education. Personalized learning aims to provide learners with tailor-made learning resources and learning paths according to their interests, levels, needs and other factors [1-2]. It can improve the efficiency and quality of learning, and by analyzing users' learning behaviors and interest preferences, the system can provide users with learning resources that are more in line with their personalized needs [3-4]. This not only reduces the time cost of users in searching for learning resources, but also improves the relevance and depth of learning, thus effectively enhancing the learning effect. And personalized learning helps to expand the learning horizons and fields, at the same time, in the era of big data, there are interdisciplinary and diversified learning resources, which can help students understand the knowledge and information more comprehensively, promote the cross-fertilization and integration of knowledge, and cultivate the user's comprehensive literacy and innovation ability [5-6]. In addition, through the analysis and mining of user learning data, personalized learning can provide educational institutions with targeted recommendations for the development and improvement of teaching resources, thus enhancing the quality of teaching and educational effects, and providing more effective support and guidance for education and teaching [7]. However, personalized learning resources are complex and diverse, how to achieve the accurate recommendation of personalized learning resources, has become the focus of research in the field of education technology.

At present, personalized student learning resources include e-book libraries, online learning platforms, learning tools and software, online learning communities and personalized learning plans [8-11]. These learning resources can meet students' personalized learning needs to a certain extent and achieve the goal of personalized learning. However, the recommendation methods of these resources are not personalized enough, and there is homogenization, while various types of technical algorithms have begun to set off research to provide students with personalized learning resources recommendation, so as to better meet students' learning needs [12-14]. For this reason, this study uses artificial intelligence to find a suitable method for personalized learning resource recommendation.

On one hand, this study collects user behavior data on the platform (such as click behavior, viewing time, problem-solving, learning paths, etc.), and by analyzing and mining user learning behaviors, it uses deep learning technology to model the user's historical learning behavior and capture personalized characteristics. On the other hand, this paper proposes a personalized learning resource recommendation algorithm based on a one-dimensional convolutional neural network (1D-CNN). By analyzing and mining diversified learning data such as student learning records, class exercises, video learning, and incorrect question records, the paper combines deep learning with personalized learning recommendation algorithms and designs a personalized learning resource ranking teaching method.

2. Related work

2.1. *User personalization modeling*

User personalization modeling leverages deep learning techniques to analyze user behavior, content features, and other information in order to provide personalized online learning resource recommendations. By personalizing user modeling, recommendation systems can better understand users' interests, preferences, and behavioral patterns, thereby improving the accuracy of recommendations and user satisfaction.

The early applications of artificial intelligence primarily relied on machine learning techniques, which aimed to enable computers to recognize patterns and regularities in data and make decisions or predictions based on the learned knowledge. However, machine learning requires manual feature extraction, a process that can be quite complex. The emergence of deep learning technologies later perfectly addressed this issue. Deep learning enables automatic feature extraction, allowing for end-to-end prediction. However, deep learning requires large-scale datasets and powerful computational hardware to support its training process.

The core of deep learning is neural networks, which are composed of layers of interconnected neurons. These networks learn patterns and features from data to perform tasks such as classification, regression, and clustering. The "depth" in deep learning refers to the use of multi-layered neural networks, often containing dozens to hundreds of hidden layers, which allows the model to learn more complex feature representations. The main mechanisms in deep learning are forward propagation and backpropagation. Forward propagation refers to the process of transmitting information from input to output, while backpropagation involves adjusting network parameters to minimize prediction errors. Currently, the mainstream deep learning models include Deep Learning Neural Networks (DNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Transformer models, and pre-trained BERT models, among others. Utilizing these models can significantly improve accuracy and user satisfaction. In personalized recommendation system modeling, the main components typically consist of three parts: user features, content features, and user interaction behavior. Furthermore, model fusion is an important technique used to enhance the overall performance of the recommendation system.

User feature modeling using deep learning techniques can effectively learn complex user behavior patterns and interest features, enabling more accurate personalized recommendations. In the modeling of user behavior sequences, sequence models such as RNN or Transformer can be used to model features that reflect user interests and learning preferences, including browsing history, video watching, assignment submissions, etc., thereby capturing the evolution of users' learning habits and interests. A DNN model can be employed to model user attribute features such as gender, age, education level, and occupation, thereby extracting the latent representations of the user. Content feature modeling mainly involves extracting and modeling the features of online learning resources, so that deep learning models can understand and leverage the similarities and relationships between these resources. The content features primarily focus on text features. For online learning resources that contain textual information (such as course descriptions, documents, papers, etc.), natural language processing (NLP) models can be used to extract text features.

2.2. Sequential recommendation

Sequential recommendation refers to the process of predicting recommendations based on users' historical behaviors or preferences, considering the temporal or sequential relationships between them. It is commonly used in various online platforms, such as e-commerce websites, video platforms, and social media, to provide personalized content or product recommendations. Early non-deep learning methods mainly relied on Markov Chain theory and matrix factorization techniques, which modeled the transition relationships between items in a sequence to capture user behavior patterns. With the widespread application and significant success of deep learning in fields like image recognition and natural language processing, these methods have gradually been applied to recommendation system research and practice, quickly becoming dominant. Notable works include the use of Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Graph Neural Networks (GNN) to achieve efficient sequential recommendations.

3. Convolutional neural networks

CNNs are commonly used in recommendation systems to process data types such as images and text. In recommendation systems, CNNs can be used to learn feature representations of users and content.

For example, the user's historical behavior sequence or content features can be represented as images or text, and then a CNN model can be used to extract the features.

For image data, a pre-trained CNN can be used as a feature extractor by feeding the image into the network and extracting the output from the convolutional layers as the image's feature representation. These feature maps contain high-level semantic information, which can effectively represent the visual features of the image. For text data, word embedding techniques can map each word to a low-dimensional real-valued vector, where these vectors are semantically related and can be used to represent the features of users and items.

For sequence data, such as the user's historical behavior sequence or item sequence features, CNNs can also be used to model the data, capturing the local feature relationships between different time steps, thereby extracting important features from the sequence.

Convolutional Neural Networks (CNN) are a type of deep learning model specifically designed to handle data with grid-like topological structures. CNNs have achieved significant success in the field of deep learning and have been widely applied in recommendation algorithms. Among them, one-dimensional convolution is a special convolution operation used for processing time-series or sequential data. By appropriately padding the data, the output at the current time step depends only on the current and previous time steps, not on future time steps. This operation preserves the sequential relationship of the data, which aligns with the time-order requirements in real-world applications.

3.1. Personalized learning resource recommendation model framework

In this study, let the user set be $U_i = \{u \in U : r_{ui} \neq 0\}$, and the item set be $I_u = \{i \in I : r_{ui} \neq 0\}$, where m and n represent the number of users and the number of items, respectively. For a target user $u \in U$, at a given time step, their historical interaction sequence can be represented as $S_u = \{S_1^u, S_2^u, \ldots, S_l^u\}$, where l denotes the length of the item sequence.

This paper mainly investigates the problem of predicting the relevance r of a target item l_s for a target user u, based on the first l-1 items in the user's history sequence S at time step (l-1), for the purpose of recommendation.

3.2. proposed convolutional neural network model

The proposed convolutional neural network (CNN) model consists of three main components: the information embedding layer, the convolutional neural network-based information extraction layer, and the item prediction layer. The specific model architecture is shown in Figure 1.

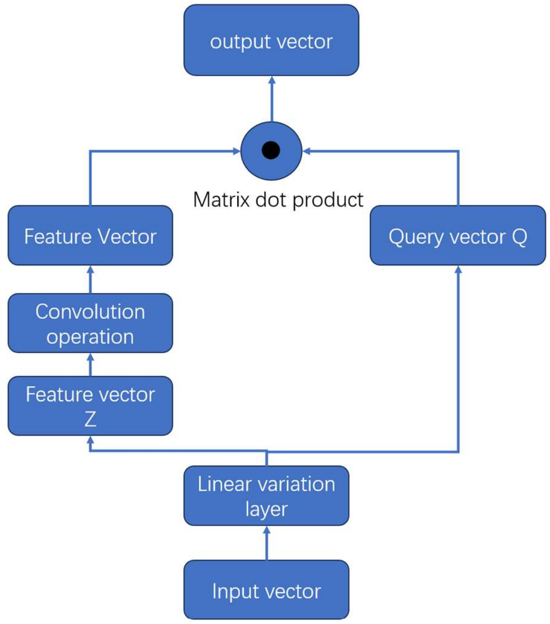

Fig. 1. Program framework diagram

The information embedding layer mainly transforms the discrete, high-dimensional item sequence (S) data into continuous, low-dimensional vector representations.

The convolutional neural network-based information extraction layer performs feature extraction through stacked modules, including the CCFE (Convolutional Collaborative Feature Extraction) module based on 1D convolutional networks and the Feed-Forward Network (FFN) module for nonlinear processing to extract user features.

The item prediction layer multiplies the item embedding with the extracted user features to generate the final item relevance prediction.

3.2.1. information embedding layer. First, an embedding matrix $E \in R^{n \times v}$ is established for the item set, where (n) is the number of items in the set, and (v) is the embedding dimension. For the target user (u), the historical interaction sequence $S = R^{n \times 1}$ is transformed into $S_1 = R^{n \times v}$ through one-hot encoding. Then, using the embedding matrix (E), S_1 is converted into the embedding features $E_u \in R^{n \times v} = \{e_1^u, e_2^u, \ldots, e_l^u\}^T$. Finally, the embedding features E_u are added to the positional encoding (P) and fed into the convolutional neural network-based information extraction layer.

3.2.2. Information Extraction Layer Based on Convolutional Neural Networks. The focus information processing layer consists of two sub-modules: the information extraction module based on one-dimensional convolutional networks (CCFE) and the non-linear processing module based on feedforward networks (FNN). The information extraction module based on one-dimensional convolutional networks is designed to deeply mine sequence information. The non-linear processing module based on feedforward networks aims to introduce non-linearity into the model and account for the interactions between different latent dimensions. Finally, by stacking the information extraction layer based on convolutional neural networks, the model is able to learn more complex features.

In the convolutional-based information aggregation module, the input features (F) undergo linear transformation to form query features q and a new feature space (Z_0). On the new feature space (Z_0), convolutional networks and gating mechanisms are used to aggregate item contextual information, producing modulated information (Z_{out}). Finally, the query features (q) and the modulated information (Z_{out}) are multiplied element-wise to obtain the final information output (y). The specific process is as follows:

Step 1: linear transformation. Given the input feature matrix (F), it is transformed into a new feature space $Z_0 = f_z(F) \in R^{n \times v}$ through a linear mapping (Z_f), which lays the foundation for subsequent processing. At the same time, the linear mapping generates query features $q \in R^{n \times v}$.

Step 2: Contextual Information Extraction. For the new feature space (Z_0), the first step is to perform a one-dimensional convolution operation to extract contextual representations from the sequential data. Specifically, the feature map (Z_0) is pre-processed using a right-padding strategy, which ensures that the information extraction focuses on the sequence content preceding each item. Then, a one-dimensional convolutional neural network with kernel size (k) is applied to capture local contextual features, and the GeLU activation function is used to introduce the necessary non-linearity. The computation process is shown in equation (1).

$$Z_1 = \mathrm{GeLU}\left(OD\,\mathrm{Conv}\left(Z_0\right)\right) \tag{1}$$

In this context, ODConv represents the one-dimensional convolution operation. Additionally, to fully integrate the global context of the sequence, a Global Average Pooling (GAP) operation is applied, producing the second layer feature (Z_2). The computation process is shown in equation (2).

$$Z_2 = GAP(Z_1) \tag{2}$$

This series of operations aggregates 2 feature sets $\{Z_1, Z_2\}$, which synergistically cover from fine-grained transient context to macroscopic sequence global information, realizing efficient encoding and parsing of complex dependency structures within sequences.

On this basis this paper uses a gating mechanism to aggregate modulation features. Specifically, by applying a linear layer to the feature matrix u, and then through a nonlinear activation function (e.g., sigmoid or tanh), the corresponding gating weights are obtained G. These gating weights are used to weight the features to achieve the aggregation of modulation features.

On this basis, this paper uses the gating mechanism to aggregate the modulation features by using a linear layer on the feature matrix E^u to obtain the corresponding gating weights $G^1 \in R^{n \times v}$. The computational procedure is shown in equation (3).

$$G^l = f_g^l(E^u) \tag{3}$$

where f_g^l is a linear transformation layer and l denotes the number of layers. Then, a weighted sum is performed by multiplying the elements to obtain a single feature mapping of the same size as the input E^u shown at: $Z_{out} \in R^{n \times v}$. The computational procedure is shown in equation (4)

$$Z_{out} = \sum_{l=1}^{2} G^l \mathrm{e}\ Z^l \tag{4}$$

where G^l is the gating weight of the lth layer, Z^l denotes the convolutional features of the lth layer, and the e symbol indicates the matrix elements corresponding to the multiplication operation.

The third step is to aggregate the features: use the query feature q to perform matrix dot-multiplication operation with the feature mapping Z_{out}. At the same time, in order to avoid the impact of the subsequent stacking strategy, the residual network design is introduced here to enhance the model generalization ability, so as to form the final information y_t. The computational procedure is shown in equation (5).

$$y_t = (q\ \mathrm{e}\ Z_{out}) + F \tag{5}$$

where the e symbols denote the matrix elements corresponding to the multiplication operation and F denotes the input identity matrix.

After obtaining the final information y_t, it is fed into the nonlinear processing layer based on feedforward network. And in the feedforward network-based nonlinear processing layer, feedforward neural network (FFN) is adopted in this paper in order to realize the nonlinear transformation of information and cross-dimensional interaction enhancement. Specifically, the final integrated information y_t is manipulated in a peer-to-peer manner by deploying a two-layer feed-forward network, aiming to capture the nonlinear features and promote the synergistic effect among the features, and finally obtaining the user features F_t . The computational procedure is shown in equation (6).

$$F_t = \mathrm{Re}LU(y_t W^1 + b^1)W^2 + b^2 \tag{6}$$

where W^1, W^2 is the learnable matrix, b^1, b^2 is the bias term, and ReLU is the activation function designed to introduce the necessary nonlinear relationships.

After initially realizing the information extraction of sequence information, in order to deepen the information extraction ability of the model for complex item sequences, this paper adopts the stacking strategy, stacking the information extraction layer by k layers to get the final user features F_t^k . For the information extraction layer of layer b, its input is the feature output of layer b-1, and the computation process is shown in Eqs. (7)

$$\begin{aligned} y^b &= CCFE(F_{b-1}) \\ F_t^b &= FFN(y^b) \end{aligned} \tag{7}$$

where b∈ {1,2,.... ,k} denotes the number of layers and k denotes the total number of stacked blocks. Also, for the first layer, the input F_0 is the embedding representation E^u.

3.2.3. Project forecasting layer. After going through k layers of information processing layers and fully extracting the deep features of users' past consumption items, for the first i items in the sequence, this paper utilizes the user feature representation F_t^k , combined with the predictive item embedding N_i , to quantify the relevance of the items to the user's interests through a specific interaction mechanism. The computational procedure is shown in equation (8).

$$r_{i,t} = F_t^k N_i \tag{8}$$

where $r_{i,t}$ denotes the correlation prediction score for item i at the given qualitative sequence $(s_1, s_2, \ldots, s_t)$. N_i denotes the embedded expression of item i. A high interaction score $r_{i,t}$ implies high relevance, so this paper generates item recommendation sequences by ranking the scores.

3.2.4. Loss function. In this paper, we use binary cross entropy as the loss function of the model. The specific form of the loss function is shown in Equation (9):

$$L = -\sum_{S^u \in S} \sum_{t \in [1,2,\ldots,n]} [\log(\sigma(r_{o,t})) + \sum_{j \notin S^u} \log(1-(r_{j,t}))] \tag{9}$$

where S denotes the set of user sequences in the training set, n is the maximum length of the sequences, o is the target item at time step t, $r_{o,t}$ is the relevance score of the model predicting the target item o at time step t, and σ is the Sigmoid function used to convert the relevance score to a probability. $r_{j,t}$ is the correlation score of the negative sample item j predicted by the model at time step t. The negative sample item j is randomly sampled, i.e., it is not in the set of items that the user actually interacts with. In this paper, for each target item o, one negative sample item j is sampled randomly.

4. Experimental Settings

This paper conducts experiments on two public datasets, MovieLens and KuaiRand. MovieLens is a benchmark dataset widely used to evaluate collaborative filtering algorithms, and its data includes user ratings, user tags, and more. This article uses version MovieLens-1M. The KuaiRand dataset is an unbiased sequential recommendation dataset collected from the recommendation log of the video sharing mobile app Kuaishou, which contains user id, video id, viewing time, video length and other information. This article uses the KuaiRand-27K version. For KuaiRand-27K, this article only uses the relevant information as of April 8, 2022 (see Table 1).

Table 1. Statistical information on the data set

data set	number of users	Number of projects	interaction number	Average sequence length
MovieLens-1M	6040	3416	987531	163.5
KuaiRand-27K	23528	1171045	3845681	163.4

For each user u, 100 negative sample items are randomly selected and these items are ranked along with the real ones. Based on the ranking of these 101 items, the evaluation metrics are computed.

In this paper, HitRate (HR) and Normalized Discounted Cumulative Gain (NDCG) are used as the evaluation metrics for the experimental results. The calculation of @HRN is shown in Equation (10):

$$HR@N = \frac{1}{N}\sum_{i=1}^{N} hit(i) \tag{10}$$

where N is the number of items, $hit(i)$ denotes whether the item that the user really accessed exists in the recommendation list, and when it exists $hit(i)=1$, when it does not exist $hit(i)=0$.

The NDCGN is calculated as shown in Equation (11):

$$NDCG@N = \frac{1}{N}\sum_{i=1}^{N} \frac{1}{\log_2(p_i+1)} \tag{11}$$

Where N is the number of items, and p_i is the position of the item in the recommendation list that the user really visited. Due to the limitation of the length of the recommendation list, in the experiment, the first 10 items are taken as the recommendation list, then the two metrics are denoted as HR@10 and NDCG@10 respectively

5. Experimental results and analysis

5.1. Hyperparameter impact analysis

In order to assess the impact of model parameters in the model on the recommendation results, comparative experiments were designed and analyzed for convolutional layer length and item embedding dimensions, respectively, and other parameters were kept constant during testing. Figures 1 and 2 demonstrate the effect of convolutional kernel length on model performance. According to the experimental results, on the MovieLens-1M dataset, the model performance gradually improves with the increase of convolutional kernel length and reaches the best at a length of 7 dimensions. On the sparser KuaiRand-27K dataset, the increase in convolutional kernel length degree has a more obvious effect on the model performance, and the model performance reaches the best at a length of 9 dimensions.

Figure 2 demonstrate the effect of embedding dimension on model performance. According to the experimental results, on the MovieLens-1M dataset, the model performance gradually improves with the increase of the embedding dimension and reaches the best when the embedding dimension is 40. In particular, the performance improvement is most significant when the embedding dimension increases from 5 to 15. After that, the further increase of embedding dimension slows down the performance improvement. In the sparser KuaiRand-27K dataset, the effect of increasing the embedding dimension on the model performance improvement is smaller, and the model performance reaches its best at an embedding dimension of 10. Instead of significantly improving the performance, further increase in embedding dimension may lead to a decrease in model performance.

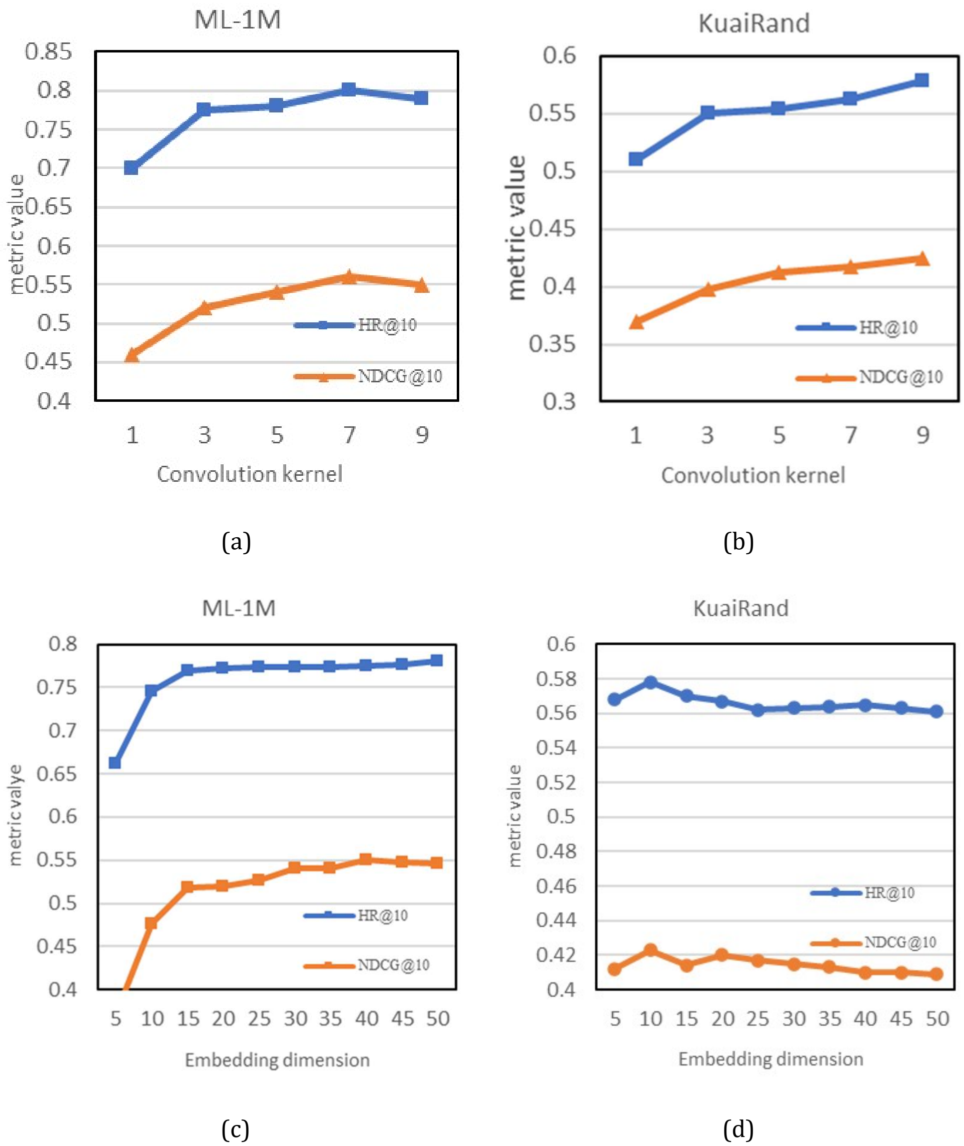

Fig. 2. The effect of embedding dimension on model performance

5.2. Ablation experiments

In this subsection, this paper explores the efficacy of several core components of the model through a series of rigorous experiments involving the convolution-based information aggregation layer, CCFE, and the feed-forward network-based nonlinear processing layer, FFN. Ablation experiments are conducted on 2 datasets, and the relevant experimental results are detailed in Table 2. First, this paper examines the contribution of the convolution-based information aggregation layer component. After removing this component, the model performance performs HR@10 and NDCG@10 indicators decreased by 9.38 percentage points and 8.53 percentage points, respectively, on the dataset MovieLens-1M. On the dataset KuaiRand-27K, the model performance performance HR@10 and NDCG@10 indicators decreased by 8.61 percentage points and 9.10 percentage points, respectively. The experimental results show that removing the information aggregation layer significantly impairs the model's ability to extract user interests.

Table 2. Statistical information on the performance of ablation experiment performance

mould	ML-1M	KuaiRand

	HR@10	NDCG@@10	HR@10	NDCG@10
CCFERec Without	0.7938	0.5578	0.5787	0.35
CCFE without	0.7010	0.4725	0.4926	0.3125
FFN	0.7781	0.5412	0.4981	0.4225

Second, this paper examines the contribution of a nonlinear processing layer based on a feedforward network. The model performance after this component is removed performs The HR@10 and NDCG@10 indicators decreased by 1.57 percentage points and 1.66 percentage points, respectively. On the dataset KuaiRand-27K, the model performance performance HR@10 and NDCG@10 indicators decreased by 8.06 percentage points and 7.25 percentage points, respectively. The experimental results show that the nonlinear processing layer can significantly improve the generalization ability of the model when enhanced by nonlinear transformation and cross-dimensional interaction.

6. Conclusion

The combination of digital technology and the Internet has led to the flourishing of online educational resources, but at the same time, it has brought many problems, the most important of which is that users are unable to choose the learning resources they need in a short period of time. The emergence of artificial intelligence, especially deep learning, has made personalized recommendation of learning resources possible and solved the problem of online learning resources selection. Although the research of deep learning in personalized recommendation has made significant progress, it still faces some challenges in practical application. For example, although the recommendation algorithm based on deep learning can tap into the real needs of users, it is easy to make them fall into the "information cocoon", which is not conducive to the expansion and improvement of learners' knowledge. At the same time, the recommendation of the learning path also needs to be further optimized. Knowledge mapping technology can be considered to model online learning resources, further analyze the relationship between knowledge points, and with the continuous development of deep learning technology, more advanced deep learning techniques such as migration learning, small sample learning, reinforcement learning, etc. can be applied to the recommendation of online learning resources. In this paper, a sequence recommendation model based on one-dimensional convolution is proposed to help solve the personalized learning resource recommendation problem. By introducing the information extraction module (CCFE) of the 1D convolutional network, the model can effectively capture the temporal features in the user's historical behavior and perform nonlinear processing by feed-forward network (FFN), which further improves the accuracy and effectiveness of recommendation. Experimental results in two real recommendation scenarios, MovieLens and KuaiRand, show that the proposed model exhibits significant improvements in metrics such as recommendation hit rate and normalized discount cumulative gain. Next, we will focus on the security prevention and issues within recommendation systems, specifically by leveraging deep learning and artificial intelligence techniques to further enhance the defense mechanisms in the context of the proposed recommendation algorithm. As recommendation systems become more widespread and complex, preventing malicious attacks and addressing data anomalies has become an important research challenge. In this regard, we plan to supplement the proposed recommendation algorithm with relevant security defense research. For example, by introducing advanced techniques such as contrastive learning and graph neural networks, we aim to achieve effective monitoring of anomalous data and potential attacks within recommendation algorithms. Contrastive learning can help identify abnormal patterns by learning the similarities and differences between data, while graph neural networks can improve anomaly detection accuracy and robustness by capturing complex relationships and structures between data. By combining these techniques, we hope to not only enhance the accuracy of recommendation systems but also ensure their security, preventing distortion of recommendation results due to data tampering or attacks.

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