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Personalized Intelligent Recommendation Model Construction Based on Online Learning Behavior Features and CNN

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The current intelligent recommendation models in online learning systems suffer from data sparsity and cold start problems. To address the data sparsity problem, a collaborative filtering recommendation algorithm model (SACM-CF) based on an automatic coding machine is proposed in the study. The model can extract the online learning behavior features of users and match these features with the learning resource features to improve the recommendation precision. For the cold-start problem, the study proposes a CBCNN model based on CNN, using the language model as the input of the model and the implicit factor as the output of the model. To avoid the problem of over-smoothing the implicit factor model, which affects the recommendation precision, an improved matrix decomposition method is proposed to constrain the output of the CNN and improve the model precision. The RMSE of SACM-CF is 0.844 and the MAE is 0.625. The MAE value of CBCNN is 0.72, the recall value is 0.65, the recommendation precision is 0.954 and the F1-score is 0.84. The metrics of SACM-CF and CBCNN are better than the existing state-of-the-art recommendation models. SACM-CF and CBCNN outperform the existing state-of-the-art intelligent recommendation models in all metrics. Therefore, the SACM-CF model and the CBCNN model can effectively improve the precision of the online learning system in recommending interesting learning resources to users, thus avoiding users' wasted learning time in searching and selecting learning resources and improving users' learning efficiency.

KEYWORDS: online learning; behavioral features; CNN; personalized recommendation; language model; automatic coder.

1. Introduction

Online learning is a way for users to learn and teach in a virtual space through the Internet and computers. Under the influence of the epidemic, online learning has become one of the important ways of education for contemporary students and one of the main ways of acquiring new knowledge for many learners. Currently, many schools are using online learning methods as the main teaching method, which enables students to learn at home and avoid delaying their learning progress due to inability to reach school. Personalized intelligent recommendation models play an important role in online learning. However, the current intelligent recommendation models in online learning systems suffer from data sparsity and cold start problems. The data sparsity problem refers to the fact that the recommendation precision of the algorithm decreases significantly when the data of users is small. The cold-start problem means that if a user is a newly registered user and lacks relevant basic information, the recommendation algorithm cannot predict the learning resources that the user may be interested in based on the user's historical data and his or her own feature data. CNN is a deep learning model based on bio-visual cognitive mechanism, which is the most mature and widely used model in the current image recognition and speech recognition fields. Sun et al. [14] applied the combination of artificial intelligence modules and knowledge recommendation to the online intelligent English teaching platform, and developed an online intelligent English teaching system with deep learning support. The test application results showed that the system effectively helped students to improve their learning efficiency and made learning more targeted [14]. Xie et al. artificially solved the cold start problem of traditional collaborative filtering scheme using simple inner product interaction mode, and proposed a hybrid recommendation model based on deep learning and stack integration strategy [20]. Experiments on MovieLens lm dataset showed that the precision of the modified hybrid recommendation model was improved to some extent [20]. Takama et al. [15] developed a matrix-based collaborative filtering recommendation method for personal values. The research results showed that the proposed method recommended more unexpected items than the method based on matrix decomposition while maintaining precision and recall [15]. Based on the above research, it can be seen that recommendation models combined with deep learning algorithms have significantly improved recommendation precision compared to traditional methods. Among them, research on the scalability of deep learning recommendation model frameworks is very important, but there is relatively little research in this area. By using deep learning to represent data and integrating data from multiple sources, recommendation effectiveness can be further improved. To solve the above problems, the research constructs a collaborative filtering recommendation algorithm model based on automatic coder and a content-based convolutional neural network recommendation model (CBCNN), aiming to solve the above two problems, improve the recommendation precision of learning resources, and improve the learning efficiency of users. The innovation of the research mainly includes the following two aspects. On the one hand, it proposes the SACM-CF model, which can effectively extend the framework by combining structured data of users or objects; on the other hand, it is to design a CBCNN model to provide intelligent and personalized learning resource service technology for students, enhance their learning autonomy and stimulate their learning enthusiasm. Although GCN, GAN and Deep reinforcement learning is better than CF and CNN at mining hidden user features and real-time online interaction, but it is difficult to train, the model is not interpretable, flexible and extensible enough, and it is not suitable for personalized intelligent recommendation technology [7, 22].

2. Related Works

With the continuous development of Internet+ education, online learning has become one of the important ways of education for contemporary students and one of the main ways for many learners to acquire new knowledge. Mukhtar et al. [10] explored the impact of the New Coronation epidemic on the education sector and the changes in students' learning behavior and learning styles during the epidemic. This was followed by an analysis of the advantages, limitations of online learning modalities during the Covid-2019 and based on the results of the analysis, recommendations for the transformation of online learning modalities were made [10]. Nambiar surveyed the views of teachers and students in several schools in India, thus exploring the role played by online learning during the Covid-2019 and the impact of the Covid-2019 on online learning modalities [11]. Fauzi et al. [5] conducted survey interviews with dozens of teachers in Banten and West Java to explore the evaluation of online learning in elementary school under the impact of the epidemic in terms of learning facilities, Internet usage, learning styles, and parental cooperation. 80% of the surveyed teachers believed that the current online learning approach should be improved. Bahasoan [3] used an online survey method to survey a of a random sample of students, thus analyzing the effectiveness of the online learning system. The results of the analysis showed that online learning is less efficient and more costly than traditional teaching methods, but it is also a better option in special cases [3]. Verawardina et al. [18] reviewed the development of schools in recent years under the epidemic and discussed the role played by online learning in it and concluded that the online learning approach helped students to fill the educational gap during the epidemic [18]. Wei et al. [19] explored the impact of students' perceptions of online learning, teachers' readiness on students' performance and satisfaction, and explored whether teachers' pre-preparation for online learning was important. Agung et al. [1] analyzed students' performance in online English learning in one region and analyzed students' evaluation and perceptions. Simamora [13] selected the papers of some performing arts education students to analyze and extract valid information from them in order to analyze the problems and solutions of online learning during the epidemic.

CNN is a deep learning model based on bio-visual cognitive mechanism, which is currently the most mature and widely used model in the field of image recognition and speech recognition. The current application of CNN contains medical imaging, public administration, financial management, security management, etc., and has received wide attention from researchers. Zhou et al. [24] introduced the downsampling operator, thus changing the network width of the convolutional layer, and conducted an in-depth discussion and analysis of the approximation theory of CNN to demonstrate the performance of CNN in data feature learning. Valueva et al. [17] applied the residual number system (RNS) to CNN for the purpose of reducing the hardware cost. The structure shows that after applying RNS, the hardware cost can be reduced by an order of magnitude and the reduction is around 7.5% to 38%. Raghu et al. [12] discussed and analyzed the phenomenon that both visual transformers and CNNs have better performance in image classification and compared the performance of CNN and visual transformers in image classification tasks. Tripathi [16] proposed an image classification technique based on CNN and validated the technique with a publicly available image dataset. The validation results show that the technique has a satisfactory image classification effect and can meet the needs of general image classification tasks [16]. A human action recognition model based on CNN was constructed by Xu et al. and analyzed for the application of this model in sports training, physical education, and dance teaching. After conducting tests, the recognition precision of the model was higher than existing action recognition techniques [21]. Lou et al. [8] applied CNN to face recognition. After its validation with a machine vision public dataset, the precision of the model was found to be able to meet the requirements of practical applications, proving the usefulness and developability of the model. Using CNN, Zhang et al. [23] constructed a fusion framework that can be applied to most types of images, making image fusion more efficient and accurate. Experimental tests found that the generalization ability of the image fusion model was significantly improved after the application of the framework and the performance of the framework model was better than the existing state-of-the-art image fusion models [23]. Allugunti [2] used CNN to identify and classify the uploaded medical images to identify and classify the skin diseases of patients. The model was tested using data from a hospital and the model has high precision for recognition and classification of skin diseases [2].

From the above, it can be seen that there are currently many research results related to online learning and CNN, indicating that the academic community attaches great importance to both online learning and CNN. However, the current research on online learning is more about the significance and shortcomings of online learning, and does not explore the problem of too many learning resources in online learning, which makes it difficult for learners to choose. In addition, for the current problem of data sparsity and cold start of recommendation algorithms in online learning, the study proposes a CNN-based intelligent recommendation algorithm for online learning resources to improve learning efficiency.

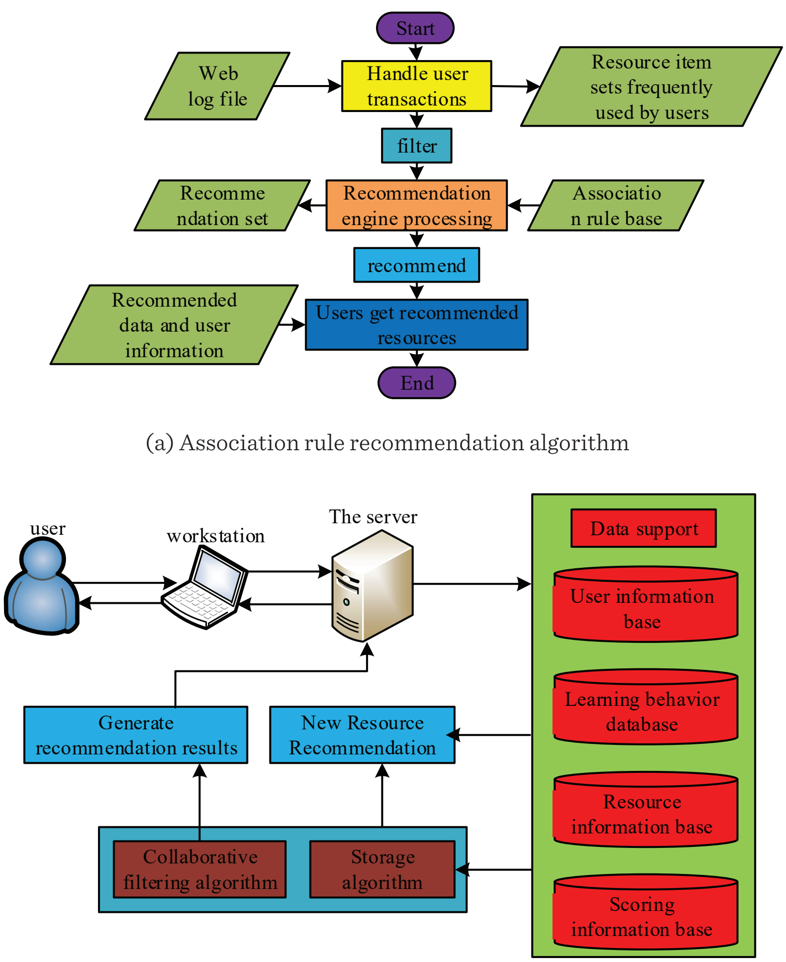
3. CNN-based Intelligent Recommendation Model

3.1. Intelligent Recommendation Algorithm Based on ACM-CF

Online learning is a way of acquiring knowledge online by using information technology and Internet technology. The mainstream way of online learning is that users learn through the learning resources in the online learning system. However, generally speaking, there are a large number of learning resources in online learning systems, and it is often difficult for users to distinguish which resources they need. Intelligent recommendation algorithms can recommend resources that may be of interest to users based on data mining. At present, the more common intelligent recommendation algorithms are association rule-based recommendation algorithm and collaborative filtering algorithm (CF), and the general process of the two recommendation algorithms is shown in Figure 1.

Since association rules require more sample data to ensure recommendation precision, and the model is not efficient and less practical, collaborative filtering (CF) model is more often used to achieve intelligent recommendation in practical applications. However,

Figure 1
The general flow of two recommendation algorithms



(a) Association rule recommendation algorithm

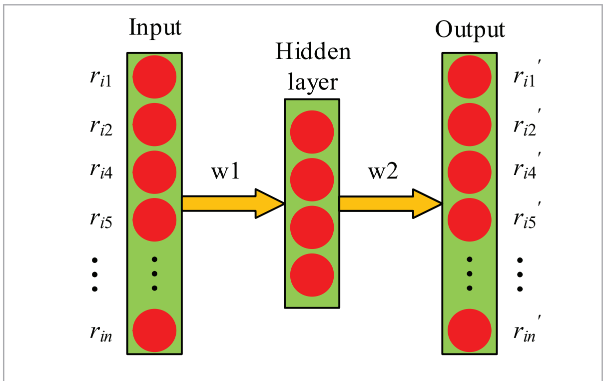
(b) Collaborative filtering recommendation algorithm on the traditional collaborative filtering recommendation algorithm suffers from the problem of data sparsity, i.e., the recommendation precision of the algorithm decreases significantly when the user's data is small. To address this problem, the study proposes an automatic coding machine based collaborative filtering recommendation algorithm (ACM-CF). ACM is essentially an unsupervised feature extraction model, which is more commonly used in image feature classification tasks of large order of magnitude. The study uses ACM to construct a recommendation model so that it extracts the features of the data input to the model, and then uses the extracted features to reduce the input data so that the output of the model is approximately equal to the input. And among intelligent recommendation tasks, the input data can be represented as a user-item evaluation matrix, as shown in Equation (1).

$$R(m,n)=\begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}. \quad (1)$$

In Equation (1), r_{mn} is the user's m rating of the item resource n. In the ACM-based recommendation model, the historical user behavior data in Equation (1) is used as input, and ACM extracts the features of the historical data to predict the user's ratings of other items based on the user's rating features for some items. Based on the above, the ACM-CF model is shown in Figure 2.

Figure 2

ACM-CF model



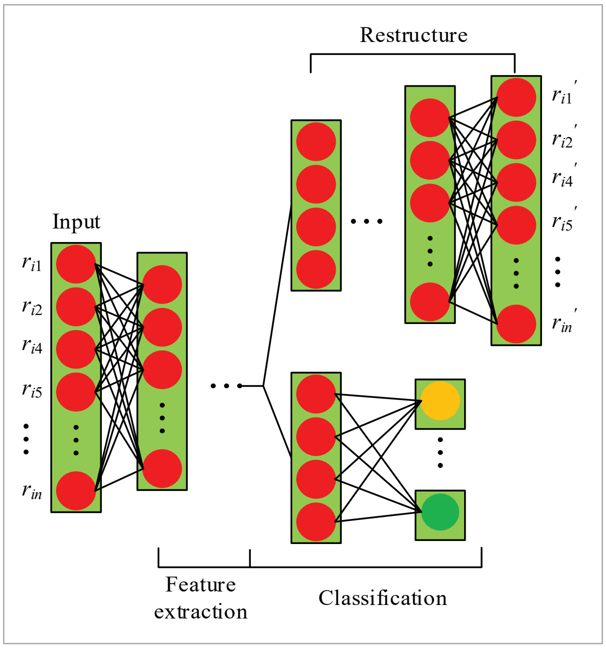
In Figure 2, w_i represents the connection weights between network layers. The object-based ACM can be expressed as Equation (2).

$$\min_{w} \sum_{r\in R} \left\| r-h(r,w) \right\|_o^2 + \frac{\lambda}{2}\left(\sum_{r\in R} \left\| w_1 \right\|_F^2 + \left\| w_2 \right\|_F^2 \right). \quad (2)$$

In Equation (2), $h(r, w)$ is a reconstruction of the input data r, $\|\cdot\|_o^2$ is the actual scoring of the items by the user, w is the set of all network parameters, λ is a canonical parameter, and $\|\cdot\|_F^2$ is the matrix Frobenius parametrization. In Equation (2), the first half is the model fitted and trained with the input data, and the second half is the set of regularization terms, which mainly prevent the model from overfitting and thus degrading the performance. In recommendation systems for online learning, the user-item rating matrix is often very sparse. To solve this problem, a supervised ACM-based recommendation method is proposed in the study. In online learning systems, in addition to the user's historical learning data, other characteristics often exist, such as the user's age, occupation, and profession. Using these data, it is also possible to construct feature models of users and

Figure 3

Supervised ACM recommendation model



items. Therefore, these data features are introduced into the recommendation model to improve the quality of feature extraction of user data by the ACM model. The principle of this operation is that if there are similar feature attributes between users or items, then similar users will also be interested in similar items. Take movie recommendation as an example, if multiple item resources that user likes are action movies, then it is assumed that the user likes action movies. The supervised ACM recommendation model is shown in Figure 3.

At this point, the supervised ACM model can be represented by Equation (3).

$$\min_{w} F_R\left(r, w_e, w_r, b_e, b_r\right) + \\ + \alpha \sum F_C\left(r, w_e, w_c, b_e, b_c\right) + \\ + \frac{\beta}{2}\left(\left\|w_e\right\|_F^2, \left\|w_r\right\|_F^2, \left\|w_c\right\|_F^2\right). \tag{3}$$

In Equation (3), w_e, b_e is the parameter in the feature extraction stage, w_r, b_r is the parameter in the feature reconstruction stage, w_c, b_c is the parameter in the feature classification stage, $F_R(\ )$ is the loss function in the feature reconstruction stage, $F_C(\ )$ is the loss function in the feature classification stage, and α, β is two regular factors, which mainly serve to control the weights of the terms in Equation (3). At this point, there is Equation (4).

$$F_R\left(r, w_e, w_r, b_e, b_r\right) = \sum_{r \in R} \left\| r - h\left(r, w_e, w_c, b_e, b_c\right) \right\|_o^2. \tag{4}$$

In Equation (4), $h(\ )$ is a superimposed ACM model accumulated from multiple ACM models. Based on the above, a supervised ACM-CF model (SACM-CF) is constructed to avoid the degradation of recommendation due to data sparsity. In the SACM-CF model, a regular term based on the matrix Frobenius parametrization is included to better avoid the data sparsity problem in the recommendation algorithm. However, this regular term also brings some problems for the recommendation algorithm, such as the parameters are too smooth and the model performance is affected by the input data distribution. Therefore, the study introduces the Huber function to constrain the regular term, as in Equation (5).

$$H(t) = \begin{cases} t^2 & |t| \le \mu \\ 2\mu|t| - \mu^2 & t > \mu \end{cases}. \tag{5}$$

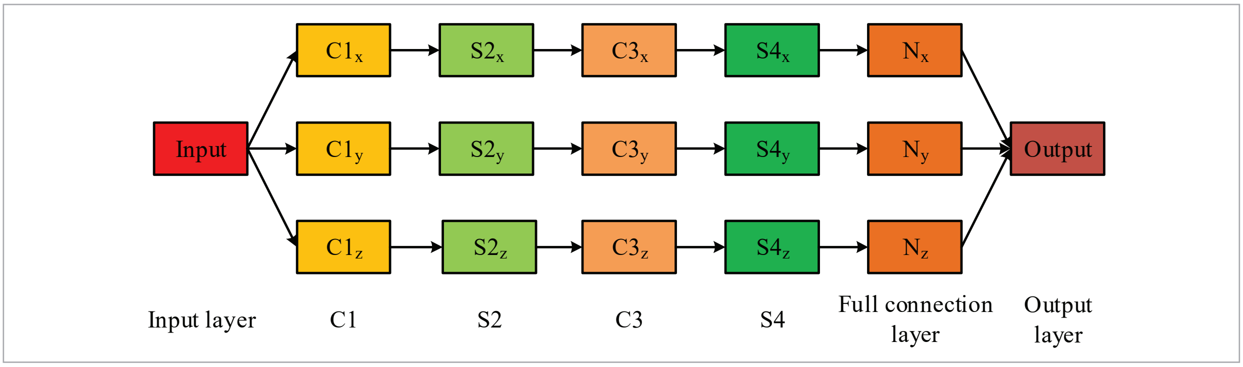
In Equation (5), μ is the truncation parameter in the Huber function, and its value is determined on a case-by-case basis. Combining the above, the construction of SACM-CF model is completed to overcome the problem of sparse data in the resource recommendation problem.

3.2. CBCNN-based Learning Resource Recommendation

The study proposes a SACM-CF model that solves the data sparsity problem in resource recommendation. However, in addition to this problem, there is a cold-start problem in resource recommendation. The cold-start problem refers to the fact that if a user is a newly registered user in an online learning system and lacks relevant basic information, the recommendation algorithm cannot predict the learning resources that the user may be interested in based on the user's historical data and his or her own characteristic data, and cannot accurately recommend resources to the user. The study proposes a content-based recommendation model (CBCNN) using CNN, a deep learning model based on bio-visual cognitive mechanisms, which is currently the most mature and widely used model in the fields of image recognition and speech recognition. Its basic topology is shown in Figure 4.

The basic principle of CBNN is that the text information in the learning resources that already exist in the learning system is used as a recommendation basis, and the feature vectors of users and learning resource items are calculated in a certain way. Subsequently, the feature vectors are fitted with the corresponding text information in CNN. After the final training, the CNN is used to achieve the recommendation of learning resources. In this model, the CNN has 4 layers with the structure of convolutional layer-local sampling layer-convolutional layer-full connection layer. A language model is used as the input of the CBCNN model. The language model is capable of transforming textual information into computable digital information while preserving the semantic features of the text. The language model used in the study is the topic model, which is capable of mining the semantic features of words

Figure 4
Basic topology of CNN



in a large amount of textual information and mapping these semantic features to particular topics, so that all words are represented as probabilities on each topic. The training of the topic model uses the hidden Dirichlet distribution (LDA). After vector features of textual information are obtained by the topic model, they are fed into the first layer. In the first layer, if the k -dimensional word vector of the i th word within the text information in the learning resource can be represented as $x_i \in \Re^k$, then the vector representation of this text information is as Equation (6) when the length of the text information is n.

$$x = [x_1, x_2, \dots, x_n], x \in \Re^{nk}. \tag{6}$$

At this point there is a convolutional filter in the convolutional layer of the CNN $\omega \in \Re^{sk}$, which can be used to compute the feature vectors of the S word vectors in the text message, as in Equation (7).

$$c_i = f(\omega \cdot x_i + b). \tag{7}$$

In Equation (7), $f(\ )$ is a nonlinear activation function and the Sigmoid function is used for the study. It is a bias parameter in a CNN. All the words in the text message are feature computed through a convolutional filter, which finally produces a feature map, expressed as Equation (8).

$$c = [c_1, c_2, \dots, c_{n-s+1}], c \in \Re^{n-s+1}. \tag{8}$$

On the feature map, a local sampling operation can be performed at the second layer to obtain λ local eigenvalues, as in Equation (9).

$$d = [d_1, d_2, \dots, d_\lambda]. \tag{9}$$

In the third layer, there exists the convolution filter $\omega \in \Re^\lambda$, which is utilized to perform the convolution operation on all the local eigenvalues to produce new eigenvalues as in Equation (10).

$$a = f(wd + b). \tag{10}$$

In Equation (10), w is the weight between the two layers of the network. After getting the new feature values, these feature vectors are input to the last layer, where the output is the implied factor. The main use of the implied factor model is to obtain features of users and learning resource items. The conventional regular factors in the implicit factor model are generally vector two parametres to prevent the problem of overfitting the data. However, such regular factors pose another problem, i.e., the model over-smoothing problem. In the CBCNN model, the features of the implied factor are the output of the CNN, and the over-smoothing problem will lead to the implied factor features not being obvious, making the training of the CNN poorer and eventually leading to poorer resource recommendation. Therefore, a sparse prior is needed to constrain the output results. Based on the above, the study proposes an improved matrix decomposition method that uses a sparse prior to constrain the output results of the CNN. At this time, the objective function of the model is shown in Equation (11).

$$J(U,V) = \sum_{ij}(U_i \cdot V_j - r_{ij})^2 + \gamma_1 \|U\|_1 + \gamma_2 \|V\|_1. \tag{11}$$

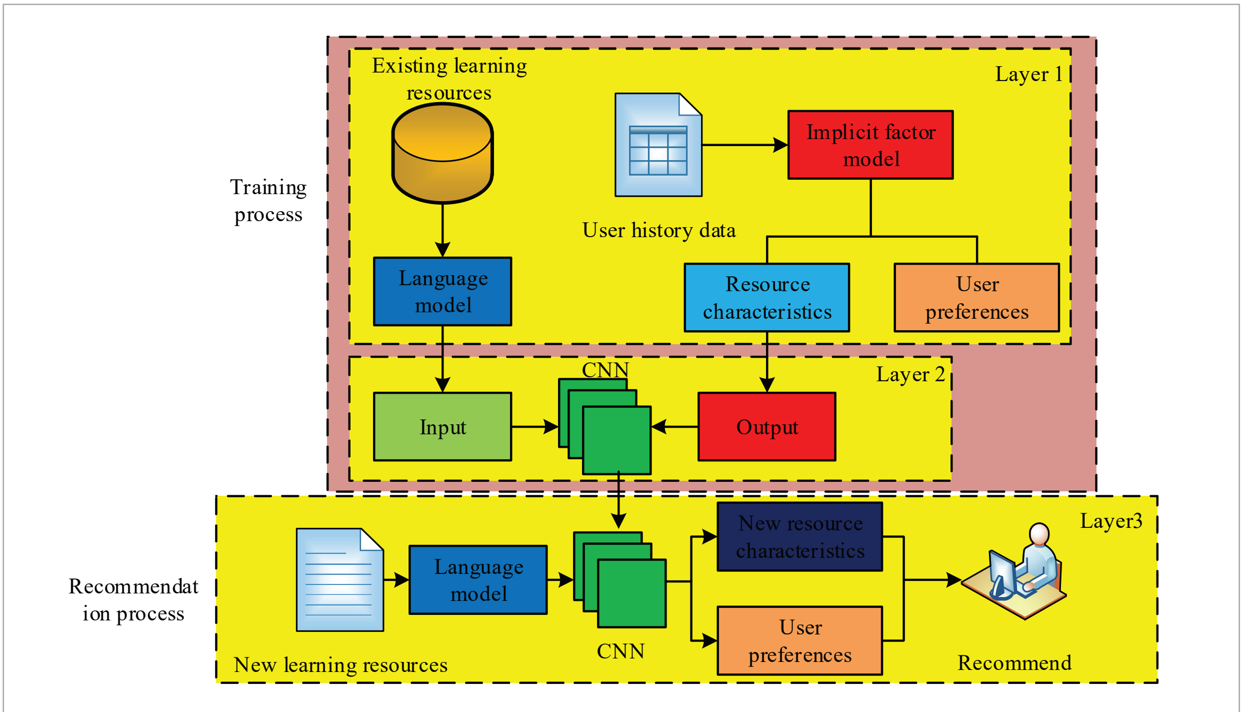
In Equation (11), the first term is the data fidelity term, and the second and third terms are the canonical terms. U is the correlation matrix between the user and the implied factor, V is the correlation matrix between the learning resource items and the implied factor, r_{ij} denotes the user's i rating of the learning resource items j, and γ_1, γ_2 is two canonical factors that adjust the relative strength between the constraint and fidelity terms in Equation (11), and the matrix U and the matrix V become more sparse when γ_1, γ_2 rises. Next, the split Bregman iteration method is used to optimally solve Equation (11). First, the two matrices U and V are randomly initialized and the matrix V is fixed as a constant to optimize the matrix U. After optimization, fix the matrix U and treat it as a constant to optimize the matrix V. Perform the above operation repeatedly until the objective function converges completely. In summary, the CBCNN model is constructed to solve the cold start problem in resource recommendation, improve the recommendation precision, and enhance the learning efficiency of users. the basic structure of the CBCNN model is shown in Figure 5.

4. Improving the Performance of Learning Resource Recommendation Models

4.1. Performance Analysis of SACM-CF Model

The rise of online learning has given learners more choices of learning methods and facilitated learners to choose the resources they want to learn at any time. However, the number of learning resources in online learning systems is too large, which makes it difficult for users to get the learning resources they want and are interested in. In this context, intelligent recommendation algorithms have been developed as a matter of course. However, in the existing intelligent recommendation algorithms, there are data sparsity problems and cold start problems, which lead to low recommendation precision of intelligent recommendation algorithms and cannot achieve the ideal recommendation effect. For the data sparsity problem, the study proposes a SACM-CF model, and for the cold start problem, the study proposes a CBCNN

Figure 5
Basic structure of CBCNN model



model, which improves the effect of intelligent recommendation. Firstly, the SACM-CF model was trained and tested using data from the online learning systems of three universities, namely Chongqing University's online open course platform, Tencent University's T-Learning online learning platform, and China University's MOOC National Quality Course online learning platform. The dataset collected a total of 50,000 learning video information and 30,000 learning book information, which were divided into a training set and a test set at a ratio of 7:3. The parameters of the CBCNN model are set as follows: the number of convolutional filters is 100, the sampling area is 5, the number of hidden factors in the hidden factor model is 40, and γ_1, γ_2 is 0.01 and 0.0038, respectively. The SACM-CF model is compared with several existing state-of-the-art collaborative filtering models, including the probabilistic matrix decomposition collaborative filtering model (PMF), the Bayesian probabilistic matrix combined with structured collaborative filtering model (BMFSI), the collaborative filtering model based on automatic coding machine extracting structured features fused into matrix decomposition (mSDA-CF), the collaborative filtering based on restricted Boltzmann machine (RBM-CM), and AutoRec (AutoRec).

After testing the models using the same datasets, the RMSEs of several models are shown in Table 1. In Table 1, the RMSE values of the SACM-CF model were higher than those of the existing improved collaborative filtering models on all three school datasets of the online learning system. On the three school datasets, the average RMSE value of the SACM-CF model is 0.844, which is 0.16 lower than that of the AutoRec model, 0.016 lower than that of the RBM-CM model, 0.021 lower than that of the mSDA-CF model, 0.027 lower than that of the BMFSI model, and 0.038 lower than that of the PMF model. this indicates that the SACM-CF model has a lower recommendation root mean square error is smaller and the recommendation effect is better. The above results show the superiority of the structured information extraction method of the SACM-CF model. Compared with other collaborative filtering algorithms based on automatic coding set, the proposed model can still achieve better results, which shows that SACM-CF model's collaborative framework has its own advantages.

The MAEs of several models are shown in Table 2. In Table 2, the MAE values of the SACM-CF model are higher than those of the existing improved collaborative filtering models on all three school datasets of the online learning system. On the three school datasets, the average MAE value of the SACM-CF model is 0.625, which is 0.31 lower than that of the AutoRec model, 0.047 lower than that of the RBM-CM model, 0.058 lower than that of the mSDA-CF model, 0.115 lower than that of the BMFSI model, and 0.094 lower than that of the PMF model. This indicates that the absolute recommendation error of the SACM-CF model is smaller and the recommendation effect is better. In summary, the SACM-CF model proposed in the study can effectively overcome the data sparsity problem, thus improving the recommendation effect of learning resources in online learning systems and enhancing users' learning efficiency and learning interest.

Table 1
RMSE of several models

Model	Database			Average
	School 1	School 2	School 3	
PMF	0.920	0.853	0.872	0.882
BMFSI	0.904	0.842	0.868	0.871
mSDA-CF	0.901	0.840	0.854	0.865
RBM-CM	0.892	0.838	0.850	0.860
AutoRec	0.884	0.832	0.841	0.852
SACM-CF	0.876	0.824	0.832	0.844

Table 2
MAE of several models

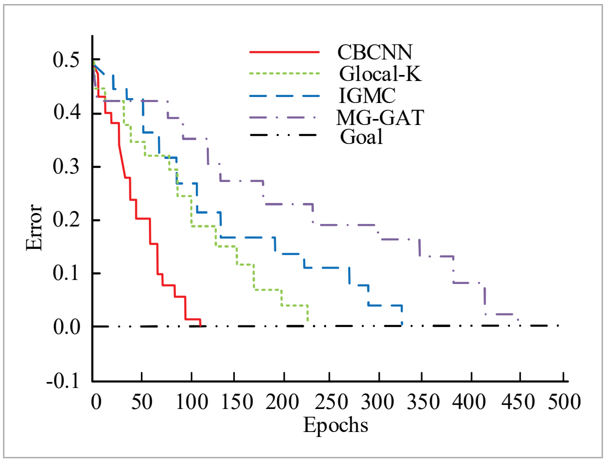
Model	Database			Average
	School 1	School 2	School 3	
PMF	0.792	0.669	0.695	0.719
BMFSI	0.774	0.763	0.682	0.740
mSDA-CF	0.700	0.674	0.675	0.683
RBM-CM	0.692	0.652	0.671	0.672
AutoRec	0.674	0.640	0.653	0.656
SACM-CF	0.654	0.608	0.614	0.625

4.2. Performance Analysis of CBCNN Model

In order to solve the cold-start problem of current intelligent recommendation algorithms, which cannot provide personalized, intelligent and accurate learning resource recommendation results for new users, the study proposes a CBCNN model with certain optimization. Compare the CBCNN model with several existing advanced recommendation algorithms, including the Glocal-K model, IGMC model, and MG-GAT model [6, 9, 4]. The variation curves of output precision of several models during training are shown in Figure 6. It can be seen that on all the same training sample sets, the CBCNN model requires the least number of iterations to achieve the target precision. At 103 iterations, the CBCNN model achieved the target precision, while the Glocal-K model required 248 iterations, 145 more than CBCNN. The IGMC model requires 342 times, 239 more than CBCNN. The MG-GAT model requires 473 times, 370 more than CBCNN.

Figure 6

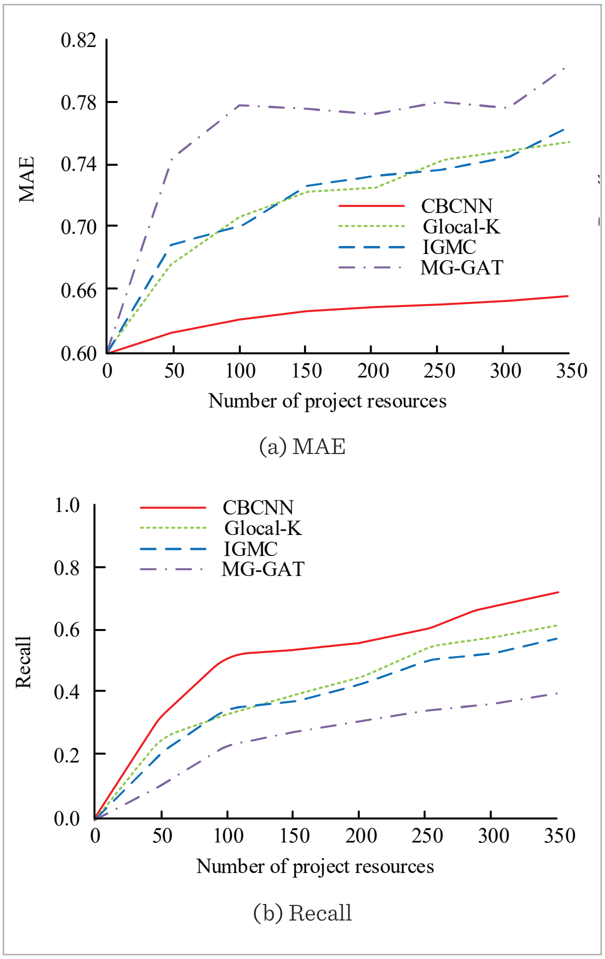
Variation curve of output precision of several models



The MAE and Recall values of the model are shown in Figure 7. It can be seen that the MAE value of CBCNN is lower than other models, while the Recall value is higher than other models. In Figure 7(a), when the recommendation number N of learning resources is 350, the MAE value of CBCNN is 0.63, which is 0.09, 0.11, and 0.16 lower than the Glocal-K model, IGMC model, and MG-GAT model, respectively. In Figure 7(b), when the recommendation number N of learning resources is 350, the Recall value of CBCNN is 0.74, which is 0.24, 0.30, and 0.34 higher than the Glocal-K model, IGMC model, and MG-GAT model, respectively. The above results show that the effect of the convolutional filter is better than that of the non-convolutional filter. This is because the CBCNN model uses the text information in the multimedia resources as the basis for recommendation, uses the causal child model to calculate the eigenvectors of users and objects through historical data, and then uses the convolutional neural network of the training network to make recommendations. This not only verifies the effectiveness of the CBCNN model, but also confirms its ability to solve the cold start problem that exists in recommendation systems to some extent.

Figure 7

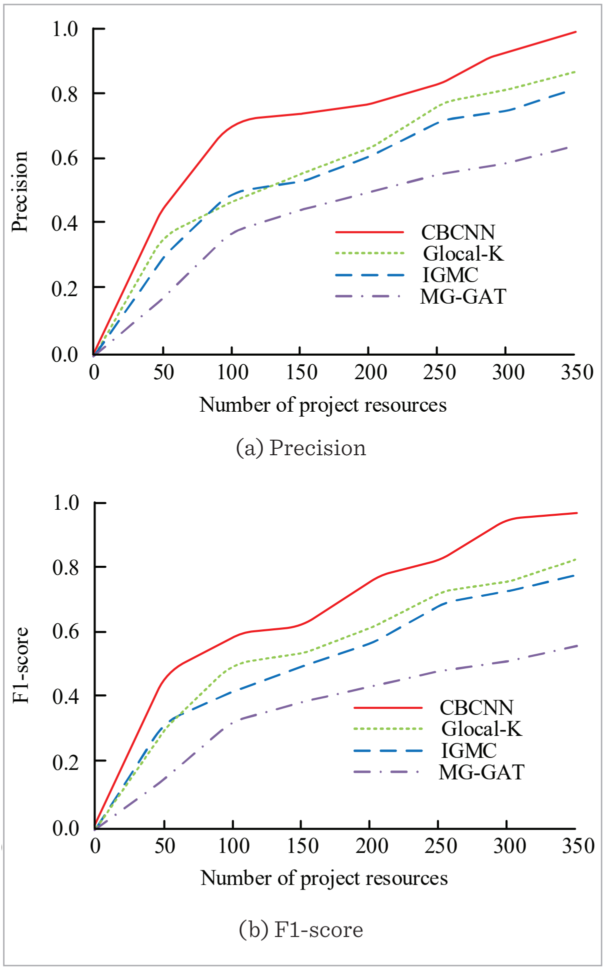
MAE value and Recall value of the model



The recommended precision and F1 value of the model are shown in Figure 8, where the recommended number N is 50. It can be seen that the recommendation precision and F1 value of CBCNN are higher than other models. As the number of recommendations continues to increase, the recommendation precision and F1 value of the model are also constantly improving. When the number of recommendations exceeds a certain number of times, the precision of the model's recommendations and the rate of increase in F1 value slow down until they no longer change. This is because after learning and training, the precision of the model has reached its optimal state. In Figure 8(a), when the number of model iterations is 350, the recommendation precision of CBCNN is 0.989, which is 0.264, 0.283, and 0.452 higher than the recommendation precision of Glocal-K model, IGMC model, and MG-GAT model, respectively. In Figure 8(b), when the number of iterations of the model is 350, the F1 value of CBCNN is 0.985, which is 0.21, 0.23, and 0.46 higher than the Glocal-K model, IGMC model, and MG-GAT model, respectively. The above results may be due to the higher data density on the object compared to the user, making the proposed model more effective in feature extraction or similarity measurement. Cold start is usually an important issue in recommendation systems. Most methods that use a complete cold start may not achieve good results, but the methods proposed in the study achieved good results, indicating that CBCNN can effectively solve the cold start problem where new resources cannot be recommended within a certain range. In summary, the study of the CBCNN model constructed based on CNN can effectively avoid the cold start problem and improve the recommendation precision of the recommendation model. The SACM-CF model and the CBCNN model can effectively improve the precision of the online learning system in recommending interested learning resources to users, thus avoiding users' wasting learning time by searching and selecting learning resources, and improving users' learning efficiency.

Figure 8

Recommended precision and F1-score of the model



5. Conclusion

In recent years, with the deep integration of the Internet and the field of education, learning models represented by online learning have received widespread attention. Personalized resource recommendation service technology can effectively solve the problems of information overload and information loss caused by the information explosion era. Therefore, this technology has become a top priority in the fields of educational informatization and intelligent information processing. However, traditional intelligent recommendation algorithms have issues with sparse data and cold start, resulting in unsatisfactory recommendation results. In response to the problem of data sparsity, the SACM-CF model was studied and constructed. In response to the cold start problem, the CBCNN model was studied and optimized. The research results show that in the performance analysis of the SACM-CF model, the average RMSE value and the average MAE value of this model are both the lowest, 0.844 and 0.625, respectively, compared with other models. In the performance analysis of the CBCNN model, the lowest MAE value of the model is 0.72, which is 0.05, 0.06 and 0.08 lower than the KNN-CF model, the EBCF model and the CTR model, respectively; the highest recall value is 0.65; the highest recommended precision is 0.954; the F1-score is 0.84, which is 0.09, 0.11 and 0.17 higher than the KNN-CF model, the EBCF model and the CTR model, respectively. This indicates that the model proposed in the study is reasonable and feasible, and can to some extent solve the cold start problem of new resources. In summary, the two models proposed in the study can solve the data sparsity and cold start problems and improve the recommendation precision. The study did not explore the fusion of multiple recommendation algorithms to make the comprehensive performance of the recommendation models better, which is a problem that needs to be addressed subsequently.

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