Application of Artificial Intelligence Technologies in Blended E-Learning Platforms

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Abstract. With the development of AI technologies, AI application in education has become increasingly important, especially in blended e-learning platforms. However, these platforms often face the problems of course recommendation accuracy and data sparsity. To this end, the study proposes an improved neural collaborative filtering algorithm that incorporates temporal information to enhance the performance of the recommendation system. The results show that in explicit feedback evaluation, the research algorithm improves 58.3% in root-mean-square error and 59.1% in mean absolute error over the traditional collaborative filtering algorithm. In the implicit feedback evaluation, the proposed algorithm achieves 0.44 at NDCG@10 and 0.5257 at HR@10, both of which are superior to the traditional collaborative filtering algorithm. It can be found that the research algorithm can effectively improve the accuracy and adaptability of the recommender system. The study not only improves the course recommendation effect on the blended e-learning platform, but also provides an important reference value on how to optimize the recommendation system using temporal information and artificial intelligence technology.

Keywords: artificial intelligence techniques; blended; e-learning; curriculum; neural collaborative filtering algorithms.

1 INTRODUCTION

With the rapid development of information technology and the Internet, artificial intelligence has become a key force driving innovation and change in education. Against this background, blended e-learning platforms have emerged, combining traditional offline teaching and modern online resources to provide a flexible and diverse learning environment [1-2]. Blended learning is designed to make full use of the advantages of both modes through the combination of online and offline, providing learners with a richer and more personalized learning experience [3-4]. However, with the increasing number of online e-learning course resources, learners are often confused when they are faced with a huge amount of information, making it difficult for them to quickly and accurately find the learning content that suits their needs [5-6], which has become a major challenge that blended e-learning platforms need to address.

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Therefore, the study proposes a Neural Collaborative Filtering (NCF) algorithm that aims to improve the accuracy and efficiency of the course recommendation system through deep learning techniques. This is not only an improvement of the existing recommendation system algorithm, but also a major innovation in the field of education technology. Considering the importance of time information in course selection, this research integrates time factor into NCF algorithm, which makes the algorithm more accurately reflect the current learning needs and preferences of learners. In addition, the study also explores the dynamic relationship between time factor, user preference and course characteristics, providing a new perspective for understanding and predicting learners' behavior. This research can not only effectively solve the problem of course recommendation on hybrid e-learning platform, but also provide powerful theoretical and practical guidance for the effective integration of artificial intelligence technology and modern education mode, and open up a new way for the future development of education mode and technology.

2 RELATED WORKS

Deep learning, as an important field of modern technology, plays a key role in the development of blended e-learning platforms. NCF algorithm, as a combination of deep learning and traditional recommender system, is widely used to optimize the course recommendation effect of these platforms [7-8]. Numerous researchers at home and abroad have achieved remarkable results in this field. The relevant researches of some scientists and scholars will be introduced as follows. Hu H et al. proposed a hybrid integrated multi-collaborative filtering algorithm, which adopts a special self-encoder method to efficiently extract the user's hidden representation that contains global structural information by utilizing the correlation matrix between friends and additional information. The final prediction is generated by overlaying multiplication to integrate different information [9]. Wu L et al. proposed collaborative filtering and web information-enriched recommendation algorithms that utilize the key source and side information of user-item interaction data, and also proposed temporal-sequential recommendation, which accounts for contextual information related to interactions in order to improve the recommendation accuracy [10]. Wang T proposed a hybrid web recommendation algorithm for online teaching and learning focusing on four dimensions of foreign language learning. To this end, a performance evaluation system for foreign language teaching and learning platform based on big data was established [11]. The results show that the recommendation algorithm is able to analyse and share information through AI data, proving its application value and promotion potential in foreign language teaching. The above research results provide some help in constructing the application of AI technology in blended e-learning platforms.

3 METHODS

3.1 Neural Collaborative Filtering Algorithm

Artificial Intelligence technology plays a key role in blended e-learning platforms, particularly the use of deep learning, which analyses and processes large amounts of data to optimize the learning experience. This technology is able to accurately identify students' learning habits and preferences to provide more personalized recommendations in the online classroom [12-13]. Neural network models are an important component of deep learning. Neural network models can not only adjust weights to solve complex problems, but also provide highly customized learning materials for students. This not only improves the quality of online education, but also greatly enhances learner engagement and satisfaction. To this end, the research proposes Neural Collaborative Filtering (NCF), an algorithm that analyses the user's historical behavioral data to reveal preferences, and then recommends the most suitable content for the user among a large number of courses, as shown in Figure 1.

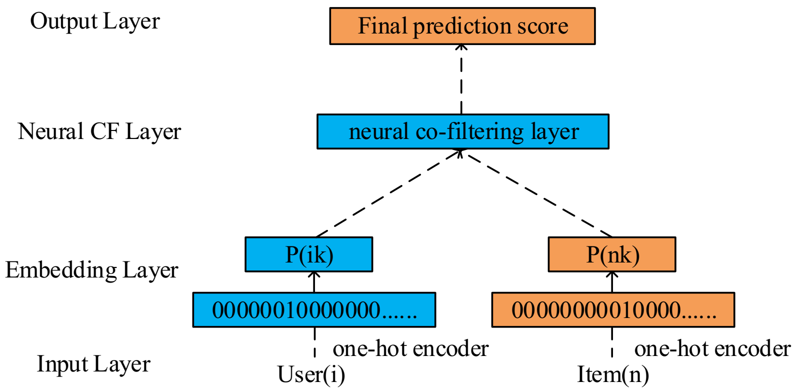


Fig. 1. Neural collaborative filtering algorithm.

The NCF algorithm is an advanced recommender system technique that effectively fuses Generalized Matrix Factorization (GMF) and Multi Layer Perceptron (MLP) to improve the accuracy and efficiency of recommendations. This convergence is especially critical in the context of hybrid web-based course recommendation. GMF is an improved matrix factorization technique for capturing the linear relationship between users and items. It predicts the user's preference for a course by representing the user and the course as vectors with an inner product. In blended learning platforms, GMF can effectively identify the relevance of the user's learning patterns and course content to recommend the most suitable courses for the user. MLP is a deep learning model that captures nonlinear and complex relationships through multiple levels of processing units. In recommender systems, MLP is able to learn complex interaction patterns between users and courses. For blended e-learning platforms, MLPs can analyse more complex user behaviors and course characteristics to provide more accurate and personalized course recommendations. The key of neural collaborative filtering algorithm is to combine two different model frameworks, GMF and MLP, to create a new recommendation system. This combination takes into account the differences in output vector dimensions between the two models and adopts the optimal embedding layer vector in each model rather than simply sharing the same embedding layer. This innovative approach not only retains the respective advantages of GMF and MLP, but also significantly enhances the performance and adaptability of the entire recommendation system. Through this combination, the NCF algorithm can more comprehensively understand and adapt to the changes in user behavior, so as to provide more accurate and satisfying user needs of course recommendation. This is not only a breakthrough at the technical level, but also shows significant advantages in practical applications, especially when dealing with large-scale user data and diverse course content. In addition, the study further advances the application of deep learning in the field of educational technology by innovatively merging these two models. NCF algorithms can not only improve the accuracy and efficiency of recommendation systems, but also provide deeper data insights to help education providers better understand the needs of learners, thereby optimizing course content and teaching methods.

3.2 Improved NCF algorithm incorporating time-aided information

In blended e-learning platforms, the application of AI techniques improves the accuracy of course recommendations by considering the time factor. Traditional recommendation algorithms usually regard user preferences as static, but in fact, user interests change over time. Especially in the recommendation of course resources, the influence of time is particularly significant. In order to better adapt to such changes, a K-means clustering algorithm is introduced in the study, which incorporates time information as a feature vector into the MLP model and the GMP model. This approach allows the model to update the user's learning interests and recommended courses in real time according to the change of time, which improves the relevance and timeliness of the recommendations. The specific calculation of this process is shown in equation (1).

$$y = \min \sum_{i=1}^{n} \min_{j=1,2,\ldots k} ||x_i - \mu|^2 \tag{1}$$

In equation (1), $\min$ denotes the minimum value, x_i represents the data points in the datasets, and μ is the centre value of the clusters. By analyzing the course creation time, user viewing time and current time, the algorithm calculates the user's relative viewing time for each course. This method effectively uses the time information, reduces the complexity of the model, and improves the accuracy of the recommendation, the specific process is shown in equation (2).

$$T = \frac{T_u - T_i}{t - T_i} \tag{2}$$

In equation (2), T_u represents the user's most recent viewing time, T_i is the upload time of the course, and t is the current time. This way of handling the time information ensures that the user's most recently watched and most recently uploaded courses receive higher time information values. Then, through the K-means algorithm, this time information is mapped into an interval, which is input into the NCF algorithm as auxiliary information. The specific framework is shown in Figure 2.

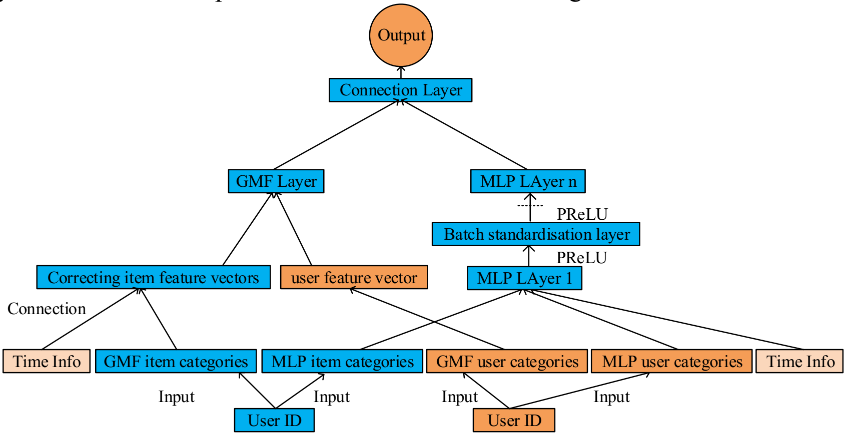


Fig. 2. Improved NCF algorithm.

Firstly, information about the user, course and time is entered at the input layer. Then by one-hot coding, this information is transformed into embedding vectors. In the MLP model, the embedding vectors of user and course are combined with time information as input. For the GMF model, the time information is used to adjust the course feature vectors, which are then combined with the user feature vectors for matrix decomposition. In addition, a batch normalization layer was added to the MLP model in order to speed up training and mitigate overfitting. Finally, the results of linear and nonlinear learning are combined and output via a Sigmoid function to provide accurate course recommendations for e-learning platforms. The specific computational procedure of this algorithm is shown in equation (3).

$$\begin{cases} X^{GMF} = p_u^{GMF} \cdot q_i^{GMF} + p_u^{GMF} \cdot t_{ui}^{GMF} \\ X^{MLP} = a_L(W_L^T(a_{L-1}(Ia_2(W_2^T \begin{bmatrix} p_u^M \\ q_i^M \\ t_{ui}^M \end{bmatrix} + b_2)I)) + b_L) \\ y_{ui} = \sigma(h^T \begin{bmatrix} X^{GMF} \\ X^{MLP} \end{bmatrix}) \end{cases} \tag{3}$$

In equation (3), p_u^{GMF}, p_u^{GMF} are the user input representations in MLP and GMF, where q_i^M, q_i^{GMF} represent the item input representations in MLP and GMF, and t_{ui}^{GMF}, t_{ui}^M represent the viewing time classification information of user u and item I in GMF and MLP as a one-dimensional vector for input. During model training, the time information is first classified using K-means clustering algorithm and converted into feature vectors by one-hot coding after combining user and course IDs. These vectors are fed into the MLP and GMF models and the two models are combined. Finally, the study was trained using explicit and implicit feedback data to improve the accuracy of the predictions, and the cross-entropy function was calculated as a loss as shown in equation (4).

$$\begin{cases} L = \frac{1}{n}\sum_{i=1}^{n} |y_{ui} - y_{true}| \\ L = \sum_{(u,i)\epsilon D\cup D^{-}} [y_{ui}\log y_{true} - (1 - y_{ui})\log(1 - y_{true})] \end{cases} \tag{4}$$

In order to be able to reduce the impact of indicators with different units, the study used data standardization. This process transforms indicators into unitless values that can be easily compared or weighted. Common methods of data normalization include normalization, which converts data to values between 0 and 1 so that a quantitative expression becomes a dimensionless expression. The min-max normalization method was used in the study, which is effective in standardizing different indicators as shown in equation (5).

$$x = \frac{x - \min}{\max - \min} \tag{5}$$

In equation (5), x represents the difference between the date the user watched the course and the date the course was uploaded, divided by the difference between the current time and the time the course was uploaded, and $\min$ and $\max$ are the creation time and current time of the e-learning course. Finally, the study proposes a variety of metrics for e-learning course recommendation, including Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Hits Ratio (HR) and Normalized Discounted Cumulative Gain (NDCG). These metrics help to assess the difference between the predicted value and the actual data, the smaller the loss value, the better the performance of the algorithm, the MSE, MAE and RMSE are expressed as shown in equation (6).

$$\begin{cases} MAE = \frac{1}{N}\sum_{i=1}^{N} |\text{observed} - \text{predicted}| \\ MSE = \frac{1}{N}\sum_{t=1}^{N} (\text{observed} - \text{predicted})^2 \\ RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N} (\text{observed} - \text{predicted})^2} \end{cases} \tag{6}$$

The HR metric focuses on assessing the accuracy of the model's predictions, i.e., whether the courses that users are really interested in are recommended by the model. The HR calculation is based on the number of all users N and takes into account the hits in the recommendation list for each user $hits(i)$. The NDCG, on the other hand, focuses more on the reasonableness of the recommendation order, i.e., whether important courses are placed in a more prominent position. The calculation of NDCG is also based on the total number of users N and the position of the access value in the recommendation list p_I . The specific calculations of HR and NDCG are shown in Equation (7).

$$\begin{cases} HR = \frac{1}{N}\sum_{t=1}^{N} hits(s) \\ NDCG = \frac{1}{N}\sum_{i=1}^{N} \frac{1}{\log_2(p_i + 1)} \end{cases} \tag{7}$$

In summary, the proposed method can not only effectively improve the accuracy and efficiency of course recommendation in hybrid e-learning platform, but also provide a new perspective and solution for understanding and adapting to the changing needs and preferences of learners.

4 RESULTS AND DISCUSSION

4.1 Analysis of experimental results of the improved NCF algorithm under explicit feedback

In order to verify the effectiveness of the improved NCF algorithm in the blended e-learning platform, the study is based on the data of Catechism e-learning platform, and 7,712 users and 566 courses are screened as the datasets. The course records of users need to be more than 15 courses. The experiment is divided into two parts: explicit and implicit feedback, the value of K-means clustering is selected as 3, the hidden layer nodes of MLP network are 64, 32 and 16, and the number of iterations is 100.The study uses MSE, RMSE, HR, and NDCG as the evaluation metrics, respectively. The study compares the traditional CF algorithm, BPNN neural network (BPNN) algorithm, NCP algorithm and the improved NCF algorithm with the values of 1 to 4. The results of the display feedback are shown in Figure 3.

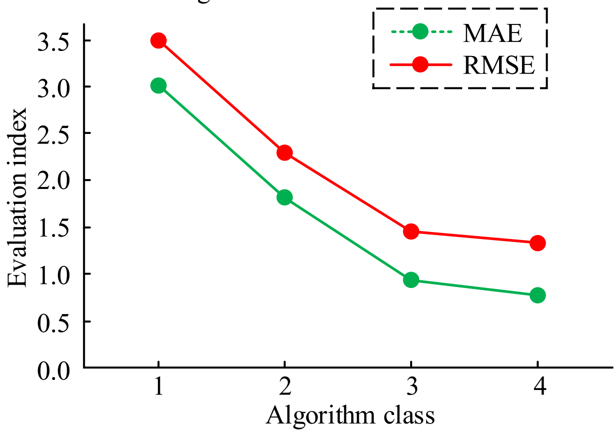


Fig. 3. Display feedback results of different algorithms.

It can be seen that the improved NCF algorithm has a significant improvement in the recommendation effect compared to the traditional CF algorithm. When using RMSE as an evaluation metric, the NCF algorithm improves its performance by 58.3% over the CF algorithm, while under the MAE metric, the improvement reaches 59.1%. This indicates that the inclusion of temporal information effectively improves the accuracy of course recommendation. Meanwhile, the experimental results also show that the NCF algorithm outperforms the BPNN and NCF algorithms under the explicit feedback evaluation condition, further proving the effectiveness of AI technology in optimizing course recommendation in e-learning platforms.

4.2 Analysis of experimental results of the improved NCF algorithm with implicit feedback

This research experiment uses implicit feedback to evaluate the effectiveness of the improved NCF algorithm for course recommendation in e-learning platforms. For this purpose, implicit feedback was performed by converting users' explicit ratings into 0 and 1 markers. No rating or 0 learning progress is marked as 0 (negative sample), and marking points is marked as 1 (positive sample). The experimental setup was the same as for explicit feedback, but with implicit feedback, the cross-entropy function was used as the loss function for algorithm training, and the results are shown in Figure 4.

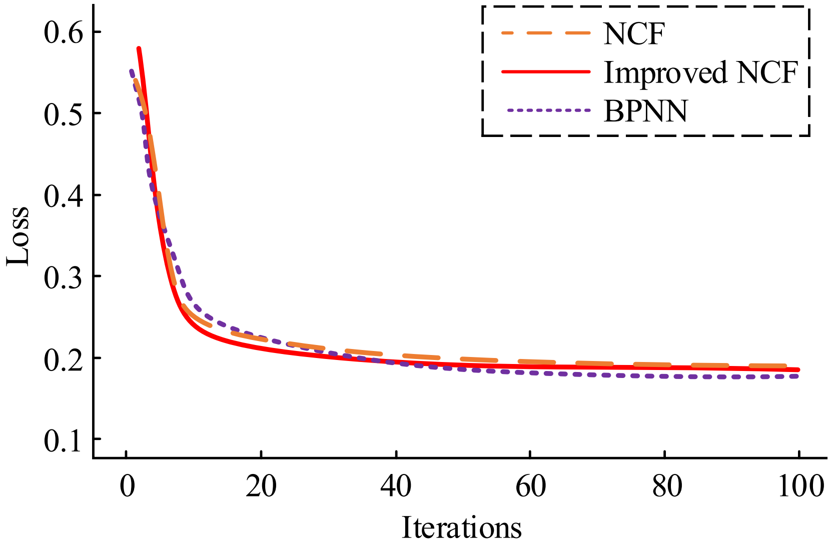


Fig. 4. Improved loss function comparison of NCF algorithm.

It can be seen that after 100 iterations, the training loss of the BPNN algorithm is 0.18031, the improved NCF is 0.19026, and the NCF is 0.19462. Although the loss error of the improved NCF algorithm is not the smallest, it is not very much different from the other two algorithms, and it converges faster, which suggests that it has the advantage of reaching a lower error quickly. It proves that it is especially important to deal with large-scale and diverse data on hybrid e-learning platform. The next study uses HR@10 and NDCG@10 as evaluation metrics, HR and NDCG can better respond to the accuracy and sequentiality of the recommended e-learning courses, the results are shown in Figure 5.

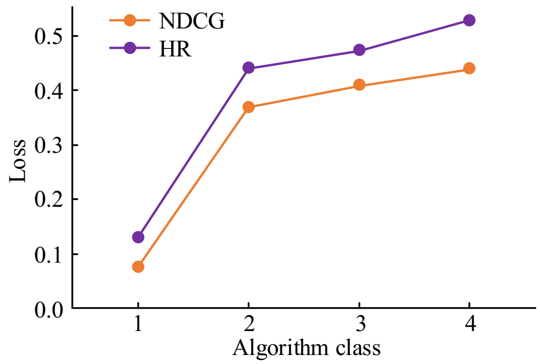


Fig. 5. Comparison of evaluation results of HR@10 and NDCG@10.

It can be observed that the improved NCF algorithm performs the best, NDCG@10 is 0.44, HR@10 is 0.5257. In contrast, the CF algorithm performs poorly under both metrics, NDCG@10 is just 0.07626, HR@10 is 0.13. This difference is due to the fact that the CF algorithm relies on user behaviour, which, in the case of implicit feedback data, is more sketchy, which is not conducive to accurate recommendation. On the contrary, the algorithm introducing neural networks can better capture the nonlinear relationship between users and courses and improve the accuracy of recommendation. The improved NCF algorithm not only takes into account the linear and nonlinear relationships between users and courses, but also incorporates the time factor, thus outperforming other methods in terms of recommendation effectiveness. The results show that the improved NCF algorithm performs best in the accuracy and sequentiality of recommended e-learning courses, which indicates its efficient ability to understand and predict user preferences. The study also explored the impact of the improved NCF algorithm on the recommendation of different numbers of courses. Different Top-K recommendation lists ranging from 6 to 20 courses were selected, using HR and NDCG as evaluation metrics, and the results are shown in Figure 6.

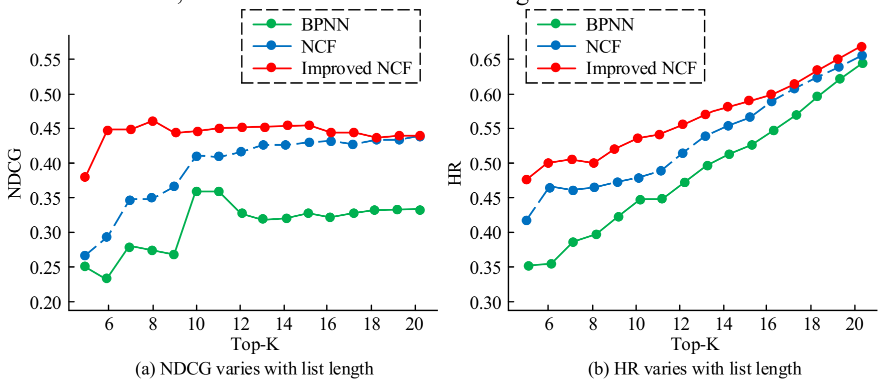
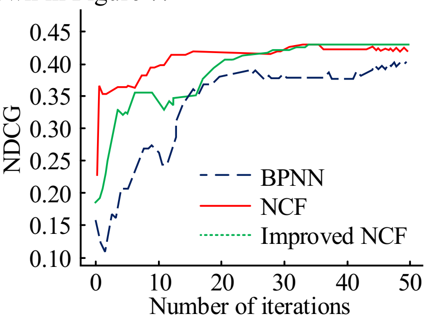
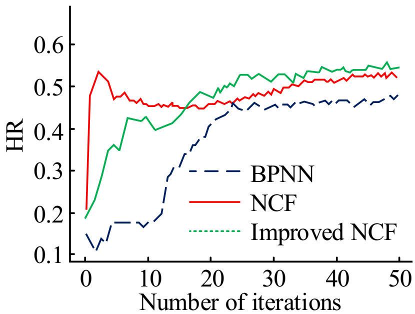


Fig. 6. HR and NDCG results for different Top-K recommendations.

It can be seen to that the improved NCF algorithm outperforms the benchmark metrics regardless of the recommendation list length. In the NDCG evaluation index, the average is 0.45, while in the HR evaluation index, the average is 0.55. This shows the robustness and adaptability of the algorithm in handling different scale recommendation tasks. This finding is particularly important for designing personalized and dynamically changing course recommendation systems, especially in massive online learning platforms such as MOOCs. In addition, the algorithm is able to integrate time factors and user historical interactions to provide more personalized and on-time course recommendations. Next, the effect of different iterations on the proposed algorithm is shown in Figure 7.



(a) NDCG@10 varies with number of iterations



(b) HR@10 varies with number of iterations

Fig. 7. NDCG@10 and HR vary with the number of iterations.

In this study, dynamic changes in algorithm performance are analyzed in depth by setting the number of iterations of changes in Figures 7(a) and 7(b). The results show that with the increase of the number of iterations, the efficiency of the algorithm is obviously improved. Especially in the early stage of training, the performance of NCF algorithm is particularly outstanding. However, this advantage is only apparent in the early stages. When the performance of the model tends to be stable, the proposed improved algorithm is superior to NCF and BPNN algorithms in terms of recommendation accuracy. The experimental results also reveal that the combination of neural network and matrix decomposition technology can effectively capture both linear and nonlinear relationships between users and items, thus surpassing the recommendation effect of simple BPNN. In addition, the study also considers the influence of time factor on the user's course selection, which can more accurately recommend the appropriate course for the user. This finding confirms the effectiveness and innovation of the proposed algorithm for course resource recommendation in hybrid e-learning platform.

5 CONCLUSION

Aiming at the data sparsity and accuracy problems of course recommendation in e-learning platforms, the study adopts the NCF algorithm and improves it by combining temporal information through the clustering and classification algorithm in order to improve the adaptability to the user's current learning needs. The results show that in explicit feedback evaluation, the improved NCF algorithm outperforms the CF algorithm by 58.3% in RMSE and 59.1% in MAE. Under implicit feedback, the training loss of BP neural network is 0.18031, the improved NCF is 0.19026, and the NCF is 0.19462, it can be seen that the improved NCF algorithm shows faster convergence speed and higher stability. In addition, using HR@10 and NDCG@10 as evaluation metrics, the improved NCF algorithm performs the best, NDCG@10 is 0.44, HR@10 is 0.5257. These results can be found that the improved NCF algorithm incorporates the time factor while taking into account the linear and nonlinear relationship between users and courses, which effectively improves the overall performance of the e-learning course recommendation system. In summary, this study combines the linear and nonlinear relationship between time factors and user courses, and provides a new course recommendation method for hybrid e-learning platform. This method not only improves the overall performance of the recommendation system, but also provides an effective solution for dealing with dynamic changes in user requirements and course content. However, the study still faced efficiency challenges when dealing with extremely large data. In order to further optimize the performance, future research will consider incorporating more auxiliary information and optimizing the algorithm structure, for example, by introducing the association analysis between user social network data and courses, so as to improve the ability to process large-scale data and further improve the course recommendation effect of the e-learning platform. Research in this direction will help to further enhance user satisfaction, promote the development of personalized learning, and bring more innovative possibilities to the field of online education.

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