UI Design and Optimization Method for Museum Display Based on User Behavior Recommendation

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In view of the lack of rich display methods in the display design of museums, it is impossible to enhance the interest of visitors. This paper proposes a museum object recommendation method based on collaborative filtering, which simplifies the display design, improves the recommendation effect, and alleviates the scalability problem. Firstly, the algorithm of recommendation system combines the advantages of memory collaborative filtering and uses smoothing processing to improve the efficiency of recommendation and achieve the best consistency. Then, the cross-domain collaborative filtering rating matrix generation model is used to establish the correlation between multiple rating matrices by finding the shared hidden clustering rating matrix, which also improves the recommendation effect. Finally, the conclusion shows that we can use single user behavior data such as forgetting mechanism to recommend to users. SVD makes full use of the interaction data of various behaviors, and NMF algorithm makes full use of the data of various user behaviors, which can effectively solve the existing problems. The stochastic gradient descent is applied to the SVD algorithm to accelerate the convergence speed of the model, improve the performance of the model, and effectively improve the accuracy of score prediction.

1. Introduction

The function of the recommendation system is to simply filter the information, and the recommendation system that recommends popular products to users can no longer meet the personalized needs of users. Based on the user’s personal basic information and behaviors such as clicks and searches, it finds the products that best meet the user’s interests from many products and pushes them to specific users. Traditional recommendation algorithms rely on user rating data to obtain user preferences. Interest clustering is achieved through name tag information. Obtain optimal values for feature attributes and interest cluster analysis [1]. Personalized recommendation system is a course recommendation algorithm that integrates user characteristics and interest clustering [2–4]. Due to the limitation of time and product display space, the different characteristics of users are counted, the characteristic attributes are weighted, and the attenuation factor is introduced at the same time, and then, the course prediction score is calculated. Therefore, it needs to maximize its utility through limited resources. On the basis of personal information and its historical behavior information, users can be understood to a certain extent. Recommender systems come into play from this. The similarity of users in each cluster is calculated, and then, the course prediction score is calculated, and the two prediction scoring mechanisms are weighted and integrated by assigning different weights. Through the system to find items that meet the purchase intention for users, their unclear needs can be turned into actual real needs. The recommendation algorithm introduces the user’s general characteristics and interest clustering mechanism, fully considers the user’s attributes, and effectively improves the accuracy of the recommendation algorithm. The user history preference fusion mechanism is introduced, and then, the user-course evaluation matrix is recomposed to construct the user history preference similarity set. Most of the data in behavior logging is very sparse [5–7]. Aiming at the dynamic change of user
interest in the research of recommendation algorithm, this dataset is widely used in the field of recommendation. In order to adapt to the diversity of user course evaluation data in different time intervals, the preference dataset constructed in the previous step is converted. In the implementation process, the dynamic change curve of user preference and the time decay function are introduced at the same time, which will affect the quality of the subsequent neighbor search and the quality of the algorithm results. Turn it into a dynamic change to fit the changing situation of the user’s interests and preferences. The effect of incorporating time factors on recommendation results. At present, there are still many problems in the display design of Chinese museums. Most of the museums focus on the external image in the display design, while ignoring the actual function of the display. The display design lacks in-depth research and sorting of cultural relics, resulting in different styles of display design and cultural relics. The recommendation algorithm based on the dynamic change of user interests can improve the recommendation accuracy. The physical hanging in the showcase has a greater visual impact on the visitors. When it is necessary to display small-sized cultural relics and utensils, the overall volume of the showcase occupies a large space, and it is impossible to customize a special showcase for it. When you look up, you can see the whole picture of the exhibits, and it is easy to notice various details when watching the vertical display exhibits while standing. This display method is suitable for large-area fabrics and clothing while standing. The distance between visitors and cultural relics is isolated, the best viewing angle will be lost [8–10]. Most artifacts appear out of place throughout the exhibition theme space. Limitations make the actual museum exhibit work against the original intent of the display design. The gravitational effect brought by the suspension will not cause too much damage to the exhibits. Some of the exhibits in the showcase will be tiled to tilt the horizontal plane so that visitors in a certain direction can view the exhibits. Directly placed horizontally is suitable for exhibits with small area, less three-dimensional tailoring and damaged exhibits, such as pieces of fabric and clothing, purses, and fan bags. The display in the showcase is like a window, which can fully display the beauty of clothing. At present, most of the exhibitions in museums only display and display the real objects, and there is no more abundant display methods. Entering the museum, people shed their real identity and become the audience. Viewing is seeing with the eyes, and the audience is the audience of the exhibition content. Common cultural relics are installed in museum display cabinets, and there is a simple introduction to the year of the cultural relics on the display cabinet. In this traditional single display, it is difficult to increase the interest of visitors. According to the user’s immediate feedback, the recommender system updates its own recommendation strategy and recommends the user’s favorite item (item). It is difficult for visitors to deeply appreciate the story background of the cultural relics in the exhibition. There is no interactive communication between the exhibits and the audience, which makes the viewing efficiency ineffective and the purpose of education promotion is weak. The emergence of digital art display forms has effectively made up for the defects of traditional museum display design [11–13]. Digital art is a modern interactive medium, which can make the audience feel immersive and has a strong sense of immersion and interaction. Behavioral streaming recommendation methods can effectively capture users’ latest preferences from new data, strengthen people’s active and positive side, and enable audiences to participate. Recommend items to users precisely based on their latest preferences. By timely using new data to train the recommendation model, it can quickly learn the preferences of new users and solve the cold start problem caused by the poor interaction data of new users. To enrich people’s spiritual and cultural life and encourage the development of individual human nature. There is no need to store a large amount of historical data, which helps to protect user privacy and reduce the negative impact caused by storage. For interactive recommender systems, the spatiotemporal relationship in time affects how humans perceive the world, information, and relationships [14, 15]. Recommendation feedback is a dynamic interactive process, which means that user preferences can change over time. The linear narrative method of organizational arrangement is very popular for its fast information dissemination and high acceptance rate. The balance between long-term benefits and short-term benefits, if the recommendation strategy is obsessed with short-term benefits and neglects to explore long-term benefits, it will not be conducive to a comprehensive modeling of user preferences. In today’s information age, the emergence of new technologies affects the way people read and the concept of time and space, and the emergence of digital display enables a nonlinear narrative method that can bring a new experience to the audience into the museum and has the ability to transcend reality to the audience. The philosophical realm and ideological reflection of the life world bring out the experience and cognitive feeling that breaks the routine.

2. Museum Display Design

2.1. Interactive Recommendation. Network-based methods and forgetting-mechanism-based methods show great potential in multiple sequential decision-making scenarios. Usually, the number of items to be recommended in a recommender system is large, resulting in huge action space and state space. Store representative historical data, and then, sample from the stored historical data and newly received data. The rewards of a large number of state-action pairs are invisible, and these constraints are not conducive to the recommendation system to learn the optimal recommendation strategy. The recommendation model is trained with the sampled data to capture both the user’s recent preferences implicit in the newly received data and the user’s long-term preferences implicit in the historical data. Methods based on interactive recommendation models usually use historical behavior records to model the current environment so that rewards for unseen state-action pairs can be predicted. When sampling, the newly received data and historical data are treated equally, ignoring the
importance of new data, and it is difficult to capture users’ recent preferences. The model-based reinforcement learning recommendation method generates adversarial network to model the environment, which is used to imitate the change process of user behavior and habits and learn the reward function and then use the connected deep Q network DQN. Optimize the current recommendation strategy. A neural memory network is used to maintain both the user’s recent and long-term preferences. A model-based multiagent reinforcement learning recommendation method, which is jointly optimized for multiple recommendation scenarios on e-commerce platforms. Frequent updates with a continuous data stream to maintain long-term user preferences. Each recommendation scenario is an agent, and the method can learn an optimal multiscenario recommendation strategy by learning the sequence correlation between multiple agents and optimizing the joint reward of multiple scenarios. Useless interaction data and outliers are filtered out, respectively, so as to effectively use newly received data and historical data to learn users’ recent and long-term preferences, respectively. Use generative adversarial networks to model the current recommendation environment to learn offline recommendation policies. Methods that rely on matrix factorization models for recommendation require modeling the current environment. However, some scenarios are difficult to model the environment, which leads to errors in the environment model, as shown in Figure 1.

2.2. The Development of Museum Display Design. People’s material needs have been satisfied to the greatest extent with the progress of society and gradually transferred to the spiritual level. The information level of Lianzhu is relatively simple, only the first layer of Lianzhu pattern evolves in a long scroll. Modern people’s thoughts are diverse, and their spiritual and cultural needs have changed from various aspects and at multiple levels. Compared with the past, evaluation standards and aesthetic concepts have also undergone great changes. The long scroll is to arrange the restored patterns of the bead pattern drawn by the author according to the known clues of the times. The structure of the bead pattern changes step by step in the process of combining with Chinese traditional culture. The presentation of the exhibition remains monotonous and rigid, and the audience will experience visual fatigue and eventually lose interest in the museum. It is necessary for us to work hard to break the shackles of traditional thinking and develop and create new theories that conform to the trend of the times. There are separate text descriptions for the bead circle, the theme pattern, and the flower, as well as a small map corresponding to the exhibitor’s current location. Many museums still maintain very traditional concepts and designs. Whether it is the display of objects or the setting of signs, they are very single and rigid, and the whole visiting process is boring and boring. The overall text description of the beaded fabric pattern, in terms of interactive design, some buttons are in fixed positions. These exhibitions are relatively independent and cannot form a system and rarely interact with people in the real environment, so it is out of reality. The recommendation system model in practical application needs to go through the stages of model design, model training, offline testing, and online operation. If we want to completely change this situation, we must make our ideological theories and concepts change and update in time. In offline testing, the model can often achieve better results by adjusting the parameters. The display space is also the most important, which itself is the spirit of the museum. When put online, model performance tends to decline over time. Through it, it can directly face the history of the museum and give visitors the most direct experience and feeling. The display space of most existing museums is still quite rigid. In practice, users and projects are constantly increasing and changing, adapting to the data model. The grasp of the visitors’ own hearts is well controlled and is not in place, and it lacks vividness. The increase of computational time complexity and space complexity causes scalability problems. Museums are mainly responsible for the dissemination and protection of culture, through careful design and planning, to provide services to the public and to promote social development. Therefore, in view of the fact that people are the main body of social change and development, it is necessary to put people first in the process of display design, as shown in Figure 2.

3. Algorithm Model

(a) OTML-MF[16–19]

\[ u = \langle r_{u1}, r_{u2}, r_{u3}, \cdots, r_{un} \rangle. \]

Weighted feature attributes:

\[ v = \langle r_{v1}, r_{v2}, r_{v3}, \cdots, r_{vn} \rangle. \]

Attenuation factor:

\[ s(u, v) = \cos(u, v) = \frac{uv}{\|u\| \times \|v\|}. \]

Predicted score:

\[ \cos(u, v) = \frac{\sum_{k \in I_u} r_{uk} \cdot r_{vk}}{\sqrt{\sum_{k \in I_u} r_{uk}^2 \sum_{k \in I_u} r_{vk}^2}}, \]

\[ s(u, v) = \frac{\sum_{k \in I_u} (r_{uk} - \tilde{r}_u) \cdot (r_{vk} - \tilde{r}_v)}{\sqrt{\sum_{k \in I_u} (r_{uk} - \tilde{r}_u)^2} \sqrt{\sum_{k \in I_u} (r_{vk} - \tilde{r}_v)^2}}. \]

(b) SVD++ [20–23]

Personal information:

\[ s(u, v) = \frac{\sum_{k \in I_u} (r_{uk} - \tilde{r}_u) \cdot (r_{vk} - \tilde{r}_v)}{\sqrt{\sum_{k \in I_u} (r_{uk} - \tilde{r}_u)^2} \sqrt{\sum_{k \in I_u} (r_{vk} - \tilde{r}_v)^2}}. \]
Historical behavior information:

\[ s(u, v) = \frac{|I_u \cap I_v|}{|I_u \cup I_v|} \quad (7) \]

Similarity:

\[ d(a, b) = \sqrt{\sum_{n=1}^{3} (x_n - y_n)^2} \quad (8) \]

Scoring mechanism:

\[ s(u, v) = \sqrt{\sum_{i=1}^{k} (r_{ui} - r_{vi})^2} \quad (9) \]

\[ F = \{ f : D \rightarrow \Gamma \} \quad (10) \]

\[ P_{ref}(f(v) = f(w)) \geq p_1 \quad (11) \]

Unclear requirements:

\[ P_{ref}(f(v) = f(w)) \geq p_2 \quad (12) \]

\[ g(v) = f_1(v), f_2(v), \ldots, f_c(v) \quad (13) \]

Historical preference similarity set:

\[ M(w, v) \leq r \quad (14) \]

Dynamic curve:

\[ W_{kn}^N = e^{-j(2\pi/N)kn} \quad (15) \]

\[ X(k) = \sum_{n=0}^{N-1} W_{kn}^N x(n), \quad k = 0, 1, \ldots, N - 1. \quad (16) \]

(c) SIM_COS [24–26]

\[ X(n) = \sum_{n=0}^{N-1} W_{kn}^N X(k), \quad n = 0, 1, \ldots, N - 1, \quad (17) \]

\[ X(k) = X_1(k) + W_{Nk}^k X_2(k), \quad k = 0, 1, \ldots, \frac{N}{2} - 1. \quad (18) \]

Time decay function:

\[ X\left(k + \frac{N}{2}\right) = X_1(k) - W_{Nk}^k X_2(k), \quad k = 0, 1, \ldots, \frac{N}{2} - 1. \quad (19) \]

Recommended accuracy:

\[ H_s(u, v) = \frac{1}{1 + \sqrt{\sum_{k=0}^{23} (u_k - w_k)^2}} \quad (20) \]
User instant feedback:

$$W_s(u, v) = \frac{1}{1 + \sqrt{\sum_{i=0}^{6} (u_i^w - v_i^w)^2}}.$$  (21)

Update referral policy:

$$u'_i = (c'_1, c'_2, c'_3, c'_4),$$  (22)

$$S_s(u, v) = \frac{1}{1 + \sqrt{\sum_{i=0}^{3} (u_i' - v_i')^2}},$$  (23)

$$T_s(i, j) = W^T S.$$  (24)

Train a recommendation model:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2}. $$  (25)

Historical data:

$$w_h = \frac{\sigma_h}{\sigma_h + \sigma_w + \sigma_s}. $$  (26)

Interactive recommender system:

$$d_k = \frac{F_k[0]}{\sum F_k}. $$  (27)

### 4. Simulation Experiment

#### 4.1. Personalized Recommendation Algorithm

It is inclined to improve the existing offline single-action recommendation methods to make them have the ability to make recommendations using streaming data. The idea of collaborative filtering becomes a highly interpretable technique to incrementally learn users’ recent preferences using data streams. Coordinate descent, stochastic gradient descent, and fast alternating least squares for incremental training of recommendation models in streaming scenarios, as shown in Table 1 and Figure 3. In the SIM_COS algorithm, 100k-RMSE = 3.24, 100k-MAE = 3.47, 1m-RMSE = 3.24, and 1m-MAE = 3.51. A nonlinear regularization kernel is designed to give the matrix factorization model more flexibility in streaming recommendation. In the SIM_PEAR algorithm, 100k-RMSE = 3.04, 100k-MAE = 3.55, 1m-RMSE = 3.04, and 1m-MAE = 3.28. Apply personalized ranking method and Bayesian inference method to optimize matrix factorization model in streaming scenarios. The ability to make recommendations for users in streaming scenarios. The SIM_MSD algorithm can simultaneously capture the user’s recent and long-term preferences, 100k-RMSE = 3.78, 100k-MAE = 3.88, 1m-RMSE = 3.23, and 1m-MAE = 3.74.

#### 4.2. Multibehavior Offline Recommendation Method

Existing recommendation methods usually only use a single user behavior data such as forgetting mechanism to recommend to users. The efficient search and processing of massive high-dimensional data fail to effectively utilize the interactive data belonging to various user behaviors, as shown in Table 2 and Figures 4 and 5. SVD effectively utilizes the interaction data of multiple behaviors ml-100k = 2.89, ml-1 m = 1.07, λu = 1.09, i = 1.38, η = 0.25, and α = 1.23. A variety of user behaviors are ubiquitous. The NMF algorithm can effectively solve the existing problems by making full use of the data of various user behaviors, ml-100k = 2.32, ml-1m = 2.84, λu = 2.08, i = 1.22, η = 1.81, and α = 0.16. Recommendation methods utilize interaction data of various behavioral types, such as browsing, to recommend users in offline scenarios. A variety of advanced learning techniques such as multitask learning and transfer learning are adopted to solve the data sparsity problem caused by insufficient data of a single behavior type. Behavioral offline recommendation method uses the main behavior and a class of auxiliary behaviors to recommend items to users. Treat the secondary behavior type interaction as the primary behavior type interaction. Learning user preferences in OTML-MF interaction data, ml-100k = 0.63, ml-1m = 2.44, λu = 1.87, i = 1.47, η = 1.44, and α = 2.02. Use the interaction of multiple behavior types to make recommendations for users through the alternating least squares method. Do not learn the user’s preference for items from the main behavior and auxiliary behavior, and then, make recommendations for the user according to the learned preference.

#### 4.3. Collaborative Filtering Algorithm

As shown in Table 3 and Figure 6, the CCLU filtering algorithm considers the user’s feature attributes and interest changes, RMSE = 11, MAE = 18, RMSE = 15, MAE = 16, ml-100k = 18, and ml-1m = 16. The factors affecting the accuracy of course recommendation also involve feature attributes and user history sequences. The MKNN algorithm takes these factors into account as comprehensively as possible, RMSE = 16, MAE = 10, RMSE = 14, MAE = 20, ml-100k = 19, and ml-1m = 15. Based on the embedded feature and user behavior course recommendation algorithm, a deep learning network is introduced to fully consider the user feature, and a course recommendation model based on the embedded feature and LSTM is established. When performing the nearest neighbor search for similar groups of users, there may be some small flaws in the effect of a single model. The OTML-MF algorithm is currently one of the best personalized recommendation algorithms with RMSE = 14, MAE = 12, and RMSE = 19. Many fields apply it to actual commercial production MAE = 12, ml-100k = 10, and ml-1m = 18. The information collaboration model is constructed.

### Table 1: Personalized recommendation algorithm.

| Dataset | Met | SIM_COS | SIM_PEAR | SIM_MSD | SIM_FM |
|---------|-----|---------|----------|---------|--------|
| 100k-RMSE | 3.68 | 3.24 | 3.04 | 3.78 | 3.21 |
| 100k-MAE | 3 | 3.47 | 3.55 | 3.88 | 3.58 |
| 1m-RMSE | 3.54 | 3.24 | 3.04 | 3.23 | 3.3 |
| 1m-MAE | 3.43 | 3.51 | 3.28 | 3.74 | 3.73 |
according to the user’s historical behavior, and the corresponding results are given by the majority voting method.

4.4. Overview of Personalized Recommender Systems. The recommendation system algorithm improves the recommendation efficiency by combining the advantages of memory-based and model-based collaborative filtering by adopting smooth processing. As shown in Table 4 and Figure 7, when the MAF is 40, the uniformity is the best, UBCF = 1.64, UICCF = 1.31, User-CT = 1.34, and User-CCIC = 1.47. Content-based recommendation algorithms originated from information retrieval. A cross-domain collaborative filtering scoring matrix generation model is used to establish the correlation between multiple scoring matrices by finding a shared implicit cluster scoring matrix, which also improves the recommendation effect and alleviates the scalability problem. When the MAF is 50, the efficiency is the highest, UBCF = 1.98, UICCF = 1.58, User-CT = 1.65, and User-CCIC = 1.91. Matrix factorization is also based on the idea of collaborative filtering and can achieve scoring prediction for any combination of users and items by means of inner product calculation. The matrix factorization algorithm has strong potential feature mining ability. The adaptive learning rate function, which combines the characteristics of exponential function and linear function, is applied to the SVD++ recommendation algorithm, which speeds up the convergence speed of the calculation and improves the accuracy and scalability of the recommendation model. The stochastic gradient descent is applied to the SVD algorithm, which accelerates the convergence of the model and improves the performance of the model. Considering the interest changes caused by time factors in SVD, the accuracy of score prediction is effectively improved.

4.5. UI Interface Design. The UI interface is shown in Figure 8. By analyzing the information architecture of multiple local museum APPs in the software market, we can find out the commonalities and differences, sort out the main display contents of the APP, and conclude that the information architecture design of the local museum APP should reflect in terms of understanding information, obtaining information, enhancing information and sharing information, the main content of the museum APP is integrated on this basis, and each functional division is classified into a detailed classification to show the reasonable logic and clear structure of the APP. This forms four main modules: Discovery Museum, Reading Museum, Experience Museum, and Sharing Museum. Among them, the “Discovery Museum” is mainly divided into the museum introduction interface, the museum positioning, and the navigation function interface. The “Reading Museum” part is mainly for the display interface and introduction interface of each exhibition hall in the museum; the “Experience Museum” module mainly provides interactive links for users, such as scanning QR code to obtain cultural relic information interface and interactive game interface; “Sharing Museum” is mainly the user’s personal center interface, which is used to obtain personal collections, concerns, personal information, and other interfaces on the personal homepage, as well as feedback to the museum.

5. Conclusion

Most museums pay attention to the external shape in the display design and lack in-depth research and sorting of cultural relics. The display is only the display and placement of
the physical objects, and there is no more abundant display method. In this traditional single display, it is difficult to improve the visitors’ interest in visiting. Very traditional concept and design, whether it is the display of objects or the setting of signs, they are very single and rigid, and the whole visiting process is boring. The recommendation display design simplifies the regression function of collaborative filtering, improves the recommendation effect, and alleviates the scalability problem. Through this paper, it is concluded that (1) the model tends to improve the existing offline single-action recommendation methods so that it has the ability to make recommendations using streaming data. The idea of collaborative filtering becomes a highly interpretable technique to incrementally learn users’ recent preferences using data streams. In the SIM_COS algorithm,

![Figure 4: Offline recommendation algorithm.](image)

![Figure 5: Multitask learning.](image)

| Algorithm   | RMSE | MAE | RMSE | MAE | ml-100k | ml-1m |
|-------------|------|-----|------|-----|---------|-------|
| CCLU        | 11   | 18  | 15   | 16  | 18      | 16    |
| BKNN        | 14   | 17  | 20   | 15  | 11      | 10    |
| MKNN        | 16   | 10  | 14   | 20  | 19      | 15    |
| SVD         | 14   | 11  | 16   | 15  | 12      | 13    |
| SVD++       | 17   | 16  | 15   | 15  | 18      | 10    |
| SLPE        | 19   | 10  | 13   | 19  | 14      | 19    |
| NMF         | 13   | 13  | 10   | 17  | 16      | 13    |
| OTML-MF     | 14   | 12  | 19   | 12  | 10      | 18    |

Table 3: The optimal performance comparison of the algorithms under different dataset densities.
and 1m-MAE = 3.51. A nonlinear regularization kernel is designed to give the matrix factorization model more flexibility in streaming recommendation. In the SIM_PEAR algorithm, 100k-RMSE = 3.04, 100k-MAE = 3.55, 1m-RMSE = 3.04, and 1m-MAE = 3.28. (2) Use a single user behavior data such as forgetting mechanism to recommend to users. SVD effectively utilizes the interaction data of multiple behaviors ml-100k = 2.89, ml-1m = 1.07, \( \lambda u = 1.09 \), \( i = 1.38 \), \( \eta = 0.25 \), and \( \alpha = 1.23 \). The NMF algorithm can effectively solve the existing problems by making full use of the data of various user behaviors, ml-100k = 2.32, ml-1m = 2.84, \( \lambda u = 2.08 \), \( i = 1.22 \), \( \eta = 1.81 \), and \( \alpha = 0.16 \). A variety of advanced learning techniques such as multitask learning...
and transfer learning are adopted to solve the data sparsity problem caused by insufficient data of a single behavior type. Learning user preferences in OTML-MF interaction data, \( ml-100k = 0.63, ml-1m = 2.44, \lambda_u = 1.87, i = 1.47, \eta = 1.44, \) and \( \alpha = 2.02. \) Use the interaction of multiple behavior types to make recommendations for users through the alternating least squares method. The user’s preference for items is learned from the main behavior and auxiliary behavior, and then, the user is recommended according to the learned preference. (3) The CCLU filtering algorithm considers the user’s feature attributes and interest changes, \( \text{RMSE} = 11, \text{MAE} = 18, \text{RMSE} = 15, \text{MAE} = 16, ml-100k = 18, \) and \( ml-1m = 16. \) The MKNN algorithm takes these factors into account as comprehensively as possible, \( \text{RMSE} = 16, \text{MAE} = 10, \text{RMSE} = 14, \text{MAE} = 20, ml-100k = 19, \) and \( ml-1m = 15. \) Based on the embedded feature and user behavior course recommendation algorithm, a deep learning network is introduced to fully consider the user feature and other features, and a course recommendation model based on the embedded feature and LSTM is established. When performing the nearest neighbor search for similar groups of users, there may be some small flaws in the effect of a single model. (4) The recommendation system algorithm improves the recommendation efficiency by combining the advantages of memory-based and model-based collaborative filtering by adopting smooth processing. When the MAF is 40, the uniformity is the best, \( \text{UBCF} = 1.64, \text{UICCF} = 1.31, \text{User-CT} = 1.34, \) and \( \text{User-CCIC} = 1.47. \) Content-based recommendation algorithms originated from information retrieval. A cross-domain collaborative filtering scoring matrix generation model is used to establish the correlation between multiple scoring matrices by finding a shared implicit cluster scoring matrix, which also improves the recommendation effect and alleviates the scalability problem. When the MAF is 50, the efficiency is the highest, \( \text{UBCF} = 1.98, \text{UICCF} = 1.58, \text{User-CT} = 1.65, \) and \( \text{User-CCIC} = 1.91. \) The adaptive learning rate function, which combines the characteristics of exponential function and linear function, is applied to the SVD++ recommendation algorithm, which speeds up the convergence speed of the calculation and improves the accuracy and scalability of the recommendation model. The stochastic gradient descent is applied to the SVD algorithm, which accelerates the convergence of the model and improves the performance of the model. Considering the interest changes caused by time factors in SVD, the accuracy of score prediction is effectively improved.
Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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