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Article

Biomechanics-inspired utilization 5G multimedia for intelligent title recommendations in low carbon smart libraries through collaborative filtering algorithms

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Abstract: With the popularization of e-readers, electronic reading rooms, digital libraries, and other new ways of reading in libraries and society, libraries have also entered a new stage of development because of "low-carbon" construction. The low-carbon development of intelligent libraries reduces the application of traditional literature carriers, increases the popularity and application of modern equipment, makes the replacement of paper materials, and reduces its own energy consumption. To achieve personalized recommendations in the lending system, this paper, inspired by biomechanical concepts, constructs a tree intelligent recommendation system via a collaborative filtering algorithm. This system functions like a neural network in a biological system, processing and analyzing data to make informed decisions. By verifying the system with actual borrowing data of students, it proves effective, much like how a biomechanical adaptation is tested and validated in nature. This approach offers a valuable reference for intelligent book management in universities, aligning library operations with the principles of efficient resource utilization and adaptation seen in the biomechanical world. book management in universities. In addition to these advancements, integrating biomechanics into the design and operation of smart libraries can enhance user experience and engagement. Understanding the biomechanics of reading—such as posture, hand movements, and eye tracking—can inform the development of ergonomic reading spaces and devices. For instance, optimizing seating arrangements and reading environments based on biomechanical principles can reduce physical strain and improve comfort for users. Moreover, incorporating biomechanical feedback into the recommendation system could personalize user interactions further. By analyzing how different users engage with reading materials—considering factors like reading speed, preferred formats, and physical interactions with devices—libraries can refine their recommendation algorithms. This approach not only enhances the effectiveness of title recommendations but also promotes a healthier reading experience, aligning with the low-carbon goals of reducing physical strain and energy consumption associated with inefficient reading practices.

Keywords: library; collaborative filtering algorithm; k-nearest neighbor search algorithm; 5G multimedia; biomechanics; ergonomic design; user experience

1. Introduction

Low-carbon smart library construction is not only about the actual benefits, but also reflects a cultural concept is an important channel to promote the concept of environmental protection. Libraries themselves shoulder the responsibility of cultural heritage, popularization of knowledge, but also need to actively advocate the green economy, low- carbon environmental protection concept through practical action, to guide the community residents to work together to build an environmentally friendly city, low-carbon earth. The digital library contains a large number of books and titles, and the readers have limited access to information, so they cannot get the widest selection of books. Zhao [1], Zhu and Zhang [2] have emphasized the bibliographic recommendation system can select information needed by readers from a large number of library information resources and display it to readers, saving readers' time to select books. Collaborative intelligent recommendation is a personalized recommendation method to recommend readers' desired books through collaborative filtering algorithm, which includes both collaborative filtering of readers and collaborative filtering of items. Collaborative recommendation is a recommendation method based on big data. Collaborative recommendation needs to mine relevant data from a large amount of data, which requires high computer storage capacity and computing power to realize data mining, and high-quality computer software and hardware background to maintain good operation of collaborative intelligent recommendation of library titles. Collaborative recommendation has been widely used in social media and e-commerce. Combining the characteristics of university library environment, a low carbon smart libraries bibliographic collaborative intelligent recommendation system is designed, and its performance is tested.

2. Status of research on personalized recommendation algorithm

Wang and Hao [3] and Ye [4] have emphasized the basis of bibliographic recommendation in university libraries is the recommendation algorithm, and the research of the recommendation algorithm mainly focuses on collaborative filtering. In addition to the traditional collaborative filtering recommendation algorithm, with the development of various platform media, academic circles have also produced other recommendation algorithms. For example, with the development of Weibo and WeChat, personalized recommendations based on social relationships have emerged. With the development of word segmentation technology, content-based collaborative filtering technology has also made great progress. With the rise of various communities, community-based recommendation has become one of the mainstream recommendation algorithms. Collaborative filtering algorithm is an early recommendation algorithm. It was put forward by Goldberg and others in 1992, and it is one of the most frequently used recommendation algorithms so far. However, the algorithm has some obvious shortcomings, namely sparse data and cold starts. The academic research on this algorithm also focuses on these aspects. 5G Multimedia Technology and Collaborative Filtering Algorithm to Enhance Library Service Landscape.

In order to solve this problem, we can first reduce the data to a low-dimensional space and then use the obtained low-dimensional features to carry out established learning or mining tasks. Effective dimensionality reduction can explore the internal structure and relationship of the original data; not only can it eliminate the redundancy between the data, simplify the data, and improve the calculation efficiency, but it can also greatly improve the understandability of the data and improve the accuracy of the learning algorithm. Dimensionality reduction is one of the main tools to solve the data sparsity problem. It is to map users or items to the hidden variable space to obtain the most salient features between them. Because the comparison between users or items is in the space of dense subsets of high-level features instead of the previous rating space, more meaningful associations can be found. Hong [5] and Yang [6] have emphasized that common methods used in dimensionality reduction means are principal component analysis and decomposition of the scoring matrix, which increase the density of the matrix by reducing the dimensionality of the scoring matrix. To solve this problem, Funk proposed a stochastic gradient descent optimization algorithm in the literature. The algorithm does a loop on the ratings in the training data and corrects the parameters by going in the opposite direction to the gradient to achieve optimization. Cao [7], Wang and Li [8] have emphasized the dimensionality reduction method will alleviate the problem of data sparsity, it will inevitably lose a part of the user's data, which will be inevitably rounded off regardless of whether it is more or less useful for recommendation.

3. Introduction of core algorithms

3.1. Collaborative filtering algorithm

Acquisition and display of user information data: The user information data in this paper comes from the real data of a university library, which mainly includes the basic information of student registration, background borrowing records, and learning behavior data. Obtaining students' basic data is the information basis for personalized recommendations of university libraries. This paper first analyzes the resource needs and book preferences of different users through scoring and praise of book resources by different users and then establishes contact with the knowledge base and display terminal through the data support module to realize personalized recommendations. Integrating all kinds of information in university libraries, there is a lot of data in this information that will not affect the personalized recommendation results. Therefore, the redundant data of this kind of information should be eliminated accordingly, and only a few basic pieces of information should be kept. If key information is missing in the data, it needs to be supplemented, such as call number, borrowing time, and user ID number. After sorting out the obtained data, if there is incomplete data, it needs to be supplemented and corrected. In the data inspection, it is found that there are few data in this situation in the past three years. In order to avoid the big errors caused by data processing in the following, this paper selects the data from the past three years to study user behavior.

Collaborative filtering is interpretable, which can explain why the nearest neighbor in the nearest neighbor list can balance the novelty and accuracy of recommendations more effectively. Li [9] and Zhao [10] have emphasized that the addition of new online items or users can maintain stability. Processing data based on collaborative filtering: Based on the collaborative filtering algorithm, this paper transforms the implicit feedback of users' borrowing records into the explicit rating of book resource categories and solves the problem of data sparseness in university libraries through data changes. That is to say, a collaborative filtering algorithm mainly assumes that users with the same or similar interest points also have similarities in demand, filters useful information by analyzing users' historical behaviors, obtains similarities between different users or different projects by using nearest neighbor technology, and predicts target preferences by using weighted average scores, thus making intelligent recommendations. In this paper, the book categories are further subdivided, and the bibliographies are divided into several categories. According to the privacy feedback of books borrowed by users, it is converted into an interest score for the bibliographic categories, and the user's interest in a certain kind of book resources is measured by the transformation data of the user's interest in the bibliographic categories. The basic idea of collaborative filtering of interest prediction scores is to judge the user's hobbies and interests according to the user's past behavior and to find similar users and become neighboring users. Recommend to the target users according to the overall scores of neighboring users on the project. A simple example is shown in **Table 1**:

Table 1. Example of collaborative filtering.

	Movie1	**Movie2**	**Movie3**	**Movie4**	**Movie5**	**Movie6**
User 1	3	0	4	0	0	5
User 2	0	0	4	0	5	0
User 3	0	5	0	3	0	5
User 4	5	0	5	0	4	0
User 5	0	0	0	4	5	4
User 6	4	0	5	5	0	3

Suppose there are $m \times n$ items in a system (e.g., 6 users and 6 items in **Table 1**), and each value in the matrix represents the user's rating of the item. For example, if user 1 rated movie 1 as 3, when the user does not rate the item, it can be considered as null and can be represented as 0. Chai have emphasized that the recommendation technique of collaborative filtering can also be thought of as the user's predicted rating for the missing value, i.e., the unrated item. Eventually, the predicted ratings are ranked and recommended to the user [11].

Users generally rate items in two ways: One is to give direct scores, which is an explicit scoring, and in some questionnaires, it is common to see how much they like something in a score system. Another way of scoring is implicit scoring; that is, if the user has interacted with an item, it is recorded as interactive; otherwise, it is recorded as no interaction. For example, if a user has checked out a book in the library, it is recorded as 1, and if not, it is recorded as 0. Pang and Zhou have emphasized that once the system has collected enough users' ratings of the items, it can find the nearest neighbor users of the target user by calculating the similarity $\mathrm{sim}(u, v)$ (the calculation of similarity will be described in detail in the next section) [12]. The selection of nearest neighbor users is a means to filter users with similar hobbies to the target user. Filtering out the nearest neighbor users for recommendation can increase the effectiveness of the recommendation and reduce the time and cost of calculation. One is to set a fixed threshold γ, and when the similarity between a user and the target user $\mathrm{sim}(u, v) > \gamma$, the user will be selected as the nearest neighbor. The second method is to set the number of pre-selected nearest neighbor users k in advance and then select the k users with the highest similarity as nearest neighbors. After the selection of nearest neighbor users is completed, all items evaluated by the nearest neighbor users can be treated as a candidate recommendation set, and the scoring formula to predict the target user's rating prediction for all items in this set is:

$$p_j = \sum_{v=1}^{k} sim(u, v_k) \tag{1}$$

In Equation (1), p_j denotes the predicted score of the target user for the *j*-th item, and I_j denotes whether the target user's nearest neighbors have evaluated item *j*. If all the nearest neighbor users have evaluated item *j*, then I_j is 1, and otherwise, it is 0. $sim(u, v_k)$ denotes the similarity between the target user *u* and the nearest neighbor user v_k After calculating the predicted scores of all items in the candidate set, it is possible to rank them and recommend the *N* items with the highest scores to the target user.

3.2. Calculation of similarity

The calculation of similarity is the core part of the collaborative filtering algorithm. Jia et al. have explained that is related to the effectiveness and accuracy of the recommendation algorithm's recommendations [13]. The mainstream similarity calculation methods are the cosine similarity, the Pearson correlation coefficient method, and the Jaccard similarity. The characteristic of cosine similarity is that it focuses more on the difference of vectors in direction rather than in length. Its calculation formula is shown in Equation (2):

$$sim(u, v) = \frac{\sum_{i \in I_{uv}} r_{ui} \times r_{vi}}{\sqrt{\sum_{i \in I_{uv}} r_{ui}^2} \times \sqrt{\sum_{i \in I_{uv}} r_{vi}^2}} \tag{2}$$

In the formula, $sim(u, v)$ denotes the similarity between the target user *u* and the near-neighbor user *v*. I_{uv} is the set of rating items common between user *u* and the near-neighbor user, r_{ui} is the rating of the target user *u* on the *i*-th item, and *vir* denotes the rating of user *v* on the *i*-th item.

The Pearson correlation coefficient method is used to measure the linear relationship of variables, and it will consider that the users' criteria are different when different users rate the items, i.e., the average scores of users may vary greatly, and the Pearson similarity coefficient method will reduce these errors as much as possible. Its calculation formula is shown in Equation (3):

$$sim(u, v) = \frac{\sum_{i \in I_{uv}} (r_{ui} \times \bar{r}_u)(r_{vi} \times \bar{r}_v)}{\sqrt{\sum_{i \in I_{uv}} (r_{ui} \times \bar{r}_u)^2} \times \sqrt{\sum_{i \in I_{uv}} (r_{vi} \times \bar{r}_v)^2}} \tag{3}$$

I_{uv} represents the set of items jointly rated by two users, r_{ui} is the rating of the *i*-th item by the target user $\bar{u}$, r_u denotes the average of all items rated by user *u*, r_{vi} denotes the rating of the *i*-th item by user *v*, and $\bar{r}_v$ denotes the average of all items rated by user *v*. Jaccard similarity is more suitable for comparing the variability between finite sample sets and is useful in data sets with high data sparsity; the larger its ratio, the higher the similarity. The formula for calculating Jaccard similarity is shown in Equation (4):

$$sim(u, v) = \left| \frac{u \cap v}{u \cup v} \right| \tag{4}$$

In the formula, *u* denotes the set of rating items of user *u* and *v* denotes the set of rating items of user *v*. The similarity calculation is the guarantee of recommendation accuracy. Chang et al. [14] have explained there are many kinds of similarity calculation methods, and only three common ones are introduced here. When choosing the similarity calculation method, we should fully consider the scenario of its application and select it according to the characteristics of the similarity calculation method.

3.3. Nearest neighbor search algorithm

The nearest neighbor search method uses the similarity of data to find the target data and is called the k-nearest neighbor search method when the target data is the first k closest. The similarity is usually characterized by the spatial distance of the data, and the closer the distance, the higher the similarity is considered. Xie [15] and Zhu [16] have explained that commonly used ones include Euclidean distance, Pearson product moment coefficient, and cosine similarity. Euclidean distance is the most intuitive, but it is not effective when scoring subjectively influenced; Pearson product moment coefficient mainly reflects the correlation of linear variables; cosine similarity usually reflects the degree of similarity by the angle between vectors.

4. Application of collaborative filtering algorithm in personalized recommendation in university libraries

4.1. User information data acquisition and display

The user information data in this paper comes from the real data of a university library, mainly including the basic information of student registration, background borrowing records, and learning behavior data. This paper first analyzes the resource needs and book preferences of different users through their scores and likes of book resources and then establishes the connection with the knowledge base and display terminal through the data support module to realize personalized recommendations. The data in this paper has 6820 students, involving 395,876 books and 134,571 borrowing records. Liu [17] and Liu [18] have emphasized that in the backend borrowing records of students, it includes information on borrowing and returning books, borrowing methods, and book information. The various types of information in the university library are integrated, and there is a large amount of data in this information that will not have an impact on the personalized recommendation results. Therefore, the redundant data of this type of information is eliminated accordingly, and only a few basic pieces of information are retained. If there is missing key information in the data, the data needs to be supplemented, such as the book request number, borrowing and returning time, and user ID number. In order to avoid errors in the data processing, the data of the last 3 years are selected to study the user behavior.

4.2. Processing data based on collaborative filtering

In this paper, the processing of the data set of university libraries mainly includes the transformation of data changes and implicit data. Implicit data shows the interaction behavior of users with the library, such as browsing and borrowing, etc.

Since implicit data cannot directly reflect students' preferences for different types of book resources and their preferences for book resources, we can only obtain users' preferences from book borrowing records of a certain category and judge users' preferences for books of that category based on the number of times of browsing and borrowing good quantities of that type of book resources. In this paper, based on a collaborative filtering algorithm, combining the views of Pan [19], we transform the implicit feedback of users' borrowing records into explicit ratings of book resource categories and solve the problem of sparse data in university libraries through data changes. In this paper, the book categories are further subdivided into several major categories, and the interest prediction scores are made based on users' private feedback on book borrowing transformed into interest scores on book categories, and the transformed data of users' interest in book categories are used to measure users' interest in a certain category of book resources, and the specific formula is.

$$s(xi) = \lambda\left(1 - \left(\frac{1}{e}\right)^{\frac{xi}{\gamma}}\right) \tag{5}$$

where: *xi* is the number of books borrowed in this category, λ and γ are the correlation coefficients of users and books are, respectively. Liu have emphasized the interest degree is positively correlated with the number of books borrowed, but the increase decreases gradually [20]. In the interest degree, the interest degree of users who consider the number of books borrowed as 5 is significantly higher than that of users who borrow 2 books, but the difference between the interest degree of users who borrow 12 and 15 books is not significant. After the implicit rating transformation, the rating matrix of users and book categories is constructed as.

$$R = \begin{pmatrix} R_{11} & R_{12} & \cdots & R_{1j} \\ R_{21} & R_{22} & \cdots & R_{2j} \\ \cdots & \cdots & \cdots & \cdots \\ R_{n1} & R_{n2} & \cdots & R_{nj} \end{pmatrix} \tag{6}$$

R_{nj} in the matrix is the predicted interest rating of the *n*th user to the *j*-th book category. After the interest rating calculation is completed, the construction of the explicit rating matrix is realized, and the data transformation is completed.

4.3. User-book similarity definition and description

The definition and description of the similarity between users and books need to calculate the similarity between users and books separately. In this paper, the inner product method is used to calculate the book similarity, which indicates the keywords and corresponding weights of different books, and the different keyword information of each type of book is constituted into a vector space. This is consistent with the point made by Zhang [21]. Two similar books are selected for similarity calculation, and the same keywords of these two books are queried, and new vector information is formed based on the same keywords to calculate the similarity of book vectors. Let the two books have *m* common keywords, and the calculation is based on the corresponding different vectors of the two books, and the specific formula is.

$$SIM(W_a, W_b) = \sum_{k=1}^{m} B_{ak} \times B_{bk} \tag{7}$$

where the two books are denoted as W_a and W_b, *Bak* and B_{bk} represent the vectors corresponding to the two books, respectively, *k* is the keyword of the book, and *B* is the weight corresponding to the keyword. The linear weighting formula for the user similarity is.

$$SIM_{A-B} = \lambda(SIM_{num} + SIM_t) + \gamma SIM_{act} \tag{8}$$

where SIM_{num} and SIM_t are the numerical attribute similarity and textual attribute similarity of users, respectively, and SIM_{act} is the active similarity of users. The similarity between user and book is defined and described by comparing the user dynamic information table and the book keyword information, listing the same keywords, recording the frequency of keywords, and using the same algorithm as above; the similarity between user and book vector is calculated by the formula.

$$SIM_{cn} = \sum_{k=1}^{m} B_{ak} \times B_{bk} \tag{9}$$

where: *Cn* is the user, and the association between the user and the book is established by the above formula. The larger the value of SIM_{cn} is, the higher the association between the user and the book is, and the higher the quality of personalized recommendations is.

4.4. Establishing personalized recommendation model for university libraries

The overall structure of the library bibliographic collaborative intelligent recommendation system is shown in **Figure 1**.

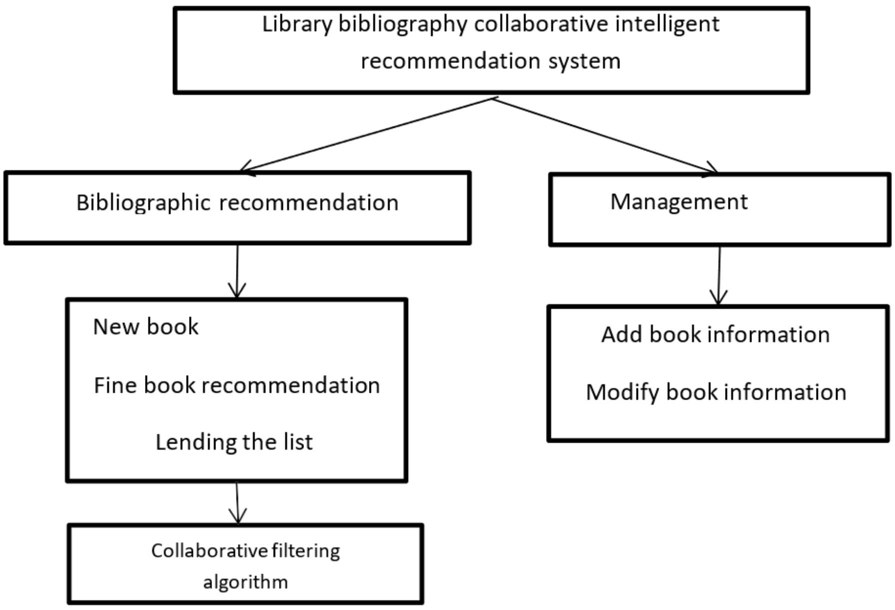

Figure 1. Overall structure of the library bibliography collaborative intelligent recommendation system.

It can be seen from **Figure 1** that the library bibliographic collaborative intelligent recommendation system mainly includes two parts: bibliographic recommendation module and management module. Huang [22], Ye and Shi [23] have mentioned the bibliographic information of the system is displayed to the readers' reading interface with the bibliographic recommendation module, which includes four parts: lending list, fine book recommendation, similar book recommendation, and new book recommendation, and the system realizes the recommendation of different types of books through a collaborative filtering algorithm. The system administrator can use the management module to add, modify, and delete books and update and dynamically release book information in real time.

5. Performance test of library bibliographic collaborative intelligent recommendation system

A university library is selected as the actual application environment, 100 students are randomly selected as the research subjects, and AP and MAP are used as the evaluation criteria of the experimental results, in which the more the system recommends and retrieves book-related information, the higher the AP and MAP values are, and when the AP and MAP values are 1, it indicates that the system recommends and retrieves the highest book-related information; the system does not recommend relevant information, and the system does not recommend relevant information. Zhao stated that the AP and MAP values are 0 [24]. The matrix decomposition system and the semantic filling system were selected for the comparison experiment. When 10 book search terms were input, the top 10 books were evaluated, the relevance of the recommended results to the retrieved books was analyzed, and the AP and MAP values of the different systems were obtained, and the comparison results are shown in **Table 2**.

Table 2. Comparison of the recommended results of different systems.

	This paper system		**Matrix decomposition system**		**Semantic filling system**	
	AP	**MAP**	**AP**	**MAP**	**AP**	**MAP**
1	0.98	0.91	0.75	0.62	0.81	0.83
2	0.93	0.93	0.86	0.81	0.75	0.73
3	0.95	0.92	0.75	0.76	0.72	0.62
4	0.94	0.93	0.83	0.69	0.76	0.46
5	0.95	0.94	0.84	0.81	0.83	0.81
6	0.93	0.94	0.73	0.79	0.76	0.71
7	0.94	0.95	0.82	0.84	0.65	0.61
8	0.95	0.94	0.83	0.76	0.58	0.64
9	0.94	0.95	0.62	0.65	0.73	0.84
10	0.94	0.92	0.64	0.58	0.69	0.76

The experimental results in **Table 2** show that the AP and MAP values of this system are significantly higher than those of the matrix decomposition system and the semantic filling system, and the changes of AP and MAP values of this system are small, so the experimental results show that the recommendation effect of this system is better, and the recommended books have higher similarity with the retrieved books. The comparison results are shown in **Table 3**.

Table 3. Comparison of recommendation time (ms) of different systems.

	This paper system	**Matrix decomposition system**	**Semantic filling system**
1	25	76	82
2	32	91	92
3	36	85	85
4	29	124	105
5	27	165	108
6	30	142	125
7	18	81	147
8	19	105	119
9	17	115	135
10	29	138	124

The experimental results in **Table 3** show that the bibliographic recommendation time of this system is less than 35 ms, while the bibliographic recommendation times of the matrix decomposition system and semantic filling system are higher than 70 ms, which indicates that this system can obtain the ideal bibliographic recommendation results in a shorter time, which can effectively save the readers' retrieval time and can effectively improve the digital library service level. The richness of recommended titles in different systems is higher than 97% in 10 retrievals, while the richness of recommended titles in the matrix decomposition system and semantic filling system is only 84%–93%. The experimental results show that the recommended books are very rich and can meet the needs of different types of readers. The space overhead of different systems is only 13.5%; the space overhead of the matrix decomposition system and semantic filling system is 22.5% and 22.9%, respectively. Carrie and Jia stated that the space overhead of this system is significantly lower than the comparison; the lower the space overhead, the faster the system runs, which proves the higher efficiency of this system [25]. The results are shown in **Table 4**, which shows that 100 students at the school rated the satisfaction of the three systems. The results of **Table 4** show that the average rating of students for this system is 4.1 points, while the average rating of the matrix decomposition system and semantic filling system is only 2.9 points and 3.1 points, which shows that this system can make the readers get higher satisfaction. The study of Chen and Zhu indicates that this method can effectively improve the quality of library services and enhance the satisfaction of readers [26].

Table 4. Comparison of satisfaction of different systems.

	This paper system	Matrix decomposition system	Semantic filling system
Very satisfied/5 points	18	6	5
Satisfaction/4 points	76	22	28
General/3 points	4	45	51
Not satisfied/2 points	2	17	9
Very dissatisfied/1 point	0	6	5
Recommendation is empty/0 point	0	4	2
Average	4.1	2.9	3.1

6. Conclusion

In summary, low-carbon smart libraries have become an important direction for the innovative construction of modern libraries. The library bibliographic intelligent recommendation system based on the low-carbon concept can reduce the consumption of paper products, recommend books to readers in a targeted manner, save resources and space, and also enhance the efficiency of the service. This paper has collected and analyzed user information data, carried out data processing through a collaborative filtering algorithm, defined and described the similarity between users and books, built a smart library bibliographic intelligent recommendation system, and carried out relevant verification, and the results confirmed that the system can improve the satisfaction of readers and improve the quality of library services and provided a corresponding reference for the improvement of low-carbon smart library service functions.

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