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Personalized Book Recommendation Method Based on the Improved Similarity

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Abstract

With the rapid development of network technology, online reading platforms have emerged one after another, providing a new opportunity for book recommendation. Collaborative filtering makes use of the preferences of neighbor users to recommend and predict the interests of target users, in which similarity calculation is the key point. Because the traditional similarity methods cannot take full benefit of the potential relationship between readers. As the result of data sparsity, the similarity matrix is too sparse, which ultimately leads to low recommendation accuracy. This article quantifies the reader's author preferences to build a readers' similarity formula incorporating author preference and Pearson coefficient by introducing Jaccard coefficient, in order to describe the association between readers more comprehensively. According to the proposed similarity, the improved collaborative filtering algorithm can improve the quality of book recommendations significantly. Finally, this paper performs simulation experiments on the Book-Crossing dataset. The results show that the collaborative filtering algorithm based on the improved similarity can effectively improve the quality of personalized book recommendation.

Keywords

Collaborative filtering, Pearson coefficient, author preference, book-recommendation.

1. Introduction

In recent years, the vigorous development of online literature have provided readers with rich reading materials. Nevertheless, how to provide readers with satisfactory recommendations accurately and efficiently in a short period of time, meanwhile, make full use of existing book resources is an urgent problem for current online reading platforms. In order to proactively provide users with information that can meet their interests and needs without importing clear search term, recommendation systems are regarded as one of the important and effective methods to solve the problem of information overload[1].

The recommender generate recommendations for target users based on the user's information needs, historical behavior data by a certain recommendation algorithm [1,2]. Collaborative filtering recommendation algorithm is currently the most widely used recommendation method. The basic principle is generating the prediction of score to a certain item from target user by exploiting similar users' preference [1,2,3]. Collaborative filtering composes of memory-based collaborative filtering and model-based collaborative filtering. Specifically, memory-based collaborative filtering can be represented by two methods: item-based collaborative filtering and user-based collaborative filtering [4]. The point is that whether item-based similarity or user similarity plays an initiative role in making recommendations. This paper mainly studies the improved recommendation algorithm based on user-based similarity.

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At present, with the ascendant development of network technology, online reading platforms, various literary works have emerged one after another, arising the 'information overload' problem, there are following two challenges:

(1) Different readers have different reading habits and requirements for books. This is specifically reflected in literary genres, narrative methods, linguistic expressions, and plot arrangements. How to predict the potential need of users based on their past behavior records?

(2) In this era of 'national creation', the quality of literary works varies widely. In order to avoid a good work to be 'cold', at the same time, improve readers' loyalty to online reading platforms, how to find classic literature, recommend high-level works for readers, and then improve readers' satisfaction?

This shows the importance of improving book recommendation algorithms in which provide readers with books that match their interests. In real life, different authors specialize in different writing categories, narrative styles and linguistic expressions. For example, Liu Cixin is good at writing science fiction novels, and readers who like the trilogy of "The Three Body Problem" can continue to read other works of the author. Therefore, the 'author' attribute can be used not only as an inherent characteristic of the book, but also to describe the characteristics of the reader's hobbies and reveal the reader's behavior habits.

In view of this, this paper will improve the similarity calculation by quantifying the reader's author preferences, construct a conprehensive readers' similarity fusing author-preference similarity, generate a personalized book recommendation model based on improved similarity.

2. Memory-based Collaborative Filtering

2.1. Traditional Collaborative Filtering Algorithm

In the collaborative filtering algorithm, in order to generate recommendations for target users, it is necessary to search the neighbors of the target user according to rating matrix, and generate ratings by the preferences of the neighbor users. Specifically, when the user-based CF needs to calculate the prediction score of the unrated item i by the user u, it first needs to find the neighbor userset N (u) of the user u, and calculate the weighted prediction score of the neighbor users on the item i. There are three main steps:

(1) In the known user rating matrix $R = [r_{ui}]_{M\times N}$, exploit Pearson similarity or modified cosine similarity (ACOS) to calculate the similarity between the target user u and all other users in the user set;

(2) Select the N users closest to the target user u as the neighbor user set N (u) according to the similarity value;

(3) The predicted score of user u for product i is obtained by calculating a weighted average of the ratings of all neighbor users for product i.

Apply to the book recommendation scenario, it means that calculate the similarity between readers based on the book's ratings, find the set of neighbor readers of the target reader u, and predict the target reader u's performance on book i by calculating the weighted average of the neighborhood reader's ratings for book i, and finally get a list of recommendations. The users'similarity computation is a key step of collaborative filter (CF) algorithm. Common similarity calculation methods include cosine (COS) similarity, Pearson similarity, and modified cosine (ACOS) similarity. These similarity calculation methods are mainly based on vectors, that is, calculate the similarity between users by regarding a user's ratings of all items as a vector. However, with the rise of online literature, both works and audiences have increased on a large scale, resulting in extremely sparsity of reader-book scoring matrices, the effectiveness of the above-mentioned similarity calculation method has been reduced. Therefore, in recent years, many studies have been devoted to improving the accuracy of similarity calculation in condition

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of sparse data. Cheng et al. introduced the user's preference similarity for non-commonly evaluated items, and redefined the user similarity based on the Penson Correlation Coefficient [5]; Nikolaos et al. proposed the the threshold of the number of commonly-rated items and threshold of the size of the Pearson correlation coefficient. The similarity calculation is divided into N stages, and the similarity is scaled according to whether the constraint is satisfied [6], and then an improved dynamic multi-stage similarity calculation method is considerd, where the number of stages is determined by the volume of the data set [7] Wu Hang et al. fused global trust value, expert system value, improved propagation trust value, and improved Pearson correlation coefficient to construct a latent trust model, using the final trust value between users instead of the similarity coefficient in the traditional method [8]; Wang Zhan, etc. constructed a user trust matrix, combined with the user similarity matrix (calculated based on Pearson correlation coefficient) to construct a users' comprehensive similarity matrix [9]. These algorithms improve the calculation of similarity to a certain extent, but still have certain defects.

In the traditional similarity calculation method, Pearson similarity is widely used because it is easy to understand and simple to calculate. The specific expression is shown in formula (1):

$$s'(u,v) = \frac{\sum_{i\in I_{u,v}}(r_{u,i}-\bar{r}_u)(r_{v,i}-\bar{r}_v)}{\sqrt{\sum_{i\in I_{u,v}}(r_{u,i}-\bar{r}_u)_2}\sqrt{\sum_{i\in I_{u,v}}(r_{v,i}-\bar{r}_v)_2}} \tag{1}$$

$I_{u,v}$ represents a book set jointly evaluated by the user u and the user v, and $\bar{r}_u$ represents the average score of the books in the book set $I_{u,v}$ by the user u, $\bar{r}_v$ represents the average rating of user v.

Pearson similarity is generally used to calculate the correlation between two interval variables. Its value defines between [-1, 1], and a value of 1 indicates that two users have completely consistent evaluations of each item.

2.2. Defects of Traditional Similarity Calculation Methods

With the rapid development of online reading platforms, the popularity of online literature has consistently increased, and the number of users and online literature has grown exponentially, which has resulted in an extremely sparse user rating matrix. Although the above-mentioned similarity calculation method has been widely used, it is still difficult to obtain a true nearest neighbor set. The main reasons are summarized as follows.

1) The effect of the number of commonly-rated items on similarity is not considered

Analyzing traditional similarity calculations, it can be found that although the number of commonly-rated items of two users is very small, they may only account for 1% of the rated items, but there is a very high similarity between them. For example, in the ratings matrix as shown in Table 1, calculate the similarity between u1, u2, and u3 by traditional Pearson similarity. Intuitively, u1 and u2 have only 2 commonly-scored items, while u1 and u3 have 4 commonly-scored items, moreover, the ratings are similar, so sim (u1, u3) should be greater than sim (u1, u2). However, the Pearson similarity between u1 and u3 is only 0.9683, still the similarity between u1 and u2 is 1, which is obviously unreasonable.

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Table 1. A sample ratings matrix

	i1	i2	i3	i4	i5
u1	5	3	0	2	1
u2	5	0	0	3	0
u3	4	3	0	2	2
u4	1	2	1	2	1
u5	4	5	4	5	4

2) Average rating

Traditional similarity calculation methods, including Pearson and ACOS, calculating the linear correlation between two user rating vectors, neglect the difference in the value in each dimension. As we know, user's rating standards are different, resulting in a difference in the specific rating for each item. As listed in figure 1, the rating vectors for u4 and u5 are (1, 2, 1, 2, 1) and (4, 5, 4, 5, 4) respectively, the Pearson coefficient between them is sim (u4, u5) = 1. But at the point of the value of scores, u4 dislike these five items, while u5 likes them. The insensitivity to numerical values leads to inaccuracy of similarity, which needs to be corrected.

3) Users' similarity is too sparse

Calculate the similarity between two users accrossing the user-item scoring matrix literally can't take full benefit of potential relationship between readers. It results in too sparse similarity matrix . In order to solve this problem, many experts and scholars introduce supplementary information such as demographic information or user trust relationships to build comprehensive similarity based on Pearson similarity. However, supplementary information in China is often difficult to obtain, since users will submit false information due to privacy protection. Consequently, it will increases the difficulty in data collection.

The above problems become more and more serious with the expansion of the scoring matrix, making traditional similarity calculation methods unable to effectively measure the similarity between users and reduce the quality of recommendations.

3. Collaborative Filtering Algorithm Based on Improved Similarity

At the basis of the Pearson coefficient, this paper introduces the Jaccard coefficient to alleviate the impact of the number of common scoring items on the similarity calculation, and uses the reader-book scoring matrix to quantify the reader's "author preference" without introducing additional information of additional dimensions , And calculate reader similarity based on" author preferences ", combined with Pearson similarity, construct a comprehensive similarity that incorporates author preferences, and more accurately calculate the association between readers.

3.1. Users'Similarity Fusing Author Preference

As we all know, we usually take film genre, director, actor and country information as the characteristics of movies, and performance and quality as the characteristics of electronic products [10]. Similarly, we can use the author, catagory, and country information as the characteristics of the book. [11] Because different authors have special writing styles, this paper chose the author set A (a1, a2, ⋯, aT) as a latent feature relevant to book content and category. Firstly, construct the reader-author scoring matrix A on the basis of the reader-book scoring matrix Y, where ru, a represents the degree of reader u's preference to author a, being calculated by Equation (3).

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$$A = \left(r_{u,a}\right)_{N\times T} = \begin{array}{c} \\ u_1 \\ u_2 \\ \vdots \\ u_N \end{array} \begin{array}{c} \begin{array}{cccc} a_1 & a_2 & \dots & a_T \end{array} \\ \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1T} \\ r_{21} & r_{22} & \dots & r_{2T} \\ \vdots & \vdots & \ddots & \vdots \\ r_{N1} & r_{N2} & \cdots & r_{NT} \end{pmatrix}_{N\times T} \end{array} \tag{2}$$

As mentioned earlier, each author has his own writing style, and the author's attributes can not only be used as the characteristics of the book, but also describe the reader's reading habits and preferences [12].

3.1.1. Users' Author Preference

The prediction of the preference of a user u for a author a of a book i, as $r_{u,a}$, can be computed as follows,

$$r_{u,a} = \frac{\sum_{i\in I_u, a\in A_i} w(i,a) * r_{u,i}}{\sum_{i\in I_u,, a\in A_i} w(i,a)} \tag{3}$$

where Iu denotes the set of books rated by the user u and a denotes the set of authors of the book i. Besides, $r_{u,I}$ denotes the rating on the book i by u. The w(i, a) is a function to indicate whether the book i has the author a, if a is in the author set of book i, $w(i,a)=1$;else, $w(i,a)=0$.

3.1.2. Users'Similarity Fusing Author Preference

The calculation of similarity between reader u and reader v based on the author preference is similar to the form of Pearson coefficient:

$$s''(u,v) = \frac{\sum_{a\in A_{u,v}} (r_{u,a} - \tilde{r}_u)(r_{v,a} - \tilde{r}_v)}{\sqrt{\sum_{a\in A_{u,v}} (r_{u,a} - \tilde{r}_u)^2}\sqrt{\sum_{a\in A_{u,v}} (r_{v,a} - \tilde{r}_v)^2}} \tag{4}$$

where $r_{u,a}$ corresponds to the predicted rating given by u on author a, and $\tilde{r}_u$ corresponds to the average rating given by u on all the authors, $A_{u,v}$ corresponds to the set of common-rated authors.

3.2. Collaborative Filtering Based on Proposed Similarity

Traditional collaborative filtering is based on common-rated items, with sufficient rating data, current calculations of similarity can perform well. However, with the rapid emergence of various literary works, as well as the extremely sparse scoring data, the traditional similarity computation is disable to measure the similarity between users accurately, which reduces the precision of the recommendation algorithm. This paper proposes to use "author preference" as an attribute to reveal user behavior habits, then incorporate readers'similarity based on "author preference" with traditional Pearson coefficient to redifine a comprehensive similarity between readers. It can effectively alleviate the extreme sparsity. Moreover, the introduced Jaccard coefficient might induce the influence which neglecting the number of common-rated items lead to. The improved similarity calculation method is as follows:

$$s = \lambda * s'(u,v) + (1-\lambda)s''(u,v) \tag{5}$$

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Where, $\lambda = \frac{1}{1+e^{-C(u,v)}}$, C(u,v) corredponds to the Jaccard coefficient between user u and v. Jaccard coefficient describes the similarity between sets, effectively making up for the shortcomings of vector-based similarity such as Pearson, which only considers user ratings and ignores the number of common scoring items, is particularly suitable for applying to data with high sparsity meanwhile. Jaccard coefficient is defined as follows:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A|+|B|-|A \cap B|} \tag{6}$$

Applied to the field of book recommendation, A represents the collection of books reviewed by user u, B represents the collection of books reviewed by user v, and J (A, B) represents the size of jointly evaluated books set divided by the size of evaluated book union of user u and v.

In the proposed similarity calculation formula, the reader's Pearson coefficient based on the scoring matrix is calculated by s' (u,v) and the similarity based on the author preference is calculated by s'' (u,v). Pearson coefficient can only exploit the ratings of co-evaluated books. s'' (u,v)can make full use of the ratings of non-co-evaluated books [13]. Explains the reader's author preference. The introduced Jaccard coefficient avoids the number of co-graded items The impact of similarity calculations more accurately explains the association between users. Therefore, the improved similarity not only can describe the reader's reading preferences more accurately, the introduced Jaccard coefficient avoids the impact of the number of common scoring items on the similarity calculation, so that explains the association between users more truely.

Now, a collaborative filtering recommendation algorithm based on improved similarity is obtained. The process of the algorithm are as follows.

1) To construct a reader-book scoring matrix based on readers' rating data for books, calculate the reader's author preferences by Equation (3), and build an author preference matrix;

2) To calculate the Pearson similarity s' and the similarity s'' based on the author preference by formulas (1) and (4), respectively;

3) To calculate the comprehensive similarity between users by formula (5).

4) To select the neighbor user set of the target user for prediction acrossing the result of step 3).

5) To predict the target user's score on the item on the basis of the preference of the neighbor user set. The prediction formula is as follows:

$$p_{u,i} = \overline{r_u} + \frac{\sum_{v \in N_u} sim(u,v) \times |r_{v.i} - \overline{r_v}|}{\sum_{v \in N_u} sim(u,v)} \tag{7}$$

where, p (u, i) represents the predicted score of user u to book i, $\overline{r_u}$ represents the average score of user u, N_u represents the set of neighbor users of u, and sim (u, v) represents the compreh ensive similarity between user u and v, $r_{v.i}$ represents user v's rating to book i.

6) Finally, a Top-K recommendation is generated according to the prediction of rating.

The specific flowchart of collaborative filtering recommendation algorithm based on improved similarity is shown in the figure:

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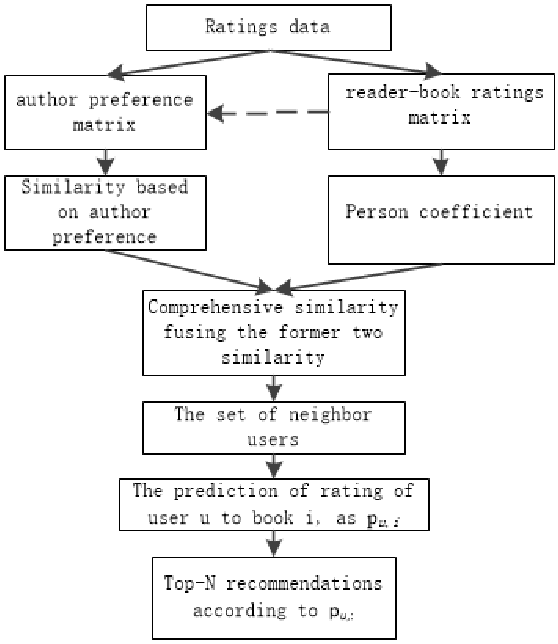

Fig 1. The flowchart of CF based proposed similarity

4. Experiment

4.1. Dataset

This paper uses the Book-Crossing data set to test the algorithm. The data set includes BX_Books, BX_Users, and BX_Book_Ratings. The BX_Books data set contains the isbn, book title, author, year of publication, and publisher attributes. The BX_Users data set contains the user's id account, location, and age attributes, the BX_Book_Ratings dataset contains user id, book isbn, and rating information.

This article selects 30475 subset of the dataset, including 448 users, 5043 books, 1998 authors, with a rating range of 1-10, in which each user has reviewed at least 100 books, and each book has been rated at least 10 readers. On this basis, 80% of the data is randomly selected as the training set, and the remaining 20% as the test set.

The sparsity of the reader-book scoring matrix for the experimental dataset is

$$\frac{30475}{448 * 5043} = 0.013489$$

The key point is the construction of comprehensive similarity fusing the author preference. First, the Pearson similarity matrix between readers is constructed according to the reader-book scoring matrix. Second, the reader-writer scoring matrix is constructed based on the second section in order to compute similarity matrix based on author preference; Finally, combining the first two similarity matrices, using the deformation of the Jaccard coefficient as the adjustment coefficient, according to formula (13), the reader comprehensive similarity matrix incorporating author preferences is constructed:

$$S = (s_{u,v})_{N\times N} = \begin{array}{c} \\ u_1 \\ u_2 \\ \vdots \\ u_N \end{array} \begin{array}{c} \begin{array}{cccc} u_1 & u_2 & \cdots & u_N \end{array} \\ \begin{pmatrix} s_{11} & s_{12} & \cdots & s_{1N} \\ s_{21} & s_{22} & \cdots & s_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ s_{N1} & s_{N2} & \cdots & s_{NN} \end{pmatrix}_{N\times N} \end{array} = \lambda \cdot \begin{array}{c} \\ u_1 \\ u_2 \\ \vdots \\ u_N \end{array} \begin{array}{c} \begin{array}{cccc} u_1 & u_2 & \cdots & u_N \end{array} \\ \begin{pmatrix} s'_{11} & s'_{12} & \cdots & s'_{1N} \\ s'_{21} & s'_{22} & \cdots & s'_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ s'_{N1} & s'_{N2} & \cdots & s'_{NN} \end{pmatrix}_{N\times N} \end{array} +$$

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$$(1-\lambda)\cdot\begin{array}{c|c} & \begin{array}{cccc} u_1 & u_2 & \dots & u_N \end{array} \\ \begin{array}{c} u_1 \\ u_2 \\ \vdots \\ u_N \end{array} & \begin{pmatrix} s"_{11} & s"_{12} & \cdots & s"_{1N} \\ s"_{21} & s"_{22} & \dots & s"_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ s"_{N1} & s"_{N2} & \cdots & s"_{NN} \end{pmatrix}_{N\times N} \end{array}$$

Where, $\lambda = \frac{1}{1+e^{-C(u,v)}}$, C(u,v) corredponds to the Jaccard coefficient between user u and v.

4.2. Evaluation Matrics

4.2.1. Presion and Recall

Generally, the recommendation performance can be evaluated according to Precision and Recall. The recall rate refers to the proportion of recommended items that meet user's interests in the user's true interests set; the accuracy rate refers to the proportion of recommended items that meet user's interests in the total recommended item set. The formulas for the Recall and Presion are shown in equations (9) and (10).

$$Recall = \sum_{i=1}^{M} \frac{L_i}{M\times P_i} \tag{9}$$

$$Precision = \frac{\sum_{i=1}^{M} L_i}{M\times N} \tag{10}$$

where, Pi represents the total number of items in the user's true interests set, Li represents the recommended items that meet the user's interest, M represents the total number of users, and N represents the total number of recommended items.

4.2.2. F-value

F-value is used to evaluate the overall performance of recommendation algorithm, shown in formula (11).

$$F-value = \frac{2\times \text{Recall x Precision}}{\text{Recall+ precision}} \tag{11}$$

F-value represents the harmonic average of Precision and Recall. The higher the F -value, the better the recommendation algorithm.

4.3. Results and Anlysis

This chapter proves the feasibility of the algorithm proposed in this paper by designing comparative experiments, comparing the results of traditional collaborative filtering algorithms and collaborative filtering algorithms based on improved similarity in book recommendations.

According to the improved similarity-based book recommendation algorithm proposed in Section 3.2, import the data into the algorithm, set the number of neighbors to 20, randomly select users with id 139, calculate the prediction of scores, and rank the results from high to low. The top 10 books are used as the recommendation list. The result is shown in figure 2. The recommendation list can show the id, name, and reason of the recommended book. The reason for the recommendation is that neighbor users who have a high similarity with user 139 have read this book and have high comprehensive evaluation generally.

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book id	book name	from userid
2515	Message in a Bottle	[385, 356, 7, 11, 14, 141, 202, 229, 293, 303, 309]
1052	Bridget Jones's Diary	[385, 385, 124, 402, 14, 172, 309]
993	The Lovely Bones: A Novel	[124, 14, 172, 198, 217, 303]
831	The Red Tent (Bestselling Backlist)	[385, 124, 172, 293, 309]
1271	Timeline	[124, 166, 356, 402, 141, 217]
1844	The Da Vinci Code	[124, 14, 91, 202, 217, 229]
133	The Client	[124, 143, 11, 14, 202]
854	The Nanny Diaries: A Novel	[124, 14, 172, 198, 309]
3704	Divine Secrets of the Ya-Ya Sisterhood: A Novel	[385, 172, 202, 303]
541	The Secret Life of Bees	[385, 124, 124, 14, 229]

Fig 2. The recommendation list of user 139

Calculate the Precision, Recall and F-value of each algorithm. The results are shown in Table 2. According to it, the collaborative filtering recommendation based on improved similarity is better than the collaborative filtering based on cosine similarity and the Pearson similarity respectively, which is more feasible on book recommendation in Book-Crossing.

Table 2. The comparation on performance of different algorithm

algorithm	Precision	Recall	F-value
COS	23.41%	17.71%	20.16%
Pearson	26.74%	19.90%	22.82%
Proposed	30.13%	23.73%	26.55%
	(28.71%↑)	(33.99%↑)	(31.66%↑)
	(12.68%↑)	(19.25%↑)	(16.35%↑)

It can be seen that the collaborative filtering based on Pearson similarity is the cosine similarity on the Book-Crossing dataset, and the improved similarity proposed in this paper has the best performance and accuracy. The Precision is improved by 12.68% and 28.71% than the former two respectively, and the F value increased by 16.35% and 31.66%, respectively. It shows that incorporating the "author preference" and the Jaccard coefficient into the similarity computation can more accurately calculate the association between readers, thereby improving the recommendation performance.

5. Conclusion

This paper analyzes the shortcomings of traditional similarity calculation methods, and introduce Jaccard coefficient and "author preference". Based on the Pearson similarity, it integrates reader similarity based on "author preference" to construct a comprehensive similarity that can more accurately describe the association between readers, propose a collaborative filtering recommendation method based on improved similarity. This algorithm can effectively reduce the impact of the number of common-rated items on the calculation of similarity, and at the same time alleviate the oversparseness of user similarity. Experimental results show that the algorithm significantly reduces the negative impact of traditional similarity calculations and improves the quality of book recommendations.

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