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A Personalized Time-Sequence-Based Book Recommendation Algorithm for Digital Libraries

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ABSTRACT Book recommendations are of great significance in colleges and universities. Although current recommendation approaches have made significant achievements, these approaches do not consider college students' similar learning trajectories in the same major. In order to recommend books more accurately, mining the knowledge system is very crucial for college students in the same major. This paper proposes a personalized book recommendation algorithm that is based on the time sequential collaborative filtering recommendation, combined with students' learning trajectories. In order to recommend books effectively, our algorithm leverages space distance. In this algorithm, we consider two important characteristics: the time sequence information of borrowing books and the circulation times of books. Our experimental results demonstrate that our book recommendation algorithm is in accordance with the college students' demand for professional learning.

INDEX TERMS Time sequence information, collaborative filtering, book recommendation.

I. INTRODUCTION

An academic library plays an important role in teaching and supporting scientific research in universities. In recent years, universities have increased their financial investment and purchased abundant electronic resources. Books share a significant proportion of these fitted resources. The number of library holdings ranges from tens of thousands to millions. The question how to guide readers to make full use of library resources is a primary issue, which the administrators need to consider.

A considerable number of readers go to the library without explicit aims. Some readers may come to the library to kill time, and they may feel hard to choose appropriate books for reading because they face a mass of books. The others go to the library with some goals, but the goals are not specific. They only know what kind of books they want to read, but they are not clear which books to borrow. It is a very common phenomenon for readers to face information overload. Someone or some tools are needed to help them filter and make a selection. If there is a person by your side at this moment, you can ask him for help to recommend a few books. However, you cannot always have an "expert" by your side to serve you. You need to choose some books with the help of some tools, which are recommendation systems.

Recommender systems link users and items automatically by the recommendation algorithm. They have attracted comprehensive attentions [1]. Recommender systems can help users find the information they are interested in and push the information to them in information overload environments. According to different recommendation strategies, recommendation algorithms can be categorized into a content-based recommendation, collaborative filtering-based recommendation, association rule-based recommendation, utility-based recommendation, knowledge-based recommendation and hybrid recommendation [1], [2]. Collaborative filtering recommendation was first proposed by Goldberg in 1992 and was applied to the research-based email recommendation system called the Tapestry [3]. Collaborative filtering recommendation algorithm determines target users' preferences for a particular product by adopting the user behavior, which is similar to target users (score, clicks, etc.), then makes a recommendation according to the preference degree [4]. Collaborative filtering recommendation algorithm has become one of the most promising recommendation algorithms.

In this paper, we propose a personalized time sequence information collaborative filtering recommendation algorithm to improve book recommendation. The main contribution of our methods is that it combines students' learning trajectories with time-sequence-based collaborative filtering recommendation algorithm in order to increase recommendation accuracy rate.

The remaining sections of the paper are organized as follows: Section II introduces the related works on recommender systems; a personalized time sequence information recommendation algorithm is proposed in Section III; Section IV demonstrates experimental results, and our conclusions are given in Section V.

II. RELATED WORK

Recommender systems have been widely applied in many domains such as book, music, and movie recommendations [4]. In recent years, with the rapid development of information technology, an increasing number of books are shared in many digital libraries. To some extent, recommender systems can help readers to find relevant books.

Recently, some scholars have made a lot of progress in recommender systems. Lu et al. [5] proposed a content-based filtering and collaborative filtering methods. The collaborative filtering recommendation algorithms can be divided into two types: the memory-based and the model-based. Some scholars also divided them into the neighbor-based and the model-based [6]. Although their names are different, the description of the core content of classification algorithm is similar. Antonio Hernando et al. proposed a prediction method of collaborative filtering recommendation for the ratings of users based on Bayesian probabilistic model [7]. Park et al. [8] proposed a rapid collaborative filtering algorithm, which uses the k-nearest neighbors to replace k similar neighbors. Kouki et al. [9] designed a hybrid probabilistic extensible hybrid recommendation method, which could automatically learn and make predictions by incorporating different information signals.

The memory-based collaborative filtering algorithm calculates the similarity between users or products according to the existing data set and selects users or products that contain high similarity as neighbors of the target users. Then calculating neighbors' rating is used to predict target user's preference degree for a particular product. This type of recommender system provides a recommendation on the basis of the preference degree [10].

The model-based collaborative filtering algorithm draws a model by learning the training data set and uses the model to predict the unknown data. Typical model-based collaborative filtering includes the clustering-technique-based collaborative filtering, probability-method-based collaborative filtering, and matrix-decomposition-based collaborative filtering, etc. [10].

The core advantage of the traditional collaborative filtering is that it can provide recommendation service for users under the circumstance of not considering the content of recommended items. Because users intervene less during the process of recommendation, and the technology is easy to implement, collaborative filtering has become a popular recommendation technology. The ratings of the related items are usually calculated in the process of recommendation, but the related time sequence behavior information is easily ignored. Many scholars proposed the improved recommendation algorithm based on time sequence information for this problem.

Time-sequence-based recommendation algorithm adds time sequence information into the existing recommendation model. This algorithm enables the model to learn the data changing over time. Furthermore, the recommended dataset will be optimized. As a consequence, the accuracy of recommendation results would be improved. Gao et al. [11] developed an improved collaborative filtering recommendation algorithm with time adjusting. Zhou et al. [12] considered time factor and proposed a hybrid recommendation algorithm to increase the accuracy of users' similarity computation. A real-time stream-based recommendation algorithm was proposed based on collaborative filtering [13]. Some scholars add time sequence information into the feature vector of the user (product) [14]. Some scholars also take time information as the third dimension and then use tensor decomposition to model dynamic change [15]. There are also some scholars assigning users (products) to different clusters dynamically by evolutionary combined clustering approach, and make further recommendations [16]. Additionally, there are some other novel recommendation approaches [17]–[20].

III. ALGORITHM DESIGN

College students with the same major have very similar learning trajectories. These students often go to the library to borrow books to assist learning. Definite time sequence regularity exists in the borrowing process. Integrating time series information into the traditional book recommendation algorithm plays an important role in improving the accuracy of book recommendations. The learning of knowledge system has an order. The recommendation algorithm that considers the time sequence information can provide reasonable and effective book recommendation for the readers who are about to learn some knowledge.

On the basis of time-sequence-based collaborative filtering recommendation algorithm combined with the time characteristics of book circulation, this paper proposes a personalized collaborative filtering recommendation algorithm based on time sequence information of book. In order to recommend books reasonably and effectively, we adopt two characteristic factors in our algorithm: the time sequence information of borrowing books and book circulation times. Our algorithm takes as input these two characteristic factors and calculates the distance. Recommendation results are generated according to the distance value.

The motivation of our algorithm is as follows:

1) Algorithm is easy to implement. Algorithm design is simple to program. Commonly used recommendation algorithm requires readers to pay extra time for rating and calculates the recommended content based on the results of the rating. While users are often not willing to pay extra time to participate in the rating process, resulting in a sparse rating matrix, the recommended effect is not effective. In this paper, two variables involved in this algorithm can be found in any circulating management system, and the recommendation

results can be given without user participation, which is easier to realize.

2) The recommendation results conform to the students' professional learning process. Students with the same major learn in accordance with the same knowledge system. That means the order of what to learn first and what to learn next are almost the same. Our algorithm constructs a book recommendation result that accords with students' professional learning knowledge system by learning and modeling historical circulation data. It can guide students to borrow, promote the professional knowledge learning and improve the utilization ratio of books.

Thus, the main contribution of our proposed book recommendation algorithm is that the recommendation results are more in accordance with the readers' learning regulation.

A. ALGORITHM DESCRIPTION

When readers borrow a book or browse a book on the website, the system will recommend related books by the time-sequence-based algorithm. Our algorithm uses distance to denote the relationships between books. The shorter distance means the closer relationships. Two variables used in the calculation of distance are the time sequence information (the time interval of the borrowing of two kinds of books) and the circulation times. With the decrease of the time interval and the increase of the circulation times, the relationships become stronger. The algorithm makes order-reverse transform to the circulation times because the inverse relationship between two variables is not conducive to the calculation.

The symbols used in the algorithm are described as follows: b_j is defined as the book that readers borrow or read. b_k is a book appeared after b_j in the borrowing set of all the readers who borrowed b_j. $L = \{\{l_1\}, \{l_2\}, \{l_3\} \ldots \{l_m\}\}$ is the borrowing set of all the readers who have borrowed b_j, m is the element number in the set L. $l_i = \{(t_{i1}, b_{i1}), (t_{i2}, b_{i2}), (t_{i3}, b_{i3}) \ldots (t_{in}, b_{in})\}$, and L is the borrowing record set of a reader who has borrowed the book b_j. t_{i1} is the borrowing time of the book b_{i1}. t_{ij} is the borrowing time of b_j in the set l_i. t_{ik} is the borrowing time of b_k in the set l_i.

Our algorithm is described as follows: First, Algorithm looks up the records of readers who have borrowed book b_j and generate the set L. Then, it calculates the time sequence information and the circulation times of b_k which appears after b_j in the borrowing set. And the time sequence information is the difference between t_{ik} of b_k and t_{ij} of b_j. The algorithm calculates the time sequence information of all the readers who borrow b_k in the set L, then calculate the average value of the time sequence information T_k (see equation (2)) and the circulation time N_k.

Equation (1) is used to calculate the relationship between (b_j, b_k) and is repeatedly used to calculate all the relationships between all the books in the set L and b_j, and generates the recommendation results according to the distance from minimum to maximum order.

$$\mathrm{dis}\left(b_j, b_k\right) = \sqrt{T_k^2 + (N' - N_k)^2} \tag{1}$$

$$T_k = \sum\nolimits_{i=1}^{m} \left(t_{ik} - t_{ij}\right) / N_k \tag{2}$$

where N_k is the number of times b_k appears after b_j in all the set l_i. $N' = \max(N_1, N_2, N_3 \ldots\ldots)$ is the biggest book circulation times. In order to obtain satisfactory results, we reverse the change of circulation times. Finally, the relatively effective method among them is $(N' - N_k)$, which produces recommended results with the highest accuracy.

Take the data in Table 1 as an example, using the above method to generate book recommendation information that is related to b_3.

TABLE 1. Readers' borrowing record.

Borrowing record l_1		Borrowing record l_2		Borrowing record l_3	
Borrowing time	Book	Borrowing time	Book	Borrowing time	Book
2013-12-08 11:34:38	b_9	2012-11-03 10:21:25	b_4	2013-06-08 08:34:22	b_3
2014-03-08 10:28:15	b_7	2012-12-06 15:09:05	b_3	2013-06-08 08:34:26	b_5
2014-03-08 10:28:20	b_3	2013-03-03 11:01:23	b_8	2013-07-09 11:09:27	b_1
2014-03-16 13:30:16	b_2	2013-03-26 10:03:16	b_1	2013-07-10 13:34:08	b_6
2014-04-15 09:10:12	b_1	2013-04-13 09:12:01	b_5	2013-08-17 11:16:16	b_2

Search the borrowing records of the books borrowed after b_3 in sets l_1, l_2, l_3 and calculate their time sequence information and circulation times one by one. For example, b_2 is after b_3 in l_1, l_3 and it requires us to calculate its time sequence information in l_1, l_3 separately.

N_2 is the times that b_2 appears and obviously it is 2 according to Table 1.

T_2 = ((borrowing time of b_2 in l_1 - borrowing time of b_3 in l_1) + (borrowing time of $b_2$in l_3 - borrowing time of b_3 in l_3))/N_2 = ((2014-03-16 13:30:16-2014-03-08 10:28:20)+(2013-08-17 11:16:16-2013-06-08 08:34:22))/2 = 39.02 (days)

We use the same calculation method to deal with b_1, b_5, b_6, b_8 and the results are in the second column and the fourth column in Table 2 below.

TABLE 2. Calculation results.

Book	T	Standardized T	N	Standardized N	Distance	Order
b1	59.54	53.82	3	100	53.82	2
b2	39.02	13.40	2	50	51.76	1
b5	63.88	62.35	2	50	79.92	3
b6	32.21	0.00	1	0	100.00	4
b8	86.83	107.54	1	0	146.85	5

The scale of magnitudes of the two indexes of time sequence information and book circulation times are different and the numerical difference is great. If the two indexes are not standardized, it will highlight the high-value index and weaken the low-value index. In order to improve the reliability of the recommended results, we take the two indexes of time sequence information and book circulation times into [0,100] standardized processing. Processing method is Min - max standardization and the standardization formula is:

New data = 100*(original data – minimum)/(maximum – minimum).

In Table 2, the data in the third column and the fifth column is the standardized T and N.

The maximum size of the data in the fifth column is 100, i.e. $N' = 100$. Using the standardized time sequence information and circulation times in equation (3):

$$\text{dis}\,(b_3, b_2) = \sqrt{T_2^2 + (N' - N_2)^2} \tag{3}$$

$\text{dis}\,(b_3, b_2) = \sqrt{13.40^2 + (100 - 50)^2} = 51.76$, we use the same calculation method to deal with the distance between b_3 and b1, b5, b6, b8. The results are in the column 'Distance' in Table 2. The ascending order of 'Distance' is the recommended results.

In Figure 1, the x-axis is standardized value of T, the y-axis is standardized value of N ($N' - N$). The distances of different points to original point are calculated using equation 3. The shorter distance indicates the stronger relativity and ranks near the top.

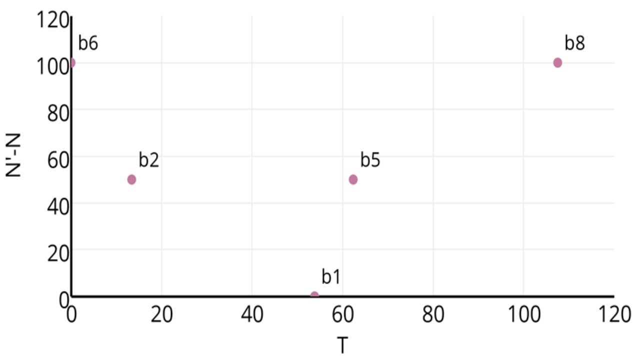

FIGURE 1. Space distribution of relative books.

B. THE PROCESSING METHOD OF DIFFERENT VERSIONS OF BOOKS

The reasons for inaccurate and inconsistent with the book information and the corresponding solutions are summarized as follows:

1) The book titles and the author's subtle differences of different versions of the same book are difficult to use a simple procedure to achieve the merger. We need to introduce a similarity-based algorithm to achieve it.
2) The translation results of different versions of the same book are different. For example, there are three different translations of the author's name who wrote the book ''The Red and the Black''. This kind of difference is difficult to distinguish by the algorithm and only can be done manually.
3) Book information input errors arise from the carelessness of book cataloging staff. So, it is difficult to merge different book titles and authors of the same book in the database. This kind of error often appears at the early age of manual cataloging and can only be dealt with manually. Nowadays, online cataloging has been realized in the cataloging system of libraries. Cataloging data can be obtained on the Internet and manually revising isn't needed anymore. The accuracy of data is almost 100 percent.

Table 3 presents the collection of the ''The Red and the Black'' in a university library. Because of the good sale of the book, it is published by many publishers and even in many editions. We can find from Table 3 that the book has eight versions yet only the titles and authors are highly consistent. In this case, if we do not deal with the data, the same books will be considered to be different during the process of book recommendation, causing the big error of the calculation results and the decline of the result accuracy.

TABLE 3. The collection of "*The Red and the Black*".

MARC_NO	M_TITLE	M_AUTHOR	M_PUBLISHER	M_ISBN
0000089680	The Red and the Black	(France)Stendhal	*Shanghai Translation Press*	7-5327-3999-8
0000072524	The Red and the Black	(France)Stendhal	*Shanghai Translation Press*	7-5312-1345-1
0000061040	The Red and the Black	(France)Stendhal	*Flower city Press*	7-5360-2448-7
0000017492	The Red and the Black	[France]Stendhal	*Yilin Press*	7-80567-521-X
0000059956	The Red and the Black	(France)Stendhal	*Shanghai Translation Press*	7-5327-0616-8
0000067902	The Red and the Black	(France)Stendhal	*Inner-Mongol People Press*	7-204-06573-5
0000084057	The Red and the Black	(France)Stendhal	*Tibet people Press*	7-223-01310-9
0000066022	The Red and the Black	(France)Stendhal	*Guangxi Normal University Press*	7-5633-3710-5

In our algorithm, we carry on combining like terms to process inconsistent data described, putting the title and author as basic items to do data merging, so the titles and the authors which are consistent are seen as the same record.

C. BOOK RENEWAL

Renewing books belong to conscious behavior, which suggests the readers' interest in the book. The weight of the recommendation of renewed book should be higher than other books whose specific practice is to change the book renewal into normal borrowing (the first time the readers borrow the book) and to shorten borrowing time interval and the distance with the target book in the timeline, and we can increase the recommendation weight of this kind of book.

D. TOP-N SHOW

In order to improve the accuracy of the Top-N recommendation, we need to process the results and remove interference data. Our recommendation algorithm is based on time sequence information, and constructs the relationship between the books of the same major by analyzing the circulation times of one kind of book borrowed by readers in a period time, and then recommends books to the readers. For example, a reader majoring in science and engineer feels interested in literature, so he wants to borrow one or more literature books. At this time, the recommendation list we got from the record data is not accurate, because there is no relationship between the book and the major. To this end, we need to filter the recommendations on the basis of library classification after the calculation of the data and then recommend to the user. For instance, if the reader is interested in a class I book, so we try to recommend the class I or close to the class I category, making sure that the recommendation results are more accurate.

E. COLD START PROBLEM

The cold start problem means recommender systems are not able to make reliable recommendations if some items have not yet been rated [21]. The cold start problem also happens in our recommendation algorithm when new readers or new books in the system can't participate in the operation of recommendation algorithm because there is no relevant borrowing record. So, the new readers can't see the recommendation result and the new books can't be recommended. To avoid such problem, we need to solve the problem of cold start by adding a corresponding processing module while implementing the recommendation system. When users use the recommendation system for the first time, they should put the data set based on the books first borrowed by readers who are in the same major as the target reader due to a reader's borrowing record set in accordance with the reader's major. The interval time between ''borrow time'' and ''reader registration time'' should be regarded as time information and get the results by using the recommendation algorithm in this paper. The recommendation of the new books can be delivered to the readers by using the new book report. When we provide the recommendation results to the readers, we can also provide a new book record set whose classification is consistent with the results to the readers.

IV. EXPERIMENTS AND ANALYSIS

Experimental data sets are all library records of Anshan Normal University library from 2012 to 2014, a total of 57,494.

A. EXPERIMENT 1: CALCULATE THE ACCURACY AND RECALL RATE OF THE ALGORITHM

We select five readers at random and use the recommendation algorithm to give readers Top 5 recommended books (five books). Figure 2 shows the relationship between recommendation results and the books borrowed. The books on connecting lines between readers and recommendation results are recommended for different readers successfully. We analyze the number of successfully recommended books and calculate the precision rate and the recall rate (the calculation results are shown in Table 4).

Precision and recall rate are two metrics that are used for estimating the qualities of recommended results. The equations used in this paper are shown as follows:

Precision Rate = a number of books successfully recommended / a number of books actually recommended

Recall Rate = a number of books successfully recommended / a number of books borrowed

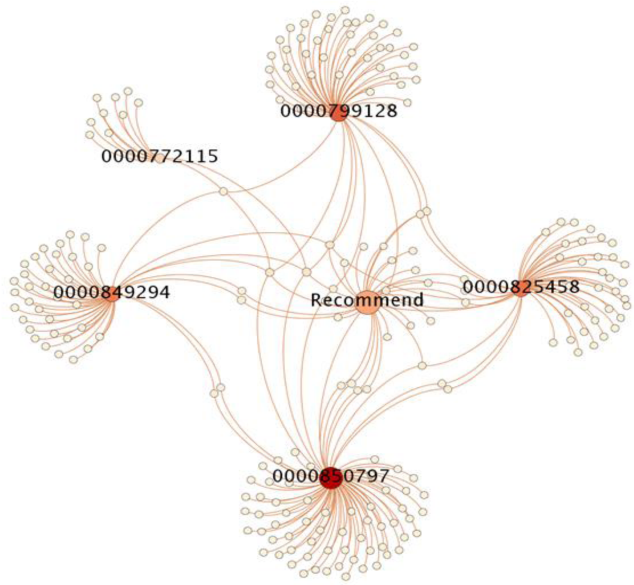

FIGURE 2. Relationship graph between recommended results and the books borrowed.

The precision rate of Top 5 is 0.44 (the average of precision rates in Table 4) while recall rate is only 0.07 (the average of recall rate in Table 5). The precision rate is desirable but the recall rate is out of satisfaction. Hence, the precision and recall of Top10, Top15, Top20, Top25, and Top30 are also shown (see Table 5).

TABLE 4. Results of recommendations for different readers.

Card number	Borrowing amount	Actual recommendation amount	Successful recommendation amount	Precision rate	Recall rate
0000772115	7	5	0	0.00	0.00
0000799128	28	5	2	0.40	0.07
0000850797	48	5	3	0.60	0.06
0000825458	24	5	4	0.80	0.17
0000849294	38	5	2	0.40	0.05

TABLE 5. Precision rate and recall rate in different amount of recommendation.

	Top5	Top10	Top15	Top20	Top25	Top30
Precision rate	0.44	0.30	0.23	0.20	0.18	0.17
Recall rate	0.07	0.12	0.13	0.15	0.17	0.19

Precision/recall curve is showed below (Figure 3), according to Table 5.

From Figure 3, precision rate and recall rate interact with each other. It is desirable that both of the values of recommendation result are higher. So in Figure 3, Top10, Top15, and Top20 are acceptable, which can be adapted.

The average precision rate is 0.25 and the recall rate is 0.14 among Top5-Top30. Compared with other recommendation algorithms, both of them are lower due to influence by the small number of book duplicates. Generally, book duplicates may be constrained in a range when an academy library

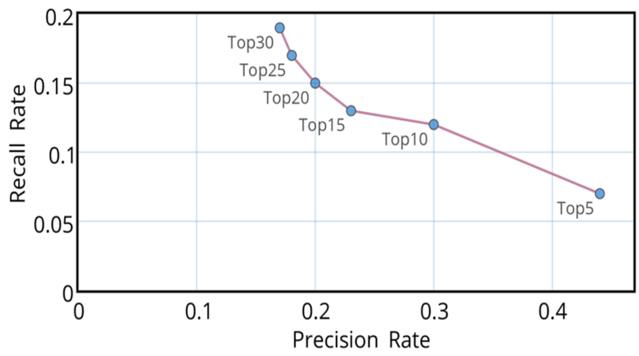

FIGURE 3. **Precision/recall curve.**

introduces a kind of book, ranging from 2 to 5. Hence, it might affect the precision rate when the recommender system recommends a book which has been already borrowed. Students cannot borrow such book although it is being recommended. If we exclude these books, the precision rate and recall rate could be enhanced. The recommendation algorithm in this paper is built on the time sequence information which is closely related to the process of professional knowledge acquisition and recommend a book set related to our future professional learning. If we exclude this part of books, we cannot get a concrete result. Hence, recommendation results are not filtered.

B. EXPERIMENT 2: TOP-N DATA PROCESSING

We found an interesting pattern in view of recommendation results. When recommendations are for liberal arts readers, the types of recommended books coincide with professional fields of the readers. When recommendations are for science readers, the types of recommended books do not coincide with professional fields of the readers and the literature books are in the majority. There are some books of other major in recommendation results, i.e. liberal arts books are in the majority among recommendation books. Figure 4 shows the different percentage of major relative books in different Top-N recommendations.

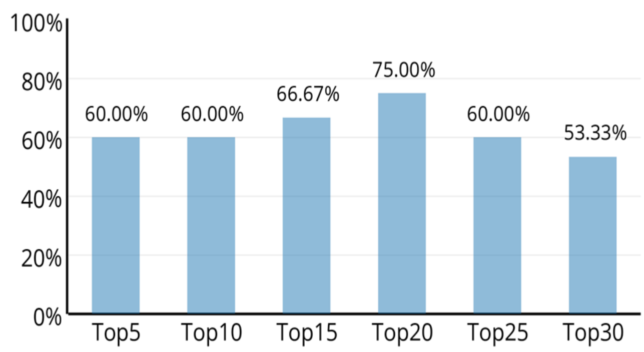

FIGURE 4. **The percentage of relative books.**

After filtering out irrelevant books with professions, we find that the types of recommended books are basically consistent with the professional knowledge learning sequence. The reason for this phenomenon is that after college students enter university, knowledge learning is more extensive. It is very common in the university that some science students who like literature spend free time in reading literary works. These reading behaviors affect the rate of accuracy of the recommendation results. Therefore, our algorithm filters out the irrelevant professional books when doing recommendation to improve the books recommendation accuracy rate.

C. EXPERIMENT 3: OTHER RELATED FACTORS

1) MAXIMUM BOOKS EACH STUDENT CAN BORROW

The maximum number of books that each student can borrow is the upper number limit of books in a period that a reader can borrow. In general, book circulation of a library is related to the maximum borrowing books. In our research, the precision of recommendation results can improve based on a lot of borrowed records. Though the range of maximum borrowing books number affects directly the precision, in this paper, we argue that a library can enhance the utilization rate of library collective books, by setting a high maximum borrowed books number.

2) DIFFERENT MAJORS

In our experiment, an interesting discovery is that the precision of recommendation results will decline if we consider recommendation related to major. In Figure 5, Precision_1 presents the precision of no considering major feature, and Precision_2 presents the precision of containing the major feature. Although the precision will decrease considering the major feature, the goodness fit of recommendation books is enhanced in accordance with the related major.

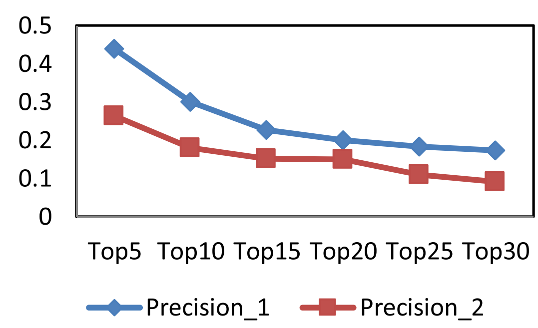

FIGURE 5. **Different precisions.**

V. CONCLUSION

This paper has proposed a novel method for book recommendations based on time sequence information. The greatest advantage of our method is that it combines knowledge learning systems of college students in different majors, providing a new way for universities' book recommender systems. The accuracy of recommendation results is affected due to our experimental dataset has certain limitations, for example, small copies of books. In the future, under the premise of keeping the accuracy of the recommendation system, we plan to explore further on the novelty and diversity of the book recommendations.

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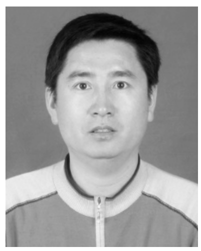

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