Use of Library Loan Records for Book Recommendation

Keita Tsuji[1], Erika Kuroo[2], Sho Sato[3], Ui Ikeuchi[4], Atsushi Ikeuchi[5], Fuyuki Yoshikane[6] and Hiroshi Itsumura[7]

Faculty of Library, Information and Media Science[1,5,6,7]
Graduate School of Library, Information and Media Studies[3,4]
College of Knowledge and Library Sciences, School of Informatics[2]
University of Tsukuba
1-2 Kasuga, Tsukuba-city, Ibaraki-ken 305-8550, Japan
{keita[1], min2fly[3], oui[4], atsushi[5], fuyuki[6], hits[7]}@slis.tsukuba.ac.jp
s0811586@u.tsukuba.ac.jp[2]

***Abstract*—To determine the most effective book recommendation method for libraries, we conducted a recommendation experiment using (1) collaborative filtering based on the library loan records, (2) association rule mining based on the same data, and (3) Amazon. The library loan records of a certain university library for the period 2006 to 2011 were used. We recommended books to 33 students and asked them to describe the books' level of interest. The results show that books recommended by collaborative filtering were least favorably evaluated, followed by those recommended by association rule and Amazon. Collaborative filtering carries the risk of breaching users' privacy and its computational costs are higher compared to those of association rule mining. Therefore, if we recommend books based on library loan records, association rule mining should be adopted instead of collaborative filtering. In addition, given the fact that the recommendations by Amazon were most favorably evaluated, utilization of Amazon should also be considered.**

Keywords—book recommendation; library loan records; university libraries; collaborative filtering; association rule

I. INTRODUCTION

The effective use of library loan records for generating recommendations has been actively discussed among librarians and LIS researchers. One method is to recommend books to users based on the loan records, which some libraries are actually doing. Some studies have proposed approaches for implementing this method. However, two issues have not been clarified: (1) Which method yields the most effective book recommendation system based on the library loan records, and (2) whether a recommendation based on loan records is more effective than that based on other information.

Concerning issue (1), to date, various recommendation methods have been proposed based on usage records, among which collaborative filtering and association rule mining are the most popular. However, it has not been clarified which method is the most effective for book recommendation in libraries. For instance, [1] used collaborative filtering based on library loan records but did not compare this with other methods, including association rule mining. Each method has different characteristics. For instance, there is a risk of the user's privacy being breached in the case of collaborative filtering since the loan records of each user have to be retained.[1 2] On the other hand, association rule mining methods do not have to retain each user's records and the risk of a breach of privacy being incurred is small. In addition, the computational cost, that is, the time required to determine which book should be recommended, is generally lower in the case of association rule mining than of collaborative filtering. Based on the above, if the association rule mining has a greater recommendation ability than collaborative filtering, libraries should recommend books using this method, which is effective, safe, and quick.

Amazon's book recommendation system is popular. Amazon provides a widespread service and its application programming interface (API) is available. If we submit information about a book that a user found interesting to Amazon's API, it returns information about other books as "Customers who bought this book also bought these books." By extracting the books that the university library holds from these recommendations and recommending them to the library user, we can easily realize a book recommendation system at a library. Concerning issue (2), it can therefore be said that, if such a recommendation is evaluated by users more favorably than a recommendation based on library loan records, libraries can effectively recommend books without using the loan records, as long as Amazon does not go out of business, stop providing the information, or change the recommendation method significantly.

Based on this background, we asked 33 students of a certain university (henceforth "T University") to name one book in which they were interested, recommended books to them based on this choice and on their library loan records, and asked them to indicate to what extent they were interested in the recommended books. We used three recommendation methods: (a) collaborative filtering as

[1] We assume that there is no perfectly secure system and if we retain some data, they can be stolen or extracted from the system.
[2] However, we should note that retaining each user's loan records could be beneficial for recommending books, although at present we do not know how to achieve this.

proposed by [1], (b) association rule mining, and (c) Amazon.

In the present paper, the library loan records to which we refer consist of the ID of the user, the ID of the material the user borrowed, bibliographic data, and the checkout date. A book recommendation consists of recommending that a user borrow a book by showing him or her the bibliographic data: title, author, publisher, and publication year of the book.

II. RELATED STUDIES

Among the methods proposed in the literature on collaborative filtering, the one proposed by [2] is regarded as a representative method of the field. This method first finds similar Netnews readers based on the evaluation scores they gave for a news item. It then recommends to the reader the news items that he/she has not read and to which the similar readers gave a high evaluation score.

Since the study of [2], collaborative filtering has been used in various fields. However, there have been few studies on using collaborative filtering to recommend books at libraries. We can name only [1], [3], and [4]. This may be because usage of loan records used to be almost taboo in the library world.

Reference [3] used collaborative filtering software called Vogoo PHP Pro v2.2 over 960,078 loan records for 8,808 users of a university library. Reference [1] also used this software. The significant difference between [1] and [3] is that the former used NDC (Nippon Decimal Classification) for weighting books, and the loan records were divided according to the checkout month/year. Reference [1] tested five patterns with regard to such weighting and identified the most effective pattern.

Reference [4] compared collaborative filtering based on library loan records with Amazon's recommendation system. However, only four subjects participated in the experiment, and a comparison with the association rule mining method was not conducted.

In addition to the above, [5] proposed a recommendation method that used a weighted graph model that is similar to the association rule method. References [6], [7], and [8] proposed some recommendation methods, but did not conduct experiments to evaluate their effectiveness.

III. DATA

A. Library Loan Records

We obtained 1,990,797 loan records from the T University library (checkout dates ranged from January 2, 2006 to March 31, 2011). Of these records, 864,704 were for books checked out by undergraduate students, 989,641 by graduate students and faculty members, and 136,452 by others. We used 1,854,345 loan records of undergraduate students, graduate students, and teachers for this study. The number of types of books borrowed was 435,817, and the number of users was 39,442. The number of so-called baskets (set of books that were borrowed together) was 708,951.

B. Subjects

Thirty-three students majoring in library and information science at T University participated as subjects in our experiment. They comprised 7 graduate students, 17 fourth-year undergraduate students, and 9 second-year undergraduate students. For convenience's sake, we will call these three groups "groups whose grades are different," although graduate students and undergraduate students are not regarded as being of different "grades" according to the normal definition.

C. One Book that the Subject Would Like to Borrow at Present

Subjects were asked to give a title (and other bibliographic information if necessary) of one "book that I would like to borrow from T University library at present, for research or study purposes." This information was used to generate recommendations based on association rule mining, as well as the Amazon recommendation system.

IV. RECOMMENDATION METHOD

A. Collaborative Filtering

References [1] and [3] used software called Vogoo PHP Pro v2.2, as previously mentioned. However, the method used by this program to calculate and recommend books is not given. In addition, this software is difficult to obtain since the distribution company no longer exists. Therefore, we adopted the method of [2] and a weighting method that [1] used collaborative filtering.

First, we will explain the method of [2]. Henceforth, we will call the target user to whom the system recommends books the "active user" and the other user the "sample user." The method of [2] recommends to the active user the items for which sample users who are similar to the active user gave high evaluation scores (and, of course, the items that the active user has not evaluated). First, we define the notations as:

Y_{ai}: The set of items that active user a and sample user i evaluated in common.
S_{aj}, S_{ij}: The evaluation scores that active user a and sample user i gave to item j.
$\bar{S}_a, \bar{S}_i$: The average of evaluation scores that active user a, and sample user i gave to the items.
X_j: The set of users who evaluated item j.

The similarity, p_{ai}, between active user a and sample user i is defined as the correlation coefficient

$$p_{ai} = \frac{\sum_{k \in Y_{ai}} (S_{ak} - \bar{S}_a)(S_{ik} - \bar{S}_i)}{\sqrt{\sum_{k \in Y_{ai}} (S_{ak} - \bar{S}_a)^2} \sqrt{\sum_{k \in Y_{ai}} (S_{ik} - \bar{S}_i)^2}}$$

The method of [2] recommends to the active user the items whose scores, $\hat{S}_{aj}$, are high. They are defined as

$$\hat{S}_{aj} = \bar{S}_a + \frac{\sum_{i \in X_j} p_{ai}(S_{ij} - \bar{S_i})}{\sum_{i \in X_j} |p_{ai}|}$$

We will now explain the weighting method of [1]. We first divide the loan records of one sample user into sets according to the checkout month/year and consider these sets as the loan records of different sample users. Evaluation scores are given to each book in the active users' loan records based on its NDC category (top level, i.e., from 0 to 9). An evaluation score of $0.5^{(n-1)}$ is given to the book whose NDC category is the n-th most frequently occurring among the books that the active user borrowed. For instance, an evaluation score of 0.25 is assigned to the book whose NDC category is the third most among the books the active user borrowed.

B. Association Rule Mining

When a user borrowed n books, X_i $(i = 1, \dots, n)$, at one time, we will call the set $\{X_1, \dots, X_n\}$ a "transaction." For instance, when a user borrowed three books, A, B, and C, at one time, the transaction can be represented as $\{A, B, C\}$. From this transaction, we can extract a rule "the user who borrows book A also borrows book B." In addition, we can also extract a rule, "the user who borrows books B and C at one time also borrows book A." Based on all the transactions of all the users, the association rule mining extracts the frequently observed, and, in that sense, "reliable" rules.

C. Amazon

We input to the Amazon recommendation system the bibliographic data of the books mentioned in Section IIIC and obtained manually the bibliographic data of the books recommended by Amazon as "the customer who purchased this book also purchased these books." From these books, we extracted the books that the T University library holds and recommended them to the subjects.

V. EVALUATION METHOD

The bibliographic data of the books recommended by collaborative filtering, association rule mining, and the Amazon system were shown to the subjects (the bibliographic data consists of title, author, publisher, and publication year). The subjects were then asked to describe their level of interest in each book using the following five-point scale, which is similar to that used by [1].

2: Very interested
1: Interested
0: Not interested
x: Have no idea
A: Already bought or have read before

VI. RESULTS

A. Overall Results

The results are shown in Table I. In Fig. 1, "x" and "0" are combined in a bar chart presentation of the results.

As seen in Table I and Fig. 1, the proportion of recommended books in which the subjects were "2: Very interested" was the largest in the case of Amazon's system, followed by association rule mining and collaborative filtering (28.7%, 18.6% and 11.1%, respectively). Likewise, the proportion of recommendation results that received a rating of "1: Interested" was the largest in the case of Amazon, followed by association rule mining and collaborative filtering (40.2%, 37.1% and 26.3%, respectively). If we regard "A: Already bought or have read before," "2: Very interested," and "1: Interested" as a "positive evaluation," the proportion of this evaluation category was the largest in the case of Amazon, followed by association rule mining and collaborative filtering (79.6% (=10.7+28.7+40.2), 60.0% and 43.0%, respectively). Significant differences between these proportions were observed at the level of 0.01. Based on the above, we can say that the recommendation performance of association rule mining is better than that of collaborative filtering, and that that of Amazon is even better.

B. Results According to Grade

The evaluation results for the graduate students, fourth-year undergraduate students and second-year undergraduate students are shown in Tables II to IV and Figs. 2 to 4. From these results, we can see that for all grades the proportion of positive evaluations is the largest in the case of Amazon, followed by association rule mining and collaborative filtering.

C. Results According to the Number of Books Borrowed

We divided the subjects into two groups: A, subjects who borrowed 21 books or more, and B, those who borrowed fewer than 21 books. Group A and B consisted of 20 and 13 subjects, respectively. The evaluation results for these two groups are shown in Tables V and VI and Figs. 5 and 6. In Group A, the proportion of collaborative filtering recommendations that received positive evaluations is 49.2% (6.7+9.2+33.3). On the other hand, this figure is just 33.3% in Group B. A significant difference between these proportions was observed at the collaborative filtering score level of 0.05, which indicates that the performance of collaborative filtering drops in the case of those who borrowed fewer books.

Reference [1] limited the selection of subjects to students who borrowed 21 books or more. However, the students who borrowed fewer than 21 books account for approximately 40% of our subjects. If our subjects are a representative sample of Japanese university students, the recommendation results of collaborative filtering for Japanese students may be worse than that indicated by [1].

D. Results According to Collaborative Filtering Score

For the books to which the collaborative filtering assigned a score of 0.1 or higher, the proportion of "2: Very interested" was 25.0% (Table VII and Fig. 7). However, in this case as well, the proportion of positive evaluations still falls short of that for the association rule mining.

E. Results by NDC Categories

We divided the subjects into groups according to the NDC categories of the books they would like to borrow at the present and examined the recommendation performances for each group. The results show that the proportions of positive evaluation were not different among these groups. We also divided the subjects into groups according to the NDC categories most frequently observed in the books they borrowed; however, the results were the same. Therefore, we may reasonably say that the recommendation performance does not significantly differ according to NDC category.

VII. Discussion

As mentioned previously, the positive evaluation by subjects of the generated recommendations was highest for Amazon's system, followed by association rule mining and collaborative filtering.[3] This was true when subjects were divided according to their grade and according to the NDC category of the books they borrowed. As discussed earlier, collaborative filtering has some drawbacks, as compared with association rule mining. Therefore, if we recommend books on the basis of library loan records, association rule mining should be adopted instead of collaborative filtering. In addition, given the facts that (1) the recommendations of Amazon's system were most favorably evaluated, and (2) Amazon's system does not need any library loan records and its use carries no risk of breaching the users' privacy, Amazon's recommendation system should also be considered for book recommendation. However, it should be noted that Amazon's recommendation system is like a black box, and the company might stop providing the API.

VIII. Conclusions

To determine the most effective method for generating book recommendations in libraries, we conducted a recommendation experiment using (1) collaborative filtering based on the library loan records, (2) association rule mining based on the same data, and (3) the Amazon recommendation system. The results show that books recommended by collaborative filtering were least favorably evaluated, followed by those recommended by association rule mining and by Amazon's system. Future tasks include (a) generating recommendations by collaborative filtering using various other parameters, (b) incorporating content-based filtering in our system, (c) incorporating seasonal change of the students' level of interest in our system, and (d) utilization of loan records at other university libraries. If university libraries in Japan cooperate with each other and allow others to use the loan records upon protecting users' privacy, a sufficient volume of information can be used for recommendation.

[3] It is true that these methods receive different types of inputs and thus they were not compared under the same condition. Unlike collaborative filtering, association rule mining and Amazon's system do not use the history of a user's interest, and a book that each user is interested in now has to be used as input. However, it should be noted that these differences are intrinsic to the three methods and cannot be modified or coordinated.

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Table I. Overall evaluation results

	A	2	1	0	x	Total
Amazon	13 (10.7)	35 (28.7)	49 (40.2)	21 (17.2)	4 (3.3)	122
Association	6 (4.3)	26 (18.6)	52 (37.1)	52 (37.1)	4 (2.9)	140
Collaborative	11 (5.6)	22 (11.1)	52 (26.3)	94 (47.5)	19 (9.6)	198

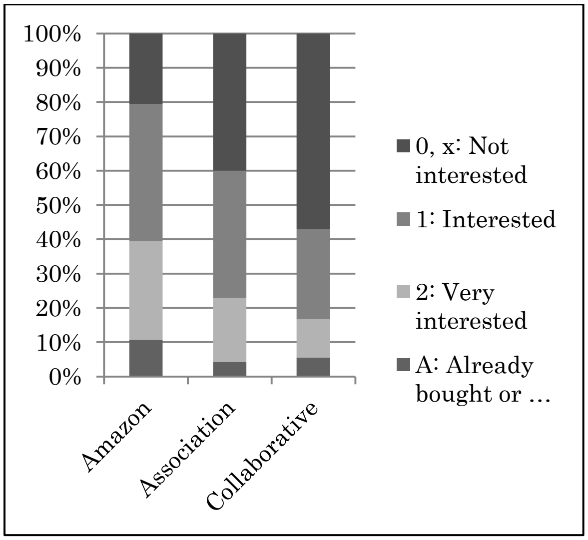

Figure 1. Overall evaluation results

Table II. Graduate students

	A	2	1	0, x	Total
Amazon	5 (17.2)	9 (31.0)	10 (34.5)	5 (17.2)	29
Association	4 (11.1)	5 (13.9)	14 (38.9)	13 (36.1)	36
Collaborative	6 (12.5)	4 (8.3)	17 (35.4)	21 (43.8)	48

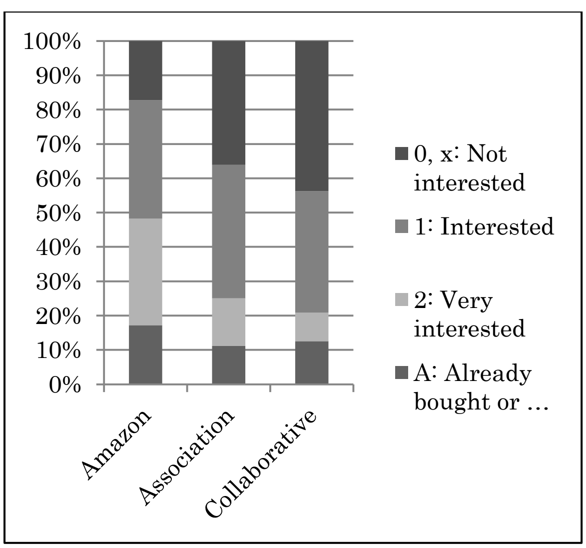

Figure 2. Evaluations of graduate students

Table III. Evaluations of fourth-year undergraduate students

	A	2	1	0, x	Total
Amazon	7 (11.7)	13 (21.7)	26 (43.3)	14 (23.3)	60
Association	2 (3.0)	7 (10.6)	28 (42.4)	29 (43.9)	66
Collaborative	3 (3.1)	9 (9.4)	18 (18.8)	66 (68.8)	96

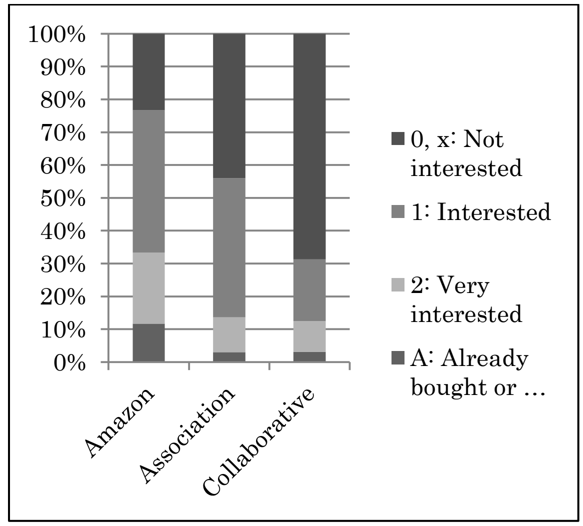

Figure 3. Evaluations of fourth-year undergraduate students

Table IV. Second-year undergraduate students

	A	2	1	0, x	Total
Amazon	1 (3.0)	13 (39.4)	13 (39.4)	6 (18.2)	33
Association	0 (0.0)	14 (36.8)	10 (26.3)	14 (36.8)	38
Collaborative	2 (3.7)	9 (16.7)	17 (31.5)	26 (48.1)	54

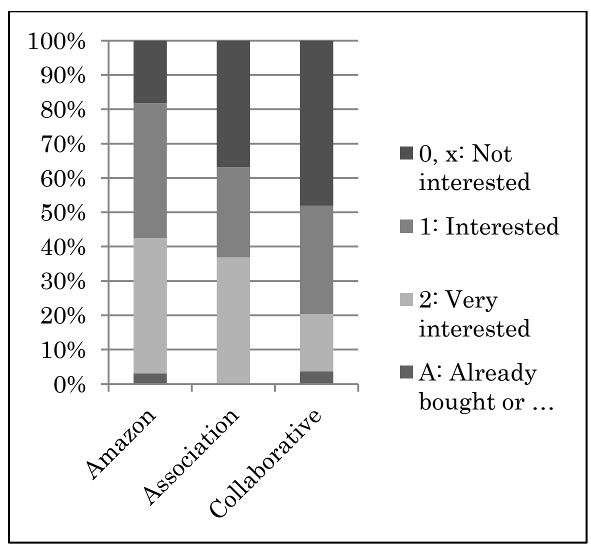

Figure 4. Evaluations of second-year undergraduate students

Table V. Evaluations of subjects who borrowed 21 books or more

	A	2	1	0, x	Total
Amazon	11 (14.5)	18 (23.7)	29 (38.2)	18 (23.7)	76
Association	5 (6.1)	13 (15.9)	30 (36.6)	34 (41.5)	82
Collaborative	8 (6.7)	11 (9.2)	40 (33.3)	61 (50.8)	120

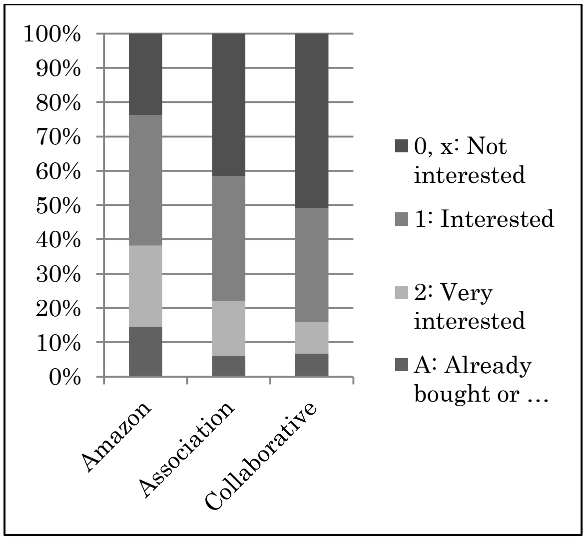

Figure 5. Evaluations of subjects who borrowed 21 books or more

Table VI. Subjects who borrowed fewer than 21 books

	A	2	1	0, x	Total
Amazon	2 (4.3)	17 (37.0)	20 (43.5)	7 (15.2)	46
Association	1 (1.7)	13 (22.4)	22 (37.9)	22 (37.9)	58
Collaborative	3 (3.8)	11 (14.1)	12 (15.4)	52 (66.7)	78

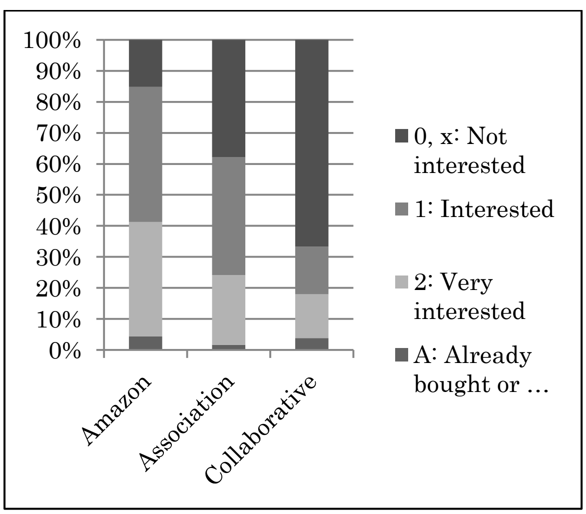

Figure 6. Evaluations of subjects who borrowed fewer than 21 books

Table VII. Results according to collaborative filtering score

	A	2	1	0, x	Total
Score≧0.1	2 (6.3)	8 (25.0)	8 (25.0)	14 (43.8)	32
Score≧0.05	3 (3.3)	13 (14.4)	20 (22.2)	54 (60.0)	90
Total	11 (5.6)	22 (11.1)	52 (26.3)	113 (57.1)	198

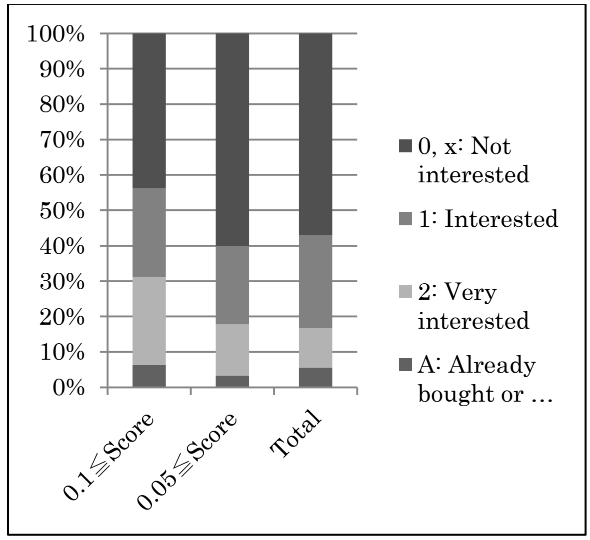

Figure 7. Results according to collaborative filtering score