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A group recommendation system for online communities☆

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ABSTRACT

Online communities are virtual spaces over the Internet in which a group of people with similar interests or purposes interact with others and share information. To support group activities in online communities, a group recommendation procedure is needed. Though there have been attempts to establish group recommendation, they focus on off-line environments. Further, aggregating individuals' preferences into a group preference or merging individual recommendations into group recommendations—an essential component of group recommendation—often results in dissatisfaction of a small number of group members while satisfying the majority. To support group activities in online communities, this paper proposes an improved group recommendation procedure that improves not only the group recommendation effectiveness but also the satisfaction of individual group members. It consists of two phases. The first phase was to generate a recommendation set for a group using the typical collaborative filtering method that most existing group recommendation systems utilize. The second phase was to remove irrelevant items from the recommendation set in order to improve satisfaction of individual members' preferences. We built a prototype system and performed experiments. Our experiment results showed that the proposed system has consistently higher precision and individual members are more satisfied.

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1. Introduction

It has been reported that more than 1.17 billion people in the world—almost 18% of the world population—surf the Web these days (Source: Internet Usage and World Population Statistics for June 30, 2007, http://www.internetworldstats.com/stats.htm). Of these Internet users, great portions are estimated to participate in one or more online communities either directly as interaction members or indirectly as customers of vendors utilizing customer communities (Albors, Ramos, & Hervasa, 2008). Online communities are virtual spaces over the Internet in which a group of people with similar interests or purposes interact with others and share information. Anyone can become a member of online communities and popular online community sites are competing to attract more members. A critical factor to the success of online community management is membership retention, which can be achieved by creation and sharing of high quality information satisfying needs of members (Arguello et al., 2006; Ozer, 2005). Creation and sharing of valuable information requires not only active participations of members, but also the community management system's functionality. In particular, if there is an information management system assisting members to easily find information in need, it can reduce search efforts and improve the shareability of information in the community.

A recommendation system supports users to find information, products, or services (such as books, movies, music, digital products, Web sites, and TV programs, to name a few) by aggregating and analyzing suggestions from other users, reviews from various authorities, and user attributes (Frias-Martinez, Magoulas, Chen, & Macredie, 2006; Frias-Martinez, Chen, & Liu, 2009). Collaborative filtering (CF) is known to be a successful recommendation technique. It makes recommendations to users based on other users' ratings on items, putting more weights on those from similar users (i.e., other users having similar personal attributes or product preferences). But to date, recommendation systems have focused mainly on recommending items to individuals rather than groups of people intending to participate in a group activity (O'Connor, Cosley, Konstan, & Riedl, 2001). In recommendation domains such as shopping and asset investment, it is not a limitation because users in general behave individually and only their personal interests should be considered. In other domains such as movies, trips, book clubs, and restaurants, however, existing recommendation systems have difficulty in aggregating individual users' tastes into a group's preference properly.

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Though there have been attempts to establish group recommendation, they focus on off-line environments. These days, many group activities and interactions are done in a virtual space, and the process of resolving conflicting group opinions and activities is different from that in off-line environment. Further, aggregating individuals' preferences into a group preference or merging individual recommendations into group recommendations—an essential component of existing group recommendation procedures—often results in dissatisfaction of a small number of group members while satisfying the majority.

This paper proposes a group recommendation system improving not only the group recommendation effectiveness but also the satisfaction of individual group members. GRec_OC (which stands for a group recommender for online communities) offers recommendation sets for members of online communities through a two-phase recommendation procedure. The first phase includes a group profile-based filtering method to satisfy the majority of group members. We build a group profile to represent a group's aggregated preference and then make a candidate recommendation set through the adjusted CF process. This phase consists of the three steps: group profile generation, neighbor group formation, and top-*n* candidate set creation. The second phase includes an individual profile-based filtering method to reduce the dissatisfaction of individual group members. It removes contents irrelevant to individual group members from the candidate set. So the second phase consists of two steps: relevance evaluation and the final recommendation set generation. In short, GRec_OC has two levels of filtering mechanism ensuring that contents or products are recommended only if individuals have deemed it relevant.

For an experimental evaluation, we implemented GRec_OC for online reading community as a promising application domain. Though the proposed system has been designed and tested specifically for book recommendations, the same functionality of the system should work as a basis of group recommendation systems for any products or services in the online group setting. We evaluated the system performance of GRec_OC and surveyed user satisfaction. They were compared with outcome from an existing group recommendation method, which simply incorporates preference records of group members into a general collaborative filtering technique. Evaluation results showed that GRec_OC achieves better recommendation qualities and higher user satisfaction through the two-phase filtering procedure than the existing group recommendation system generating recommendation for groups but not tuning it for individual members.

The overall structure of the study follows the design science framework (Hevner, March, Park, & Ram, 2004). We propose a core artifact for group recommendation (Section 3) after presentation of related literature (Section 2). The proposed method is validated through experimental comparison with an existing group recommendation method (Section 5). Section 4 is dedicated to a small example to help readers understand the method.

2. Related work

2.1. Collaborative filtering-based recommendation systems

A recommendation system provides users with recommendation of items of their interest based on their past preferences, history of purchases, demographic information, and other relevant information (Ziegler, McNee, Konstan, & Lausen, 2005). It has been used not only in E-commerce environments such as Amazon.com and CDNow but also in mobile, P2P, and ubiquitous environments.

Collaborative filtering (CF) is known to be the most successful recommendation technique used by many of E-commerce systems (e.g., Amazon.com and CDNow.com). CF makes recommendation based on item ratings by neighbors who are those having attributes or preferences similar to a user to whom recommendation is made. In general, CF systems make recommendation according to following three steps (Sarwar, 2000):

- User profile creation: User profiles are built from historical purchase transactions or rating information on items. This is a basis of CF systems.
- Neighbor formation: CF systems apply statistical or machine learning techniques to find a set of users, known as neighbors, who had in the past exhibited similar behaviors. Based on user profiles, systems evaluate the preference similarity between users. For instance, either they have used similar items or they have given similar ratings.
- Recommendation generation: Once a neighborhood is formed for a target user, CF systems generate a set of items that the target user is most likely to purchase by analyzing the items that neighbors have shown interests in.

2.2. Group recommendation systems

A group recommendation system suggests items to a group of people engaged in a group activity. There have been relatively a small number of studies on group recommendation systems so far. They are as follows. MusicFX (McCarthy & Anagnost, 1998) selects music stations that broadcast to a gym full of people. Members of the gym rate all stations beforehand, and MusicFX plays one of the stations with the highest average rating. The system thus attempts to maximize the satisfaction of the group. A crucial prerequisite of MusicFX is that users must rate all stations in advance. For the selection of music stations out of a small number of choices, MusicFX would be a good system, but MusicFX or its variations would not be good for recommendation of items such as books out of a large number of choices, which must be rated by users in advance.

PolyLens (O'Connor et al., 2001) recommends movies to small groups of people who watch movies together. It applies the standard CF algorithm to find recommendations for each of the group members, and then combines them into a group recommendation. Unlike MusicFX, PolyLens attempts to satisfy all users to some degree, without necessarily maximizing the group's average satisfaction. PolyLens bases its recommendations on the expected satisfaction of the least satisfied group member. Therefore, a movie that is marginally acceptable to most group members may be recommended over one that one member dislikes but everyone else would enjoy immensely.

Pocket RestaurantFinder (McCarthy, 2002) recommends restaurants to groups of diners, based their locations and culinary preferences. Prospective diners fill out profiles of their preferences in portable devices. The profile includes restaurant selection attributes, such as how far they are willing to travel, how much they are willing to spend, what types of cuisine they like and dislike, and what types of restaurant amenities they like and dislike. Pocket RestaurantFinder pools group members' preferences together and presents a set of potential restaurants sorted in the order of expected desirability for the group.

Adaptive Radio (Chao, Balthrop, & Forrest, 2004) is a system that broadcasts songs to a group of listeners who share a same environment. Most music recommendation systems determine what kinds of songs users prefer, usually using surveys or online profiles of their listening habits. Adaptive Radio, in contrast, keeps track of the songs that users dislike and avoids playing them. As a side effect of the use of negative preference, Adaptive Radio often plays songs that are unfamiliar or marginally acceptable to users.

The adaptive in-vehicle multimedia recommendation system (Yu, Zhou, & Zhang, 2005) provides multimedia contents for groups of travelers in vehicles such as buses, trains, and airplanes. This sys-

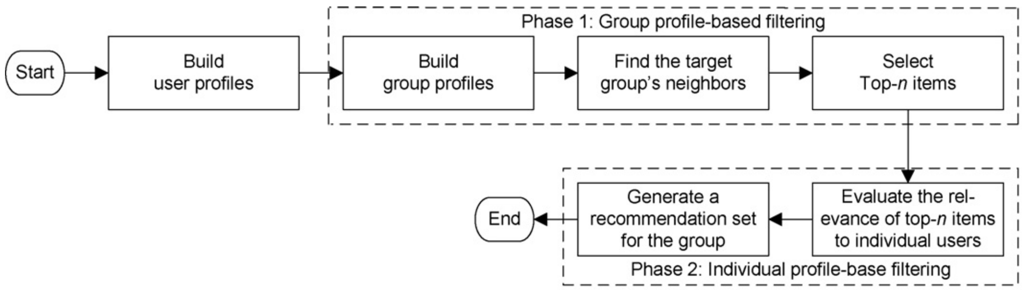

Fig. 1. Recommendation procedure of GRec_OC.

tem aggregates user profiles through wireless mobile devices, such as laptops, PDAs, and cell phones. The procedure of aggregating user profiles consists of two steps. First, it selects features to represent common interests of travelers. Second, it determines appropriate weights on the selected features. It is known to satisfy the majority of group members.

TV4M (Yu, Zhou, Hao, & Gu, 2006) recommends TV programs to groups of viewers using their profiles merged based on the total distance minimization in a vector space of features. A user profile is represented as features (e.g. genre, actor, and keyword about TV programs) with weights indicating the relative importance of features. Using an aggregation algorithm, it selects a feature subset to represent common interests in the first step and then determines proper weights for selected features. Through experiments, TV4M is shown to work better when members in a group have a closer relationship and share more common interests.

Flytrap (Crossen, Budzik, & Hammond, 2002) recommends music to a group of listeners based their numeric votes. INTRIGUE (Ardissono, Goy, Petrone, Segnan, & Torasso, 2002), a travel site recommendation system, focuses resolution of conflicting preferences among members in a group.

Group recommendation systems differ from individual recommendation systems in two aspects. The first difference is that group recommendation systems need to aggregate individual measures into a group measure. For such a purpose, existing studies use one of two basic approaches: aggregating individual user profiles or preferences into a group profile or preference (Chao et al., 2004; Crossen et al., 2002; McCarthy, 2002; McCarthy & Anagnost, 1998; Yu et al., 2005, 2006) and merging individual recommendation sets to a group recommendation set (O'Connor et al., 2001). By representing the taste of the group before making recommendations, the first approach increases the chance of finding valuable recommendations. On the other hand, it can produce recommendations that satisfy many, but not all, members of the group.

Instead of aggregating individual users' preferences into a group preference, the group recommendation systems that use the second approach generate recommendation sets for each group member and then merge them into a final recommendation set for the group. The strategy of merging recommendation sets has several advantages. The presented results can be directly related to those seen by individual group members. Thus, the results are relatively easy to explain. Further, because this approach finds individual recommendations, it can display them side by side with the group recommendation, giving users more information with which they make decisions. On the other hand, group recommendations based on this approach are less likely to identify unexpected, serendipitous items and can be very time-consuming if groups are large. In this paper, we take the first approach of aggregating user profiles into a group profile and utilize a nearest-neighbor algorithm in identifying neighbor groups from whom recommendation sets are generated.

Second, we need to consider how well recommendations for a group match with individuals' tastes, since it is difficult and often impossible to satisfy all of group members. This is about a social value function that defines group satisfaction (O'Connor et al., 2001). Group satisfaction may be measured as the average satisfaction of the members, the satisfaction of the most satisfied member, or the satisfaction of the least satisfied member. In existing studies (e.g., MusicFX and Pocket RestaurantFinder), the average value is used generally, but it may lead to recommendations biased toward users providing more ratings of contents or products. Another method, used by PolyLens and Adaptive Radio, adopts the satisfaction of the least satisfied member. This method may ignore the majority's preferences while supporting a small number of dissatisfied members. Our method in GRec_OC takes limitations of these two methods into consideration. To reduce the dissatisfaction of group members while maintaining the majority's preference satisfaction, GRec_OC removes items from the recommendation set whose features do not match well with individual user profiles. This added phase of irrelevant item elimination is an essential component of GRec_OC's recommendation procedure.

3. Group recommendation procedure of GRec_OC

GRec_OC is designed to increase sharing of information and improve group members' satisfaction. GRec_OC is composed of two phases of recommendation set generation. The first phase uses the typical collaborative filtering (CF) method to generate recommendations based on group profiles and the second phase uses a relevance-based filtering method to fine-tune the recommendations and improve individuals' satisfaction.

In the first phase, we build a group profile by merging individual members' profiles. That is, a group profile is represented as aggregated features of group members' profiles. The next step is to find the target group's neighbors using a similarity measure on group profiles. The last step is to select top-n books obtained from neighbor groups. We call these top-n books the candidate recommendation set, which will be refined in the second phase.

In the second phase, we evaluate the relevance between books in the candidate recommendation set and individual group members. One of the goals of GRec_OC is to actively satisfy individual members. For this, we find and eliminate books that are not preferred by members in the group. Fig. 1 shows the overall procedure of GRec_OC. Details of both phases are as follows.

3.1. Phase I: group profile-based filtering

An item-based user profile, or simply a user profile, is a description of a user's interests or preferences on items, which is the basis of CF recommendation. In this phase, GRec_OC merges individual user profiles into a group profile. Define

$$p_{ik}^{c} = \begin{cases} 1 & \text{if user } c \text{ belonging to group } i \text{ has read book } k, \\ 0 & \text{otherwise.} \end{cases}$$

The profile of group i having members $c = 1, 2, \ldots, C$ is vector $(p_{i1}, p_{i2}, \ldots, p_{iK})$ where

$$p_{ik} = \sum_{c=1}^{C} p_{ik}^{c}$$

for books $k = 1, 2, \ldots, K$.

The next step is to compute the similarity between group profiles and find neighbors of a target group. The process follows the typical nearest-neighbor algorithm. Given group profiles, the similarity between two groups i and j, denoted by sim(i, j), can be obtained by using either the Pearson-r correlation or the cosine measure (Sarwar, Karypis, Konstan, & Riedl, 2000). GRec_OC uses the Pearson-r correlation as the similarity measure because it is immune to both ratio and interval scaling, but the cosine measure is immune to only ratio scaling and differs upon interval scaling. Also previous studies have empirically shown superiority of the correlation similarity in recommendation performance over the cosine similarity (Breese, Heckerman, & Kadie, 1998). That is, the similarity between two groups i and j is measured by calculating the Pearson-r correlation:

$$\mathrm{sim}(i,j) = \frac{\sum_{k=1}^{K}(p_{ik}-\bar{p}_i)(p_{jk}-\bar{p}_j)}{\sqrt{\sum_{k=1}^{K}(p_{ik}-\bar{p}_i)^2 \sum_{k=1}^{K}(p_{jk}-\bar{p}_j)^2}}, \tag{1}$$

where $(p_{i1}, p_{i2}, \ldots, p_{iK})$ and $(p_{j1}, p_{j2}, \ldots, p_{jK})$ are i's and j's profile vectors respectively, and $\bar{p}_i = \sum_{k=1}^{K} p_{ik}/K$ and $\bar{p}_j = \sum_{k=1}^{K} p_{jk}/K$ are i's and j's average ratings of books respectively. The result has a value between -1 and 1, where a bigger value indicates more similarity between two groups.

Once we obtain the similarity scores between target group i and all other groups, we choose a number of groups as i's neighbors. Two well-known techniques are correlation-thresholding and best-m-neighborhood (Herlocker, Konstan, Borchers, & Riedl, 1999). The correlation-thresholding technique is to form neighborhood as those with absolute similarity measures greater than a given threshold, while the best-m-neighborhood technique is to select m groups with the best similarity measures. In GRec_OC, the best-m-neighborhood technique is adopted because it is empirically validated to be superior (Herlocker et al., 1999).

The final step is to ultimately derive the top-n recommendation from the neighborhood of group. For each group, we produce a recommendation set of n books that the target group is most likely to select. Previously selected books are excluded from the recommendation set. When generating a recommendation set for a given group, GRec_OC selects the most frequently purchased products (Sarwar et al., 2000). This technique looks into the neighborhood and, for each neighbor, scans through a sales database and counts the purchase frequency of books. After all neighbors are accounted for, the system sorts the books according to their frequency counts and returns n most frequently purchased books as the candidate recommendation set.

3.2. Phase 2: individual profile-based filtering

Most existing group recommendation methods (McCarthy, 2002; McCarthy & Anagnost, 1998; O'Connor et al., 2001) stop at the first phase. As a result, there may exist neglected members because of their inactive behaviors or less frequent expression of their opinions in communities. Inactive members do not express their positive or negative reaction and just leave their groups when their needs are not satisfied any more. In an online environment, member retention is a very important issue. Thus, the second phase of GRec_OC is designed to improve satisfaction of individual members in a group. This phase is composed of two steps: calculation of the relevance of the candidate books and filtering of books based on the degree of relevance.

The first step is to calculate the relevance between each member in a group and the candidate books. GRec_OC uses feature-based profiles of individual members from their previous records of book reading. Because all books have keywords to represent their contents, we use the content-based approach to evaluate the compatibility between feature-based user profiles and book profiles (Balabanovic & Shoham, 1997). A book profile includes information about the characteristics of books. The profile of book k is represented as a vector $(v_{k1}, v_{k2}, \ldots, v_{kL})$, where

$$v_{k\ell} = \begin{cases} 1 & \text{if book } k \text{ contains keyword } \ell, \\ 0 & \text{otherwise.} \end{cases}$$

The feature-based profile of user c belonging to group i is represented as a vector $(q_{c1}, q_{c2}, \ldots, q_{cL})$, where

$$q_{c\ell} = \sum_{k=1}^{K} p_{ik}^{c} v_{k\ell}.$$

That is, a feature-based profile vector of user c is the sum of profile vectors of all books c has read. The element $q_{c\ell}$, measuring the frequency of keyword ℓ in c's book-reading records, indicates the preference degree of user c on keyword ℓ. The compatibility score between an individual user and a candidate book is obtained by the Pearson-r correlation measure between the book profile and the feature-based user profile as in Eq. (1).

The second step in this phase minimizes dissatisfaction of individual members in groups by eliminating some books from the candidate recommendation set based on the book-user compatibility scores. A higher compatibility score between a book profile and a feature-based user profile indicates that the user would be more satisfied with the book. Existing studies deal with the average preference of all members, and in the first phase we do, too. A group profile, however, reflects active members' preference more because of larger numbers of book-reading records of the active members. As a result, recommendation is biased toward active members and tends to neglect inactive members. Before deciding a final recommendation set, GRec_OC removes irrelevant books—books both active and inactive members would be not satisfied with—from the candidate recommendation set obtained in first phase. First, we determine a threshold, which can be the average compatibility score value, the minimum compatibility score, or any arbitrary value. For a book in the candidate recommendation set obtained from the first phase, if there exists any member whose book-user compatibility score is below the threshold, it is eliminated from the set.

4. An illustrative example

To help understand the procedure of GRec_OC, we present a simple example of the "IT Wizards" group in a recommendation environment. We suppose that there are five groups with varying sizes of membership, whose profiles generated by aggregating their item-based member profiles are as shown in Table 1. We will consider the process of generating a recommendation set for the "IT Wizards" group.

Table 1
Group profiles.

Group (size)	Optimal Database Marketing	The MIS Behavior of Markets	Data Mining Techniques	CRM at the Speed of Light, 3G	Semantic Web and P2P	Executive Recommendation for the Best Products	Link	The Hidden Power of Social Networks
IT Wizards (5)	3	1	1	0	3	0	2	4
Best CRM (7)	0	5	0	1	0	3	3	3
Case Review (9)	1	0	3	0	2	2	1	1
AI World (10)	4	0	0	5	4	1	1	4
Next e-Biz (8)	3	2	1	0	2	4	3	2

Note: The figure in each cell indicates the number of group members who have read the book.

Table 2
Group similarity values.

	Best CRM	Case Review	AI World	Next e-Biz
IT Wizards	−0.17	0.05	0.41	0.17

4.1. Phase 1: group profile-based filtering

To represent the similarity between the "IT Wizards" group and other groups, we use the Pearson-*r* correlation measures as shown in Table 2. We find the "Case Review," "AI World." and "Next e-Biz" groups having high similarity values. Thus, they are selected as the neighbors of the "IT Wizards" group.

After neighbors are found, the candidate recommendation set for the "IT Wizards" group is generated by selecting top-*n* books from neighbors' book-reading records based on the adoption likelihood scores. As the result, six books are selected as the candidate recommendation set: "*Optimal Database Marketing*," "*CRM at the Speed of Light, 3G*," "*Semantic Web and P2P*," "*Executive Recommendation for the Best Products*," "*Link*," and "*The Hidden Power of Social Networks*."

4.2. Phase 2: individual profile-based filtering

To prevent excluding inactive members' tastes, the candidate recommendation set is filtered through book-user compatibility measures. In this step, we check whether feature-based profiles of members in the "IT Wizards" group match well with profiles of candidate books as shown in Table 3 and remove those whose values are lower than a threshold. We properly select a filtering threshold (i.e., −0.16) to reduce the recommendation set size by half. As the result, "*Semantic Web and P2P*," "*Executive Recommendation for the Best Products*," and "*Link*" are removed. After all, the final recommendation set is composed of "*Optimal Database Marketing*," "*CRM at the Speed of Light, 3G*," and "*The Hidden Power of Social Networks*."

5. Experiments

To evaluate the performance of GRec_OC, we developed a prototype Web-based group recommendation system and conducted experiments. We collected data through the experiments and surveyed users' reactions to the recommendations. The analysis results supported the effectiveness of GRec_OC. The details are as follows.

5.1. Data set

Throughout the experiments conducted on business-major graduate and undergraduate students at a University, we collected 1876 transactional data points generated by 265 users over 889 books. We also collected the users' demographic data (including gender, age, major, career objective, and other) and data of books they read. These data were used to build item-based user profiles. Groups of participants were formed based on individuals' ages, majors, personal interests, and career objectives so that individuals sharing similar and related profiles were grouped together. Group sizes were randomly selected ranging from 5 to 30. Upon recommendations, each group was asked to select an unspecified number of books that its members will read together. Some selected one book, some selected two books, some selected more than two books, and yet there were groups that selected no book at all. After recommendation and book selection sessions were completed, we conducted a quick survey to measure individual users' satisfaction of group recommendations. We collected data from 160 users (60.4% of participants). Books and keywords used in the experiment were obtained from a major bookseller utilizing online and off-line distribution channels.

5.2. Experiment process

Groups of participants were presented with a number of recommended books and asked to choose books, if any, from the recommended set. We considered the varying contexts of group recommendations. First, we controlled the number of recommended books, shortly the recommendation set size, as it has been discussed as a major element for recommendation and personalization (Tam & Ho, 2005). We had recommendation sets of 6, 10, and 20 books. Those with 5 or less books resulted in substantially low effectiveness (which is defined in the next section). Recommending more than 20 books is not practical.

Second, to observe the effect of group sizes, we performed several rounds of experiments with groups of fixed sizes of 5, 10, 20, and 30 and varying sizes of 5–20 and 10–30. In group decision making contexts and group task performance problems, the group size has been found to affect the quality of the group process and individuals' job satisfaction (Frank & Anderson, 1971; Mason & Griffin, 2003; Porter & Lawler, 1965). Since the book selection task in our experiments was not as complex as those studied in previous liter-

Table 3
Compatibility between individual members and candidate books.

Member	Optimal Database Marketing	CRM at the Speed of Light, 3G	Semantic Web and P2P	Executive Recommendation for the Best Products	Link	The Hidden Power of Social Networks
Member 1	0.02	0.28	−0.10	0.71	0.81	0.22
Member 2	0.04	0.01	0.40	0.20	0.60	0.24
Member 3	0.20	0.10	−**0.40**	−**0.16**	0.41	0.60
Member 4	0.52	0.6	0.01	0.21	−**0.40**	−0.10
Member 5	0.44	0.48	0.20	0.02	0.46	0.52

Table 4
Precision results for the benchmark system.

Recommendation set size	Group size					
	5	10	20	30	5–20	10–30
6	0.51	0.49	0.51	0.56	0.47	0.56
10	0.43	0.43	0.45	0.44	0.46	0.45
20	0.28	0.37	0.41	0.39	0.64	0.38

ature, we did not expect to see the previously known effect of the group size. Nevertheless, we chose the group size as a dimension to vary in our experiments due to its potential impact.

During the experiments, a proper relevance threshold for the second phase of the procedure was selected to reduce the number of recommended books by half. Though this was somewhat arbitrary, we wanted to see the effect of the relevance filtering clearly. To verify the effectiveness of GRec_OC, we compared the results of GRec_OC with the benchmark system. Benchmark system refers to an existing group recommendation system using the standard CF-based recommendation procedure, which is the first phase of GRec_OC.

5.3. Evaluation metrics

The existing studies of recommendation systems use a number of different measures to evaluate success of recommendation systems (Schafer, Konstan, & Riedl, 2001). For evaluation of our method, we adopted the precision measure, which is one of popular evaluation metrics in information retrieval systems (Herlocker, 2004). Precision measuring correctness of recommendation is defined as the ratio of the number of selected items to the number of recommended items:

$$\text{precision} = \frac{\text{the number of selected items}}{\text{the number of recommended items}}.$$

That is, precision represents the probability that recommended books are chosen by a group.

In addition to precision for the effectiveness of the recommendation algorithm, we measured the degree of individual users' subjective satisfaction with the recommendations for groups using a seven-point Likert scale for each recommended book on sets. We considered the average point value for each book as the degree of overall satisfaction. We also considered the fraction of dissatisfied users (whose satisfaction measures were less than four) in order to see if the second phase of the procedure actually resolved the dissatisfaction of individual users.

5.4. Results and discussion

We observed precision values varying on group sizes (5, 10, 20, 30, 5–20, and 10–30) and recommendation set sizes (6, 10, and 20), as summarized in Tables 4 and 5. The overall precision average of the benchmark system was 0.46 and that of GRec_OC was 0.50. Though the difference was rather small, GRec_OC consistently resulted in better recommendations than the benchmark system for all group sizes and for all recommendation set sizes except one experiment case.

Table 5
Precision results for GRec_OC.

Recommendation set size	Group size					
	5	10	20	30	5–20	10–30
6	0.63	0.57	0.59	0.58	0.57	0.68
10	0.48	0.51	0.48	0.53	0.51	0.49
20	0.28	0.39	0.43	0.40	0.50	0.40

Table 6
Satisfaction of the benchmark system and GRec_OC.

	Group size					
	5	10	20	30	5–20	10–30
Benchmark system	4.71	4.63	4.70	4.77	4.88	4.93
GRec_OC	5.21	5.07	5.06	5.02	5.06	5.26

Table 7
The result of normality tests.

	Kolmogorov–Smirnov[a]			Shapiro–Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Benchmark system	.136	137	.000	.831	137	.000
GRec_OC	.078	130	.049	.975	130	.015

[a] Lilliefors significance correction.

We continued the experiments to find out individual users' subjective satisfaction of recommendation over a seven-point Likert scale. Since these experiments involve more participation from users, we carried out experiments for the recommendation set size of 6 only. We selected the recommendation set size of 6 not only because the average precision for the size 6 is better that those of other sizes but also because it is a more realistic and practical value in book recommendation. The average satisfaction values are shown in Table 6. Like the precision measures, GRec_OC had higher satisfaction values than the benchmark system. (The correlation between precision and satisfaction values for all experiment cases was 0.33 and significant enough to confirm their correlation.)

We performed detailed statistical analysis to find the significance of difference between satisfaction values of GRec_OC and those of the benchmark system. We compared the average satisfaction values of recommendations from GRec_OC and the benchmark system when the recommendation set size is 6. As shown in Table 7, satisfaction data values were not normally distributed. Thus, we used the Mann–Whitney test (a non-parametric test) for the comparison of experiment results. Table 8 shows that GRec_OC had a higher mean value of satisfaction than the benchmark system as they were measured by their mean rank values. Table 9 confirms that the difference was statistically significant at the 95% confidence level.

GRec_OC in its second phase of procedure attempts to reduce dissatisfied users through individual profile-based filtering. To measure the user satisfaction from a different angle, we counted fractions of users whose satisfaction rating values were less than four in the seven-point Likert scale. In the benchmark system, 10.77% of users rated their satisfaction levels below four, while only 4.37% of users who received recommendations from GRec_OC did so. Table 10 shows the fractions of dissatisfied users varying on group sizes. Except for the group sizes between 10 and 30, there

Table 8
Mann–Whitney test: mean ranks.

	N	Mean rank	Sum of ranks
Benchmark system	137	123.91	16975.50
GRec_OC	130	144.63	18802.50

Table 9
Test statistics.

Measure	Value
Mann–Whitney U	7522.500
Wilcoxon W	16975.500
Z	−2.195
Asymptotic significance (2-tailed)	.028

Table 10
Fractions of dissatisfied users.

	Group size					
	5	10	20	30	5–20	10–30
Benchmark system	9.61%	12.50%	8.33%	22.22%	13.04%	0%
GRec_OC	4.25%	7.69%	0%	0%	0%	7.14%

were less dissatisfied users with GRec_OC. In sum, the experiments evidenced that GRec_OC provided recommendations with better performance, more user satisfaction, and less dissatisfied users.

6. Conclusion

6.1. Summary and implications

Existing recommendation systems provide personalized recommendations for individual customers. Thus they are not useful for activities performed by a group of individuals. A small number of studies proposed recommendation systems for groups, but they used simple aggregation of group members' preferences when generating recommendations. As a result, preferences of certain members, in particular less active ones, are neglected. Our study attempts to introduce a new group recommendation procedure focusing on the improvement of not only the group recommendation quality but also individual members' satisfaction. We developed a recommendation system called GRec_OC for online book reading clubs. It contains two phases of the recommendation procedure. The first phase uses the collaborative filtering recommendation technique on group profiles and the second phase provides individual profile-based filtering that removes less favored books from the set generated by collaborative filtering of the first phase.

To evaluate GRec_OC, we implemented a prototype system, established online book clubs, generated recommendations for book reading clubs, and surveyed users' responses. Our experiment results showed that GRec_OC offered better quality of recommendations than the existing CF-based group recommendation system. That is, GRec_OC resulted in higher precision values than the benchmark system. Further, most users were more satisfied with GRec_OC than benchmark system. We validated that the satisfaction difference between two systems was statistically significant. Furthermore the number of dissatisfied users was reduced in GRec_OC when compared with benchmark system.

The two-phase recommendation procedure of GRec_OC can be used for various group recommendation problems including book clubs' reading list generation, movie recommendation, and group travel destination selection. For instance, a book seller may organize an online reading club facilitating not only an environment for discussion and book information sharing but also reading group activities. In fact, such virtual communities are emerging in the Internet (e.g., see book-clubs-resource.com). Currently, group activity facilitation focuses on the organization of reading groups. The proposed group recommendation procedure can improve such virtual communities' group activity effectiveness.

6.2. Limitations and future research

Our experiments were conducted in a relatively small scale. In order to claim general viability of our group recommendation procedure, we need more experimental evaluations in a larger scale and in other domains. We are continuing the book recommendation with our prototype system to collect more data, and planning other applications including movie recommendation.

The group recommendation procedure of GRec_OC extends the standard CF method with individual-level relevance filtering. The overall procedure can be further improved with the use of an advanced CF method, a hybrid approach, or a model-based method (Adomavicius & Tuzhilin, 2005). A hybrid approach, for instance, can make the recommended item selection more relevant to users if item attributes together with users' ratings on items are readily available. Furthermore, we are investigating the opportunity of taking advantage of recent development in information management technology in the group recommendation context.

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