Development of Recommender Systems Using User Preference Tendencies: An Algorithm for Diversifying Recommendation

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Abstract. Many e-commerce sites use a recommendation system to filter the specific information that a user wants out of an overload of information. Currently, the usefulness of the recommendation is defined by its accuracy. However, findings that users are not satisfied only with accuracy have been reported. We consider that a recommendation having only accuracy is unsatisfactory. For this reason, we define the usefulness of a recommendation as its ability to recommend an item that the user does not know, but may like. To improve user satisfaction levels with recommendation lists, we propose an alternative recommendation algorithm that increases the diversity of the recommended items. We examined items that appeal to several different taste tendencies to create a list and achieved diversity in that list. First, we created a similarity network of items by using item rating data. Second, we clustered the items in the network and identified the topics that appealed to the same preference tendency. Our proposed algorithm was able to include items covering several topics in the recommendation list. To evaluate the effect on user satisfaction levels, we used our algorithm to make a recommendation list for DVD items carried by Amazon.co.jp and conducted a questionnaire survey. The results showed higher levels of user satisfaction with our list than a list created using Collaborative Filtering (CF).

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1. Introduction

The massive growth of the Internet has made an enormous amount of information available to us. However, it is becoming very difficult for users to acquire an applicable one. Therefore, some techniques such as information filtering have been introduced to address this issue. Recommender systems filter information that is useful to a user from a large amount of information. Many e-commerce sites use recommender systems to filter specific information that users want out of an overload of information [2]. For example, Amazon.com is a good example of the success of recommender systems [1]. Over the past several years, a considerable amount of research has been conducted on recommendation systems. In general, the usefulness of the recommendation is measured based on its accuracy [3]. Although a high recommendation accuracy can indicate a user's favorite items, there is a fault in that only similar items will be recommended. Several studies have reported that users might not be satisfied with a recommendation even though it exhibits high recommendation accuracy [4].

For this reason, we consider that a recommendation having only accuracy is unsatisfactory. The serendipity of a recommendation is an important element when considering a user's long-term profits. A recommendation that brings serendipity to users would solve the problem of "user weariness" and would lead to exploitation of users' tastes. The viewpoint of the diversity of the recommendation as well as its accuracy should be required for future recommender systems.

The purpose of this research is to introduce diversity into recommendations, and to build useful recommender systems for users. For this purpose, we define the usefulness of a recommendation as its ability to recommend items that the user does not know, but may like. To improve user satisfaction levels with recommendation lists, we propose an alternative recommendation algorithm that increases the diversity of recommended items.

2. Related Works

2.1. Existing Recommender Systems

Recommender systems are based on two general techniques: Content-based Filtering and Collaborative Filtering [5, 6]. Content-based Filtering is a technique in which items are recommended if their feature information is similar to feature information based on user preferences [7, 8]. The quality of recommendation of content-based filtering does not depend on the number of users. Therefore, this technique is advantageous in that recommendations are stable even in the early stage of performance. However, it has some problems such as the difficulty of extracting feature information on items, or how an item's feature information is described. Moreover, there is a fault in that the items recommended will be alike. Collaborative Filtering is a technique of selecting recommendation items based on users' information whose tastes are similar [9, 10]. The degree of similarity is calculated by information obtained on item ratings. This technique is applicable also to the item of a different kind. However, the disadvantage is that much information is needed on item evaluations in order to understand users' tastes [8].

In addition, a technique using a hybrid system that unifies Content-based Filtering and Collaborative Filtering has also been proposed [11, 12]. Many of these recommendation system studies, however, are aiming at increasing the accuracy of recommendations. We emphasize that the problem is not about accuracy alone.

2.2. Research on Diversity of Recommendations

Shimizu et al. [13] proposed a Collaborative Filtering technique based on known/unknown information in users' items, in order to recommend favorite items that users do not know. An experiment focusing on novelty indicated that their technique was able to recommend many favorite items that users did not know compared to other collaborative filtering techniques. However, this technique is difficult to actually use because acquiring the information on unknown items is hard: Users do not answer, "I don't know" for an unknown item. Moreover, the validity of recommendations is also brought into question in their research because only the evaluation of the novelty was tested. An evaluation of recommendations should consider direct evaluations by users.

Ziegler et al. [4] proposed an index that calculates the degree of similarity of items in a recommendation list using category information on the items (classification of genres and authors). Moreover, they proposed a diversification technique that minimizes the degree of similarity of items in the recommendation list using their index. The results of a questionnaire experiment show that the degree of user satisfaction improved by introducing diversification into the recommendation. However, there is a fault in that the applicable scope must be limited since the technique demands category information on items. The items had similar relationships to each other that could not be expressed with manual category classification. The similarities between items varied, for example, market trends and similarities of movie themes. Therefore, diversification of genres in a recommendation list is not necessarily useful for users.

The target of our research is to provide recommendations with diversity that are useful to users, , which means recommendations of favorite items that users did not know, i.e., were “unknown” to them. Therefore, we tried to develop a method of diversified recommendation in consideration of user preferences.

3. Diversification of Recommendation by Diversification of Preference Tendency

Recommending items that have different taste tendencies would be an effective method for recommending an item unknown to the user. For this reason, we propose a recommendation algorithm that diversifies the preference tendency of items in recommendation lists. Presumption of preference tendency requires information on users' item rating data. The method is as follows. First, we create a similarity network of items by using users' item rating data. Second, we cluster the items in the network and identify topics that appeal to the same preference tendency. Finally, we create a recommendation list that is diversified so that it might contain several different topics. The proposed technique is designed to recommend unknown items to users by using a little information about the users.

3.1. Outline of Our Algorithm

Figure 1 illustrates the overall concept of our recommendation technique. The proposed technique is divided into three steps.

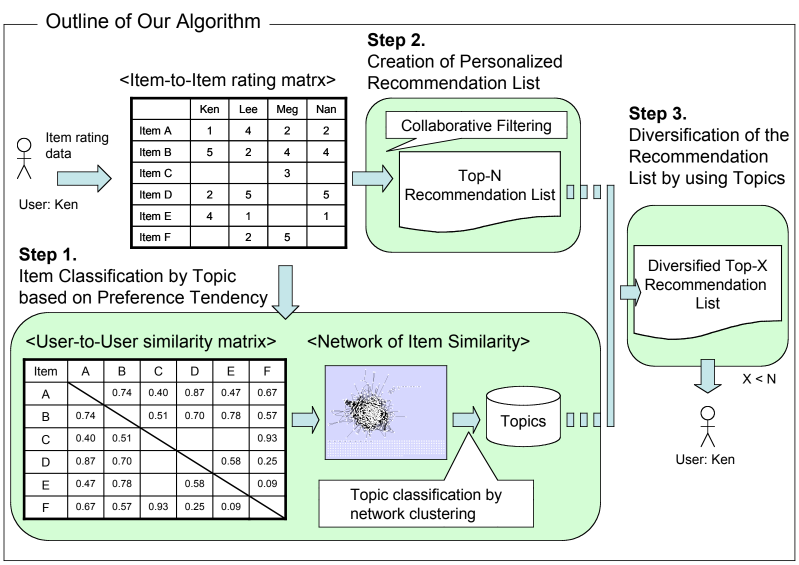

Fig. 1 Overall concept of recommendation technique

- Step 1: Grouping of items according to topic by using preference tendency
- Step 2: Creation of personalized recommendation list
- Step 3: Diversification of recommendation list by using topics

In Step 1, we classify topics according to users' item rating data in order to acquire classification information on the item that reflects users' tastes. In this classification, we express a network of similar relationships of users' tastes of items by using the rating data. Next, we cluster the network and classify the items as topics to ensure that the taste tendencies are similar.

In Step 2, we create a personalized recommendation list. To raise the degree of user satisfaction, both diversity and accuracy of a recommendation list are required [4]. We make a personalized recommendation list by using user-based Collaborative Filtering. Thereby, an accurate list is created.

In Step 3, we select items of different preference tendency from the recommendation list in Step 2. Preference tendency in this paper is defined as topic information acquired using Step 1. Based on the above steps, we make a recommendation list that is compatible in accuracy and diversity.

3.2. Item Classification by Topic Based on Preference Tendency (Step 1)

We propose a technique to classify topics that involves clustering an item network. Some related studies have been done on network categorization. Toda et al. [15] proposed a method of extracting topics from document sets by using graphic analysis. Matsuo et al. [16] analyzed researcher communities from a network of collaboration-related papers. Yuta et al. [17] analyzed a community consisting of linked relationships in social networking systems (SNS). These studies are useful for discovering potential communities and topics, and for categorizing information that changes topicality. Moreover, calculation of the degree of similarity between items by using user item rating data, which also adopts Item-based collaborative filtering, is effective in recommending similar items [18]. As mentioned above, we found that topics could be classified into preference tendency according to network clustering of item similarities. A networking method for topic classification is described in section 3.2.1. Then, we explain a method of network clustering in 3.2.2.

3.2.1. Network of Item Similarity

We use a weighted undirected network to classify topics. The network describes an item as a node and the similarity between rating data of items as an edge. The network is constructed as follows. First, we calculate an item-to-item similar value matrix using equation (1) from a user-to-item rating value matrix. Next, we construct a weighted network by connecting items with the edges. Thereby, we create a similar item network which reflects the user's preference tendency. In equation (1), $r_{i,a}$ is a rating value over user's U_i item I_a.

$$sim(I_a, I_b) = \frac{\sum_i r_{i,a} r_{i,b}}{\sqrt{\sum_i (r_{i,a})^2}\sqrt{\sum_i (r_{i,b})^2}} \quad (1)$$

3.2.2. Topic classification by Network Clustering

The topic classification is performed using a clustering algorithm of Newman [19] to apply the similar item network constructed in section 3.2.1. Newman proposed an index of modularity Q, which evaluates clustering performance, and proposed a clustering technique using the index [19, 20]. The value of Q is obtained by subtracting a theoretical value of the rate of a link in the module at the time of assuming that it is a random network, from the actual measurement of the probability that a link exists between the nodes in a module. The Q increases if links in the module are dense and those between modules are sparse. This is why the Q value is regarded as a useful index by which the performance of clustering can be evaluated objectively. Newman stated that an independent modular structure emerges when the Q value became larger than 0.3. The Q value formula is expressed in equation (2). In this equation, C is the total of a cluster, m is the number of edges that exist in the whole network, and l_{ij} is the number of edges of cluster i and cluster j.

$$Q = \sum_i^C \left(\frac{li}{m} - a_i^2 \right) \quad (2)$$

$$a_i = \sum_j e_{ij}$$

$$e_{ij} = \frac{l_{ij}}{2m}$$

This clustering technique is a greedy algorithm that continues the merger with the node from which the increased value (ΔQ) of Q serves as the maximum. In an initial state, one node is one cluster. Although this algorithm is used to calculate semi-optimal rather than optimal solutions, it has been used in many studies [17, 22] to perform effective clustering because of the computational complexity of $O(n\,m^2)$. Equation (3) is the formula of ΔQ_{ij}, which is an incremental value of Q when combining clusters i and j.

$$\Delta Q_{ij} = 2\left(e_{ij} - a_i a_j\right) \quad (3)$$

Although the above-mentioned equation is applied as the clustering technique in a non-weighted network, it can also be applied in weighted networks [21]. Moreover, if weight is set as an edge, it has been reported that the size of a cluster can be equalized and improved [22].

For the above reason, we think that the proposed technique is effective for classifying item groups that have similar ratings into topics.

3.3. Creation of Personalized Recommendation List (Step 2)

The second step involves creating the personalized recommendation list. This is because both diversity and accuracy (personalized) are required for a recommendation list in order to raise the degree of user satisfaction [4]. Therefore, we create the personalized recommendation list using user-based Collaborative Filtering.

User-based Collaborative Filtering is a technique applied to discover user groups, in which users have similar likings, and to recommend favorite items of the user group. This technique has two processes: calculating the degree of similarity, and calculating a prediction rating value. In the first process, the degree of similarity is calculated between users using user's item rating, in order to find users with preference similar to those who are recommended. The Pearson correlation coefficient [9] is often used for this calculation. In the second process, the prediction rating value P of a non-rated item is calculated based on the rating of a similar user. A prediction rating value is calculated for every user, and the top-N items of this value become the recommendation list. Equation (4) is the formula of the prediction rating value of User U_x's non-rated item I_a, and $ave\ (r_x)$ is the average of all the rating values User U_x voted on. Moreover, $\Sigma_k \in K$ is User U_x and top K neighborhood users with a high degree of similarity.

$$P_{x,a} = ave(r_x) + \frac{\sum_{k \in K} sim(x,k)\left(r_{x,a} - ave(r_k)\right)}{\sum_{k \in K} \left|sim(x,k)\right|} \quad (4)$$

3.4. Diversification of Recommendation List by Using Topics (Step 3)

In order to achieve diverse recommendations, we select the items of a different preference tendency using topic information and the personalized recommendation list. First, we classify the personalized list according to topic. Next, by calculating the average of the prediction rating value of the item for every topic, we determine the priority of a topic. Finally, we choose one item in order of a topic with a high priority, and add it to the recommendation list. We repeat this process for all of the items that are finally recommended. Using this process, we create diverse recommendation lists with several different topics.

4. Evaluation of Recommendation List

We evaluate a recommendation list using a questionnaire on user degree-of-satisfaction. Conventionally, precision and recall are often used as an index of the accuracy of a recommendation list [3]. However, these evaluation indices are indices of accuracy, and they depend on the first evaluation of an item. An evaluation of a recommendation must evaluate which has discovered the user's potential interest. Therefore, precision and recall alone are not sufficient for evaluating a user's potential interest.

In this research, our target recommendation is a recommendation with diversity that is useful for a user, that is, a recommendation that recommends favorite items that may be unknown to the user. Therefore, we use a questionnaire to evaluate whether the proposed technique can recommend "favorite items unknown to a user."

Specifically, we evaluate the distribution of items and the average rating value of items in a recommendation list that were unknown to the user.

5. Evaluation Experiment

To evaluate our technique, we compare recommendations obtained by using the proposed technique and an existing technique (collaborative filtering).

5.1. Experiment Outline

5.1.1. Experimenter

The experiment was conducted using 14 university students as experimenter.

5.1.2. Data Set

In this experiment, 1,000 DVD items listed in Amazon.co.jp were used as an item set. We selected the item of the sales high order in consideration of the rate of a genre. In addition to the item evaluations obtained from the experimenter, we used item evaluations by 1,609 Amazon.co.jp reviewers as evaluation information.. The number of reviews used was 5,692, and the average rating value was 4.2. These data were acquired using Amazon API [23]. We conducted the crawling between 2007/4/18 - 2007/4/20.

5.1.3. Experimental Procedure

The procedure of the experiment is described below.

(1) Collection of item evaluation data

To obtain data on a user's present tastes, we had each user evaluate items. First, we showed experimenter a list of 30 DVD items at random. Next, the experimenter was asked to evaluate whether an item was “known” or “unknown”, and to rank items as “favorite” items (on a scale of 1-5).

(2) Classification of a topic

We classified the topics based on taste tendencies from item rating information. First, we created a similar-item network using item rating information obtained from experimenter and Amazon.co.jp reviewers. Next, we clustered this network and classified items as a topic.

(3) Creation of diversified recommendation list

We created the diversified recommendation list using the topic information from (2). First, the top 50 items were selected by user-based Collaborative Filtering in the data from (1) using the item (seen or known, although not looked at) that the user knew. Next, we used the topic information from (2) and the top 50 items, and created the diversified recommendation list of top X items ($X \in [10, 20, 30, 40, 50]$).

(4) Evaluation of user degree of satisfaction

To evaluate the diversified recommendation list, we showed a user the recommendation list created in (3), and obtained data on the user degree of satisfaction. Each user answered known/unknown on the evaluation (seen or known although not looked at, or did not know), and indicated favorites (on a scale of 1-5) for each item on the recommendation list.

5.2. Experimental Result

5.2.1. Result of Topic Classification

We created an item network similar to that in Fig. 2 using the collected item rating data. Table 2 shows the results of clustering this network. As a result of the topic classification by clustering, 659 items out of 1000 were connected as one network. High clustering performance (Q= 0.43) was achieved as a result of the clustering in this network. Moreover, the topics were alike in genre, series, etc., and they reflected the preference tendency to some extent.

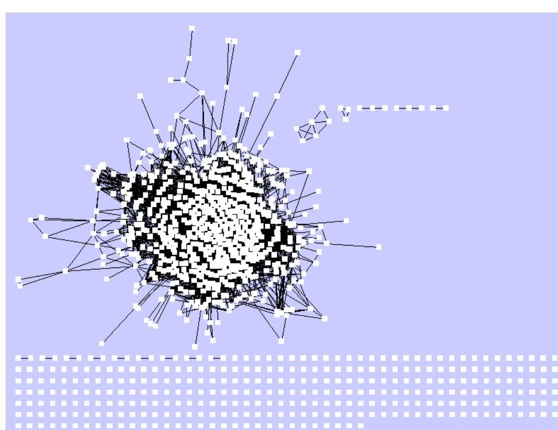

Fig. 2 Network of item similarity

Table 2 Result of clustering

Extracted number of topics	343
Number of items in 1 topic (ave.)	2.92
Number of items of the maximum network	659
Modularity of the maximum network	0.43

5.2.2. Results of Diversification of Recommendation List

Table 4 shows the number of topics in a recommendation list. As the table indicates, the recommendation list created by using the proposed technique was able to cover all the topics with only the top 20 items in a recommendation list.

Table 4 Kinds of topics in recommendation list (Top-X items)

Top-X	Kinds of topics in a recommendation list	
	Diversification of Topics (DT)	Collaborative Filtering (CF)
10	9.9	5.9
20	16.1	10.1
30	16.1	13.2
40	16.1	14.9
50	16.1	16.1

5.2.3. Results of User Degree of Satisfaction

Fig. 3 shows the distribution of "items unknown to a user" in a recommendation list. As indicated in the figure, when the number of items in a recommendation list was 10-40, as with the proposed technique, many more "items unknown to a user" were recommended compared to the existing technique. Table 5 lists the average of item rating value and t-test. As a result of the t-test, a significant difference (*p<.05) was found between the proposed technique and the existing technique in the top 20-30 "items unknown to user." Moreover, the proposed technique acquired a rating value as high as that for the existing technique for "items known to user."

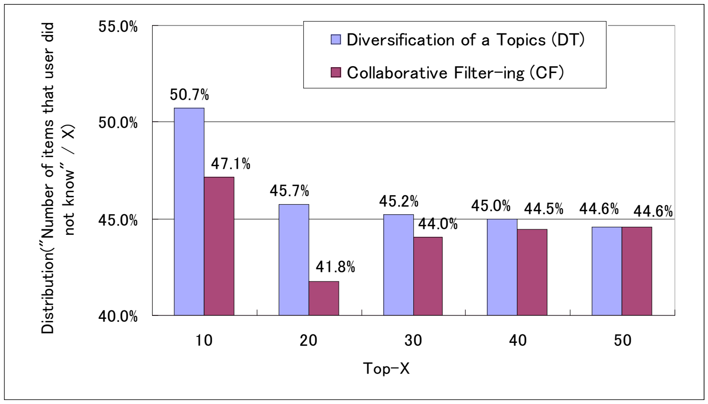

Fig. 3 Distribution of items unknown to user in a recommendation list

Table 5 Results of rating value (user average) and t-test

Top-X	Items known to user			Items unknown to user		
	DT	CF	*p* value	DT	CF	*p* value
10	3.35	3.67	.074	2.86	2.71	.085
20	3.67	3.63	.732	2.87	2.67	.040*
30	3.69	3.63	.429	2.86	2.70	.026*
40	3.67	3.67	.912	2.82	2.81	.809
50	3.67	3.67	—	2.80	2.80	—

* $p < .05$

6. Discussion

In this research, our target recommendation was a recommendation with diversity that is useful for a user. Specifically, our goal was to recommend favorite items that a user does not know. From the viewpoint of recommending "items unknown to a user," the proposed technique was able to recommend more "items unknown to a user" than the existing technique, based on the results in Fig. 3. Moreover, for "favorite items unknown to a user," the proposed technique recommended items with a higher evaluation than those recommended by the existing technique, based on the results of Table 5. For this reason, when we select an item from each topic, we think that giving priority to and choosing an item with the highest predicted rating value leads to the recommendation of items the user is interested in. As mentioned above, it can be said that the proposed technique, which diversifies the topic based on the preference tendency in a recommendation list, was an effective technique for recommending "favorite items unknown to a user."

This experiment had the following limitations. The first limitation is that the only type of item used for the experiment was a DVD (movie, drama, animation, etc.). The algorithm of the proposed technique can be applied to any item, as long as the user's rating of the item is obtained. However, without trying the experiment with other items, there is no way of knowing whether the technique will actually be useful for users. However, we expect that the proposed technique will be effective to the same extent for other tasty things (e.g. book, music, news) as it was for the DVD. The second limitation is that the only experimenter was a student. A user's characteristics (e.g. age, vocation) might affect the user's taste. It will be necessary to try the experiment with various experimenters.

7. Conclusion and Future Work

The purpose of this research was to introduce diversity in recommendations, and to build recommender systems useful for users. In order to improve the user degree of satisfaction of a recommendation list, we proposed a recommendation algorithm that raises the diversity in a recommendation list. Specifically, we achieve diversity of recommendation by keeping items that reflect a different preference tendency on a recommendation list. The process of the proposed technique was as follows. First, we created a similarity network of items by using item rating data. Second, we clustered the items in the network and identified the topics that appealed to the same preference tendency. Finally, we created a diversified recommendation list that might have several different topics. Our proposed algorithm can include items that cover several topics in the recommendation list. To evaluate the effect on user satisfaction levels, we used our algorithm to make a recommendation list for DVD items listed on Amazon.co.jp and conducted a questionnaire survey. From the viewpoint of diverse recommendations, the proposed technique was able to recommend more "favorite items unknown to user," than the existing technique.

We will expand our research in the future as follows. The first objective is to create a recommendation list that is personalized using methods other than user-based collaborative filtering. This is because collaborative filtering has a "rating value sparse problem" [12] and a "cold-start problem". In the "rating value sparse problem," a deviation occurs in the evaluated item. In the "cold-start problem," it is not possible to create a recommendation that a user is satisfied with in the early stage of employment when there is little user's item rating data. A solution may be reached by using a default rating for items the user is not evaluating. The second objective is to solution of the problem of trade-off in accuracy and diversity. The usefulness of a recommendation may be different according to a user's properties, a user's situation, and the kind of item. It will be necessary to consider these properties and to consider how the balance of accuracy and diversity should be adjusted.

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