Recommendation Method That Considers the Context of Product Purchases

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Abstract: - We propose herein a technique for product recommendation in E-commerce by considering the context of product purchases, and verify the effectiveness of the technique through an evaluation experiment. Researchers have been aggressively studying techniques that can be used by stores to recommend to customers products that have relatively high purchase potential. Collaborative filtering is representative of conventional techniques. However, the collaborative filtering technique is based on the hypothesis that similar customers purchase similar products, and the context of product purchases is not considered in full.

In the present study, a context matrix by which to manage the context history of product purchases is proposed. Collaborative filtering cannot distinguish the following two facts that `Product B was purchased after Product A' and `Product A was purchased after Product B'. The context matrix, however, enables such information to be expressed and managed separately. We also propose four types of context matrix update methods which differs in subset selection on purchase history and user selection on obtaining purchase history.

The results of an evaluation experiment revealed the following:

i) The proposed technique can improve the recommendation precision by taking into account the context of purchases when making recommendations.

ii) As the amount of available purchase history and context data increases, the recommendation precision improves.

iii) The highest recommendation precision among four types of context matrix update methods is obtained, if all contexts of purchases along time axis by customers of similar taste only are considered.

Key-Words: - Recommendation, database, data mining, and E-commerce.

1 Introduction

Recently, researches on E-Commerce have been activated([1]-[3]). Especially, in a trend of one-to-one marketing, recommendation is attracting a great deal of attention as an effective technique by which to increase E-commerce sales. Recommendation is a technique whereby stores precisely recommend to customers products of relatively high purchase potential by considering the characteristics of both products and customers[4]. Various techniques, representative among which is collaborative filtering[5], have been applied in attempts to realize recommendation. However, none of these techniques fully considers the context of product purchases.

In addition to collaborative filtering, we herein consider the context of the order of product purchases when recommending products. The present paper proposes a technique for making recommendations based on the contexts of product purchases. In the proposed technique, we introduce a context matrix in which the contexts of product purchases are expressed and managed as an N×N square matrix, where N is the number of products considered. The context matrix ensures higher precision of recommendation than collaborative filtering alone. In addition, the present paper also evaluates the context matrix experimentally and compares the recommendations produced by four methods of updating values in the context matrix.

The remainder of the present paper is organized as follows. Section 2 describes recommendation and collaborative filtering, as related to the proposed technique. Section 3 describes the proposed context matrix for considering the context of product purchases. Section 4 verifies the effectiveness of the context matrix by evaluation experiment and compares four possible methods for updating values in the context matrix. Section 5 presents conclusions and topics for future consideration.

2 Previous Studies

2.1 Conventional Recommendation Techniques

Existing recommendation techniques can be classified into three types [4]:

1) <u>Checkbox technique:</u> Technique that makes recommendations based on data entered by customers using checkboxes to outline their interests,
2) <u>Rule-based technique:</u> Technique that makes recommendations according to rules determined by the administrator of the E-commerce site, and
3) <u>Collaborative filtering technique:</u> Technique that groups together customers having similar tastes based on the history of clicks by customers visiting the site and the history of purchases. Collaborative filtering technique recommends products that have not yet been purchased by the customer, but that have been purchased by customers in the same group.

Generally, for new E-commerce sites, since data pertaining to customer purchasing preferences have not yet been collected, only techniques of types 1) and 2) are effective. However, as the amount of such data increases, technique of type 3) becomes increasingly effective.

2.2 Collaborative Filtering

This section describes the above-mentioned collaborative filtering in detail.

2.2.1 Definition

Collaborative filtering was originally proposed as a technique for recommending network news to attract specific users[5]. The range of application of this technique has been extended from recommending network news to recommendation in numerous fields, including the recommendation of web pages, as well as books, music, movies, software functions, and other merchandise handled in E-commerce([6]-[9]).

In the present paper, a matrix expressing the history of purchases, in which customer names are given in columns and product names are given in rows, is referred to as a `purchase history matrix'. Both Tables 1 and Table 2 are purchase history matrixes for purchases of five products by five customers.

Values in the purchase history matrix are set or updated either using or not using evaluation values, which are customer scores regarding recommendation usefulness, as follows:

- <u>Using evaluation values</u> (Table 1): The score given by *Customer ci* with respect to *Product pj* is registered.
- <u>Not using evaluation values</u> (Table 2): The value 1 is set to register only the fact that *Customer ci* has purchased *Product pj*. In this case, all elements in the purchase history matrix are either 0 or 1.

In order to use evaluation values, all customers must cooperate in scoring. This is a serious defect for an E-commerce site, and using evaluation values on an E-commerce site is not necessarily practical. In addition, by considering automatic data collection, the present paper discusses only the technique of not using evaluation values.

When no purchase history data exists, the purchase history matrix is a zero matrix. If

Customer ci has purchased *Product pj*, then the value at *Column i*, *Row j* is updated from 0 to 1.

Table 1 Purchase history matrix
(Using evaluation values)
×: Bad
Δ: Neither good nor bad
○: Good
◎: Very good

Customer \ Product	*p1*	*p2*	*p3*	*p4*	*p5*
c1	○		◎	○	
c2		○			Δ
c3	×				
c4	○	Δ	○	◎	
X			○	○	

Table 2 Purchase history matrix
(Without using evaluation values)

Customer \ Product	*p1*	*p2*	*p3*	*p4*	*p5*
c1	1	0	1	1	0
c2	0	1	0	0	1
c3	1	0	0	0	0
c4	1	1	1	1	0
X	0	0	1	1	0

In order to determine whether a product is recommendable to *Customer X*, products previously purchased by customers similar to *Customer X* are selected from among products not yet purchased by *Customer X*. In Table 2, *Customers c1* and *c4* can be considered as similar to *Customer X* because they have purchased both *Products p3* and *p4*. Therefore, products that have not yet been purchased by *Customer X* but were purchased by *Customer c1* or *c4* are searched. Here, *Products p1* and *p2* satisfying these conditions are recommended.

2.2.2 Recent topics

In this subsection, we introduce some recent topics concerning collaboratove filtering.

Adomavicius *et al.* propose to divide an evaluation granularity of an item into smaller hierarchy such as taste, service, and interior for restaurant, or scenario and casting in addition to overall evaluation for movie[10]. It leads to better performance in their recommendation. Cho *et al.* propose to distinguish reading, sample viewing, and purchase in their video example, and to derive similarity among customers based on each behavior[11]. It improves implicit acquisition of evaluation value. They also propose to provide heavy weight to sample customers who evaluate lots of items in the same category as a target item.

Das *et al.* propose to use collaborative filtering after a user restricts recommendation candidate news with language, genre, and/or freshness by himself/herself, in their news summary site ‘Google News’[12]. Beforehand restricting of recommendation candidate by some conditions efficiently improve his/her satisfaction level. The paper [13] and [14] investigate the method of dealing with empty evaluation value. According to their papers, candidate approaches are (i) to utilize item sets which all customers evaluate, (ii) to utilize mean value instead of empty value, and (iii) to neglect the empty value and calculate the level of loss. Weimer *et al.* also investigate the method of dealing with sequential update by insert of an item or a customer[14].

Mobasher *et al.* investigate ‘shilling attach’ which is one of the behaviors of interfering with a recommender system in order to gain an advantage over others[15]. Melamed *et al.* propose a promotion method to obtain evaluation value for an item[16]. Concretely, in their system, a user has to pay his/her own point in order to obtain information. On the other hand, he/she can obtain his/her point by providing an evaluation value to an item.

Fleder *et al.* investigate a recommender system from marketing area[17]. They discuss whether a recommender system influences to a customer’s purchase behavior and promote oligopoly or not, by using mathematical market model which contains two items. According to their results, the more an item is purchased, the more it obtains recommend frequency. It leads to oligopoly.

2.3 The Contexts of Product Purchases

The contexts of product purchases are not fully considered in the above recommendation techniques. For example:

- In some cases, *Product p3* is appropriate for experienced users, whereas *Product p1* is appropriate for inexperienced users.
- *Product p3* is a general-purpose part or accessory, such as a screw, battery, or table tap, intended for use with *Product p1*(Fig. 1).

Even when several customers purchase *Product p3* after *Product p1*, there may be very few customers who purchase *Product p1* after *Product p3*. In this case, it is questionable as to whether recommending *Product p1* to *Customer X* is appropriate.

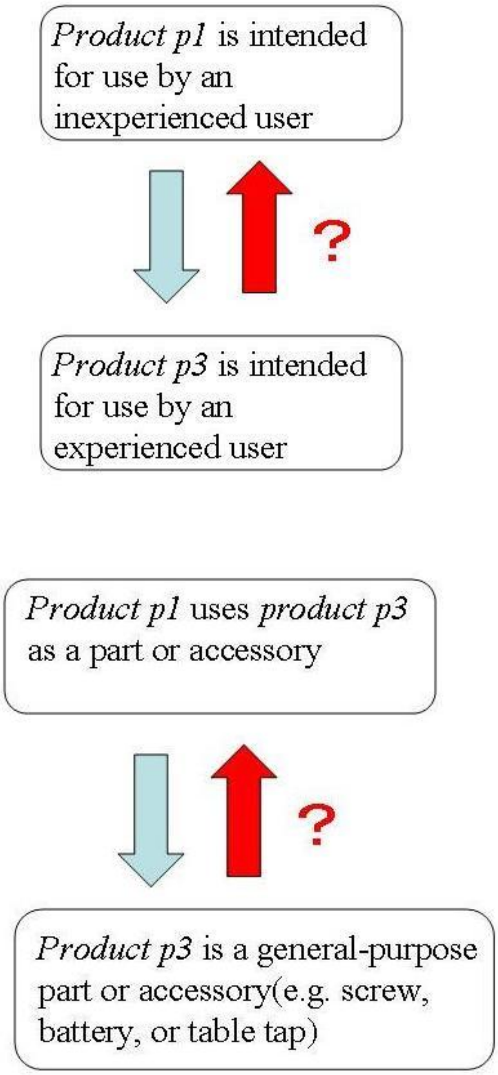


Fig.1 Context of product purchase.

We have introduced the recent topics of collaborative filtering technique in subsection 2.2.2. When we survey the research of collaborative filtering including until more older, their main target has been how to derive similar customers and improve estimation of the usefulness of information ([7], [18]-[21]). Previous studies have not been examined the contexts of product purchases in full.

The present paper attempts to utilize the context information of product purchases for recommendation. This information has the advantage of automatic collection without forced cooperation from customers. Verification of the effectiveness of such information will show that the use of context in E-commerce is practical.

3 Context Matrix

3.1 Definition

In the present study, a context matrix is proposed by which to manage the context history of product purchases. As the basic context, the present paper discusses context as a pair of product purchases like "Purchasing *Product p3* after *Product p1*" or "Purchasing *Product p2* after *Product p4*".

In order to express and manage such contexts, we propose a context matrix (Fig. 2). The proposed context matrix is an N×N square matrix, where N is the number of products. In this matrix, the rows indicate products that have been purchased previously and the columns indicate products that have been newly purchased. The matrix is first initialized into a zero matrix. Each time *Product pj* is purchased after *Product pi*, element m_{ij} is incremented by 1. With respect to Fig. 2, if *Product p3* is purchased after *Product p1*, then the value *m* in *Column 1*, *Row 3* is incremented.

Collaborative filtering cannot capture order-of-purchase information, i.e. whether *Product p2* was purchased after *Product p1* or vice versa. The context matrix, however, enables order-of-purchase information to be expressed and managed separately. The fact that *Product pi* has been previously purchased and now it is purchased again can be expressed by incrementing diagonal element m_{ii}.

Newly purchased

Previously purchased		*p1*	*p2*	*p3*	*p4*	*p5*
	p1	0	5	m	8	4
	p2	2	0	4	5	3
	p3	6	3	0	5	6
	p4	6	3	8	0	7
	p5	5	4	5	3	0

Fig.2 Context matrix.

3.2 Usage

Assume that *Customer X* has already purchased *Product p4*. If the products are arranged in descending order of purchase potential in the Fig. 2, their order is *p3*, *p5*, *p1*, *p2*. Thus, we may be able to determine recommendable products using only the context matrix.

However, if recommendable products are determined by the above method, they will be recommended uniformly to all customers. If *Customer X* has already purchased one product among *Products p3*, *p5*, *p1*, or *p2* and the product has the characteristic that it will not be purchased twice, then recommendation of the product is useless.

Since the context matrix has products as both row and column elements, it is preferable to consider the purchasing characteristics of customers in additional way.

In order to enhance the precision of recommendation, we apply context matrix evaluation to recommendations created by collaborative filtering considering both customer and product characteristics. In general, the promotion of too many products is not effective. Therefore, it is useful to determine the priority order appropriately.

3.3 Method of Updating Values

When updating values in the context matrix, the question arises as to which values in the context matrix should be incremented. In other words, “What is the true context?” Fig. 3 shows an example in which we assume that a customer has already purchased products *p4*, *p2*, *p1*, and *p5*, in the order given, where t denotes the time axis. If *Product p3* is newly purchased, any combination of *p4→p3*, *p2→p3*, *p1→p3* and *p5→p3* may be regarded as the context. It is not clear that how far we should go back and examine a customer’s purchase history, and should treat it ‘context’.

On the other hand, it is also not clear that how much range of customers we should examine the purchase history, and count the number of context. For example, we can consider all customers or a certain its subset as its evaluation.

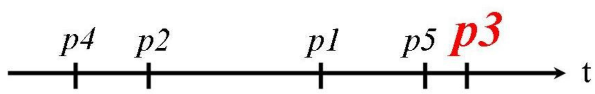


Fig.3 Range of context before and after product purchase.

We propose four types of context matrix update methods which differs in subset selection on purchase history and user selection on obtaining purchase history. Concretely, from the viewpoint of a particular product purchase, we propose the four methods below and determine experimentally the most appropriate method.

Method *M1*: Assume that all past purchases are related to the current purchase. For the example of Fig. 3, *p5→p3*, *p1→p3*, *p2→p3*, and *p4→p3* are all considered, and the four corresponding elements (m_{53}, m_{13}, m_{23}, and m_{43}) in the context matrix are incremented.

Method *M2*: Assume that the previous purchase and the purchase before that are related to the current purchase. For the example of Fig. 3, the two elements (m_{53} and m_{13}) corresponding to *p5→p3* and *p1→p3* are incremented.

Method *M3*: Assume that only the previous purchase is related to the current purchase. For the example of Fig. 3, by considering only *p5→p3*, only one element (m_{53}) is incremented.

Method *M4*: Create a context matrix for each group of customers having similar tastes. Since groups of similar customers may change dynamically, each context matrix should also be created dynamically. Here, we assume that all past purchases are related to the current purchase.

4 Evalution Experiment

4.1 Experimental Method

In addition to the above four methods, **Method *M5*** (which gives no consideration to context) is included in a comparison of the precision of the recommendation. In this experiment, purchase history data is collected by questionnaire survey, hereafter referred to as simply the `survey’(Fig. 4-5).

In order to confirm that the proposed technique can deal with various product categories, the two product categories below are used. The categories are 45 PC-related products and 31 daily-use products. The PC-related products include Windows desktop personal computers, Windows A4-size notebook personal computers, Windows B5-size notebook personal computers, ink-jet printers, laser printers. The daily-use items include TV sets, microwave ovens, bookshelves, motorbikes and motorcycles.

The survey consists of two requests, as follows:

1.) Circle all of the products that you have purchased.

Customers are asked to select purchased products from a list.

2.) List the products circled in 1.) in order of purchase.

Customers are asked to provide information about the order of purchases.

Q1. Circle all of the products that you have purchased.

1. Windows desktop personal computers
2. Windows A4-size notebook personal computers
3. Windows B5-size notebook personal computers
4. Macintosh desktop personal computers
5. Macintosh notebook personal computers
6. PDA(pen type)
7. PDA(keyboard type)

…

43. MP3 players
44. speakers
45. headphones

Q2. List the products circled in Q1. in order of purchase. (You can use the number in order to represent each product.)

__ -> __ -> __-> __ -> __ -> __ -> __

Fig.4 Questionnaire survey in PC-related products.

Q1. Circle all of the products that you have purchased.

1. TV sets
2. bookshelves
3. DVD players
4. CD players
5. components
6. refrigerators
7. microwave ovens

…

29. motorcycles
30. automobiles
31. car navigation systems

Q2. List the products circled in Q1. in order of purchase. (You can use the number in order to represent each product.)

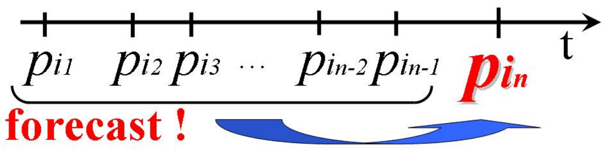
__ -> __ -> __-> __ -> __ -> __ -> __

Fig.5 Questionnaire survey in daily-use products.

The survey results are then checked for conformity rate with respect to the following two items(Fig.6):

(i) The product at the end of the purchase history for an individual, in other words, the product purchased last, and

(ii) The product recommended by the system based on the purchase history up to the purchase immediately before (i).



forecast of p_{in}	The number of recommended product
p_{j1} ?	1
p_{j1} or p_{j2} or p_{j3} ?	3
p_{j1} or p_{j2} or … or p_{j5} ?	5

Fig.6 Hit ratio test of forecasted product towards actually purchased product.

The survey was conducted on a total of approximately 800 teachers and students at the faculty of computer science in a university. The completion of an on-web survey was requested through some mailing lists. Replies were received from 128 respondents for the PC-related products and from 133 respondents for the daily-use products.

4.2 Experimental Results

Tables 3 and 4 list the experimental results for the PC-related products and daily-use products, respectively.

The numeric precision and absolute value of a recommendation change depending on the level of detail of the product classification, because reducing the number of recommendable products by rough classification raises the apparent precision of the recommendation. However, since the types of recommendable products depend on rough classification, a separate discussion regarding the appropriateness of the classification may be necessary. Therefore, it is appropriate to view the numeric values in Tables 3 and 4 relatively between methods or between the number of recommendable products.

In the present study, the collected survey data were classified as follows:

- PC-related products were classified as having either an LCD or CRT screen, and also by screen size
- In the daily-use products survey, motorcycles were classified by engine as either 50 cc or less, or greater than 50 cc

Table 3 Precision of recommendation for PC-related products

Method \ The number of recommended product	one	three	five
M1	12.5%	18.8%	21.9%
M2	10.1%	17.2%	21.1%
M3	11.7%	17.2%	21.9%
M4	14.8%	27.3%	36.7%
M5	8.6%	13.3%	17.2%

Table 4 Precision of recommendation for daily-use products

Method \ The number of recommended product	one	three	five
M1	14.3%	24.1%	30.8%
M2	12.8%	21.8%	27.1%
M3	15.0%	22.6%	29.3%
M4	18.8%	30.8%	39.8%
M5	11.3%	18.8%	24.8%

If Tables 3 and 4 are examined based on the above criteria, Method *M5* has the lowest precision of recommendation. In other words:

(Finding 1): The precision of recommendation improves if the contexts of product purchases are considered.

In this case,

``No extreme discrepancies in precision are found among Method *M1* through *M3*.” …(*)

In a preliminary experiment, we found that when the volume of purchase history data was too small, the following problem arose. Before discussing the precision of the recommendation, recommendable products often could not be derived. This means that both the purchase history matrix and the context matrix are nearly zero matrixes. Comparison of Methods 1 through 3 reveals that this problem is more serious for Methods 2 and 3, in which the non-zero elements in the context matrix increase slowly.

As the volume of data increases, does this problem disappear? We have carried out additional evaluation shown in Fig. 7. We have tested the relationships between the volume of data and the precision of the recommendation for each method when the number of recommendable product is fixed at one.

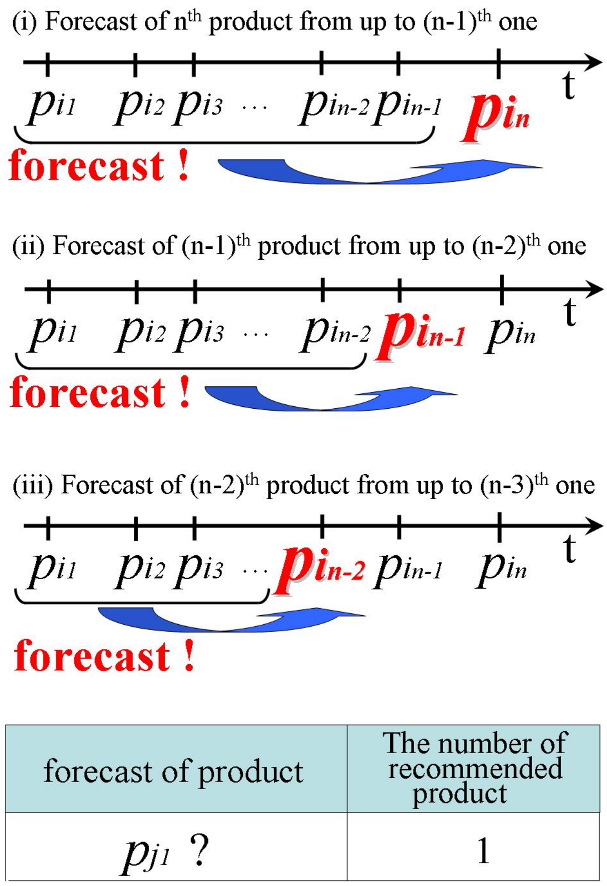


Fig.7 Three forecast patterns from past product purchases.

For a customer who purchased n products in the past, we have tested the precision of recommendation for the following cases:

(i) If the purchase of the n^{th} product is forecasted and recommended using the purchase history up to (n-1),

(ii) If the purchase of the (n-1)th product is forecasted and recommended using the purchase history up to (n-2), and

(iii) If the purchase of the (n-2)th product is forecasted and recommended using the purchase history up to (n-3).

Tables 5 and 6 show the result. We see that the precisions of the recommendations are stable for (*).

Table 5 Precision of recommendation for PC-related products

Method \ The number of learning data to forecasted product	(*n-1*) to *nth*	(*n-2*) to (*n-1*)th	(*n-3*) to (*n-2*)th
M1	12.5%	11.7%	9.4%
M2	10.1%	10.2%	8.6%
M3	11.7%	11.9%	9.4%
M4	14.8%	14.1%	13.3%
M5	8.6%	8.6%	8.6%

Table 6 Precision of recommendation for daily-use products

Method \ The number of learning data to forecasted product	(*n-1*) to *nth*	(*n-2*) to (*n-1*)th	(*n-3*) to (*n-2*)th
M1	14.3%	12.0%	11.3%
M2	12.8%	10.5%	10.5%
M3	15.0%	11.3%	10.5%
M4	18.8%	16.5%	15.3%
M5	11.3%	9.8%	8.3%

Like collaborative filtering without a context matrix, we found the following:

(Finding 2): Consideration of the contexts of product purchases becomes more effective as the volume of data increases.

In order to increase the number of non-zero elements in the context matrix quickly for a newly opened E-commerce site, a direct method is to increment values by assuming the correlation of context in a wider range in the direction of the time axis. In other words, the application of Methods 1, 2, and 3 are more appropriate in that order. Extending the range might cause the precision of recommendation to deteriorate. However, judging from the experimental result (*), the deterioration in precision is insignificant. In other words,

- In the case of a product purchase, all past purchases may be incremented by assuming correlations to the current purchase. …(**)

As shown in Tables 3 through 6, we could obtain higher precision of recommendation from Method *M4* than from Method *M1* under the condition that all purchases are considered to be a correlated to the current purchase. Method *M4* produces a greater processing load than Method *M1* because similar customers are derived and a context matrix is created dynamically. However, with respect to the precision of recommendation, Method *M4* is superior. We therefore obtain the following finding:

(Finding 3): The highest precision of recommendation was obtained when similar customers were grouped and a context matrix was dynamically created for each similar customer based on the assumption that the contexts of all products purchased in the past were considered.

5 Conclusion and Future Research Directions

In the present paper, we proposed a technique by which to make recommendations by considering the contexts of product purchases. In addition, we verified the effectiveness of the proposed technique experimentally. The following three findings were obtained:

- The proposed recommendation technique considering the contexts of product purchases can improve the precision of recommendation compared to conventional techniques that do not consider context.
- The precision of recommendation improves as the volumes of purchase history and context data increase.

- The highest precision of recommendation was obtained when similar customers were grouped and a context matrix was dynamically created for each similar customer based on the assumption that the contexts of all products purchased in the past were considered.

Database marketing is becoming increasingly common in industries in which customers can be identified, such as retail, service and financing industries. Techniques such as the distribution of industry point cards or service industry membership systems are widely used. The proposed technique is expected to be applicable to not only E-commerce sites of virtual stores but also to the above-mentioned industries.

In the present study, as a preprocess for considering context in product purchases, collaborative filtering with no vote values is adopted. The proposed technique, however, will not disturb the use of collaborative filtering with vote values at the preprocess. Therefore, in the future, the method by which to decide the priority order of the recommendation by combining vote values and values in the context matrix should be investigated.

Moreover, in the future, we are planning several future works: (i) investigation of uncertainty on subjects' response, (ii) increasing the volume of sample data or using actual purchase history data, rather than survey data, and (iii) a study of the purchase time interval.

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