Proposal and Evaluation of a Recommendation Technique
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. The results of an evaluation experiment reveal that our proposition is useful.

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

1 Introduction
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[1]. Various techniques, representative among which is collaborative filtering[2], have been applied in attempts to realize recommendation[1]. 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 [1]:

1) Checkbox technique: Technique that makes recommendations based on data entered by customers using checkboxes to outline their interests,

2) Rule-based technique: Technique that makes recommendations according to rules determined by the administrator of the E-commerce site, and

3) Collaborative filtering technique: 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. 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'. Tables 1 is purchase history matrix for purchases of five products by five customers.

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. 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 1, 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.

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. In addition, regarding general collaborative filtering, previous studies have examined the derivation of similar customers and improved estimation of the usefulness of information [3-8]. However, recommendation considering the contexts of product purchases has not been examined.

<table>
<thead>
<tr>
<th>Table 1 Purchase history matrix</th>
</tr>
</thead>
<tbody>
<tr>
<td>Customer</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>c1</td>
</tr>
<tr>
<td>c2</td>
</tr>
<tr>
<td>c3</td>
</tr>
<tr>
<td>c4</td>
</tr>
<tr>
<td>X</td>
</tr>
</tbody>
</table>
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 a product in Row j is purchased after Product pi, element mij 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 mii.

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 p3→p3 may be regarded as the context. From the viewpoint of a particular product...
purchase, we propose the four methods below and determine experimentally the most appropriate method.

![Fig.3 Range of context before and after product purchase.](image)

**Method M1**: Assume that all past purchases are related to the current purchase. For the example of Fig. 3, \(p_5 \rightarrow p_3\), \(p_1 \rightarrow p_3\), \(p_2 \rightarrow p_3\), and \(p_4 \rightarrow p_3\) are all considered, and the four corresponding elements \((m_{53}, m_{13}, m_{23}, \text{and } m_{43})\) 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 \((m_{53} \text{ and } m_{13})\) corresponding to \(p_5 \rightarrow p_3\) and \(p_1 \rightarrow p_3\) 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 \(p_5 \rightarrow p_3\), 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 Evaluation 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’.

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

(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).

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

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

If Tables 2 and 3 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.” …(*)

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.

Table 2 Precision of recommendation for PC-related products

<table>
<thead>
<tr>
<th>Method</th>
<th>one</th>
<th>three</th>
<th>five</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>12.5%</td>
<td>18.8%</td>
<td>21.9%</td>
</tr>
<tr>
<td>M2</td>
<td>10.1%</td>
<td>17.2%</td>
<td>21.1%</td>
</tr>
<tr>
<td>M3</td>
<td>11.7%</td>
<td>17.2%</td>
<td>21.9%</td>
</tr>
<tr>
<td>M4</td>
<td>14.8%</td>
<td>27.3%</td>
<td>36.7%</td>
</tr>
<tr>
<td>M5</td>
<td>8.6%</td>
<td>13.3%</td>
<td>17.2%</td>
</tr>
</tbody>
</table>

Table 3 Precision of recommendation for daily-use products

<table>
<thead>
<tr>
<th>Method</th>
<th>one</th>
<th>three</th>
<th>five</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>14.3%</td>
<td>24.1%</td>
<td>30.8%</td>
</tr>
<tr>
<td>M2</td>
<td>12.8%</td>
<td>21.8%</td>
<td>27.1%</td>
</tr>
<tr>
<td>M3</td>
<td>15.0%</td>
<td>22.6%</td>
<td>29.3%</td>
</tr>
<tr>
<td>M4</td>
<td>18.8%</td>
<td>30.8%</td>
<td>39.8%</td>
</tr>
<tr>
<td>M5</td>
<td>11.3%</td>
<td>18.8%</td>
<td>24.8%</td>
</tr>
</tbody>
</table>

As shown in Tables 2 and 3, 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 2): 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 two findings were obtained:

- The proposed recommendation technique can improve the precision of recommendation compared to conventional techniques that do not consider context.
- 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.

In the future, a recommendation technique of higher precision may be developed by increasing the volume of sample data or using actual purchase history data, rather than survey data. In addition, a study of the purchase time interval would be beneficial.

References:


