On picking up method of expectable customers in recommendation

T. Takayama, M. Etsumori, N. Sato, and Y. Murata

Abstract**—**Recently, researches on recommendation are attracting a great deal of attention as an effective technique by which to increase 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. We have ever proposed a technique for product recommendation by considering the context of product purchases. We have ever also verified its effectiveness experimentally by a simulation using product purchase history data obtained from the questionnaire survey. Based on them, we now try to obtain an effective result by recommending some products from some real purchase history data in a department store. In case of making recommendation to a customer, we can consider to apply a knowledge of sequential pattern mining. That is, if a pattern '*A*→*B*' often appears, we recommend a product *B* to *Cust(A)*, a set of customers who had purchased product *A*. However, it is not yet clarified that which customer of *Cust(A)* we should recommend.

In *Cust(A)*, there exist both two types of customers: one is *Cust_Y(A*→*B)*, a set of customers who can be easily leaded to '*A*→*B*' recommendation, and the other is *Cust_N(A*→*B)*, a set of customers who cannot be easily leaded to it. Although they are relative in actual, we assume that there exists a boundary between them, and we divide *Cust(A)* into two sets: *Cust_Y(A*→*B)* and *Cust_N(A*→*B)*. If we can pick up *Cust_Y(A*→*B)* from *Cust (A)* before making a recommendation, it is effective for improvement of recommendation precision. In the present study, we propose a picking up method of expectable customers *Cust_Y(A*→*B)* who can be easily leaded to a certain recommendation '*A*→*B*'. More specifically, we propose a measure: '*chance sign level*'. The results of an evaluation experiment have revealed that the proposed technique would be effective and could improve the recommendation precision. Based on the experiment results, we have also analyzed whether it is possible to sort customers in an order that is easily leaded to a recommendation, by relative comparison among four methods. As a result, we have obtained the following knowledge as a customers sorting method to a stable recommendation hit ratio. Concerning the proposed '*chance sign level*', we should adopt the following two policies:

- We adopt ranking order of '*chance sign level*' than the value of itself. The value range of the former does not violate than the latter depending upon a certain pattern, and
- We adopt a policy not taking into account 'non-chance sign'. Its policy treats as positive sign than negative one, even if a purchase history contains an element whose *chance sign level* is not high.

T. Takayama is with Graduate School of Software and Information Science, Iwate Prefectural University, Iwate 020-0193, Japan (corresponding author to provide phone: +81-19-694-2614; fax: +81-19-694-2614; e-mail: takayama@iwate-pu.ac.jp).

M. Etsumori is with Fuchu Solution Center, Toshiba Solutions Corporation Tokyo183-8512, Japan (e-mail: Etsumori.Masahito@toshiba-sol.co.jp).

N. Sato is with Graduate School of Software and Information Science, Iwate Prefectural University, Iwate 020-0193, Japan (e-mail: nobu-s@iwate-pu.ac.jp)

Y. Murata is with Graduate School of Software and Information Science, Iwate Prefectural University, Iwate 020-0193, Japan (e-mail: y-murata@iwate-pu.ac.jp)

Keywords**—**Data mining, expectable customers, information filtering, recommendation.

I. Introduction

RECENTRY, in a trend of one-to-one marketing, recommendation is attracting a great deal of attention as an effective technique by which to increase sales ([1]-[4]). We have ever proposed a technique for product recommendation by considering the context of product purchases. We have ever also verified its effectiveness experimentally by a simulation using product purchase history data obtained from the questionnaire survey [5].

In here, we overview some recent research directions to recommendation.

Abbassi *et al.* [6] investigate an efficient recommendation method for online exchange market. Our research is different from it in the following point. That is, in exchange market, each user has possibility to become a person who sells an item. However, in another trade, the same user has possibility to become a person who buys another item. On the other hand, in target environment of our research, a department store always sells its item to a customer in one way. We can point out another difference. In general, at a department store, an item is stocked in multiple times, and sold to multiple customers. On the other hand, in general at an exchange market, a trade is basically once as a unit. The same type of item as traded in the past cannot always be stocked.

Recently, researches on trying to effectively utilize a knowledge obtained on a social media have been activated.

Machanavajjhala *et al.* [7] quantitatively analyze a trade-off relation between privacy violation and recommendation accuracy, in case of personalizing a recommendation based on a social media. However, this research discusses a personalization of a recommendation, under the condition that a customer has already been selected. It is not a discussion whom we should select as target customers of a recommendation.

Yang *et al.* [8] model 'link prediction/ friendship prediction' and 'interest targeting/ service recommendation' that have close relation in *SNS*, using a framework 'FIP (Friendship-Interest Propagation) model'. However, they have only achieved to a binary link prediction: exist or not. It can be only applied until a limitation that it recommends an item which a person who predicted link to an active user likes. They have not achieved to a level that each customer is ranked quantitatively based on analysis.

Freyne *et al.* [9] propose to recommend a relevant feed, based on the action that an active user had taken on a social network in the past, such as view, friending, browsing, and interacting with other users. More specifically, they evaluate regularity of each action. If a feed that usually taken a positive action happens, such as a feed by a good friend, they recommend it. However, this research recommends a feed itself always in a social network, based on an action in the same social network. On the other hand, our research is different from it in the following point. That is, we propose how to recommend an item that is sold in a store, not an item itself fed on the social network.

Hereafter, we often abbreviate 'Direct Mail' to 'DM', and 'sequential pattern' to 'pattern'. In case of recommendation to a customer of a department store using DM, we can consider to apply a knowledge of sequential pattern mining [10]. That is, if a pattern '$A \rightarrow B$' often appears, we recommend a product B to *Cust(A)*, a set of customers who had purchased product A. However, it is not yet clarified that which customer of *Cust(A)* we should recommend.

In *Cust(A)*, there exist both two types of customers: one is *Cust_Y(A→B)*, a set of customers who can be easily leaded to '$A \rightarrow B$' recommendation, and the other is *Cust_N(A→B)*, a set of customers who cannot be easily leaded to it. Although they are relative in actual, we assume that there exists a boundary between them, and we divide *Cust(A)* into two sets: *Cust_Y(A→B)* and *Cust_N(A→B)*. If we can pick up *Cust_Y(A→B)* from *Cust (A)* before making a recommendation, it is effective for improvement of recommendation precision. In the present study, we propose a picking up method of expectable customers *Cust_Y(A→B)* who can be easily leaded to a certain recommendation '$A \rightarrow B$'. We also verify its effectiveness.

The remainder of the present paper is organized as follows. Section 2 describes the proposed picking up method of expectable customers *Cust_Y(A→B)*. Section 3 verifies the effectiveness of our proposition by an evaluation experiment. Section 4 provides with consideration, mainly devoted to customer ranking generaiton. Finally, in section 5, we present conclusions and topics for future consideration.

Note that we write the present paper in the range that does not violate non-disclosure agreement with the collaborating department store company '*X*'. More specifically, we cover the exact name of the company '*X*', and we avoid to write some information that the readers have possibility to infer what is the '*X*' company, mainly such as some inherent nouns.

II. Picking up Method of Expectable Customers

A. Analysis Unit

In the present study, we adopt *'dept'* as a data unit. Although we have a few exceptions, we may consider that a *dept* corresponds to each shop or floor in a department store. Based on the discussion with the department store '*X*', we adopt *dept* unit not a product one, in the present study.

B. Referential Period and Leading Period

Since products provided in a shop of a department store vary depending upon season, frequent pattern '$A \rightarrow B$' also varies season to season. Therefore, we call a preceding period in a pattern as *'referential period'*, and a following one as *'leading period'*. For example, when we treat from March 1st to April 30th as a referential period and from July 1st to August 31st as the corresponding leading period, if we use frequent pattern '$A \rightarrow B$' in the past years, we can make the following recommendation. That is recommendation in summer season based on the purchase history in the immediate before spring.

C. Proposition of a Measure: 'Chance Sign Level'

In general, a frequent pattern '$A \rightarrow B$' is produced from past data. It has possibility for a customer who had purchased in a *dept* A to have also purchased at the either of *dept* H_i (i=1, …, n-2; n is the total numbers of *dept*) except for *dept* A and B, in addition to *dept* A. Therefore, in the present study, we investigate that a purchase at which *dept* in addition to *dept* A in the past referential period is easy to lead to purchase at the *dept* B in the corresponding past leading period. First, we define the following two variables '$Y\_num(A \rightarrow B, H_i)$' and '$N\_num(A \rightarrow B, H_i)$':

- $Y\_num(A \rightarrow B, H_i)$: the numbers that the fact 'a customer who had purchased at both the *dept* A and H_i in a past certain referential period had also purchased at the *dept* 'B' in the past corresponding leading period' has occurred, and
- $N\_num(A \rightarrow B, H_i)$: the numbers that the fact 'a customer who had purchased at both the *dept* A and H_i in the same past certain referential period had not purchased at the *dept* 'B' in the past corresponding leading period' has occurred.

Second, we define the *chance sign level* $K(A \rightarrow B, H_i)$ per each *dept* H_i for the pattern '$A \rightarrow B$'as follows.

$$K(A \rightarrow B, H_i) = \frac{Y\_num(A \rightarrow B, H_i)}{N\_num(A \rightarrow B, H_i)} \tag{1}$$

In here,

- if $Y\_num(A \rightarrow B, H_i) = N\_num(A \rightarrow B, H_i) = 0$, then $K(A \rightarrow B, H_i) = 0$ and
- if $Y\_num(A \rightarrow B, H_i) \neq 0$ and $N\_num(A \rightarrow B, H_i) = 0$, then $K(A \rightarrow B, H_i) = \infty$

We show a simple example. We suppose that

- we have only four *depts* from H_1 to H_4 except for *dept* A, B,
- the elements of *Cust(A)* is only three customers from C_1 to C_3, and
- each purchase history from C_1 to C_3 is like the Table 1.

Table 1 purchase histories of all customers from C_1 to C_3 included in the *Cust(A)*

customer	referential period	leading period
C_1	A, H_1	B, H_2
C_2	H_1, A, H_2, H_1	B, B, H_3
C_3	A, H_3, H_2	H_2, H_4

In this case, each value of $Y\_num(A \rightarrow B, H_i)$, $N\_num(A \rightarrow B, H_i)$, and the corresponding *chance sign level* $K(A \rightarrow B, H_i)$ per each *dept* is like the Table 2.

Table 2 the value of $Y\_num(A \rightarrow B, H_i)$, $N\_num(A \rightarrow B, H_i)$, and $K(A \rightarrow B, H_i)$ per each *dept* for pattern $A \rightarrow B$

dept	$Y\_num(A \rightarrow B, H_i)$	$N\_num(A \rightarrow B, H_i)$	$K(A \rightarrow B, H_i)$
H_1	3	0	∞
H_2	2	1	2
H_3	0	1	0
H_4	0	0	0

D. Picking up of Expectable Customers and Recommendation

Taking into account $K(A \rightarrow B, H_i)$ in Table 2, for example, we can say the following. A customer who had purchased at the *dept* H_1 in addition to *dept A* in a certain referential period is more expectable for purchasing at the *dept B* in the corresponding leading period than a customer who had purchased at the *dept* H_3. Therefore, we call a *dept* satisfying the following conditions as '*chance sign dept*'. Its conditions are:

(a) its *chance sign level* for a certain frequent pattern is relatively high, and

(b) we treat it as chance sign for the recommendation along the sequential pattern and utilize it when making the recommendation.

We change the numbers of *chance sign dept* adopted from the *chance sign level* ranking, according to the numbers of customers who we need to pick up.

In the present study, we propose to make recommendation of *dept B* in the leading period, to the customers who had purchased at the *chance sign dept* in addition to the *dept A* in the corresponding immediately before referential period.

III. Evaluation Experiment

A. Experimental Method

We make four types of recommendations shown in Table 4 based on frequent patterns picked up from the settings shown in Table 3. Per each pattern, we prepare two kinds of one hundred customers who had purchased at the referential period side *dept*:

Table 3 each setting in our evaluation experiment

analyzed customers	member's card holders of '*X*' department store who have purchase history in the '*Z*' branch
referential period	from March 1^{st} to August 31^{st}
leading period	from November 1^{st} to November 30^{th}
registration of *Cust(A)*	from purchase history in year '*Y*'
picking up of frequent pattern and calculation of *chance sign level*	from purchase history in year '*Y-1*' and '*Y-2*' (past two years)

Table 4 used frequent four patterns and each *chance sign dept*

	referential period side *dept*	leading period side *dept*	*chance sign dept*
(1)	1(one of the clothes *dept* for lady or child)	2(one of the clothes *dept* for family)	6(one of the lady carrier *dept*)
(2)	1(one of the clothes *dept* for lady or child)	3(one of the underwear or sox *dept* for lady)	7(one of the sports dept for lady) 8(one of the lady casual *dept*)
(3)	3(one of the underwear or sox *dept* for lady)	4(one of the lady Mrs. *dept*)	9(one of the dressing general merchandised *dept*)
(4)	5(one of the lingerie *dept* for lady)	4(one of the lady Mrs. *dept*)	9(one of the dressing general merchandised dept) 10(one of the belongings goods *dept*)

- one had also purchased at either of the *chance sign dept*, and
- the other had not purchased at neither of the *chance sign dept*.

In addition, we make recommendations of leading period side *dept* by delivering DM, to both one hundred customers. Results are analysed as follows: that is, we count *m* (= the numbers of customers who purchase at the leading period side *dept* in the leading period on the year *y*), and relatively compare the recommendation precision *p*:

$$p(\%) = \frac{m}{100} \times 100 = m \quad (2).$$

B. Experimental Results

We show the experimental results per each recommendation in Table 5.

Table 5 experimental results

	purchase at the *chance sign dept* in the referential period	recommendation precision(%)
(1)	Yes	15
	No	7
(2)	Yes	25
	No	5
(3)	Yes	1
	No	0
(4)	Yes	2
	No	0

In all four types of recommendations, we have obtained the results that the customers who had purchased at either of the *chance sign dept* have purchased more than ones who had not purchased at neither of them. It means that when we take into account *chance sign level*, we can improve the recommendation precision.

We can observe that the recommendation precisions of pattern (3) and (4) are relatively lower than the ones of pattern (1) and (2). We can consider its reason as follows: that is, their *support values* [10] of these two patterns are relatively low in the past years, too.

IV. Consideration

Based on the data obtained from the experiment, we investigate whether it is possible to sort customers in the order that is easily leaded to the leading side *dept*. In some methods, we sort customers whom we have delivered DM. If a sorting method is adequate, customers who had purchased at the leading side *dept* would lie on the upper range in its expectable customers ranking. It has possibility to lead to save the numbers of DM, and to improve hit ratio of the DM.

A. Sorting Methods of Customers

In the present study, we investigate four sorting methods based on:

- value of *chance sign level* itself, or
- ranking order in the *chance sign level* ranking.

Before we describe each definition of the four methods, we slightly modify the definition of the *chance sign level* on the section II.C in order to improve its representation ability.

A.1 Modification of the definition of 'chance sign level'

According to the definition in the section II.C, K can become 0 (zero) or ∞ (infinity).

First, 'K=0' arises in the case of 'Y_num=0'. In the case of '$N\_num \neq 0$', it is effective if we can represent the difference of *chance sign level* based on the value of N_num. For example, we compare the following two cases:

- Y_num = 0, N_num = 30, and
- Y_num = 0, N_num = 1.

The following two inequalities should be satisfied:

$$K(Y\_num = 0, N\_num = 30) < K(Y\_num = 1, N\_num = 30) = \frac{1}{30}$$

and

$$K(Y\_num = 0, N\_num = 1) < K(Y\_num = 1, N\_num = 1) = \frac{1}{1} = 1$$

Therefore, we introduce a variable L_1 and slightly modify the definition of K for the case: 'Y_num=0 and $N\_num \neq 0$':

$$K(Y\_num, N\_num) = \frac{Y\_num + 1}{N\_num} - L_1 = \frac{1}{N\_num} - L_1 \quad (3).$$

In here, the inequalities:

$$0 < \frac{1}{N\_num} \leq 1$$

are satisfied. So, in order to represent the difference of *chance sign level* in the negative range, '$L_1 > 1$' should be satisfied.

Second, 'K=∞' arises in the case of 'N_num=0'. In the case of '$Y\_num \neq 0$', it is effective if we can represent the difference of *chance sign level* based on the value of Y_num. For example, we compare the following two cases:

- Y_num = 30, N_num = 0, and
- Y_num = 1, N_num = 0.

The following two inequalities should be satisfied:

$$K(Y\_num = 30, N\_num = 0) > K(Y\_num = 30, N\_num = 1) = 30$$

and

$$K(Y\_num = 1, N\_num = 0) > K(Y\_num = 1, N\_num = 1) = 1$$

Therefore, we introduce a variable L_2 and slightly modify the definition of K for the case: '$Y\_num \neq 0$ and N_num = 0':

$$K(Y\_num, N\_num) = \frac{Y\_num}{N\_num + 1} + L_2 = Y\_num + L_2 \quad (4).$$

By the way, in the case of 'Y_num = 0' and 'N_num = 0', this *dept* (H_i) does not influence to the pattern '$A \rightarrow B$'

. So we eliminate H_i from the *chance sign level* ranking.

A.2 'Value method' or 'ranking order method'

Under the modified definition like the previous subsection, we suppose that *chance sign level* ranking to a certain pattern '$E \rightarrow F$' is like the Table 6.

Table 6 an example of chance sign level ranking after modification of its definition

ranking order	*dept*	*Y_num*	*N_num*	*K*
1	H_{11}	2	0	3.1
2	H_{14}	2	1	2
3	H_{13}	1	1	1
4	H_{12}	0	1	-0.1
5	H_{15}	0	2	-0.6

If a customer C_{11} has purchased at the *dept* H_{11}, whose ranking order is '1', we can consider two types of approaches:

- '*value method*': we use the value '3.1' itself, and provide him/her with the point '3.1', or
- ranking order method': we provide him/her with point '5', because the *chance sign level* of *dept* H_{11} is the best in the *chance sign level* ranking, and there exists total five *depts* in the *chance sign level* ranking.

A.3 Policy taking into account 'non-chance sign'or not

We may read the *chance sign level* ranking to a pattern '*E* →*F'* as the following: if a customer has purchased at the *dept* 'H_{low}' whose ranking order is not high, it is difficult to expect to purchased at the *dept F* in the corresponding leading period. Based on this observation, we introduce a concept: 'non-chance sign'. More specifically, in this non-chance policy, we treat

- upper half *depts* in the *chance sign level* ranking as chance sign, and
- lower half ones as non-chance sign.

For example, in the Table 6, we treat

- ranking order one and two as chance sign
- its four and five as non-chance sign, and
- three as neutral.

If the number of *depts* is even, neutral *dept* becomes virtual. When a customer has purchased at a certain *dept* on the *chance sign level* ranking in a referential period, it is evaluated by relative value for neutral *dept*. For example, in the Table 6, the neutral *dept* is 'H_{13}' and purchasing at the 'H_{14}' whose ranking order is 2 is evaluated as the following:

- 'value method': (2 - 1 =) 1, and
- 'ranking order method': (4 – 3 =) 1.

Purchasing at the 'H_{12}' whose ranking order is four is evaluated as the following:

- 'value method': (-0.1 - 1 =) -1.1, and
- 'ranking order method': (3 - 4 =) -1.

On the other hand, it is not easy to decide either of the following two customers is relatively more expectable: in a referential period, in addition to referential period side *dept*,

- customer 'C_{high}' who has purchased at only a single *dept* H_{high} with high *chance sign level*, and
- customer '$C_{high+low}$' who has purchased at both *dept* H_{high} with high *chance sign level* and H_{low} with low *chance sign level*.

Even if the ranking order of 'H_{low}' is not high, such as '$C_{high+low}$', customers who have purchased at many *depts* may be easy to be leaded to a recommendation. This policy does not fit to 'non-chance' concept. So, we class this policy: 'not taking into account *non-chance sign*'. In this policy, there does not exist a neutral *dept*.

In this way, we propose 'value method' and 'ranking order' method in the subsection IV.A.2. We also introduce 'policy taking into account non-chance' and 'not taking one' in this subsection. By the combinations of each two options, we investigate four sorting methods of customers.

B. Result of Sorting Customers

B.1 Chance sign level ranking

Table 7-10 shows the *chance sign level* ranking for four patterns of the experiments in chapter III. Note that each *chance sign level* value is modified according to the modification in subsection IV.A.1. In order to confirm how much 0 (zero) arises in *Y_num* and/or *N_num*, on the other hand, in order to avoid redundancy, we write top ten *depts* and worst ten ones in each ranking. As we described in the subsection IV.A.1, the case '*Y_num* = *N_num* =0' is excluded.

As a value of 'L_1' in the formula (3), 'L_1=1.1' is adopted based on the preliminary experiment, since its value vibration is not too big and not too small. Actually, the case '*Y_num*=0 and *N_num* ≠ 0' arises in all four patterns.

On the other hand, 'L_2' in the formula (4) is not used because the case '*Y_num* ≠ 0 and *N_num* = 0' does not arise in all four patterns at all. According to the definition of *Y_num* and *N_num*, it is natural that *N_num* becomes larger than 0 when *Y_num* is not 0 and the volume of purchase history increases.

B.2 Result of sorting customers

Table 11 shows the relative comparison in results of sorting customers based on each *chance sign level* ranking.

From Table 11, method 1: 'ranking order method and policy not taking into account non-chance' is relatively better and more stable than the other three methods. Although average order after sorting of customers who had purchased at leading period side *dept* is not good in the case of 'without DM delivery', it is not always terribly worse than the other three methods. This result means that:

- concerning *chance sign level*, we should use 'ranking order' than 'the value of itself', and
- 'we should adopt a policy not taking into account '*non-chance sign*'.

Table 12 show the result when we change referential period, leading one, and frequent four patterns. This case also brings us the same consideration.

V. Conclusion

In the present paper, we have proposed a technique by which to make recommendations by picking up a set of expectable customers who can be easily leaded to a certain recommendation. More specifically, we have proposed a measure: '*chance sign level*' in order to pick up them. We have also verified the effectiveness of the proposed technique experimentally. According to its results, the proposed recommendation technique can improve the precision of recommendation compared to the conventional techniques that do not consider the measure: '*chance sign level*'.

In addition, based on the experiment results, we have analyzed whether we can sort customers in an order that is easily leaded to a recommendation, by relative comparison among four methods. As a result, we have obtained the following knowledge as a customers sorting method to a stable recommendation hit ratio. We should adopt the following two policies:

- We adopt ranking order of '*chance sign level*' than the value of itself. The value range of the former does not violate than the latter depending upon a certain pattern, and
- We adopt a policy not taking into account '*non-chance sign*'. Its policy treats as positive sign than negative one, even if a purchase history contains an element whose *chance sign level* is not high.

Table 7 *chance sign level* ranking of pattern 1

ranking order	*dept*	*Y_num*	*N_num*	*chance sign level*
1	3241	149282	2660943	0.0561012
2	3279	4924	209219	0.0235351
3	3438	18137	858382	0.0211293
4	3309	521	25072	0.0207803
5	3271	141127	7202908	0.0195931
6	3209	5086	274377	0.0185365
7	3200	2822	152672	0.0184841
8	3275	6654	364293	0.0182655
9	3556	196	11801	0.0166088
10	3312	1479	89529	0.0165198
…	…	…	…	…
39	3300	3065	398686	0.0076878
40	3351	2193	287560	0.0076262
41	3553	294	40258	0.0073029
42	3305	233	33942	0.0068647
43	3350	274	42006	0.0065229
44	3357	213	34237	0.0062213
45	3601	238	89918	0.0026469
46	3339	17	9519	0.0017859
47	9510	0	24	-1.0583333
48	9212	0	989	-1.0989889

Table 8 *chance sign level* ranking of pattern 2

ranking order	*dept*	*Y_num*	*N_num*	*chance sign level*
1	3217	52007	2503464	0.0207740
2	3556	239	11758	0.0203266
3	3307	5048	318383	0.0158551
4	3279	3353	215626	0.0155501
5	3312	1310	89869	0.0145768
6	3345	925	73168	0.0126421
7	3203	2108	168010	0.0125469
8	3247	3770	309746	0.0121713
9	3200	1839	153677	0.0119667
10	3209	3304	276595	0.0119453
…	…	…	…	…
39	9500	5238	695058	0.0075361
40	3271	52162	7303603	0.0071420
41	9211	11374	1746840	0.0065112
42	3202	3712	570145	0.0065106
43	3429	427	65638	0.0065054
44	3601	330	89826	0.0036738
45	3553	136	43676	0.0031138
46	3339	21	9515	0.0022070
47	9212	2	987	0.0020263
48	9510	0	24	-1.0583333

Table 9 *chance sign level* ranking of pattern 3

ranking order	*dept*	*Y_num*	*N_num*	*chance sign level*
1	3345	349301	1573026	0.2220567
2	3390	115602	5743954	0.0201259
3	3205	19279	1311711	0.0146976
4	3209	10997	961638	0.0114357
5	3204	29599	2715718	0.0108991
6	3200	6911	680236	0.0101597
7	3247	16460	1703038	0.0096651
8	3511	18538	1979577	0.0093646
9	3217	165967	25751944	0.0064448
10	3556	421	88085	0.0047795
…	…	…	…	…
47	3218	0	82	-1.0878049
48	9165	0	124	-1.0919355
49	3335	0	174	-1.0942529
50	3545	0	487	-1.0979466
51	3267	0	536	-1.0981343
52	3595	0	1226	-1.0991843
53	9510	0	1245	-1.0991968
54	3235	0	7519	-1.0998670
55	9212	0	9752	-1.0998975
56	3553	0	63848	-1.0999843

Table 10 *chance sign level* ranking of pattern 4

ranking order	*dept*	*Y_num*	*N_num*	*chance sign level*
1	3345	50849	227962	0.2230591
2	3205	5571	208255	0.0267509
3	3595	4	185	0.0216216
4	3204	4400	328036	0.0134132
5	3390	19861	1548662	0.0128246
6	3217	26053	2219763	0.0117368
7	3207	1623	214442	0.0075685
8	3200	867	119330	0.0072656
9	3246	897	154476	0.0058067
10	3250	2731	586089	0.0046597
…	…	…	…	…
42	3351	101	416600	0.0002424
43	3601	7	41518	0.0001686
44	3275	2	89825	0.0000223
45	3267	0	11	-1.0090909
46	9165	0	12	-1.0166667
47	3235	0	434	-1.0976959
48	9212	0	1088	-1.0990809
49	3429	0	3570	-1.0997199
50	3553	0	6446	-1.0998449
51	3590	0	8686	-1.0998849

Table11 relative comparison of sorting result

		sorting method	1	2	3	4
		chance sign level	ranking order	value itself	ranking order	value itself
		policy taking into account *non-chance*	No		Yes	
DM delivery		pattern				
Yes	average order after sorting of customers who had purchased at leading period side *dept*	1	155.955	157.864	182.636	166.409
		2	121.8	123.833	184.1	160.366
		3	90	168	143	206
		4	21	211	18	210.5
		average of 1-4	97.1886	165.174	131.934	185.819
		adequate ranking among method 1-4	1	3	2	4
	adequate ranking of sorting	1	1	2	4	3
		2	1	2	4	3
		3	1	3	2	4
		4	2	4	1	3
		average of 1-4	1.25	2.75	2.75	3.25
		adequate ranking among method 1-4	1	2	2	3
No	average order after sorting of customers who had purchased at leading period side *dept*	1	122.077	115.462	142.846	132.692
		2	133.065	136.839	160.807	135.581
		3	194.5	133	149.5	118
		4				
		average of 1-4	149.881	128.433	151.051	128.758
		adequate ranking among method 1-4	3	1	4	2
	adequate ranking of sorting	1	2	1	4	3
		2	1	3	4	2
		3	4	2	3	1
		4				
		average of 1-4	2.33333	2	3.66667	2
		adequate ranking among method 1-4	2	1	3	1
overall	average order after sorting of customers who had purchased at leading period side *dept*	1	139.016	136.663	162.741	149.551
		2	127.432	130.34	172.453	147.974
		3	142.25	150.5	146.25	162
		4	21	211	18	210.5
		average of 1-4	107.425	157.125	124.861	167.506
		adequate ranking among method 1-4	1	3	2	4
	adequate ranking of sorting	1	2	1	4	3
		2	1	2	4	3
		3	1	3	2	4
		4	2	4	1	3
		average of 1-4	1.5	2.5	2.75	3.25
		adequate ranking among method 1-4	1	2	3	4

Table 12 relative comparison of sorting result in the case changing referential period, leading period, and used four frequent patterns

		sorting method	1	2	3	4
		chance sign level	ranking order	value itself	ranking order	value itself
		policy taking into account *non-chance*	No		Yes	
DM delivery		pattern				
Yes	average order after sorting of customers who had purchased at leading period side *dept*	1	115.333	198.667	315.333	251
		2	364	370	305	352
		3	166.9	145.2	152.9	139.2
		4	95.75	178.5	216	286.75
		average of 1-4	184.596	221.967	246.158	255.9
		adequate ranking among method 1-4	1	2	3	4
	adequate ranking of sorting	1	1	2	4	3
		2	3	4	1	2
		3	4	2	3	1
		4	1	2	3	4
		average of 1-4	2.25	2.5	2.75	2.5
		adequate ranking among method 1-4	1	2	3	2
No	average order after sorting of customers who had purchased at leading period side *dept*	1	114.75	150	261	198.25
		2	148.625	144.125	190.375	148.25
		3	145.167	135.333	126.833	134.333
		4	176.5	166.5	133.5	111
		average of 1-4	145.479	148.083	177.208	146.969
		adequate ranking among method 1-4	1	3	4	2
	adequate ranking of sorting	1	1	2	4	3
		2	3	1	4	2
		3	4	3	1	2
		4	4	3	2	1
		average of 1-4	3	2.25	2.75	2
		adequate ranking among method 1-4	4	2	3	1
overall	average order after sorting of customers who had purchased at leading period side *dept*	1	115.042	174.333	288.167	224.625
		2	256.313	257.063	247.688	250.125
		3	156.033	140.267	139.867	136.767
		4	136.125	172.5	174.75	198.875
		average of 1-4	165.879	186.041	212.618	202.598
		adequate ranking among method 1-4	1	2	4	3
	adequate ranking of sorting	1	1	2	4	3
		2	3	4	1	2
		3	4	3	2	1
		4	1	2	4	3
		average of 1-4	2.25	2.75	2.75	2.25
		adequate ranking among method 1-4	1	2	2	1

As a related work, we can consider the study [11] that promotes to repeat a certain product purchase. Different from it, our proposition in the present study is effective in the sense that it enlarges the range where a customer purchases.

In the future, we are planning several future works: (i) investigation of serendipity in recommendation, (ii) investigation of customer's psychological influence by receiving a recommendation, and (iii) hybrid type recommendation by the combinations of other method.

REFERENCES

[1] B. Sarwar, G. Karypis, J. Konstan, J. Riedl: "Analysis of Recommendation Algorithms for E-Commerce," *Proceedings of the ACM Conference on Electronic Commerce*, 2000, pp.158-167.

[2] T. Takayama, K. Matsumoto, A. Kumagai, N. Sato, and Y. Murata, "Waiting/Cruising Location Recommendation for Efficient Taxi Business," *NAUN International Journal of Systems Applications, Engineering and Development*, Vol.5, Issue2, pp.224-236, 2011.

[3] M. Corniel, F. Gil, J. Molero, J. Ferrer, A. M. Borges, R. Gil, L. Contreras, "Studies orientation and recommendation system (SORS): use case model and requirements," *NAUN International Journal of Systems Applications, Engineering & Development*, Issue 3, Volume 5, pp.387-395, 2011.

[4] Taowei Wang, Yibo Ren, "Research on Personalized Recommendation Based on Web Usage Mining Using Collaborative Filtering Technique," *WSEAS Transactions on Information Science and Applications*, Issue 1, Volume 6, pp. 62-72, 2009.

[5] T. Takayama, T. Ikeda, H. Oguma, R. Miura, Y. Murata, and N. Sato: "Recommendation Method That Considers the Context of Product Purchases," *WSEAS Transactions on Information Science and Applications*, Issue10, Vol.6, pp.1687-1696, 2009.

[6] Z. Abbassi and L. Lakshmanan: "On Efficient Recommendations for Online Exchange Markets," *Proceedings of the 25th ICDE (ICDE 2009)*, 2009, pp. 712-723.

[7] A. Machanavajjhala, A. Korolova, A. D. Sarma: "Personalized Social Recommendations - Accurate or Private?," *Proceedings of the 37th International Conference on VLDB (VLDB2011)*, 2011, pp. 440-450.

[8] S. H. Yang, B. Long, A. Smola, N. Sadagopan, Z. Zheng, H. Zha: "Like Like Alike - Joint Friendship and Interest Propagation in Social Networks," *Proceedings of the 20th International Conference on WWW (WWW2011)*, 2011, pp. 537-546.

[9] J. Freyne, S. Berkovsky, E. Daly, and W. Geyer: "Social networking feeds: recommending items of interest," *Proceedings of the 4th ACM International Conference on Recommender Systems (RecSys2010)*, 2010, pp. 277-280.

[10] R. Agrawal, and R. Srikant: "Mining Sequential Patterns," *Proceedings of the 11th International Conference on Data Engineering(ICDE1995)*, 1995, pp.3-14.

[11] M. Pei, S. Taniguchi, T. Hara, and S. Nishio: "Discovering Important Rules and Loyal Customer by Considering the Repetition in Association Rules", *Proceedings of the International Conference on Innovations in Information Technology (IIT'06)*, 2006.