A Recommendation Method Considering Users' Time Series Contexts

Kenta Oku
Graduate School of Information Science
Nara Institute of Science and Technology
Ikoma City, Nara, 630–0101, Japan
kenta-o@is.naist.jp

Shinsuke Nakajima
Faculty of Computer Science and Engineering
Kyoto Sangyo University
Motoyama, Kamigamo, Kita-Ku, Kyoto-City, 603-8555, Japan
nakajima@cse.kyoto-su.ac.jp

Jun Miyazaki
Graduate School of Information Science
Nara Institute of Science and Technology
Ikoma City, Nara, 630–0101, Japan
miyazaki@is.naist.jp

Shunsuke Uemura
Department of Informatics
Faculty of Informatics
Nara Sangyo University
12–1, Tatsuno-kita 3-chome, Sango-cho, Ikoma-gun, Nara, 636–8503, Japan
uemurashunsuke@nara-su.ac.jp

Hirokazu Kato
Graduate School of Information Science
Nara Institute of Science and Technology
Ikoma City, Nara, 630–0101, Japan
kato@is.naist.jp

ABSTRACT

This paper proposes a recommendation method considering users' time series contexts which are situations that have occurred / will occur in the past/future. There are some recommendation methods that provide information suitable for users' action patterns as the recommendation methods considering them. These methods provide information referring to the other users that have a similar action pattern to that of an active user. However, since a user's action pattern changes depending on the user's contexts, the methods need to refer to the other users' action patterns related to the current user's contexts. In this paper, we propose a recommendation method considering the user's time series contexts considering that the user's action pattern changes depending on the user's contexts.

Categories and Subject Descriptors

H.4 [**Information Recommendation**]: Information Recommendation

General Terms

Human Factors

Keywords

Recommendation Method, User's Contexts, Time Series Contexts, User's Action Pattern

1. INTRODUCTION

Context-aware recommendation methods have received much attention [1]. Users have been able to access much information with the advance of Internet technology. A recommendation method provides the users with information suitable for the users' preferences. In addition, users have been able to use information systems at any time and anywhere with the advance of mobile technology. A context-aware system provides the users with services suitable for the users' contexts, i.e. situations or conditions.

One of the context-aware systems is a location-aware system. Cheverst et al. [2] proposed GUIDE and Setten et al. [3] proposed COMPASS. These systems provide a travelers' guide for tourists based on their locations. There are many studies related to location-aware systems because users' location data can be acquired easily by using devices such a GPS.

However, we think that users' values in their information choice are influenced by not only users' locations but also the other various contexts. In the case of restaurant recommendation, a restaurant a user wants to go to changes according to contexts such as date and time, weather, budget, companions and so on. Therefore, it is important to consider which contexts influence users' values in their information choice.

We define users' contexts as "users' situations and conditions that influence their values in their information choice [1]." We categorize the users' contexts as follows based on time relation with when the user receives a recommendation:

i Contexts that occurred in the past;

ii Contexts when the user is just receiving a recommendation;

iii Contexts that may occur in the future.

We call the contexts of type (ii) "users' current contexts" and the contexts of type (i) and (iii) "users' time series contexts." In our previous work, we proposed a context-aware recommendation method considering the users' current contexts [1].

However, to complete the context-aware recommendation method, it is important to consider the time series contexts besides the current contexts.

One of the time series contexts is the userÕs actions taken before. For example, we can imagine some scenes like "I want to go to a bar after having a meal.", "I want to take a break at a cafe after I go shopping." In the first example, he / she chose a bar under the influence of what he / she had to eat before. In the second example, he / she chose a cafe under the influence of what shopping he / she did before. In these examples, a userÕs actions influence his / her information choice.

There are several recommendation methods based on a userÕs action history data. Shinoda et al. [4] propose an action navigation method based on a userÕs action history data. Their method compares the active user's action history data with that of other users. Then the method extracts action patterns of the users who have similar action history data. Finally, the method provides action navigation for the active user referring to the action patterns.

It is effective to use the userÕs action patterns in recommendation, but we think that the userÕs action patterns also depend on his / her current contexts. For example, even after having a meal, a user might think, "When I am with my friends, I want to go to karaoke.", but "When I am with my girlfriend, I want to go to a bar." Therefore, it is necessary to calculate similarity between a users' action history data related to the active user's current contexts. In this paper, we propose a context-aware recommendation method considering that userÕs action patterns depending on the userÕs current contexts.

2. RELATED WORK

2.1 Recommendation Method Based on UserÕs Action History Data

There are several recommendation methods based on a userÕs action history data.

Yamamoto et al. [5] utilize a web access log for web page recommendation. Their method finds frequent access patterns by analyzing a userÕs web access log. Then the method recommends web pages based on the access patterns. Suppose that there are web pages a, b, c, d and e. And suppose that an access pattern $< a, b, c, d, e >$ is found from the access log. When an active user browses web pages $< a, b, c >$ in sequence, web pages d and e are recommended to this user based on the frequent access pattern $< a, b, c, d, e >$.

Ishizuka et al. [6] propose a content-based similarity search for trajectory data. Their method calculates similarity between an active user's trajectory data and many other users' trajectory data in a tourist resort. Then their method provides information such as tourist attractions based on the similar users' trajectory data.

Shinoda et al. [4] propose an action navigation method based on a userÕs action history data. Their method compares the active user's action history data with that of other users. Then the method extracts action patterns of the users who have similar action history data. Finally, the method provides action navigation for the active user referring to the action patterns.

These methods recommend information based on an active user's action pattern extracted from a userÕs access log or action history data. Although, it is effective to use the users' action patterns in recommendation, we think that the users' action patterns also depend on the userÕs current contexts. Therefore, it is necessary to calculate similarity between users' action history data related to the active user's current contexts.

Our recommendation method considers that users' action patterns are changed depending on the current userÕs contexts.

2.2 Method for Extracting User's Action Pattern

There are the sequential pattern mining method (SPM) [7], the Hidden Markov Model (HMM) [8] and a method extracting LCS (Longest Common Subsequence) [5] as methods for extracting users' action patterns.

In this section, we explain the SPM. The SPM [7] is a method for extracting frequent sequences from a sequence database. A sequence is an ordered list of item sets. The sequence is denoted by $< a, b >$. The $< a, b >$ means that item b occurred after item a occurred. A support for a sequence s is defined as frequency of the sequence s in the sequence database. Sequences with larger support than minimum support are extracted as frequent sequential patterns. It can extract frequent user action patterns by applying this SPM to a database of a user's action history.

3. DEFINITION OF USER'S CONTEXTS

We define users' contexts as "users' situations and conditions which influence their values in their information choice [1]."

The following is an example of the users' contexts following the above definition:

Time information: seasons, days of the week, time of days, etc.

Weather information: weather, temperature, humidity, etc.

User's information: weekdays / holidays, budgets, spare time, purposes, feeling, conditions, etc.

User's companions: relationship with the user (family, boy / girlfriend, friend, boss or subordinate), the number of companions, etc.

Surrounding environment: type of area where the user is now (a bustling street, an amusement center, the suburbs or a tourist resort), the number of visitors, etc.

We categorize the users' contexts as follows based on time relation with when the user receives a recommendation:

i Contexts that occurred in the past;

ii Contexts when the user is just receiving a recommendation;

iii Contexts that may occur in the future.

We call the contexts of type (ii) "userÕs current contexts" and the contexts of type (i) and (iii) "userÕs time series contexts." In our previous work, we proposed a context-aware recommendation method considering the users' current contexts [1].

However, to complete the context-aware recommendation method, it is important to consider the time series contexts besides the current contexts.

One of the time series contexts is the userÕs actions taken before. For example, we can imagine some scenes like "I want to go to a bar after having a meal.", "I want to take a break at a cafe after going shopping." In the first example, he / she chose a bar under the influence of what he / she had to eat before. In the second example, he / she chose a cafe under the influence of what shopping he / she did before. In these examples, a userÕs actions influence his / her information choice.

Table 1: Example of Database of User's Action History

SID	Date and Time	Action	User's Contexts			
			Time	Weekday / Holiday	Budget (yen)	Companions
1	8/1/08 12:00	*a*	12:00	*Weekday*	3,000	*No one*
	8/1/08 15:00	*b*	15:00	*Weekday*	3,000	*No one*
2	8/2/08 13:00	*c*	13:00	*Holiday*	5,000	*Friends*
	8/2/08 16:00	*d*	16:00	*Holiday*	5,000	*Friends*
	8/2/08 18:00	*e*	18:00	*Holiday*	5,000	*Friends*
:	:	:	:	:	:	:

Table 2: Active User A's Current Session

Date and Time	Action	User's Contexts			
		Time	Weekday / Holiday	Budget (yen)	Companions
8/22/08 9:00	*a*	9:00	*Holiday*	3,000	*Friends*
8/22/08 11:00	*b*	11:00	*Holiday*	3,000	*Friends*
8/22/08 12:00	*current*	12:00	*Holiday*	3,000	*Friends*

In this paper, we employ the users' actions taken in the past as the time series contexts. Then, we propose a context-aware recommendation method considering both the users' current contexts and the time series contexts, i.e. the users' actions taken in the past.

4. DATABASE OF USER'S ACTION HISTORY

A database of a user's action history stores the user's actions such as eating, drinking, shopping, etc. with the date and time. An example of the database is shown in Table 1. Data in the database is represented by the following information.

- Session ID (SID)
- The date and time the user took the action.
- The action the user took.
- User's contexts when the user took the action.

Here, the user's contexts are represented by multi-dimensional feature vectors. The vectors have elements that denote the contexts such as "time," "weekday / holiday," "budget," "companions," etc. For example, c_i, each element of the vectors $\boldsymbol{C}$, can be defined as follows:

$$\begin{aligned} &c_1 : Time (0 \le c_1 \le 1) \\ &c_2 : Weekday/Holiday (c_2 \in \{0,1\}) \\ &c_3 : Budget (0 \le c_3 \le 1) \\ &c_4 : Companions = No\ one (c_4 \in \{0,1\}) \\ &c_5 : Companions = Family (c_5 \in \{0,1\}) \\ &c_6 : Companions = Friends (c_6 \in \{0,1\}) \end{aligned} \quad (1)$$

Then, $\boldsymbol{C}_1$, the contexts for the first data in Table 1, is represented as follows:

$$\boldsymbol{C}_1 = \{c_1, c_2, c_3, c_4, c_5, c_6\} = \{0.5, 0, 0.3, 1, 0, 0\} \quad (2)$$

5. PROPOSED METHOD

We propose a recommendation method considering both users' current contexts and time series contexts. As we stated in section 3, we employ users' actions taken in the past as the users' time series contexts in this paper. In this section, the users' actions are represented by $\{a, b, c, d, e\}$ in the explanation of our proposed method.

Suppose that an active user A is at his / her current session as shown in Table 2. The user A is at his / her current contexts:

$$\begin{aligned} \boldsymbol{C}_A = \{&[Time = 12:00], [Weekday/Holiday = Holiday], \\ &[Budget = 3,000 yen], [Companions = Friends]\} \end{aligned} \quad (3)$$

In addition, the user A is at his / her time series contexts:

$$\boldsymbol{T}_A = < a|_{9:00}, b|_{11:00}, current|_{12:00} > \quad (4)$$

Here, the formula (3) means that user A is at $12:00$, on holiday, with $3,000$ yen and with his / her friends. The formula (4) means that user A took an action *a* at $9:00$, an action *b* at $11:00$ and he / she is at 12:00 now.

In this case, both contexts $\boldsymbol{C}_A$ and $\boldsymbol{T}_A$ may influence user A's values in his / her information choice. Our proposed method decides recommendation items for user A considering the influence of both $\boldsymbol{C}_A$ and $\boldsymbol{T}_A$ on his / her values.

Our method is based on a collaborative filtering method, that is, our method decides recommendation items referring to other similar users' action patterns. Here, similar users are determined based on similarity between the $\boldsymbol{T}_A$ and the other users' action history data. The users' action patterns mean a series of actions taken by them. We represent the action patterns as $< a, b, c >$, which means that users took actions *a*, *b* and *c* in sequence. The action patterns are extracted from their action history data.

Table 3 shows databases of action history of the other users B, C and D as an example. The databases have data shown in section 4. We define that one session has data of a series of the user's actions taken on one day. Here, by applying the sequential pattern mining method explained in section 2.2 to these databases, the users' action patterns $< a, b, c >$ and $< a, b, d >$ are found. In this case, the items related to the actions *c* and *d* may be decided as recommendation items.

However, this approach is based on the assumption that the user who has similar action patterns takes the same actions. We think that this assumption is not always true because the user's action patterns also depend on the user's current contexts. For example, even after having a meal, a user might think, "When I am with

Table 3: Other Users' Action History Database

(a) User B's Action History Database

SID	Time and Date	Action	User's Contexts				Contexts Similarity
			Time	Weekday / Holiday	Budget (yen)	Companions	
1	8/2/08 11:00	*a*	11:00	*Holiday*	2,000	*Friends*	0.998
	8/2/08 12:00	*b*	12:00	*Holiday*	2,000	*Friends*	0.998
	8/2/08 14:00	*c*	14:00	*Holiday*	2,000	*Friends*	0.996
2	8/5/08 18:00	*d*	18:00	*Weekday*	1,000	*No one*	0.211
	8/5/08 19:00	*e*	19:00	*Weekday*	1,000	*No one*	0.218
3	8/16/08 10:00	*a*	10:00	*Holiday*	3,000	*Friends*	0.999
	8/16/08 12:00	*b*	12:00	*Holiday*	3,000	*Friends*	1.000
	8/16/08 13:00	*c*	13:00	*Holiday*	3,000	*Friends*	1.000
4	8/20/08 17:00	*a*	17:00	*Weekday*	2,000	*No one*	0.218
	8/20/08 18:00	*b*	18:00	*Weekday*	2,000	*No one*	0.225
	8/20/08 20:00	*d*	20:00	*Weekday*	2,000	*No one*	0.237
5	8/21/08 17:00	*a*	17:00	*Weekday*	1,000	*No one*	0.204
	8/21/08 19:00	*b*	19:00	*Weekday*	1,000	*No one*	0.218
	8/21/08 20:00	*d*	20:00	*Weekday*	1,000	*No one*	0.224
	8/21/08 21:00	*e*	21:00	*Weekday*	1,000	*No one*	0.229

(b) User C's Action History Database

SID	Time and Date	Action	User's Contexts				Contexts Similarity
			Time	Weekday / Holiday	Budget (yen)	Companions	
1	8/3/08 11:00	*c*	11:00	*Holiday*	3,000	*Friends*	1.000
	8/3/08 12:00	*d*	12:00	*Holiday*	3,000	*Friends*	1.000
2	8/5/08 19:00	*b*	19:00	*Weekday*	2,000	*No one*	0.231
	8/5/08 20:00	*d*	20:00	*Weekday*	2,000	*No one*	0.237
3	8/10/08 12:00	*a*	12:00	*Holiday*	2,000	*Friends*	0.998
	8/10/08 14:00	*e*	14:00	*Holiday*	2,000	*Friends*	0.996
4	8/15/08 19:00	*b*	19:00	*Weekday*	2,000	*No one*	0.231
	8/15/08 20:00	*c*	20:00	*Weekday*	2,000	*No one*	0.237
5	8/17/08 11:00	*b*	11:00	*Holiday*	2,000	*Friends*	0.998
	8/17/08 12:00	*a*	12:00	*Holiday*	2,000	*Friends*	0.998
	8/17/08 14:00	*c*	14:00	*Holiday*	2,000	*Friends*	0.996

(c) User D's Action History Database

SID	Time and Date	Action	User's Contexts				Contexts Similarity
			Time	Weekday / Holiday	Budget (yen)	Companions	
1	8/2/08 12:00	*a*	12:00	*Holiday*	3,000	*Friends*	1.000
	8/2/08 13:00	*e*	13:00	*Holiday*	3,000	*Friends*	1.000
2	8/9/08 10:00	*a*	10:00	*Holiday*	2,000	*Friends*	0.997
	8/9/08 11:00	*e*	11:00	*Holiday*	2,000	*Friends*	0.998
	8/9/08 12:00	*a*	12:00	*Holiday*	2,000	*Friends*	0.998
3	8/16/08 11:00	*a*	11:00	*Holiday*	3,000	*Friends*	1.000
	8/16/08 13:00	*e*	13:00	*Holiday*	3,000	*Friends*	1.000
4	8/18/08 17:00	*a*	17:00	*Weekday*	1,000	*No one*	0.204
	8/18/08 18:00	*b*	18:00	*Weekday*	1,000	*No one*	0.211
	8/18/08 19:00	*e*	19:00	*Weekday*	1,000	*No one*	0.218
	8/18/08 20:00	*d*	20:00	*Weekday*	1,000	*No one*	0.224
5	8/20/08 18:00	*d*	18:00	*Weekday*	2,000	*No one*	0.225
	8/20/08 19:00	*e*	19:00	*Weekday*	2,000	*No one*	0.231

Table 4: Support of Each Action Pattern

Action Pattern	Support	Action Pattern	Support	Action Pattern	Support
$<a, a>$	0.125	$<b, a>$	0.125	$<(a, b), a>$	0
$<a, b>$	0.25	$<b, b>$	0	$<(a, b), b>$	0
$<a, c>$	0	$<b, c>$	0	$<(a, b), c>$	0.375
$<a, d>$	0	$<b, d>$	0	$<(a, b), d>$	0
$<a, e>$	0.5	$<b, e>$	0	$<(a, b), e>$	0

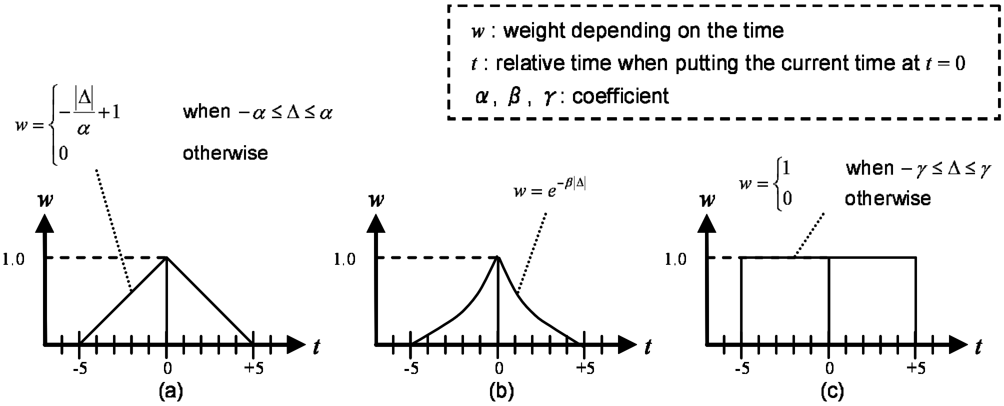

Figure 1: Definition of Weight of Recommendation Scores

my friends, I want to go to karaoke.", but "When I am with my girlfriend, I want to go to a bar." Therefore, it is important to find the action patterns related to the active user's current contexts.

Our method decides recommendation items according to the following steps:

i Extracts action history data related to the active user's current contexts;

ii Finds frequent action patterns matching the active user's time series contexts;

iii Calculates a recommendation score based on the frequent action patterns.

We explain each step after the next subsection.

5.1 Extracts Action History Data Related to Current Contexts

Our method extracts action history data related to the $\boldsymbol{C}_A$, the active user A's current contexts, from the action history databases of other users B, C and D.

Now, we represent the $\boldsymbol{C}_A$, shown in the formula (3), as shown in the following formula:

$$\boldsymbol{C}_A = \{c_1, c_2, c_3, c_4, c_5, c_6\} = \{0.5, 1, 0.3, 0, 0, 1\} \tag{5}$$

Then, our method calculates similarity between the $\boldsymbol{C}_A$ and $\boldsymbol{C}_{ui}$, current contexts at the i^{th} data in a database of user u's action history. We use cosine measure to calculate the similarity between vectors as follows:

$$\cos(\boldsymbol{C}_A, \boldsymbol{C}_{ui}) = \frac{\boldsymbol{C}_A \cdot \boldsymbol{C}_{ui}}{||\boldsymbol{C}_A||||\boldsymbol{C}_{ui}||} \tag{6}$$

The calculated similarity is shown in the column "contexts similarity" in Table 3. Then our method extracts the sessions with larger similarity than a certain threshold as action history data related to the $\boldsymbol{C}_A$ (we call this AHD_A). In this example, we use 0.5 as the threshold. Finally, our method extracts sessions with SID = $\{1, 3\}$ in user B's action history database, SID = $\{1, 3, 5\}$ in user C's and SID = $\{1, 2, 3\}$ in user D's as AHD_A.

5.2 Finds Frequent Action Patterns Matching Time Series Contexts

Based on the $\boldsymbol{T}_A$, active user A's time series contexts shown in formula (4), our method finds users' action patterns $< a, b, x >$ ($x \in \{a, b, c, d, e\}$) from AHD_A. If the action patterns $< a, b, x >$ are found frequently, then items related to the action x are decided as recommendation items.

The frequent action patterns can be found by the methods explained in section 2.2. In this paper, we employ the sequential pattern mining method (SPM). By the SPM, we find action patterns $< a, x >$, $< b, x >$ and $< (a, b), x >$. Here, the (a, b) in the $< (a, b), x >$ means that actions a and b are taken together in random order. It is not necessary to consider $< c, x >$, $< d, x >$ and $< e, x >$, since actions c, d and e are not included in the $\boldsymbol{T}_A$.

We calculate support of each pattern $< a, x >$, $< b, x >$ and $< (a, b), x >$ in AHD_A by the SPM. Table 4 shows the support. As shown in Table 4, the support of $< (a, b), c >$ is 0.375, and $< (a, e) >$ is 0.5. Then, items related to actions c and e may be regarded as recommendation candidates.

5.3 Calculates Recommendation Score Based on Frequent Action Patterns

Our method calculates recommendation scores for items based on the support of each action pattern.

In this example, a recommendation score of an item related to action x is calculated by the following formula:

$$\begin{aligned} S_x = {} & w_a \cdot \sup(< a, x >) + w_b \cdot \sup(< b, x >) \\ & + (w_a + w_b) \cdot \sup(< (a, b), x >) \end{aligned} \tag{7}$$

Table 5: Support of Each Action Pattern at Other Contexts

Action Pattern	Support	Action Pattern	Support	Action Pattern	Support
$<a, a>$	0	$<b, a>$	0	$<(a, b), a>$	0
$<a, b>$	0.375	$<b, b>$	0	$<(a, b), b>$	0
$<a, c>$	0	$<b, c>$	0.125	$<(a, b), c>$	0
$<a, d>$	0	$<b, d>$	0.125	$<(a, b), d>$	0.375
$<a, e>$	0	$<b, e>$	0	$<(a, b), e>$	0.25

Here, $\sup(< l, m >)$ denotes support of an action pattern $< l, m >$. w_k denotes time relation weight of an action k for the recommendation scores. If the active user A took the action k nearer the current action, w_k is larger.

Figure 1 shows definitions of the w_k. The horizontal axis denotes t, which is relative time when putting the current time at $t = 0$. The minus value means the past. The vertical axis denotes the weight w depending on t. When $t = 0$, w is maximized, and w is smaller as t is further from the current time.

Figure 1 shows three types of definitions of the weight w_k as examples. Each weight means the following:

(a) w decreases linearly as t is further from the current time;

(b) w decreases exponentially as t is further from the current time;

(c) w is constant within a certain threshold.

Based on the definition of (a) in Figure 1, recommendation scores of items related to each action are calculated as follows:

$$\begin{aligned} S_a &= 0.4 \times 0.125 + 0.8 \times 0.125 = 0.15 \\ S_b &= 0.4 \times 0.25 = 0.1 \\ S_c &= (0.4 + 0.8) \times 0.375 = 0.45 \\ S_d &= 0 \\ S_e &= 0.4 \times 0.5 = 0.2 \end{aligned} \tag{8}$$

Here, S_x denotes the recommendation score of the item related to the action x. Finally, the item related to the action c with the largest score is decided as the recommendation item for user A.

5.4 Importance of Considering User's Contexts

Now, we change the active user A's current contexts $\boldsymbol{C}_A$ to $\boldsymbol{C}'_A$ as follows:

$$\begin{aligned} \boldsymbol{C}'_A = \{&[Time = 20:00], [Weekday/Holiday = Weekday], \\ &[Budget = 1,000 yen], [Companions = No\ one]\} \end{aligned} \tag{9}$$

Then, extracted sessions are sessions with SID = $\{2, 4, 5\}$ in user B's action history database, SID = $\{2, 4\}$ in user C's and SID = $\{4, 5\}$ in user D's as AHD'_A. Support of each action pattern is shown as Table 5.

Then recommendation scores of items related to each action are calculated as follows:

$$\begin{aligned} S_a &= 0 \\ S_b &= 0.4 \times 0.375 = 0.15 \\ S_c &= 0.8 \times 0.125 = 0.1 \\ S_d &= 0.8 \times 0.125 + (0.4 + 0.8) \times 0.375 = 0.55 \\ S_e &= (0.4 + 0.8) \times 0.25 = 0.3 \end{aligned} \tag{10}$$

As a result, items d and e are regarded as recommendation items. It is clear that our method can change recommendation items depending on the user's current contexts.

6. CONCLUSION

In this paper, to complete a context-aware recommendation method, we proposed a recommendation method considering both users' current contexts and time series contexts. Particularly, our method considers that users' action patterns are changed according to their current contexts. Our method can change recommendation items depending on the user's current contexts.

In future work, we will implement our method and do experiments for evaluation. In the experiments, we would like to verify the appropriateness of the methods for extracting users' action patterns, weight of recommendation scores and methods for calculating recommendation scores of items.

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8. REFERENCES

[1] Kenta Oku, Shinsuke Nakajima, Jun Miyazaki, Shunsuke Uemura, and Hirokazu Kato. A ranking method based on users' contexts for information recommendation. In *The Second International Conference on Ubiquitous Information Management and Communication (ICUIMC 2008)*, pages 306–312, January 2008.

[2] K. Cheverst, N. Davies, K. Mitchell, and A. Friday. Experiences of developing and deploying a context-aware tourist guide: the guide project. In *Proceedings of the 6th Annual international Conference on Mobile Computing and Networking (MobiCom2000)*, 2000.

[3] M. van Setten, S. Pokraev, and J. Koolwaaij. Context-aware recommendations in the mobile tourist application compass. In *Nejdl, W. and De Bra, P. (Eds.). AH 2004, LNCS 3137*. Springer-Verlag, 2004.

[4] Hiroyuki Shinoda, Susumu Takeuchi, Yuuichi Teranishi, Kaname Harumoto, and Shinji Shimojo. A study of action navigation method by collaborative filtering in ubiquitous environment. In *IPSJ SIG Notes*, volume 2007, pages 77–82, 2007. (in Japanese).

[5] Yamamoto Rie, Kobayashi Dai, Yoshihara Tomohiro, Kobayashi Takashi, and Yokota Haruo. Analyses of the effects of utilizing web access log lcs for web page recommendation. In *IPSJ-TOD*, volume 48, pages 38–48. June 2007. (in Japanese).

[6] Jun Ishizuka, Yu Suzuki, and Kyoji Kawagoe. A content based similarity search for trajectory data. In *DEWS2007*, pages E1–7, 2007. in Japanese.

[7] R. Agrawal and R. Srikant. Mining sequential patterns. In *ICDE1995*, pages 3–14, 1995.

[8] A. D. Wilson and A. F. Bobick. Parametric hidden markov models for gesture recognition. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, volume 21, pages 884–900. September 1999.