# A Recommendation System Considering Users' Past / Current / Future Contexts


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## ABSTRACT

This paper proposes a recommendation system considering users' past / current / future contexts. We define users' contexts as "users' situations and conditions that influence their preference in their information choice. The current contexts mean situations when the user just receives recommendation. The past contexts mean actions the user has taken up to the present and occured situations at that time and the future contexts mean actions the user plans from now on and expected situations at that time. There are several recommendation methods based on user's action histories which is one of his/her past contexts. The methods recommend information based on users' action patterns extracted from the users' action histories. Although it is effective to use the users' action patterns in recommendation, we think that the user's action patterns also depend on situations at each time when the user took the actions. Therefore, it is necessary to extract the user's action patterns considering the situations at each time when the user took the actions. Our recommendation system considers the past, current and future contexts which include both the user's actions and the situations.



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## Keywords

context-aware recommendation, past / current / future contexts, action patterns


## 1. INTRODUCTION

Context-aware recommendation systems have received much attention[3]. A recommendation system provides the users with information suitable for the users' preference. 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 the GUIDE. The system provides travelers' guides for tourists based on their location. There are many studies related to the location-aware systems.

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

We define users' contexts as "users' situations and conditions that influence their preference in their information choice[3]." As shown in Table 1, We categorize the users' contexts as follows based on time relation with when the user receives recommendation: current contexts, past contexts and future contexts.

In our previous work, we proposed a context-aware recommendation system considering the users' current contexts[3].

However, to complete the context-aware recommendation system, it is important to consider the past and future contexts besides the current contexts[4].

There are several recommendation methods based on user's action histories which is one of his/her past contexts. Shinoda et al.[6] propose an action navigation method based on the user's action histories. Their method compares the active user's action histories with that of other users. Finally, the method provides action navigation for the active user referring to their similar users' action patterns.

It is effective to use the user's action patterns in recommendation, but we think that the user's action patterns also depend on situations at each time when the user took the actions. 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 extract the user's action patterns considering the situations at each time when the user took the actions. In this paper, we propose a context-aware recommendation system considering the past, current and future contexts which include both the user's actions and the situations.

## 2. RELATED WORK

Yamamoto et al.[7] utilize web access logs for web page recommendation. Their method finds frequent access patterns by analyzing users' web access logs. Then the method recommends web pages based on the access patterns. Suppose that there are web pages $a$, $b$, $c$, $d$ and $e$. And an access pattern $< a, b, c, d, e >$ is found from the access logs. When the 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 $< a, b, c, d, e >$.

Shinoda et al.[6] propose an action navigation method based on user's action histories. Their method compares the active user's action histories with that of other users. Then the method extracts action patterns of the users who have similar action histories to the active user. Finally, the method provides action navigation for the active user referring to their action patterns.

These methods recommend information based on users' action patterns extracted from the users' access logs or action histories. Although, it is effective to use the user's action patterns in recommendation, we think that the user's action patterns also depend on situations at each time when the user took the actions. Therefore, it is necessary to extract the user's action patterns considering the situations at each time when the user took the actions.

Our recommendation system considers the past, current and future contexts which include both the user's actions and the situations.

## 3. DEFINITION OF USER'S CONTEXTS

In our study, we define user's situations and conditions that influence his/her preference in information choice as user's contexts[3]. In our previous work[3], we focused on just user's current contexts and proposed a recommendation method considering the current contexts. However, user's current preference is influenced by not only the current contexts but also his/her actions taken in the past, actions he/she plans in the future and each situation at that each time as following examples: "I want to drink with my boy/girlfriend at a bar after eating at a restaurant with him/her at night."

Table 1: Examples of user's contexts.

| Type of contexts | Example |
|---|---|
| Current contexts | Situations : month, day of week, time, weather,<br>temperature, humidity, holiday / not holiday,<br>before holiday / not before holiday, budget, spare time,<br>type of companions, number of companions, etc. |
| Past contexts | Actions user has taken up to the present :<br>did shopping at ..., ate at ..., etc.<br>Situations at that time : same as the current contexts |
| Future contexts | Actions user plans from now on :<br>will eat at ..., will do shopping at ...<br>Expected situations at that time : same as the current contexts |

Based on time relation with when the user receives recommendation, we categorize the user's contexts as follows as shown in Table 1: current contexts, past contexts and future contexts. Our proposed system in this paper recommends items for the user considering all of the past / current / future contexts.

### *Representation of user's contexts.*

We represent the current contexts as a $p$-dimensional feature vector. The vector consists $p$ elements representing values of contexts parameters $c_i (0 \leq c_i \leq 1)(1 \leq i \leq p)$ such as "time" and "user's budget" (cf. [3]). The vector is represented as follows:

$$\boldsymbol{C} = (c_1, c_2, \ldots, c_p) \tag{1}$$

In the same way, situations of the past and future contexts are represented by the vectors.

We can calculate similarity between two different contexts by representing the user's contexts as such a feature vector. The similarity between contexts $\boldsymbol{C}_1$ and contexts $\boldsymbol{C}_2$ is calculated as follows by using cosine correlation measure[5]:

$$\mathrm{sim}(\boldsymbol{C}_1, \boldsymbol{C}_2) = \frac{\boldsymbol{C}_1 \cdot \boldsymbol{C}_2}{||\boldsymbol{C}_1||||\boldsymbol{C}_2||} \tag{2}$$

We represent actions as $q$-dimensional feature vector. The vector consists $q$ elements representing $q$ types of action categories such as {"eating", "taking a coffee break", "drinking at a bar", "shopping", "playing"}. The vector is represented as follows:

$$\boldsymbol{A} = (a_1, a_2, \ldots, a_p) \tag{3}$$

When the user took / will take an action, '1' is given to the element corresponding to the action and '0' is given to the element not corresponding to the action.

Similarity between two actions $\boldsymbol{A}_1$ and $\boldsymbol{A}_2$ is calculated as follows in the same as similarity of contexts:

$$\mathrm{sim}(\boldsymbol{A}_1, \boldsymbol{A}_2) = \frac{\boldsymbol{A}_1 \cdot \boldsymbol{A}_2}{||\boldsymbol{A}_1||||\boldsymbol{A}_2||} \tag{4}$$

We also define similarity of the contexts and actions as follows:

$$\mathrm{sim}((\boldsymbol{A}_1, \boldsymbol{C}_1), (\boldsymbol{A}_2, \boldsymbol{C}_2)) = \mathrm{sim}(\boldsymbol{A}_1, \boldsymbol{A}_2) \times \mathrm{sim}(\boldsymbol{C}_1, \boldsymbol{C}_2) \tag{5}$$

To synthesize the past / current / future contexts, the contexts are represented as follows:

$$< \ldots, (\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}), (\boldsymbol{A}_0, \boldsymbol{C}_0), (\boldsymbol{A}_{+1}, \boldsymbol{C}_{+1}), \ldots > \tag{6}$$

After all, the past / current / future contexts are represented by action sequences with contexts. Here, $t$ in $(\boldsymbol{A}_t, \boldsymbol{C}_t)$ denotes relative time when defining current time as 0. When $t < 0$, $t$ means the past, and when $t > 0$, $t$ means the future.

### *Acquiring user's contexts.*

Some user's contexts can be acquired automatically, others required inputs from the user. For example, "time", "weather" and "temperature" can be acquired from watch and web easily. But, it is difficult to acquire information such as "holiday / not holiday", "user's budget", "user's companions" and future plan automatically. They require user's inputs. However, by combining a schedule management service, a cell phone wallet service, SNS and GPS, we can expect to be able to acquire the contexts automatically. Since many researchers discuss how to acquire the contexts in the field of context awareness, we assume that various contexts can be acquired automatically in user's daily life in this paper.

## 4. ACTION HISTORY DATABASE

A user's action history database (an action history DB) is a database logging actions taken by the user with the date and time. Data in the DB is represented by the following information: (1) date and time, (2) the item ID the user used, (3) actions related to the item, (4) user's contexts when the user used the item, and (5) user's satisfaction rate for the item. The user takes an action by using an item such as a facility and a shop. A datum in the DB corresponds to an action the user took that is an item the user used.

### *Representation of items.*

Information about items is managed by an item DB. The DB has following information as attributes of an item: (1) an item ID, (2) a name of the item, (3) a genre of the item, (4) features of the item, and (5) actions related to the item. The item ID and the actions related to the item are logged in the action history DB when the user used the item.

### *Preference similarity between users.*

By making each user's action history DB including his/her satisfaction rate, we can calculate preference similarity between users. By calculating the similarity we can adopt a collaborative filtering which recommends items to users based on other similar users' experiences.

The preference similarity between users based on the action history DB can be calculated as Table 2. Table 2 shows averages of satisfaction rates of user A, user B, user C and user D for items when they "eat". We calculate the similarity between user A and other users based on the satisfaction rates. Specifically, we represent the rates as vectors and calculate the vectors similarity by using cosine correlation measure.Although, we show the only case of "eating" as an example in the Table 2, we define an average of similarity in all actions as users' preference similarity.

The similarity between user $u$ and user $v$ are calculated as follows:

$$\mathrm{sim}(u,v) = \frac{1}{q}\sum_{j=1}^{q} \mathrm{sim}(u,v)|_{a_j} \tag{7}$$

Here, $\mathrm{sim}(u,v)|_{a_j}$ denotes the similarity between user $u$ and user $v$ on action $a_j$. It is represented as follows:

$$\begin{aligned}\mathrm{sim}(u,v)|_{a_j} &= \mathrm{sim}(\boldsymbol{e}_u|_{a_j}, \boldsymbol{e}_v|_{a_j}) \\ &= \frac{\boldsymbol{e}_u|_{a_j} \cdot \boldsymbol{e}_v|_{a_j}}{||\boldsymbol{e}_u|_{a_j}||\,||\boldsymbol{e}_v|_{a_j}||}\end{aligned} \tag{8}$$

Table 2: Preference similarity between users.

| | Japan-ese | Chin-ese | Steak | Cafe | Curry | Similarity to user A |
|---|---|---|---|---|---|---|
| User A | +1.0 | 0 | −1.5 | 0 | +2.2 | 1.000 |
| User B | +1.5 | 0 | −1.1 | +2.1 | +2.5 | 0.809 |
| User C | 0 | +1.1 | +2.8 | 0 | −1.5 | −0.784 |
| User D | 0 | +2.9 | 0 | +1.2 | 0 | 0.000 |

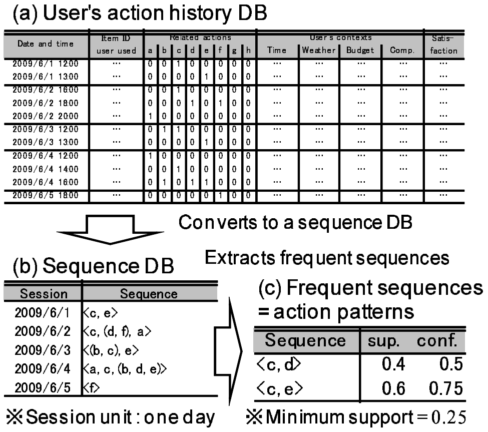


Figure 1: Extracting action patterns by the sequential pattern mining method.

Here, $\boldsymbol{e}_u|_{a_j}$ denotes a vector representing the user $u$'s satisfaction rates on action $a_j$.

For instance, in case of user A and user B in Table 2, $\boldsymbol{e}_A|_{\mathrm{eat}}$ and $\boldsymbol{e}_B|_{\mathrm{eat}}$ are respectively as follows:

$$\boldsymbol{e}_A|_{\mathrm{eating}} = (+1.0, 0.0, -1.5, 0.0, +2.2) \tag{9}$$

$$\boldsymbol{e}_B|_{\mathrm{eating}} = (+1.5, 0.0, -1.1, +2.1, +2.5) \tag{10}$$

Then similarity between them on action "eating" $\mathrm{sim}(A,B)|_{\mathrm{eating}} = 0.809$ by equation (8). Finally, given similarity on all actions, similarity between them $\mathrm{sim}(A,B)$ can be calculated.

## 5. USER'S ACTION PATTERN

Generally, human beings have their action patterns in their daily life. For example, some have an action pattern like that they drink at a bar after eating at night, others have an action pattern like that they sing at a karaoke after eating at night. There are their preference in their action patterns.

User's action patterns can be extracted from the user's action history DB. There are several methods for extracting the user's action patterns such as the sequential pattern mining method[1].

Figure 1. shows a process of extracting the user's action patterns from the user's action history DB by using the sequential pattern mining method. The procedure is as follows:

1. Represent actions by feature vectors as symbols (e.g. $(1,0,0,0,0) \to a$, $(0,1,0,1,0) \to \{b,d\}$).

2. Convert the action history DB to a sequence DB (Figure 1. (b)). Here, the sequence denotes an action

sequence, and it is represented as $< a, b >$. $< a, b >$ means that the user takes action $b$ after action $a$. The sequence is separated by fixed session unit. In Figure 1., we define the session unit as one day.

3. Calculate support of sequences, and extract sequences with larger than minimum support minsup as frequent sequences. (Figure 1.(c)). Support of a sequence $< a, b >$ means frequencies of the sequence $< a, b >$ in the sequence DB. It is calculated by following expression:

$$\mathrm{sup}(< a, b >) = \frac{n(< a, b >)}{N} \tag{11}$$

Here, $n(< a, b >)$ denotes the number of sequences including the sequence $< a, b >$ in the sequence DB. $N$ denotes the total number of sequences in the sequence DB.

4. Regard the frequent sequences as action patterns. Then, calculate confidence of each action pattern. $\mathrm{conf}(< a, b >, b)$ denotes confidence of action $b$ in sequence $< a, b >$. It means confidence of that the user took action $b$ after action $a$ in the sequence DB. It is calculated by following expression:

$$\mathrm{conf}(< a, b >, b) = \frac{\mathrm{sup}(< a, b >)}{\mathrm{sup}(< a >)} \tag{12}$$

In the same way, $\mathrm{conf}(< a, b >, a)$ denotes confidence of action $a$ in sequence $< a, b >$. It means confidence of that the user took action $a$ before action $b$ in the sequence DB. It is calculated by following expression:

$$\mathrm{conf}(< a, b >, a) = \frac{\mathrm{sup}(< a, b >)}{\mathrm{sup}(< b >)} \tag{13}$$

Besides, we can extract conditional action patterns by setting conditions on the user's contexts or satisfaction rates when extracting the action patterns. In this paper, we call action patterns on condition that the user's satisfaction rates $> 0$ "positive action patterns, " and action patterns on condition that the user's satisfaction rates $< 0$ "negative action patterns." The positive action patterns mean succeeded experiences like that the user wants to take the action again. On the other hand, the negative action patterns mean failed experiences like that the user never wants to take the action.

# 6. RECOMMENDER CONSIDERING PAST / CURRENT / FUTURE CONTEXTS

Our proposed system recommends items suitable for user's past / current / future contexts based on action history DBs of the other users. In this paper, we call a user who is target user of recommendation an active user, and users who use the system except the active user other users.

In the example of Consider that the active user faces at past / current / future contexts represented as $< (\boldsymbol{A}_{-2}, \boldsymbol{C}_{-2}), (\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}), (\boldsymbol{x}, \boldsymbol{C}_0), (\boldsymbol{A}_{+1}, \boldsymbol{C}_{+1}) >$. Here, $\boldsymbol{x}$ is unknown, while $\boldsymbol{A}_*$ and $\boldsymbol{C}_*$ are known contexts. Our system predicts the actions $\boldsymbol{x}$ the active user will take based on the past contexts $< (\boldsymbol{A}_{-2}, \boldsymbol{C}_{-2}), (\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}) >$, current contexts $\boldsymbol{C}_0$ and future contexts $< (\boldsymbol{A}_{+1}, \boldsymbol{C}_{+1}) >$. Then our system shows items related to the actions $\boldsymbol{x}$ to the user.

First of all, we show preconditions. Suppose that action history DBs of the active user and the other users are made based on their daily life. Each user's action history DB is updated every time he/she uses items. Preference similarities between all users are calculated. As a result, a preference similarity matrix is made. We explain each step of the procedure of our system.

### *(1) Select reference DBs.*

Our system selects action history DBs refered in our system (reference DBs) from all users' action history DBs based on preference similarity matrix. Users with larger preference similarity than $\sigma$ are selected as similar users. Here, the $\sigma$ denotes threshold for deciding similar users.

### *(2) Select data that are similar to active user's contexts.*

Our system selects data that are similar to the active user's past / current / future contexts from all data in the reference DB. Specifically, our system selects data meeting the following conditions: Here, we show conditions when we look the $k$th data in the reference DB.

$$\begin{cases} \mathrm{sim}(\boldsymbol{C}_t, \boldsymbol{C}_k^r) \geq \tau & (\text{when } t = 0) \\ \mathrm{sim}((\boldsymbol{A}_t, \boldsymbol{C}_t), (\boldsymbol{A}_k^r, \boldsymbol{C}_k^r)) \geq \tau & (\text{when } t \neq 0) \end{cases} \tag{14}$$

Here, $\boldsymbol{A}_t, \boldsymbol{C}_t$ denote the active user's contexts at time $t$. $\boldsymbol{A}_k^r, \boldsymbol{C}_k^r$ denote contexts in the $k$th data in the reference DB. That is, data $k$ with larger similarity than $\tau$ are selected. Here, $\tau$ denotes threshold for selecting similar data.

### *(3) Extract action patterns from the reference DB.*

Our system extracts action patterns from the reference DB by using the sequential pattern mining method. Particularly, our system extracts positive and negative action patterns respectively.

### *(4) Select action patterns related to past / current / future contexts.*

Our system selects action patterns related to the past / current / future contexts $< (\boldsymbol{A}_{-2}, \boldsymbol{C}_{-2}), (\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}), (\boldsymbol{x}, \boldsymbol{C}_0), (\boldsymbol{A}_{+1}, \boldsymbol{C}_{+1}) >$ in all extracted action patterns. In this example, the system selects action patterns matched following all sequences:

$$\begin{cases} < (\boldsymbol{A}_{-2}, \boldsymbol{C}_{-2}), (z, \boldsymbol{C}_0) > \\ < (\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}), (z, \boldsymbol{C}_0) > \\ \cdots \\ < (\boldsymbol{A}_{-2}, \boldsymbol{C}_{-2}), (\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}), (z, \boldsymbol{C}_0), (\boldsymbol{A}_{+1}, \boldsymbol{C}_{+1}) > \end{cases} \tag{15}$$

Here, $z$ denotes optional actions. That is, the $z$ denotes actions expected that the active user will take.

### *(5) Calculate prediction score of actions based on action patterns.*

Our system calculates confidence for action $z$, $\mathrm{conf}(< \ldots >, z)$, based on the selected action patterns. Then we regard the confidence $\mathrm{conf}(< \ldots >, z)$ as prediction score of action $z$, $s(z)$. Specifically, we regard the confidence based on positive action patterns as positive value, and the confidence based on negative action patterns as negative value. Finally, our system can predict actions the user will take with considering the negative action patterns by regarding sum of the both values as prediction score of actions.

Table 3: Examples of confidence of action patterns.

| Positive / Negative | Action pattern | conf(<...>, $x$) |
|---|---|---|
| Positive action pattern | $<(\boldsymbol{A}_{-2}, \boldsymbol{C}_{-2}), (a, \boldsymbol{C}_0)>$ | 0.8 |
| | $<(\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}), (b, \boldsymbol{C}_0)>$ | 0.6 |
| | $<(\boldsymbol{A}_{-2}, \boldsymbol{C}_{-2}), (b, \boldsymbol{C}_0), (\boldsymbol{A}_{+1}, \boldsymbol{C}_{+1})>$ | 0.5 |
| | $<(\boldsymbol{A}_{-2}, \boldsymbol{C}_{-2}), (c, \boldsymbol{C}_0)>$ | 0.6 |
| Negative action pattern | $<(\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}), (a, \boldsymbol{C}_0), (\boldsymbol{A}_{+1}, \boldsymbol{C}_{+1})>$ | 0.5 |
| | $<(\boldsymbol{A}_{-1}, \boldsymbol{C}_{-1}), (c, \boldsymbol{C}_0)>$ | 0.8 |

Suppose that action patterns as shown in Table 3 are extracted for actions $\{a, b, c\}$. Each confidence is as shown in Table 3. Then prediction scores of the actions $\{a, b, c\}$ are follows respectively: $s(a) = 0.8 - 0.5 = 0.3$, $s(b) = 0.6 + 0.5 = 1.1$ and $s(c) = 0.6 - 0.8 = -0.2$. Finally, our system shows recommendation items to the active user based on the prediction score of actions. As a result, our system can expect that the active user will take the action $b$.

## 7. BASIC EXPERIMENT

We did basic experiments to evaluate our proposed system. The number of users participated in this experiment is five. We gave each of them the following three contexts: $<$ ("eating," "alone"), ($\boldsymbol{x}$, "alone") $>$, $<$ ($\boldsymbol{x}$, "with friends"), ("drinking," "with friends") $>$ and $<$ ("playing," "with boy/girlfriend"), ($\boldsymbol{x}$, "with boy/girlfriend"), ("eating," "with boy/girlfriend") $>$.

Under the above contexts, we did experiments by the following step:

(1) The users make their action histories in the above each context ("alone," "with friends," and "with boy/girlfriend") with imagining their daily life. Here, the context is fixed in one day. The users make four action histories in each context. Here, let $\sigma = 0$, described in Section 6 (1), that is that we regard all of other users as similar users, and then make the refference DB based on the users.

(2) Let $\tau = 1$, described in Section 6 (2), then select data matching the active user's contexts completely as the refference DB.

(3) Extract the users' action patterns from the refference DB. Here, let minsup = 0.2, described in Section 5, for extracting the action patterns.

(4) Calculate the prediction score for $\boldsymbol{x}$ in the three situations. Here, our system shows the candidate actions to the active user. Then the user evaluates each action by giving positive / negative values based on whether the user wants to take the actions.

Finally, we calculate the users' satisfaction rate, given by (the number of positive values / total number of actions shown by the system), to evaluate our system.

As a result, we got 0.67, which is the average of the all users' satisfaction rate. In our future work, we would like to compare the other recommendation systems which does not consider the contexts. Although, in this experiment, we did not consider the similar users based on their preference, we expect that we can improve the users' satisfaction by considering them.

## 8. CONCLUSION

In this paper, to complete a context-aware recommendation system, we proposed a recommendation system considering users' past / current / future contexts. Our system can change recommendation items depending on these contexts. This paper showed how to represent the contexts and how to decide recommendation based on the contexts.

Although we did an experiment, it is basic. In future work, we would like to do more detailed experiments, for example, by considering users' similarity in our future work. We expect that we can improve the users' satisfaction by considering them. Also, we would like to compare our method and the other recommendation systems which do not consider the contexts. Moreover, we would like to analyze how to decide each threshold, i.e. $\sigma$, $\tau$ and minsup.

Furthermore, we would like to discuss the positive / negative action patterns and how to extract them with contexts from users' action histories.


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