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Mobile Information Recommendation Using Multi-Criteria Decision Making with Bayesian Network

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The advancement of network technology and the popularization of the Internet lead to increased interest in information recommendation. This paper proposes a group recommendation system that takes the preferences of group users in mobile environment and applies the system to recommendation of restaurants. The proposed system recommends the restaurants by considering various preferences of multiple users. To cope with the uncertainty in mobile environment, we exploit Bayesian network, which provides reliable performance and models individual user's preference. Also, Analytical Hierarchy Process of multi-criteria decision-making method is used to estimate the group users' preference from individual users' preferences. Experiments in 10 different situations provide a comparison of the proposed method with random recommendation, simple rule-based recommendation and neural network recommendation, and confirm that the proposed method is useful with the subjective test.

Keywords: Information recommendation; Bayesian network; multi-criteria decision making; analytical hierarchy process; mobile environment.

1. Introduction

The advancement of high-speed network technology and the popularization of the Internet increase the amount of accessible data exponentially. Accordingly, information recommendation becomes an important issue for research.[1] Recently, as 'personalization' becomes a keyword for various services, many companies investigate it and supply the related functionalities.[2] Many web portals including Google and Yahoo provided services considering personalization such as personalized layout of contents, and most online shopping malls such as Amazon started to offer item recommendation service for individual customers.[3] As the amount of digital contents is expected to increase exponentially, it gets more important for information

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recommendation service to help individual users to find what they target the individual users.

However, some services such as restaurant and movie recommendation need to consider the preference of several persons because they should be served in a group. The users want to get served together at the same time. Therefore, recommendation for group users has to deal with an additional issue of considering preferences of more than two persons. The target domain used to include recommendation of traveling sites, movies, and music. Lieberman *et al.* proposed 'Let's Browse' which recommended a group of people with common interest based on the single user web browsing agent Letizia, and O'Connor *et al.* presented a new collaborative filtering recommender system designed to recommend items for group users.[4,5] Yu *et al.* proposed a TV program recommendation strategy for group viewers based on user profile merging.[6] Most of them cannot incorporate each person's importance in a group even though a certain person's opinion can be more important than others.

This paper uses Bayesian network to model the preference of each user in an uncertain mobile context and Analytic Hierarchy Process (AHP) of multi-criteria decision making to integrate the preferences of individual users, so as to recommend information to group users. AHP is a multi-criteria decision-making method, which decomposes the decision problem into a hierarchy of easier sub-problems.[7] Using Bayesian network and AHP, we apply the group recommendation method to restaurant recommendation in mobile context. Finally, an implemented system is presented in mobile environment to evaluate the performance.

The rest of the paper is organized as follows. Section 2 provides the literature reviews of recommendation with mobile context and recommendation for group users. The proposed mobile recommendation system using Bayesian networks and multi-criteria decision making is described in Sec. 3. Section 4 presents the dataset used to evaluate the proposed system, and analyzes experimental results. Finally, Sec. 5 concludes the paper and discusses the future works.

2. Related Works

This section provides the literature reviews on mobile recommendation and group recommendation. They are divided into two parts: mobile context for recommendation and recommendation for group users.

2.1. *Mobile context for information recommendation*

A user's preference to a certain service is subject to change as context, which often changes and accordingly becomes a key factor in mobile environment.[8] Therefore, information recommendation in mobile environment requires the context inference first. Dey defined a context as any information that can be used to characterize the situation of an entity such as person, place, or object that is considered relevant to the interaction between a user and an application, including the user and the

Table 1. Literature summary on recommendation in mobile context.

Author	Application domain	Context	Method
Tewari *et al.*[10]	Restaurant	Location	Location-specific brokering
Yuan and Tsao[11]	Mobile advertising	Location, time, contents, fare	Neural network learning
Kim *et al.*[12]	Image in a mobile web	Time, moving path, emotion, location, people, social context	Combining collaborative and content-based filtering
Setten *et al.*[13]	Travel information	Location, time, weather, etc.	Multiple prediction strategy
Choi *et al.*[14]	Several recommendations in a mobile web	Location, time, etc.	Prediction strategy
Kwon and Kim[15]	General recommendation problem	Location, weather	Rule generation from profiles

application themselves.[9] Mobile environment has all the information available for an entity, whereas mobile context provides some information relevant and useful to characterize the situation of an entity.

Table 1 summarizes the literature on information recommendation in mobile environment. Tewari *et al.* used user location as context to recommend restaurant information, and Yuan and Tsao used location, time, contents, and fare contexts for mobile advertising.[10,11] Kim *et al.* classified the context into private context (time, moving path, and emotion) and environment context (location, people, and social context) and used that information to recommend wall paper images in a mobile web.[12] Setten *et al.* provided information for travelers using context of location, time, weather, etc.[13] Choi *et al.* presented a context-sensitive recommendation system on the mobile web.[14] Kwon and Kim proposed a method which generates rules for context-triggered recommendations.[15]

Mobile environment is uncertain due to the incomplete and missing information, and so is the mobile context. Therefore, probabilistic models, one of the representative solutions for uncertainty handling, have been used a lot, and Bayesian networks, which show reliable performance in uncertain environment, also have been exploited intensively.[16] Korpiaa *et al.* in VTT Technical Research Center used naïve Bayes model to learn and classify the mobile user context, and Horvitz *et al.* in MS Research proposed the system to infer what a user is focusing in uncertain environment.[17,18] However, since mobile devices are private tools, most mobile recommendation is presented for individual users. In this paper, we presented mobile recommendation for group users using multi-criteria decision-making method.

2.2. *Information recommendation for group users*

As stated previously, it is required to recommend the information not for individual but for group users in some cases such as movie and TV program recommendations. Table 2 shows the summary of corresponding literature. O'Connor *et al.* presented PolyLens, which is an expansion of MovieLens, using collaborative filtering method,

Table 2. Literature summary on recommendation for group users.

Author	Application domain	Method
O'Connor *et al.*[5]	General item, Movie	Collaborative filtering
Masthoff[20]	TV program (interactive television)	Combining user models with diverse strategies and analyzing the results of user study
Goren-Bar and O. Glinansky[19]	TV program	User profile merging
Yu *et al.*[6]	TV program	User profile merging
McCarthy *et al.*[21]	General item, Ski package	Weighted average, joint, and average individual models
Chen *et al.*[22]	General item, Movie	Collaborative filtering, GA

and evaluated the system with the data from 800 MovieLens users.[5] TV program is a representative example where the recommendation is required. Goren-Bar and Glinansky and Yu *et al.* similarly exploited the user profile merging in order to recommend TV program to group viewers.[6,19] Masthoff attempted to use various strategies of user model combination to adapt a user model to group users for interactive television.[20] He also analyzed how people selected the program for group users with user study. McCarthy *et al.* compared several aggregation methods of individual user models focusing on how the preferences can be used to generate recommendations that satisfy the individuals as well as the group, and they used data of European ski packages for evaluation.[21] Chen *et al.* proposed a novel recommendation method for group users by combining collaborative filtering and genetic algorithm, and they evaluated the method with MovieLens data.[22]

Most of these works used simple merging or averaging of individual user models or profiles. While it is easy to implement, it cannot be applied to general recommendation problems. For example, when user A wants a Korean restaurant and user B wants a Japanese restaurant, this type of system might recommend a Chinese restaurant because preferences cannot be averaged in this simple way, so that both users are not satisfied with the result. For this reason, this method targets mostly on application domain like TV program recommendation. We use AHP for group decision making because it can make a complex decision as measuring information, knowledge and experience of decision makers.

3. The Proposed Method

Figure 1 summarizes the proposed recommendation process. The whole process divides into three steps: preference modeling of individual users, decision-making process using AHP, and recommendation. Bayesian networks are used for preference modeling of individual users based on user profiles and context logs collected to handle uncertainty in mobile environment, and AHP is used for decision-making process for recommendation. We have selected the restaurant recommendation as a target application because it can be a service which people may need it most frequently. The details will be described in the following sections.

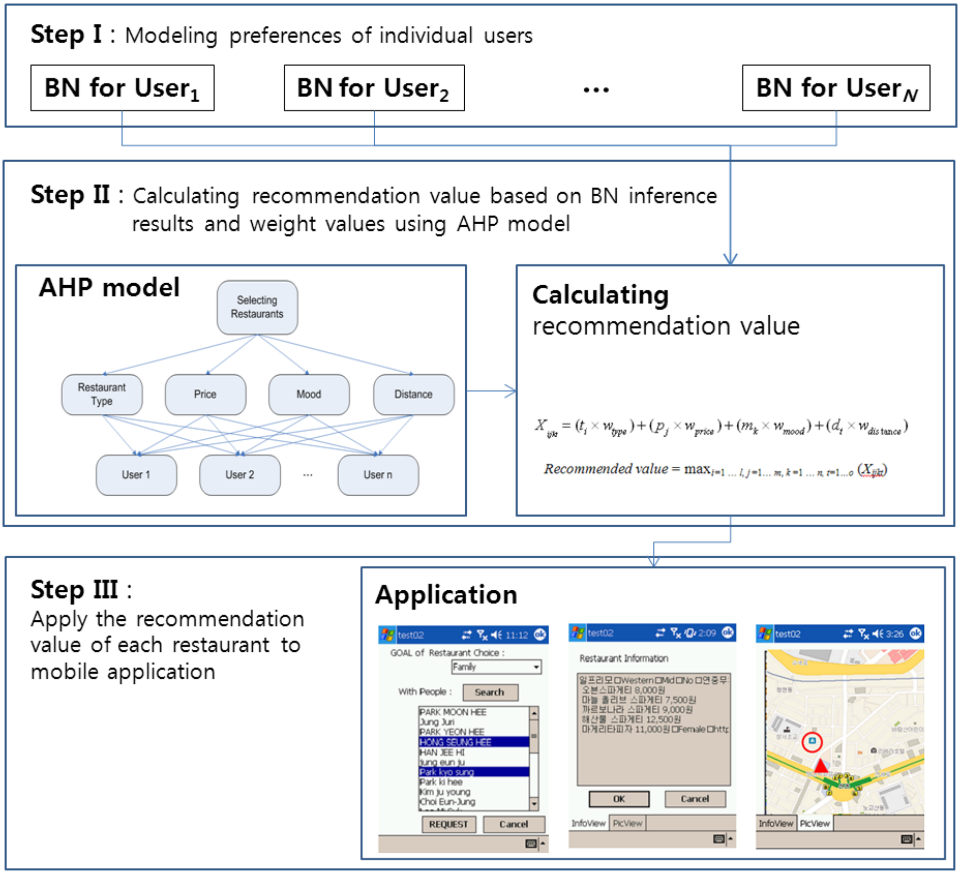


Fig. 1. The recommendation process of the proposed method using Bayesian network and AHP.

3.1. *Context-log collection in mobile environment*

Mobile context used in this paper includes temperature and weather information from Web, temperature, weather, and time information from operating system, latitude, and longitude from GPS receiver, and various user input from application program. User input includes basic user profiles such as age and gender, and user preferences for restaurant selection. Registered schedule information can be also used. Figure 2 shows context logs explained above. Temperature and weather information were captured from both Web and system. In Web, we can get the temperature information of large area like a city, and system can measure the temperature of the place a user locates in. They complement each other when one of them does not work. Similarly, we can infer the temperature from the date provided by system. This context information is preprocessed to be used as input of Bayesian network model.

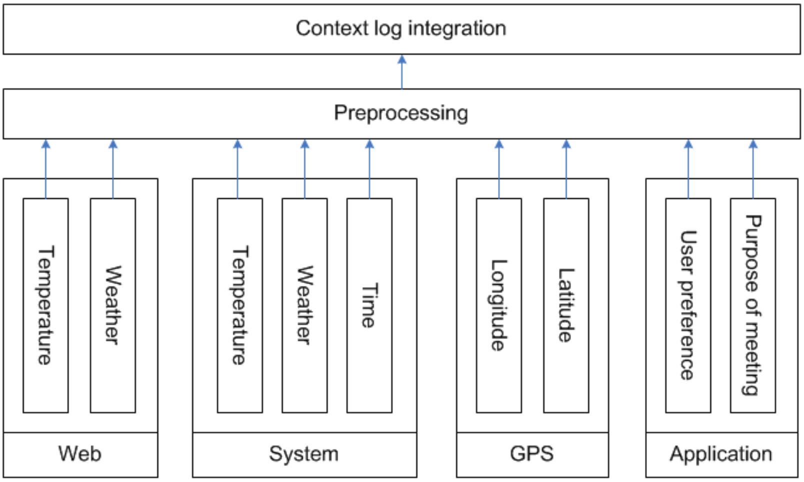


Fig. 2. Context log collected in mobile environment.

Data preprocessing means discretization of each input as the Bayesian network we have designed requires. For example, season data are encoded into four states: spring (from March to May), summer (from June to August), fall (from September to November), and winter (from December to February). The variables and the states used for Bayesian network model are summarized in Table 3. Context information in Fig. 2 constitutes variables in Table 3. Specifically, temperature, weather, and time context in Fig. 2 correspond to time and weather in Table 3, longitude and latitude in Fig. 2 correspond to location in Table 3, and application context (user preference and purpose of meeting) in Fig. 2 corresponds to user request variables in Table 3.

Table 3. Context logs and the states after preprocessing.

Context	Variable	State
Time	Season	{Spring, Summer, Fall, Winter}
	Period	{Breakfast, Lunch, Evening, Night}
User request	Priority	{Category, Mood, Price, Distance, Seat, Parking}
	Category	{Date, Group, On duty, Business, With friend, Meeting, For wedding, Family, Birthday, With children}
	Type	{Korean, Japanese, Chinese, Western, Alcohol}
	Mood	{Romantic, Tidy, Exotic, Normal}
	Price	{Low, Mid, High}
	Seat	{Comfortable, Mid, Uncomfortable}
	Parking	{Provided, Not provided}
Location	Distance	{Near, Mid, Far}
weather	Weather	{Sunny, Rainy, Cloudy, Snowy}
	Temperature	{Warm, Hot, Cool, Cold}

3.2. *Modeling preference of individual user with Bayesian network*

Bayesian network is represented as a Directed Acyclic Graph (DAG) where each node corresponds to the probabilistic variable and the arcs between the variables correspond to the probabilistic dependencies.[23] If two nodes have no connection between them, we can consider that they are independent of each other. In detail, nodes in Bayesian networks have conditional probability tables (CPTs), and they calculate the probabilities using Bayes' rule when probabilities of their parents' nodes are decided. This process requires much less computation than previous probability theory.

The inference in Bayesian networks is based on Bayes' rule which is defined as follows.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}. \tag{1}$$

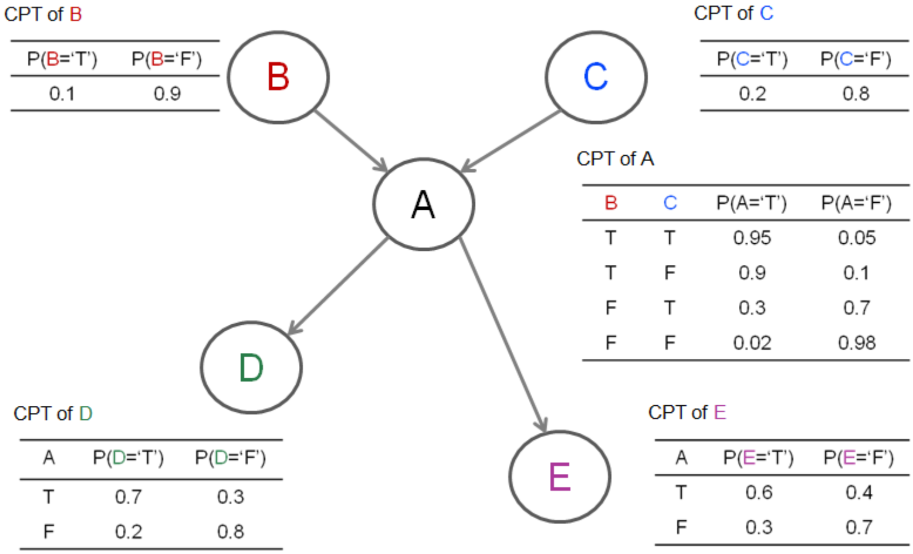
$P(A)$ and $P(B)$ are prior knowledge, and $P(A|B)$ is a conditional probability. Assuming that B is a set of observable variables, and A is a set of variables that are not observed but targeted, if $P(B|A)$, $P(A)$, and $P(B)$ are given, $P(A|B)$ can be calculated. The strength of Bayesian networks lies in that these probabilities can be calculated even though not all evidence variables are observed. If a set of observable variables (B) are divided into that of observed variables (B_1) and that of not-observed variables (B_2), $P(A|B)$ can be defined as follows.

$$P(A|B) = \frac{P(B_{11} = \text{observed value}, B_{12} = \text{observed value}, \ldots, B_{21}, B_{22}, \ldots \mid A)P(A)}{P(B_{11} = \text{observed value}, B_{12} = \text{observed value}, \ldots, B_{21}, B_{22}, \ldots)}, \tag{2}$$

$$B_1 = \{B_{11}, B_{12}, \ldots\}, \quad B_2 = \{B_{21}, B_{22}, \ldots\}. \tag{3}$$

Bayesian networks have been known as a useful tool for modeling and reasoning in various domains for several decades. This can be a good method to model user preference in mobile environment because it contains much more uncertainty. A structure of Bayesian network stands for the relations of cause and effect from their probability, and it can infer the result based on the conditional probability of cause nodes. Figure 3 shows an example of Bayesian network and its CPT. With these values in conditional probability tables and Bayes' rule, the probability of a certain decision node can be calculated given observed evidences. Here, T and F mean true and false, respectively.

Bayesian network for modeling individual user's preference is learned from collected data and profile of each user, and the K2 algorithm and maximum likelihood estimation are used to learn network structure and parameters. The K2 algorithm proposed by Cooper and Herskovits constructs the network structure as narrowing down the search space by fixed order of attributes.[24] Figure 4 shows a pseudo code of the K2 algorithm, which heuristically searches for the most probable network structure given a database of cases. If the first value of $g()$ is smaller than 0



CPT of B

P(B='T')	P(B='F')
0.1	0.9

CPT of C

P(C='T')	P(C='F')
0.2	0.8

CPT of A

B	C	P(A='T')	P(A='F')
T	T	0.95	0.05
T	F	0.9	0.1
F	T	0.3	0.7
F	F	0.02	0.98

CPT of D

A	P(D='T')	P(D='F')
T	0.7	0.3
F	0.2	0.8

CPT of E

A	P(E='T')	P(E='F')
T	0.6	0.4
F	0.3	0.7

Fig. 3. An example of Bayesian network and its CPT.

The K2 Algorithm

Input:

A set of n nodes,

An ordering on the nodes,

An upper bound u on the number of parents a node can have,

A dataset D including m cases.

Output:

A printout of each node and its parents.

{ **for** (i=1; i<n; i++) {

$\Pi_i = 0$;

$P_{old} = g(i, \Pi_i)$;

OK2Proceed = TRUE;

while (OK2Proceed && $|\Pi_i| < u$) {

Let Z be the node in Pred(X_i)- Π_i that maximizes $g(i, \Pi_i \cup \{Z\})$;

$P_{new} = g(i, \Pi_i \cup \{Z\})$;

if ($P_{new} > P_{old}$) {

$P_{old} = P_{new}$;

$\Pi_i = \Pi_i \cup \{Z\}$;

}

Else OK2Proceed = FALSE;

}//end {While}

print("node: ", X_i, "parents: ", Π_i);

}//end {for}

}//end {K2}

Fig. 4. The K2 Algorithm.

(initial condition), the loop is executed only once. However, at the worst case, the loop is executed for the number of data.

Figure 5 illustrates Bayesian network model learned by the K2 algorithm from user profile and mobile logs collected by a certain user. Here, six nodes of Prefer_1 through Prefer_6 are query nodes, which represent user preference and are used for recommendation (we use Prefer_1 to Pefer_6 to represent the specific type of preferences such as price and mood for each user, because they are different depending on the users). Prefer_1 is the most important node that represents the preference most while Prefer_6 is the least important one in terms of preference. Using six variables together, we make more detailed user preference model. The others except Prefer_1 to Prefer_6 can be considered as observation (or input) nodes, which are set by observed or sensed evidences. We have used the probabilistic evidence for more flexible inference.[24] That is, the model can infer user preference even though there is no input evidence with Bayesian network. In this model, therefore, we can infer that this user considered the distance to the restaurant as the most important factor when

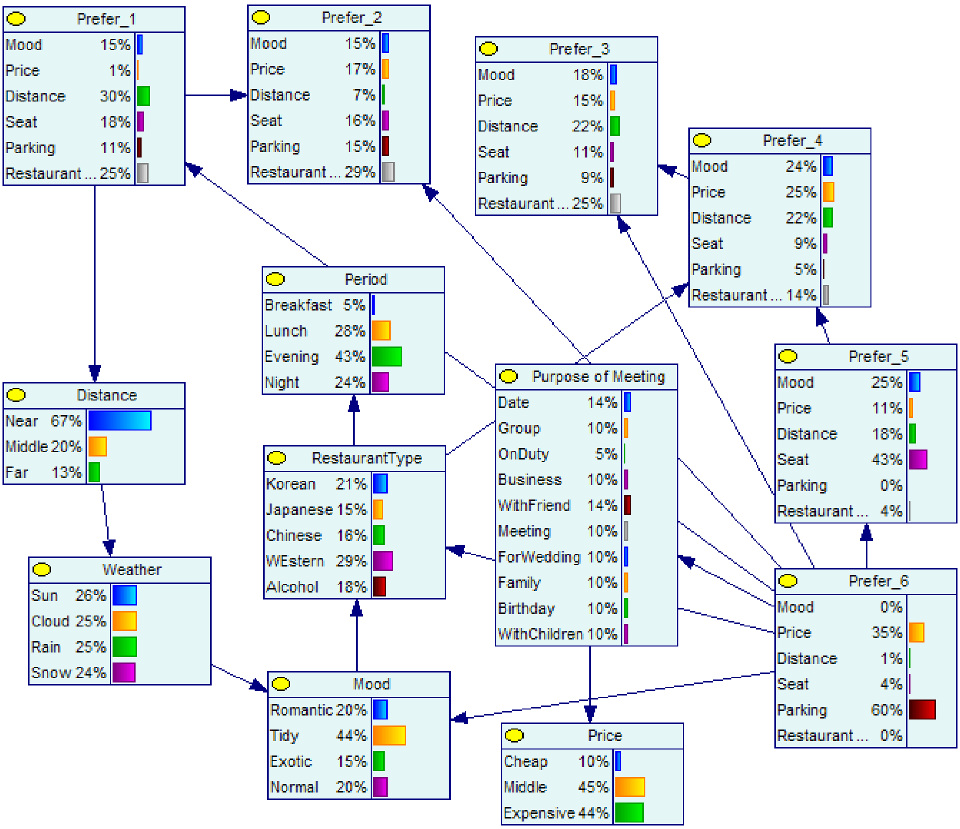


Fig. 5. An example of Bayesian network model learned for an individual user.

she/he selects restaurant (in the node Prefer_1) while the parking condition and price of foods are less important factor (in the node of Prefer_6).

3.3. *Multi-criteria decision making using AHP*

AHP proposed by Saaty[25] is a frequently used multi-criteria decision-making model to solve several interesting problems. For example, Srdevic *et al.* used AHP to rank loan applicants objectively to quantify decision makers' opinions.[26] Nazari-Shirkouhi *et al.* proposed the fuzzy AHP, which combines the fuzzy logic and AHP, to evaluate and select proper IT projects to outsource.[27] The derivation of a priority vector from a pair-wise comparison matrix (PCM) is an important issue in the AHP. Kou and Lin proposed a cosine maximization method based on similarity measure to maximize the sum of the cosine of the angle between the priority vector and each column vector of a PCM.[28,29] Also, Kou *et al.* presented an MCDM-based approach to rank a selection of popular clustering algorithms in the domain of financial risk analysis,[30] and Kou *et al.* proposed an approach to resolve disagreements among MCDM methods based on Spearman's rank correlation coefficient.[31]

The primary advantage of this method is the use of pairwise comparisons to get a ratio scale of measurement by asking a decision maker. This paper utilizes AHP together with Bayesian networks to select a restaurant for a group of users, which may have different preferences. Restaurant recommendation can also be a useful application of AHP because decision making is a practically difficult problem when there are many decision makers (users).

The process of multi-criteria decision making using AHP is as follows.[32]

(1) Construct AHP hierarchy.
(2) Conduct pairwise comparison of each alternative to make a pairwise comparison matrix.
(3) Calculate the weights of alternatives.
(4) Make a decision with calculated weights.

Figure 6 illustrates the AHP hierarchy constructed. (Note that this AHP has only four criteria in the 2nd hierarchy, because the BN trained by K2 algorithm produces only the four criteria out of six.) Basically, an element in the 1st hierarchy represents the goal of decision making, elements in the 2nd hierarchy represent several criteria for decision making and elements in the last hierarchy represent alternatives. Based on this hierarchy, the pairwise comparisons of alternatives using each decision-making criterion in the 2nd hierarchy are conducted, and PCMs are generated. Each value in the matrix is set with the relative importance value in Table 4 after questionnaire survey. If the factor 1 is a little more important than factor 2 in terms of a recommendation factor of restaurant type, a_{12} and a_{21} of the restaurant recommended are set by 3 and 1/3 (see the relative importance in Table 4). Matrix (4) can be obtained by conducting pairwise comparison for all users. After adding each column in this matrix using Eqs. (5) and (6) divides each

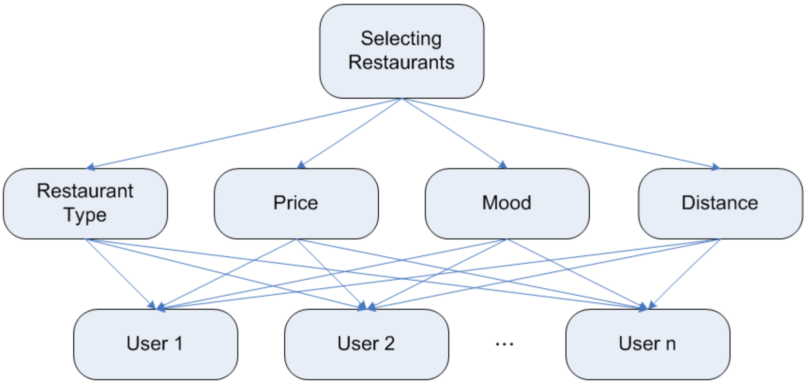


Fig. 6. The proposed AHP hierarchy.

Table 4. Relative importance table in pair-wise comparison.

Importance	Definition
1	A and B are equally important
3	A is a little more important than B
5	A is more important than B
7	A is much more important than B
9	A is absolutely more important than B

value by the sum of columns and gets the average from each row. Computed averages are used as weights.

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix}, \tag{4}$$

$$S_i = \sum_{k=1}^{n} a_{ki}, \tag{5}$$

$$w_i = \frac{\sum_{k=1}^{n} \frac{a_{ki}}{S_k}}{N}. \tag{6}$$

In Eqs. (5) and (6), w_i and N represent the weight of the ith criterion and the number of all alternatives for selecting restaurants, respectively. Repeating this process for all criteria in the 2nd hierarchy, the final weight of each criterion is calculated. This final set of weights, $\{w_{\text{type}}, w_{\text{price}}, w_{\text{mood}}, w_{\text{distance}}\}$, and the inferred probabilities of candidate restaurants by each criterion are used to compute the value for recommendation by Eq. (7). Here, t_i, p_j, m_k and d_t are elements in an inferred probability set by restaurant type $= \{t_1, t_2, \ldots, t_l\}$, that by price $= \{p_1, p_2, \ldots, p_m\}$, that by mood $= \{m_1, m_2, \ldots, m_n\}$ and that by distance $= \{d_1, d_2, \ldots, d_o\}$, respectively.

$$X_{ijkt} = (t_i \times w_{\text{type}}) + (p_j \times w_{\text{price}}) + (m_k \times w_{\text{mood}}) + (d_t \times w_{\text{distnace}}), \tag{7}$$

$$\text{Recommended value} = \max_{i=1\ldots l, j=1\ldots m, k=1\ldots n, t=1\ldots o} (X_{ijkt}). \tag{8}$$

The largest X_{ijkt} of all combination of attributes is assigned as a recommendation value, and the corresponding restaurant is displayed in the mobile application.

3.4. *A simple example*

To give accounts of the characteristics of the proposed method, let us consider a simple example. Suppose that the proposed method recommends a restaurant to the group of users in a scenario where she (User 1) dates with a boyfriend (User 2) in front of the department store in snowy evening in January. Table 5 illustrates the results of the probability of BN.

In this table, E represents the set of evidences which are obtained in the scenario for calculating the probability. In this case, the evidences are three: Weather is "snow", Period is "night", and Category is "Date". The evidences are set to the Bayesian networks for each user and the probability of each node is calculated using Bayes rule.

Now consider the case of group recommendation. First of all, the pairwise comparison matrix is generated for determining the importance of factors: Restaurant type, price, mood, and distance. This matrix is obtained from users as follows.

$$A = \begin{bmatrix} 1 & 3 & 3 & 3 \\ 1/3 & 1 & 1 & 1 \\ 1/3 & 1 & 1 & 1 \\ 1/3 & 1 & 1 & 1 \end{bmatrix}. \tag{9}$$

Table 5. Results of probability of BN.

Probability	User 1	User 2	(User 1 + User 2) / Number of users
$t_1 = P(\text{PreferRestaurant} = \text{Korean}\|E)$	0	0.15	0.075
$t_2 = P(\text{PreferRestaurant} = \text{Japanese}\|E)$	0.034	0.321	0.178
$t_3 = P(\text{PreferRestaurant} = \text{Chinese}\|E)$	0	0.255	0.127
$t_4 = P(\text{PreferRestaurant} = \text{Western}\|E)$	0.948	0.249	0.599
$t_5 = P(\text{PreferRestaurant} = \text{Alcohol}\|E)$	0.018	0.025	0.021
$p_1 = P(\text{Price} = \text{Low\_}p\|E)$	0.333	0.38	0.356
$p_2 = P(\text{Price} = \text{Mid\_}p\|E)$	0.417	0.579	0.498
$p_3 = P(\text{Price} = \text{High\_}p\|E)$	0.250	0.041	0.145
$m_1 = P(\text{Mood} = \text{Romantic}\|E)$	0.929	0.307	0.618
$m_2 = P(\text{Mood} = \text{Tidy}\|E)$	0	0.056	0.028
$m_3 = P(\text{Mood} = \text{Exotic}\|E)$	0.071	0.541	0.306
$m_4 = P(\text{Mood} = \text{Normal}\|E)$	0	0.096	0.048
$d_1 = P(\text{Distance} = \text{Near}\|E)$	0.876	0.921	0.899
$d_2 = P(\text{Distance} = \text{Middle}\|E)$	0.382	0.054	0.218
$d_3 = P(\text{Distance} = \text{Far}\|E)$	0.085	0.025	0.055

Next, the weights of each factor are calculated. First of all, we have to calculate S_i from the matrix A. Because the matrix is 4×4, the parameter n in the equation for S_i is 4 and the parameter k is 4, as well. The result of S_i is as follows.

$$\begin{gathered} S_i = \sum_{k=1}^{n} a_{ki}, \quad \text{where } n = 4, \\ S_1 = \sum_{k=1}^{4} a_{k1} = a_{11} + a_{21} + a_{31} + a_{41} = 1 + \frac{1}{3} + \frac{1}{3} + \frac{1}{3} = 2, \\ S_2 = 6, \quad S_3 = 6, \quad S_4 = 6. \end{gathered} \tag{10}$$

Then, the weights are calculated using Eq. (6). In this case, the parameter N is set as 4 as the same to the number of factors.

$$\begin{gathered} w_i = \frac{\sum_{k=1}^{n} \frac{a_{ki}}{S_k}}{N}, \quad \text{where } N = 4, \\ w_1 = w_{\text{type}} = \frac{\sum_{k=1}^{4} \frac{a_{k1}}{S_k}}{4} = \frac{\frac{1}{2} + \frac{\frac{1}{3}}{6} + \frac{\frac{1}{3}}{6} + \frac{\frac{1}{3}}{6}}{4} = 0.5, \\ w_2 = 0.16667, \quad w_3 = 0.16667, \quad w_4 = 0.16667. \end{gathered} \tag{11}$$

Finally, we calculate the recommended value of each restaurant. The parameter X in Eq. (7) represents the restaurant ID and t_i represents the type of the restaurant X. Assuming that the information of restaurant 1 is (Korean, Tidy, Mid_P, Middle), the proposed method sets the parameter i as 1, the parameter j as 2, the parameter k as 2, and the parameter t as 2. After the setting, the recommended score of the restaurant 1 is calculated as follows.

$$\begin{aligned} X_{ijkt} &= 1_{1222} = (t_1 \times w_{\text{type}}) + (p_2 \times w_{\text{price}}) + (m_2 \times w_{\text{mood}}) + (d_2 \times w_{\text{distnace}}) \\ &= (0.075 \times 0.5) + (0.498 \times 0.16667) + (0.028 \times 0.16667) + (0.218 \times 0.16667) \\ &= 0.161. \end{aligned} \tag{12}$$

We calculate all the X_{ijkt} for all the restaurants and select the restaurant ID which has the maximum score. When the recommended score is the same, lower ID is selected. The restaurant 13 is selected for the final recommendation in this case. Table 6 shows the result of calculation and the final recommended restaurant ID.

Table 6. Result of calculation of recommended score.

Ranking	Restaurant ID	Recommended score	Maximum recommended value	Minimum ID
1	13	0.49459	√	√
2	29	0.49459	√	
3	37	0.49459	√	
4	47	0.49459	√	
5	14	0.485418		
6	56	0.485418		

3.5. *Implementation of the recommender system*

Samsung M4300 smartphone is used for implementation of the recommender system. Figure 7 shows screen shots of the recommender system implemented in a mobile device. In Fig. 7(a), the system loads the learned preference model of a user.

Fig. 7. Recommender system implemented in a mobile device. (a) Log-in interface, (b) user input, (c) recommendation result (text viewer), and (d) recommendation result (image viewer).

In Fig. 7(b), user sends information of the group and a goal of the meal. Figures 7(c) and 7(d) show the recommendation result in text view and image view, respectively.

4. Experiments

This section describes the experimental data used for evaluation, provides recommendation results and an application, and analyzes the results.

4.1. *Experimental data*

For experiments, we collected the information of 90 restaurants in an area of $870 \times 500\,\mathrm{m}^2$ in Shinchon (a well-known downtown area located in Seoul, Korea). User data consist of questionnaire surveys of 20 men and women for constructing the information of type, mood, and price for the 90 restaurants.

10 situations shown in Table 7 were presented to the subjects, and then we conducted evaluation of the recommended results and usability of the system. Situation #1 and situation #2 target to five groups with two persons, and situation #3 through situation #10 target to five groups with three or four persons. Experiments were performed with 153 people in 50 groups.

4.2. *Recommendation result using individual user's preference model*

First, we attempted to evaluate the recommendation using individual user's preference model. Figure 8 illustrates the accuracy comparison of a simple rule-based recommendation, random recommendation, the recommendation with neural network and the recommendation with the proposed method. The accuracy is calculated by the ratio of correct guesses by the method to all the user answers. Rules in a

Table 7. Situation presented to subjects.

Situation #	Specific situation presented to subjects
1	Date with a boy (or girl) friend in front of the Hyundai department store in snowy evening in December
2	Date with a boy (or girl) friend at the front gate of Yonsei University in sunny afternoon in April
3	Official dinner engagement in front of the Hyundai department store in clear night in mid-August
4	Lunch with co-worker at the front gate of Yonsei University in rainy afternoon in late June
5	Meeting at the front gate of Yonsei University in a rainy evening in early October
6	Dinner with friends at the front gate of Yonsei University in clear evening in late July
7	Birthday party with friends at the front gate of Yonsei University at cloudy night in mid-December
8	Birthday party with friends in front of Hyundai department store in clear evening in mid-December
9	Dinner with family at the front gate of Yonsei University in clear evening in mid-October
10	Lunch with family in front of Hyundai department store in clear afternoon in mid-May

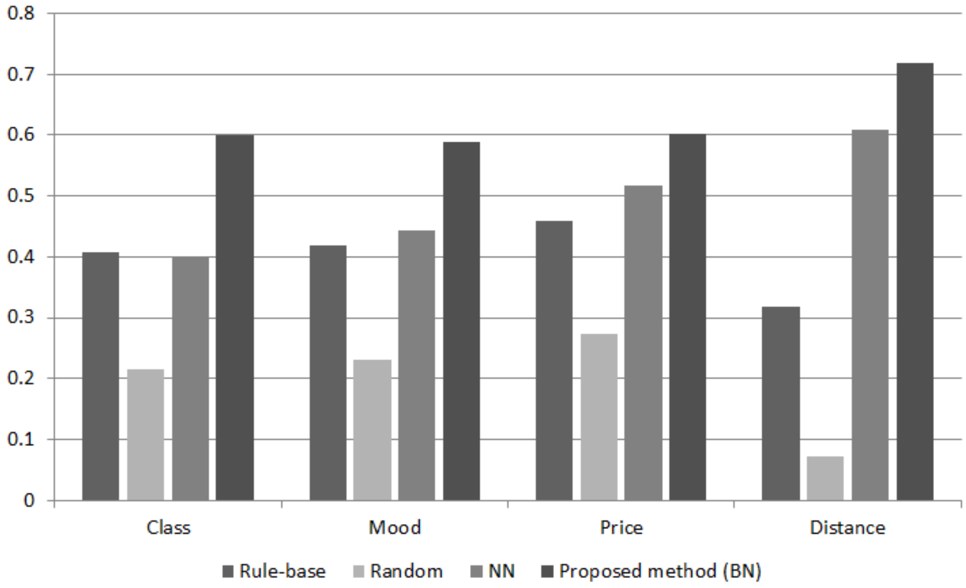


Fig. 8. Accuracy of individual user's preference model.

rule-based recommendation model utilized simple rules based on the common sense. The whole list of rules is as follows.

- Recommend the nearest restaurant if it is rainy or snowy.
- Recommend a restaurant, which usually serves warm foods, if it is cold.
- Recommend a romantic restaurant if it is a date.
- Recommend a restaurant with high price if it is an official dinner.
- Recommend a restaurant with low price if it is a dinner with friends.
- Recommend a tidy restaurant if it is a dinner with family.
- Recommend a Korean restaurant if it is rainy (one of Korean social habit).
- Recommend an alcohol restaurant for a party.

Comparing with other three methods, Bayesian network model provides much better accuracy.

4.3. *Analysis of recommended result*

Figure 9 demonstrates how the proposed recommendation was useful for recommendation for group of people. In situation 7 presented in Table 8, three users (User 1, User 2, and User 3) in a single group have preferences as follows by attributes. As shown in Fig. 9(a), Users 1 and 2 prefer a restaurant with the type 'Alcohol,' and User 3 does not prefer the 'Japanese' restaurant. In Fig. 9(b), User 2 prefers the 'Tidy' restaurant, and in Fig. 9(c), User 1 prefers a restaurant of 'High' price while Users 2 and 3 prefer one of 'Mid'. Similarly, it can be seen that

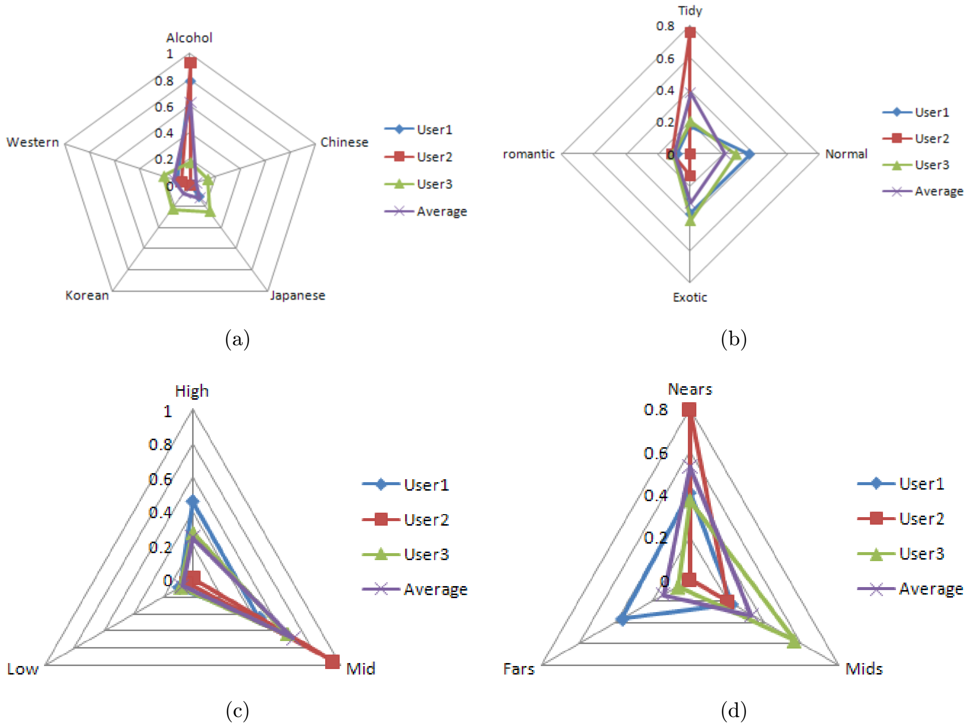


Fig. 9. Preference of three users by four attributes. (a) Restaurant type, (b) mood, (c) price, and (d) distance.

User 2 prefers 'Near' restaurant, but Users 1 and 3 give a low weight to the distance.

The recommended result using the proposed method is shown in Table 8. It shows the recommended restaurants for both of three individual users and their group. Comparing the preferences in Fig. 10 with the recommended result by the proposed method, it can be accepted as a reasonable result considering that it is impossible to satisfy all three users at the same time. It refers to situation 7 in Table 7. Figure 10 illustrates the screen shots of the application implemented in a mobile device. Figures 10(a) through 10(d) show the results provided in Table 8.

Table 8. Recommended result.

Recommendation		Restaurant	Type	Mood	Price	Distance
For individual	User 1	Chodang	Alcohol	Normal	High_p	400 m (Far)
	User 2	Hot chicken	Alcohol	Tidy	Mid_p	160 m (Near)
	User 3	Kokichon + Bar	Korean	Exotic	Mid_p	223 m (Near)
Proposed recommendation		Playmate	Alcohol	Tidy	Mid_p	160 m (Near)
Rule-based recommendation		Beer warehouse	Alcohol	Normal	Low_p	130 m (Near)
NN-based recommendation		Hot chicken	Alcohol	Tidy	Mid_p	160 m (Near)

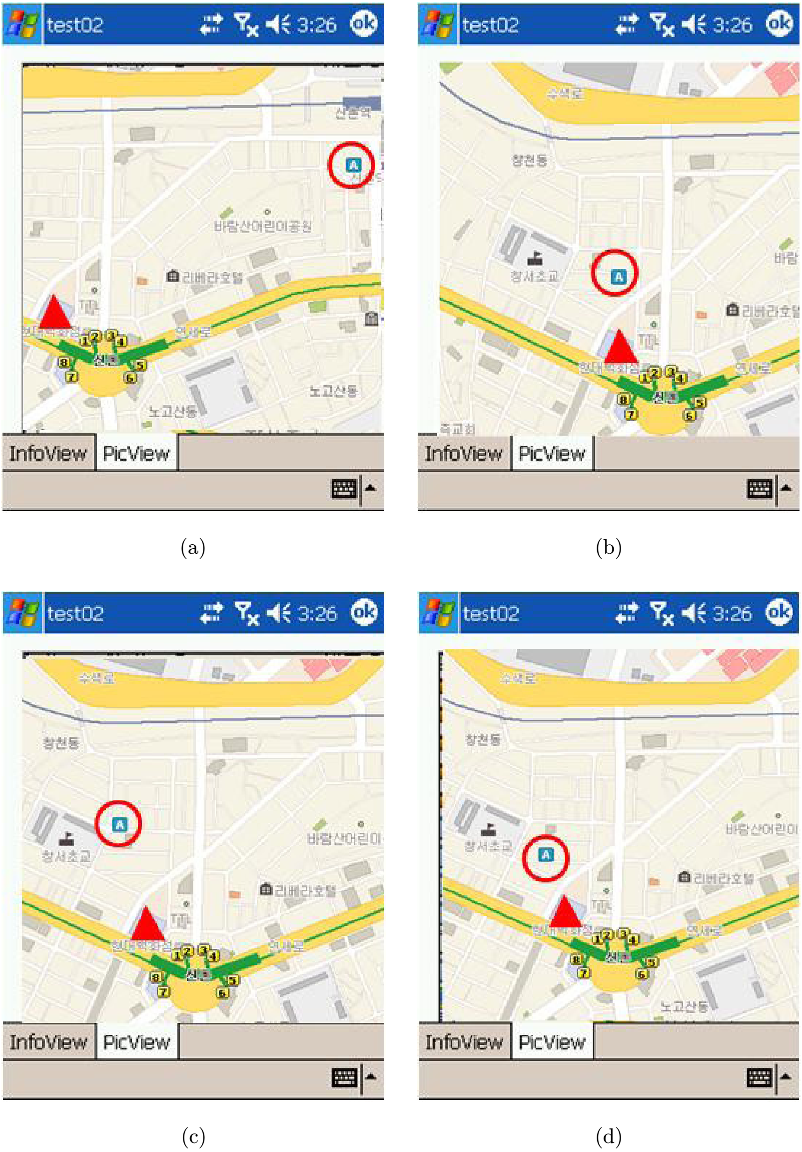


Fig. 10. Screen shots of the application in a mobile device (IR: Information Recommendation). (a) IR for User 1, (b) IR for User 2 and proposed method, (c) IR for User 3, and (d) random IR for group users.

4.4. *Usability test of the system*

To evaluate the usability of the proposed system, we have requested the answers after we have let users experience the system. For evaluation, 10 questions in System Usability Scale (SUS), which has been proved a robust, reliable, and low-cost usability assessment tool, were used. SUS test of 13 subjects measures three aspects of

Table 9. SUS scores by subject ID and the average score.

Subject ID	1	2	3	4	5	6	7	8	9	10	11	12	13	Avg
SUS score	60	60	67.5	70	67.5	62.5	87.5	80	65	82.5	80	75	65	70.58

the system: effectiveness (can users successfully achieve their objectives), efficiency (how much effort and resource are expended in achieving those objectives), and satisfaction (the experience satisfactory).[33,34] Subjects should give answer of five degrees from "strongly disagree" to "strongly agree". The result is a single score on a scale of 0 to 100, and our result shows a range of 60–82.5 (average of 70.58). A single score is calculated based on the following equation.

$$\begin{aligned} \text{SUS result} &= (\text{odd numbered question} - 5) \times 2.5 \\ &\quad + (25 - \text{even numbered question}) \times 2.5. \end{aligned} \tag{13}$$

Table 9 summarizes the results. According to the literature,[35] these scores can be regarded as good (OK for around 52, GOOD for around 73, and EXCELLENT for around 85).

5. Concluding Remarks

This paper has exploited Bayesian networks to model the preference of individual user in a mobile context and integrated the preferences of individual users using AHP of multi-criteria decision-making method. To apply this method to the restaurant recommendation for group users, we implemented the recommendation system in mobile device. In experiments, we confirmed that the proposed method provided better performance than a random recommendation, a simple rule-based recommendation, and neural network-based recommendation. The result of usability test also showed that the proposed method was promising.

The proposed method for group recommendation has strengths as follows. As using Bayesian networks to model the individual preference, it can handle the uncertainty in a mobile environment, and as using AHP to integrate the preferences of several users in a group, it can provide both subjective and objective evaluation measures. However, some problems also remain. To use AHP, we have to ask some questions to decision makers, so we can use the result as an important part of decision-making process. Besides, this method treats opinion of all users equally not considering the strength of each opinion. Sometimes it may recommend a restaurant because no one does not dislike seriously, even though all of them are not satisfied enough with the recommendation.

There are solutions for the problems raised. In order not for users to answer a lot of questions to construct matrix (4), learning method from data set can be used. If the recommender system can infer the answer for questions that we should ask to decision makers from the collected data, it can be used without surveying process though it does require more data and does not guarantee the high accuracy. The second problem also can be solved if the system considers the status or character of each decision maker. For example, it can reflect more opinion of a user who is important or insists strongly than other persons who are normal or yield all the time.

For future work, we need to compare the proposed method to other approaches such as user profile combining and collaborative filtering. Applying the proposed method to problems in other domains can be an interesting issue. Recommendation of movie for friends and recommendation of couch in a shopping mall for family members can be good examples. Moreover, negotiation among the users might be an interesting approach for the group decision making. Because the AHP does not consider this process, we will extend the proposed method to incorporate the collaboration between users in the final group decision making.

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