Restaurant Recommendation for Group of People in Mobile Environments Using Probabilistic Multi-criteria Decision Making

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Abstract. Since 1990s, with an advancement of network technology and the popularization of the Internet, information that people can access has proliferated, thus information recommendation has been investigated as an important issue. Because preference to information recommendation can be different as context that the users are related to, we should consider this context to provide a good service. This paper proposes the recommendation system that considers the preferences of group users in mobile environment and applied the system to recommendation of restaurants. Since mobile environment has plenty of uncertainty, our system have used Bayesian network which showed reliable performance with uncertain input to model individual user's preference. Also, restaurant recommendation mostly considers the preference of group users, so we have used AHP (Analytic Hierarchy Process) of multi-criteria decision making method to get the preference of group users from individual users' preferences. For experiments, we have assumed 10 different situations and compared the proposed method with random recommendation and simple rule-based recommendation. Finally, we have confirmed that the proposed system provides high usability with SUS (System Usability Scale).

Keywords: Information recommendation, Bayesian network, AHP, Multi-criteria decision making.

1 Introduction

With the advancement of high-speed network technology and the popularization of the Internet, the amount of data accessible is growing exponentially. Accordingly, information recommendation is an important issue for research [1]. Recently, as 'personalization' became a keyword for various services, many companies investigate it and provide the functionalities for it. Many web portals including Google and Yahoo provided services considering personalization such as personalized layout, and most online shopping malls such as Amazon started to provide item recommendation service for individual customers. Because the amount of digital contents will be expected to increase exponentially, it will be more important job for information recommendation service to help individual users find the information they need.

Mostly, recommendation services target the individual users, but services such as restaurant or movie recommendation should consider the preference of several

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persons because they are in the same group and want to get the service together. Recommendation for group users is another issue in information recommendation, and the target domain includes recommendation of traveling sites, movies, and music. Lieberman *et al.* proposed 'Let's Browse' which recommends a group of people with common interest based on the single user web browsing agent Letizia [2], and O'Connor *et al.* presented a new collaborative filtering recommender system designed to recommend items for group users [3].

This paper uses Bayesian network to model the preference of each user and AHP of multi-criteria decision making to integrate the preference of individual users, so that can be used to recommend information to group users. Implemented system has been applied to restaurant recommendation in mobile environment, and its' evaluation has been conducted successfully with recommendation experiment and usability test.

2 Mobile Context and Information Recommendation

Preference of user to a certain service is easy to change as the context, and context often changes in mobile environment. Thus, information recommendation in mobile environment requires context inference first. Dey defined context as any information that can be used to characterize the situation of an entity such as a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and the application themselves [4]. Tewari *et al.* used user location, ID, time as context [5], and Kim *et al.* classified the context into private one and environment context and used for the mobile web [6].

Mobile context includes uncertainty because people use mobile devices while they are moving. Therefore, Bayesian networks, which provide reliable inference, have been used frequently [7]. Korpiaa *et al.* in VTT used naïve Bayes model to learn and classify mobile user context [8], and Horvitz et al. in MS Research proposed the system that infers what a person is focusing in uncertain environment [9].

3 Proposed System

Figure 1 summarizes the proposed recommendation method using multi-criteria decision making. Whole process divides into four steps: context-log collection, preference modeling of individual users using Bayesian network, their integration using multi-criteria decision making, and recommendation.

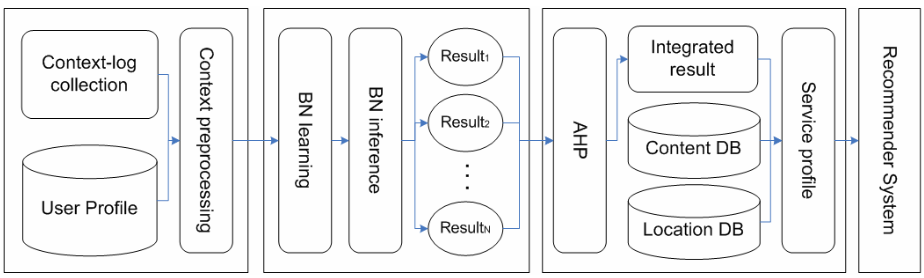


Fig. 1. An overview of information recommendation using AHP (Analytical Hierarchy Process) and Bayesian network

3.1 Context-Log Collection in Moblie Environment

Mobile context used in this paper includes temperature and weather from Web, season and period information from operating system, latitude and longitude from GPS receiver, and various user input from application program. Figure 2 shows context logs explained above. This context information is preprocessed to be used as input of Bayesian network model.

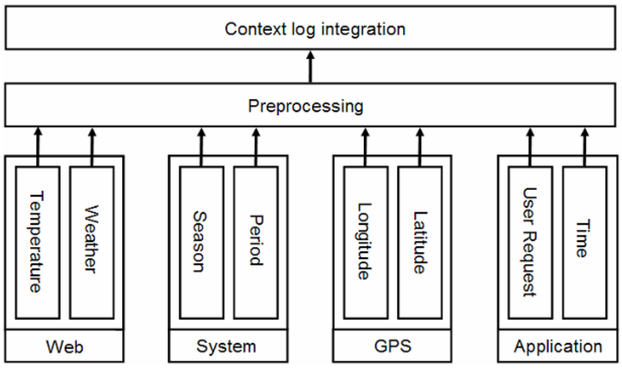


Fig. 2. Context log collected in mobile environment

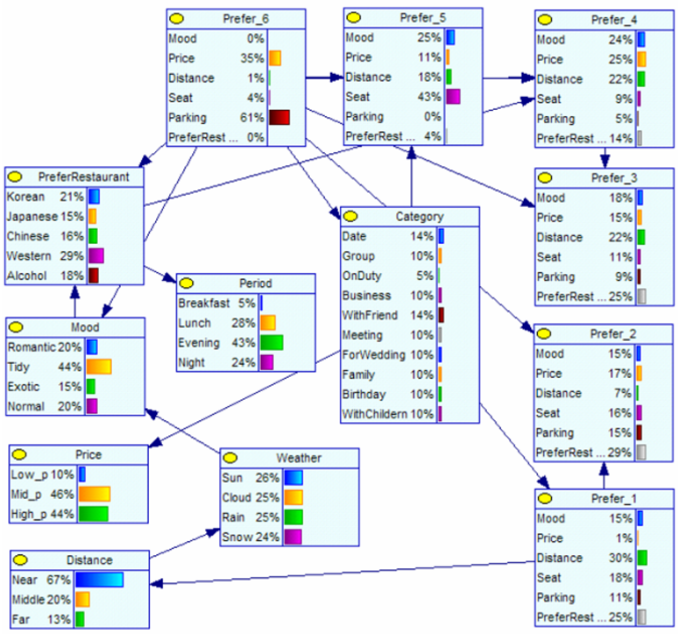


Fig. 3. An example of learned Bayesian network model for individual user

Preprocess is to discretize each input because Bayesian network requires one. For example, season data are discretized into four states: spring (from March to May), summer (from June to August), fall (from September to November), and winter (from December to February), and restaurant type are discretized into five: Korean, Japanese, Chinese, western, and alcohol.

3.2 Modeling Preference of Individual User with Bayesian Network

Bayesian network to model preference of individual user is learned from collected data based on the scenario, and the K2 algorithm and maximum likelihood estimation are used to learn BN structure and parameter [7]. Figure 3 illustrates learned Bayesian network model.

In Figure 3, six nodes of Prefer_1 through Prefer_6 are query nodes. Here, node Prefer_1 is the most important one, and Prefer_6 is the least. Thus, this user prefers the distance to the restaurant than other factors.

3.3 Multi-criteria Decision Making Using Analytical Hierarchy Process

Inferred result in Bayesian network model let us know which restaurant each user prefers, but the decision will be difficult if more than two persons want to go to the restaurant together. AHP (Analytic Hierarchy Process) is a multi-criteria decision making method that makes conclusion considering the preferences of several users [10].

We assumed that the inferred probability set containing the probabilities that each type of restaurant is selected is Type = $\{t_1, t_2, \ldots, t_l\}$, the probabilities that each restaurant of a certain range of price is selected is Price = $\{p_1, p_2, \ldots, p_m\}$, the probabilities that each restaurant of a certain mood is selected is Mood = $\{m_1, m_2, \ldots, m_n\}$, and the probabilities that each restaurant of a certain range of distance is selected is Distance = $\{d_1, d_2, \ldots, d_0\}$, and called each attributes t_i^{name}, p_j^{name}, m_k^{name}, d_t^{name}, respectively. After that, we have decided the weights for each attributes with AHP. Figure 4 depicts the proposed AHP hierarchy. The criteria to decide restaurant for n persons are restaurant type, price, mood and the distance to the restaurant, and the alternatives are n users. Final goal is to select the preferred restaurants for n users.

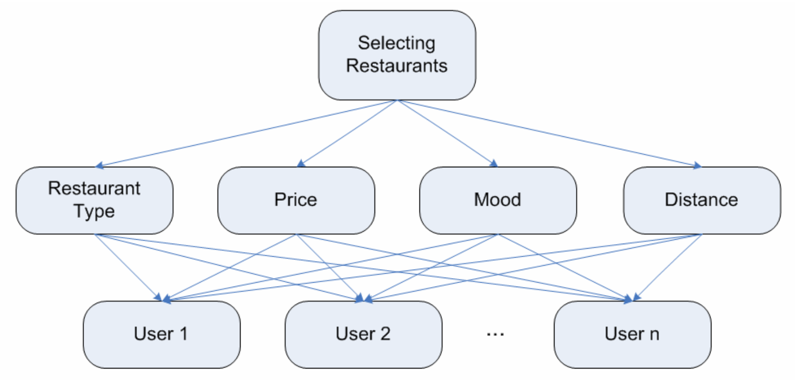


Fig. 4. Proposed AHP hierarchy

Based on AHP hierarchy in Figure 4, the pair-wise comparison matrix shown in Equation (1) is generated. Each value in matrix is set with the following pair-wise comparison criteria. An importance value in matrix is 1 if A and B are equally important, and the value in matrix is 9 if A is much more important than B. Values inbetween have importance between A and B as those. After adding each column in the matrix using Equation (2), Equation (3) divides each value by the sum of column and gets the average from each row. Computed averages are used as weights.

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

$$S_i=\sum_{k=1}^{n} a_{ki} \tag{2}$$

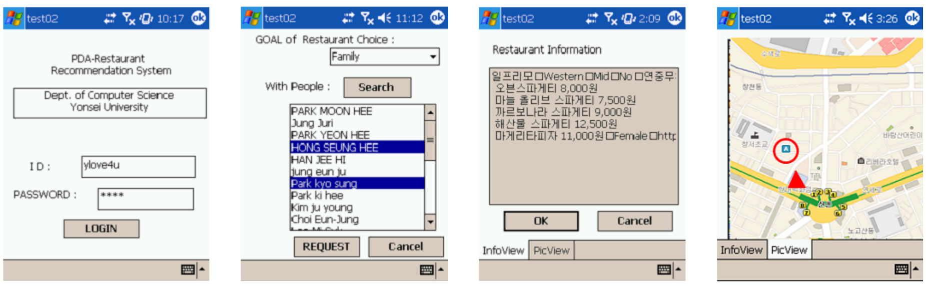
$$w_i=\frac{\sum_{k=1}^{n}\frac{a_{ki}}{S_k}}{N} \tag{3}$$

In Equation (2) and (3), w_i and N represent the weight of ith criterion and the number of all criteria for selecting restaurants. Weight = $\{w_{type}, w_{price}, w_{mood}, w_{distance}\}$ is a set of weights obtained by Equation (3), and the value for recommendation with this weight is computed with Equation (4).

$$X_{ijk}=(t_i\times w_{type})+(p_j\times w_{price})+(m_k\times w_{mood})+(d_t\times w_{distance}) \tag{4}$$

$$Recommended\ value = \max_{i=1\dots l,\, j=1\dots m,\, k=1\dots n}(X_{ijk}) \tag{5}$$

Among all combination of attributes, we assigned the maximum value of X_{ijk} as a recommendation value and selected the corresponding restaurant.



(a) Log in interface (b) User input (c) Recommendation result (text viewer) (d) Recommendation result (image viewer)

Fig. 5. Recommender system implemented in mobile device

3.4 Implementation of the Recommender System

Figure 5 shows the recommender system implemented in a mobile device. In (a), the system load the learned preference model of a user. In (b), user sends information of the group and a goal of the meal. (c) and (d) provide the recommendation result in test view and image view, respectively.

4 Experiments

4.1 Experimental Data and Scenario

For experiments, we have collected the information of 90 restaurants in area of $870\times 500\text{m}^2$ in Shinchon (Located in Seoul, Korea). User data consist of questionnaire surveys of 20 men and women.

10 situations were presented to subjects, and then we conducted evaluation of the recommended results and usability of the system. For example, situation #1 is “A date with a boy (or girl) friend in front of the Hyundai department store in snowy evening in December.” Experiments were performed with 50 groups and 153 people.

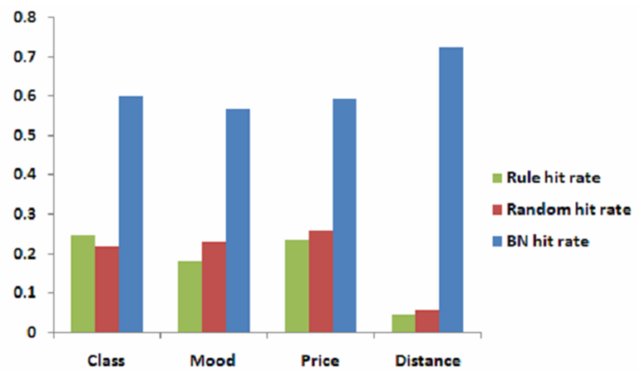


Fig. 6. Accuracy of individual user’s preference model

4.2 Recommendation Result of Individual User’s Preference Model

First, we attempt to evaluate the recommendation using individual user’s preference model. Figure 6 provides accuracy comparison of a simple rule-based recommendation, random recommendation, and the recommendation with Bayesian network model. Comparing with other two methods, Bayesian network model provides much better accuracy. To compute the accuracy, we regarded the user answer in a given situation as a correct one.

4.3 Recommendation Result as Scenario and Group

In this section, we have analyzed the results of one user who experienced all situations. Table 1 summarizes the changes of situations and groups and the recommendation results according to them.

Situation ID, group ID, and restaurant ID represent 10 different situations presented in Section 4.1, the ID of made groups for experiments, and each restaurants, respectively. As shown in Table 3, the proposed multi-criteria decision making recommends restaurants according as the situation and the group changes while other two models recommend restaurants according to the situation only. Rules used in a rule-based recommendation model are simple ones based on the common sense like "Select the restaurant A, which usually serves warm foods, if it is rainy and cold day."

Table 1. Recommendation results considering changes of situations and groups

Person ID	Situation #	Group ID	Restaurant #		
			Individual's preference model	Multi-criteria decision making	Rule-based recommendation
1	S1	G6	16	**16**	11
	S2	G6	58	**88**	88
	S3	G1	89	**49**	49
		G4	89	**49**	49
		G5	89	**83**	49
	S4	G1	71	**2**	88
		G4	71	**6**	88
		G5	71	**71**	88
	S5	G1	44	**2**	71
		G4	44	**44**	71
		G5	44	**44**	71
	S6	G1	36	**42**	44
		G4	36	**6**	44
		G5	36	**88**	44
	S7	G1	50	**50**	38
		G4	50	**50**	38
		G5	50	**49**	38
	S8	G1	36	**46**	89
		G4	36	**58**	89
		G5	36	**46**	89
	S9	G1	36	**88**	71
		G4	36	**88**	71
		G5	36	**88**	71
	S10	G1	16	**46**	48
		G4	16	**11**	48
		G5	16	**30**	48

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 questionnaire, 10 questions in SUS (System Usability Scale) have been used. SUS test measures three aspects of the system: effectiveness (can users successfully achieve their objectives), efficiency (how much effort and resource is expended in achieving those objectives), and satisfaction (was the experience satisfactory) [11]. Subjects should 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).

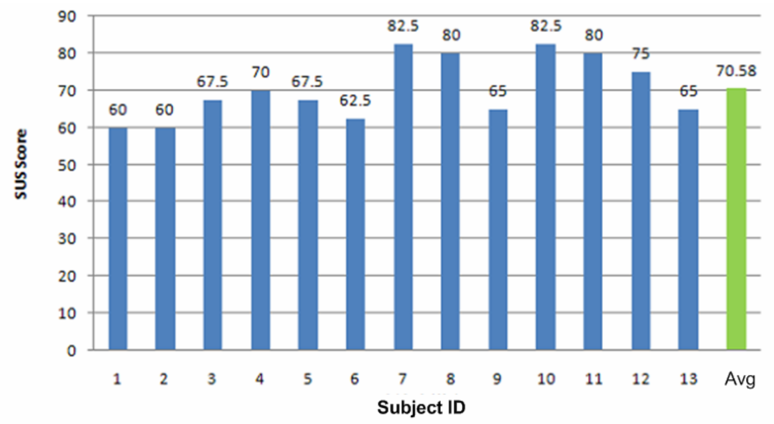


Fig. 7. SUS score by subject and average score

5 Conclusion

This paper exploited Bayesian network to model the preference of individual user and integrated the results of group users using AHP of multi-criteria decision making process to apply it to restaurant recommendation for group users. In experiments, we confirmed the proposed recommender system provides better performance than a random recommendation and a simple rule-based recommendation. The result of usability test also shows our system is usable. For future works, we will attempt to apply the proposed recommendation model to other services like movies.

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