# Location-Based Recommendation System Using Bayesian User's Preference Model in Mobile Devices

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**Abstract.** As wireless communication advances, research on location-based services using mobile devices has attracted interest, which provides information and services related to user's physical location. As increasing information and services, it becomes difficult to find a proper service that reflects the individual preference at proper time. Due to the small screen of mobile devices and insufficiency of resources, personalized services and convenient user interface might be useful. In this paper, we propose a map-based personalized recommendation system which reflects user's preference modeled by Bayesian Networks (BN). The structure of BN is built by an expert while the parameter is learned from the dataset. The proposed system collects context information, location, time, weather, and user request from the mobile device and infers the most preferred item to provide an appropriate service by displaying onto the mini map.

## 1 Introduction

Recently, personalized techniques have been widely studied to automatically recommend or find customized information [1]. Personalized recommendation systems recommend an item to which a user prefers by using automatic information filtering method. Moreover, as mobile computing progresses, various resources can be available to model user preference. A Mobile device provides a user with information and services related to the physical location based on user's location. Since there are lots of information and services, it is difficult to find a proper service to one's preference at proper time.

In particular, such research has focused on user interface and location. The "MovieLens Unplugged" project [2] explores the usability of such recommender systems on devices with limited display and intermittent connectivity to the backend data store. Their focus is on improving the recommender interface for the mobile user. In this paper, we build a map-based recommendation system to overcome the limitation with mobile device such as small-size screen and interface.

## 2 Related Works

### 2.1 The Context and Recommendation in Mobile Environment

The context means information which can be a feature of environment such as time and a location. In context-aware computing restaurant recommendation [3,4], tour

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guide [5] and commercial recommendation[6] are serviced by using context information (location, ID and time). Geographical location represents where mobile device user stays [7]. Time is information related to system or service request [8]. ID means a current user of device. Due to the limitation of mobile device such as latency, users request a personalized service recommendation at proper situation. Mobile phone provides user with more direct recommendation through 'push' service using SMS or other interaction channel [9]. Recommendation and personalization in the mobile web have interest in the user preference based recommendation method [6]. Many researches define context in the mobile web and apply context information to recommend service and contents. The some of service recommendation system are summarized in Table 1.

**Table 1.** Context-aware recommendation systems

| | MIT Media Lab | National Tsing Hua Univ. | Telematica Institute | Fu-Jen Univ. |
|---|---|---|---|---|
| Recommendation type | Restaurant | Restaurant | Travel information | Commercial |
| Context information | Location | Location, Time, Weather | Location, Time, Weather, Shopping list, Schedule | Location, Time, Fare, Contents |
| Recommendation method | Interaction between 2 agents | Search after requesting | Variable prediction strategy | Neural network learning |
| Device | PDA, GPS | Pocket PC, GPS | Mobile phone, GPS | Mobile phone |

## 2.2 Recommendation Systems

Traditional recommendation systems use collaborative filtering to predict the rating of a product to a particular user. The general idea behind collaborative filtering is that similar users vote similarly on similar items. There are two major flavors of collaborative filtering [10]. Memory-based collaborative filtering, known as user-based collaborative filtering, these algorithms try to establish a correlation between users based on their voting pattern. Such correlation is dynamically computed among different groups of users whoever prediction is made. This puts big computational and memory loads on the system if the prediction is to be delivered in real time. For that reason, such systems do not scale particularly well for large datasets and are not popular in real applications [10]. Model-based collaborative filtering, known as item-based collaborative filtering, these algorithms are widely popular today and are used primarily because of their scalability with huge datasets. Instead of focusing on similarity between users, such systems compute the similarity between voted items [10].

Microsoft (MS) evaluated the algorithm for three separate datasets as follows [11]:

1. MS Web: individual visit to various areas of the MS web sites (visited or not).
2. Television: Neilsen network television view data for individuals for a two-week period (watched or not).
3. EachMovie: Collaborative filtering site deployed by Digital Equipment Research Center during 2 years (ranged in value from 0 to 5).

The dataset is applied to Bayesian networks, the correlation, Bayesian cluster and vector similarity, respectively. Bayesian networks and the correlation techniques showed the best performance [11]. In this paper, we implement BN-based recommendation system suitable for mobile environment that requires data processing in real time.

# 3 BN-Based Personalized Recommendation System

## 3.1 Overview

The proposed method consists of 3 parts as shown in Figure 1: context log collection, recommendation module and system mapping module. User profile and context information are collected by using mobile device. The collected context information is preprocessed to train the parameters of BN. We obtain CPT (conditional probability table) by EM algorithm with preprocessed context data. When a user requests a new demand, we select the highest probability parameter of each attribute the learned BN-model. We find the real information in accordance with the high-order data set through search of contents database. The proposed method is implemented for mobile devices to collect information and to provide a service.

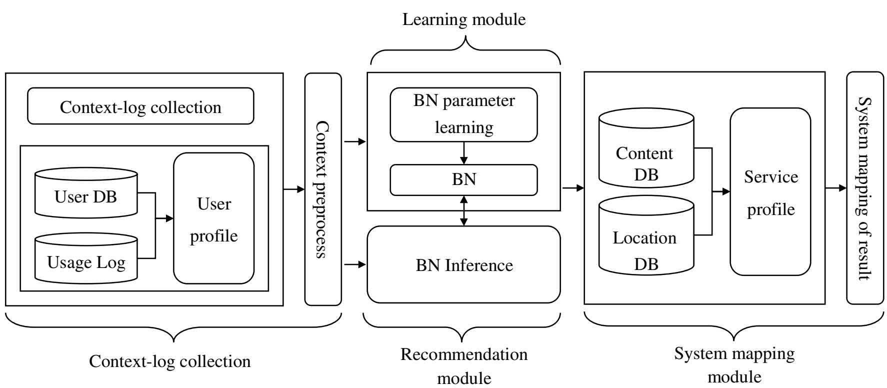



**Fig. 1.** The overview of the proposed system

## 3.2 Context Information

As shown in Figure 2, various kinds of context log information are used, including weather information, temperature and weather from web sites, and season, time of day, periods and user location collected from mobile devices. Some information such as user requests are collected directly from users through a mobile application implemented as shown in Figure 3. After preprocessing the context information collected by each device, we integrate each data file on the basis of the time.

## 3.3 Bayesian Network Based User Preference Model

BN were built by an expert as shown in Figure 4. In addition, Bayesian networks built by an expert cannot reflect a change of environment. To overcome this problem, we

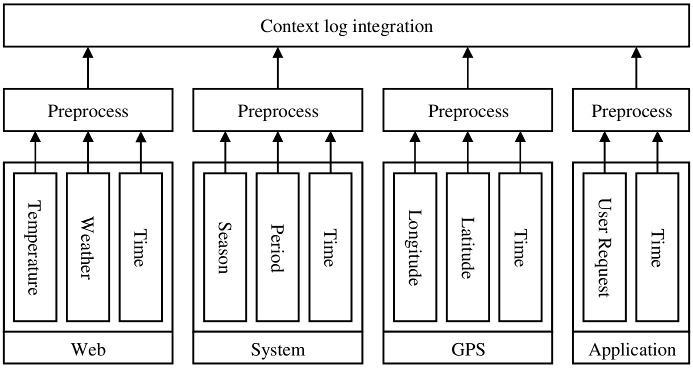



**Fig. 2.** Context log information

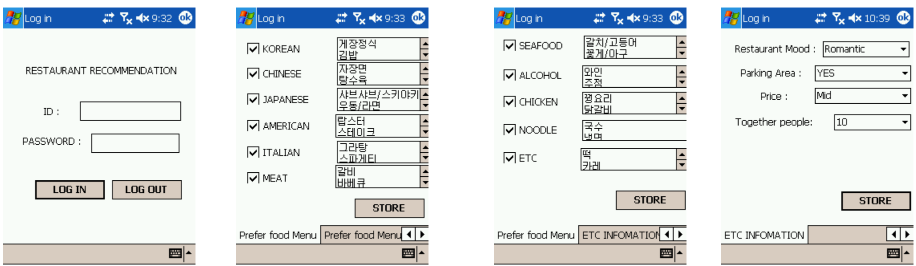



**Fig. 3.** Mobile application to collect context log information

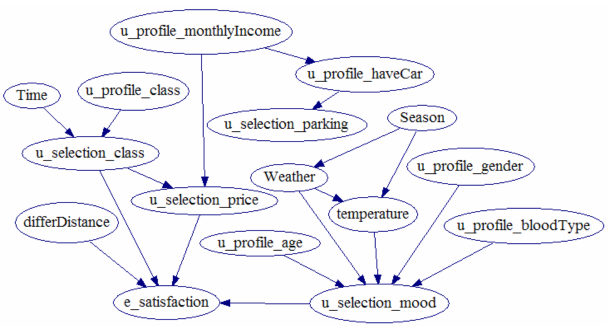



**Fig. 4.** BN structure for inferring user preference

apply a parameter learning technique. Based on collected data, CPTs are learned by using EM (Expectation Maximization) algorithm as shown in Figure 5.

## 3.4 Restaurant Recommendation

To overcome the limitation of display and resource of mobile devices, we have implemented map-based interface which is intuitive to user as shown in Figure 6. The implemented system consists of the user-input module that stores user's personal

**Input:**

$k$ : # of clusters,

$Y=\{y_1, y_2, \cdots, y_n\}$: set of n $p$ - *dimensional* points,

$\in$ : a tolerance for loglikelihood,

*max-iterations*, maximum number of iterations.

**Output:**

$C, R, W$ : the matrices containing the updated mixture parameters.

$X$ : a matrix with cluster membership probabilities.

1.***Initialization:*** Set initial values for $C, R$ and $W$

2.***While:*** $\delta(llh) \rangle \in$ and *max-iteration* has not been reached

**DO** E and M steps

**E step:**

$C'=R'=W'=llh=0$

**for** $i=1$ **to** $n$

$\sum p_i = 0$

**for** $j=1$ **to** $k$

$\delta_{ij} = (y_i - C_j)^t R^{-1} (y_i - C_j)$

$$p_{ij} = \frac{w_j}{(2\pi)^{\frac{p}{2}} \mid R \mid^{\frac{1}{2}}} \exp(-\frac{1}{2}\delta_{ij})$$

$\sum p_i = \sum p_i + p_{ij}$

**end-for**

$$x_i = \frac{p_i}{\sum p_i},\ llh = llh + \ln(\sum p_i)$$

$C' = C + y_i x_i^t,\ W' = W + x_i$

**end-for**

**M step:**

**for** $i=1$ **to** $k$

$$C_j = \frac{C_j}{W_j}$$

**for** $j=1$ **to** $n$

$R' = R' + (y_i - C_i) x_{ij} (y_i - C_j)^t$

**end-for**

**end-for**

$$R = \frac{R'}{n},\ W = \frac{W'}{n}$$

**Fig. 5.** EM algorithm for BN parameter learning

profiles and the management module that manages content log information. Naver Map Open API is used to show the real map. In order to model personal traits, we collect user's general information such as name, gender, age, birthday, blood type, possesses of car and monthly income, and user's prefer food information. The management module embodies the ability to search, delete and update restaurant information so as to directly input through the map. Inference results are used to find proper restaurants and they are mapped on the map so that users can intuitively obtain information through the map.

In order to find proper restaurants, in this paper, we calculate the preference on restaurants based on the inference results of BN. A restaurant consists of three attributes

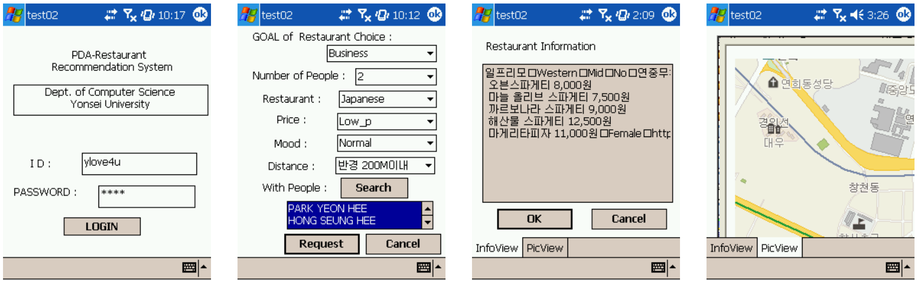



**Fig. 6.** The personalized recommendation system

such as class, price, and mood. The preference on a restaurant is calculated as the following formula.

$$X_{ijk} = (c_i \times w_{class}) + (p_j \times w_{price}) + (m_k \times w_{mood})$$
$$\mathrm{Re}commendValue = \max_{i=1\cdots l,\, j=1\cdots m,\, k=1\cdots n}(X_{ijk}) \tag{1}$$

$Class = \{c_1, c_2, \cdots, c_l\}$, $Price = \{p_1, p_2, \cdots, p_m\}$, and $Mood = \{m_1, m_2, \cdots, m_n\}$ means the restaurant class probability, the price probability, and the mood probability, respectively, where $Weight = \{w_{class}, w_{price}, w_{mood}\}$ is the weight for the corresponding node. According to the results, several restaurants of high value are displayed on the map of the mobile application.

# 4 Experimental Results

## 4.1 Experimental Environment

In this paper, we used about the information of 50 restaurants [12] in the Shinchon area (870×500㎡). Current data were collected by 4 registered users for 7 days (11/1~11/7). We conducted the parameter learning through 7-fold cross validation. As shown in Table 2, user profile consists of age, gender, blood-type, possession of car, monthly income and food preference. Generally researches about preferences of food include traits of subjects for an experiment such as age, gender, occupation, economic strength and educational level [13]. We collected a possession of car to know parking area of recommended restaurants.

Table 3 shows the preprocessed data set which consists of context information such as time, user request, user profile, location and weather. Time is composed of season and period: the former includes with spring (March ~ May), summer (June ~ August), fall (September ~ November), and winter (December ~ February), and the latter includes with breakfast (3:00~11:00), lunch (11:00 ~18:00), and dinner (18:00~3:00). User requests are obtained from direct inputs which include restaurant class, mood, price and parking area. Location has three attributes such as Near (in 100m), Mid (in 200m), and Far (in 300m) according to user's current location. Weather represents Sunny, Rain, Cloudy and Snow according to the weather service on web. Temperature is categorized into Warm(13~20℃), Hot(20~30℃), Cool(7~13℃), and Cold(-5~7℃) [14].

**Table 2.** User profile information (K: Korean, J: Japanese, C: Chinese, A: American)

| | user1 | user2 | user3 | user4 |
|---|---|---|---|---|
| Age | Mid-20 | Early 30 | Late 20 | Early 30 |
| Gender | Female | Female | Male | Male |
| Blood Type | B | AB | B | O |
| Own Car | No | Yes | No | Yes |
| Income (1,000won) | 150~200 | 250~300 | 100~150 | 250~300 |
| Prefer Food | K, J, C, A | K, J, A | K, J, C | K, J, C, A |

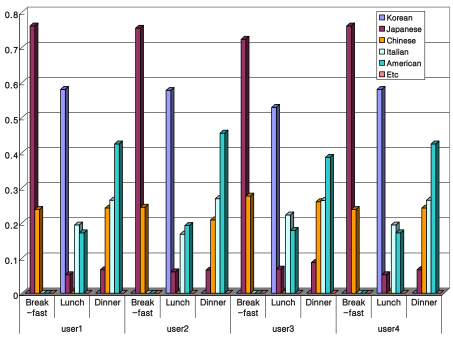
**Table 3.** Collected log dataset

| | Node | | Value |
|---|---|---|---|
| Time | Season | | Spring, Summer, Fall, Winter |
| | Time | | Breakfast, Lunch, Dinner |
| User Request | Restaurant | Class | Korean, Japanese, Chinese, American, Italian, Etc |
| | | Mood | Romantic, Tidy, Exotic, Normal |
| | | Price | Low, Mid-Low, Mid, Mid-High, High |
| | | Parking Area | Yes, No |
| User Profile | Preference | | Korean, Japanese, Chinese, American, Italian, Etc |
| | Gender | | Male, Female |
| | Age | | 10~19, 20~29, 30~39 |
| | Own Car | | Yes, No |
| | Income | | 100~150, 150~200, 200~250, 250~300 |
| | Blood Type | | A, B, AB, O |
| Location | DifferDistance | | Near, Mid, Far |
| Weather | Weather | | Sunny, Rain, Cloudy, Snow |
| | Temperature | | Warm, Hot, Cool, Cold |

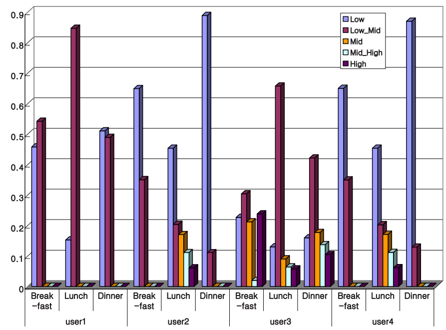
## 4.2 Experimental Results

User-preference restaurant class, price and mood were inferred by the BN-model. Attribute probability distributions of nodes of time, user profiles, system information and weather are represented in Figure 7, which shows probability distributions about restaurant class, price and mood, respectively. Accordingly the system consists of probability distributions of are the highest attribute dataset, and then it recommends the most similar real data. For instance, user1 prefers Japanese class, Low-Mid price and Tidy mood in breakfast, Korean class, Low-Mid price and Romantic mood in lunch and American class, Low price and Romantic mood in dinner as showing Figure 7.

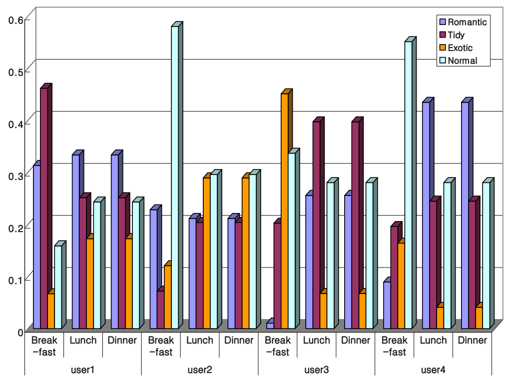
User1 prefers Japanese class, Low-Mid price and Tidy mood in breakfast, Korean class, Low-Mid price and Romantic mood in lunch and American class, Low price and Romantic mood in dinner. Table 4 shows the highest probability distribution set of each node in accordance with the user through calculation. Table 5 shows restaurants recommended to the user. In comparison with the result of Table 4 and Table 5, restaurant class items faithfully implemented for BN probability to infer correct




**(a) recommended classes**




**(b) recommended prices**




**(c) recommended moods**

**Fig. 7.** The probability distribution

**Table 4.** An example of recommended attributes to each user

| | | Restaurant class | R_price | R_mood |
|---|---|---|---|---|
| user 1 | Breakfast | Japanese | Mid-Low | Tidy |
| | Lunch | Korean | Mid-Low | Romantic |
| | Dinner | American | Low | Romantic |
| user 2 | Breakfast | Japanese | Low | Normal |
| | Lunch | Korean | Low | Normal |
| | Dinner | American | Low | Normal |
| user 3 | Breakfast | Japanese | Mid-Low | Exotic |
| | Lunch | Korean | Mid-Low | Tidy |
| | Dinner | American | Mid-Low | Tidy |
| user 4 | Breakfast | Japanese | Low | Normal |
| | Lunch | Korean | Low | Romantic |
| | Dinner | American | Low | Romantic |

results. However, the price and mood are often the different from these of inferred data. Since the amount of content data accorded with the recommended attributes is few.

**Table 5.** The result of actual recommended restaurants (Upper 2 Ranking)

| | | R-Name | R-Class | R-Price | R-Mood |
|---|---|---|---|---|---|
| user 1 | Breakfast | Kuma ZZang<br>Yoisis | **Japanese**<br>**Japanese** | **Mid-Low**<br>**Mid-Low** | **Tidy**<br>**Tidy** |
| | Lunch | Nolbu BudeaZZiGe<br>HongCho Hot Chicken | **Korean**<br>**Korean** | **Mid-Low**<br>**Mid-Low** | Normal<br>Normal |
| | Dinner | ILPRIMO<br>Net-Bar | **American**<br>Italian | Mid<br>Mid | **Romantic**<br>**Romantic** |
| user 2 | Breakfast | Kuma ZZang<br>Yoisis | **Japanese**<br>**Japanese** | Mid-Low<br>Mid-Low | Tidy<br>Tidy |
| | Lunch | One Chicken<br>GumTer | **Korean**<br>**Korean** | Mid<br>Mid-Low | **Normal**<br>**Normal** |
| | Dinner | Outback Steak<br>Uno | **American**<br>**American** | Mid<br>Mid | Exotic<br>Exotic |
| user 3 | Breakfast | Kuma ZZang<br>Yoisis | **Japanese**<br>**Japanese** | **Mid-Low**<br>**Mid-Low** | Tidy<br>Tidy |
| | Lunch | Pumpkin<br>Nolbu BudeaZZiGe | **Korean**<br>**Korean** | **Mid-Low**<br>**Mid-Low** | **Tidy**<br>Normal |
| | Dinner | Outback Steak<br>Uno | **American**<br>**America** | Mid<br>Mid | Exotic<br>Exotic |
| user 4 | Breakfast | Kuma ZZang<br>Yoisis | **Japanese**<br>**Japanese** | Mid-Low<br>Mid-Low | Tidy<br>Tidy |
| | Lunch | GumTer<br>Pumpkin | **Korean**<br>**Korean** | Mid-Low<br>Mid-Low | Normal<br>Tidy |
| | Dinner | ILPRIMO<br>Net-Bar | **American**<br>Italian | Mid<br>Mid | **Romantic**<br>**Romantic** |

## 5 Concluding Remarks

To overcome the limitation of display and resource of mobile devices, we implemented a map-based interface which is familiar to user. We proposed BN-based recommendation system reflecting user's preference using user profile and context information which can obtain from mobile devices.

For future works, we will verify the usefulness from usability tests, and enlarge the data set including the number of case samples as well as restaurants to confirm the stability.

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