

# PREDICTING USER ACTIVITIES IN THE SEQUENCE OF MOBILE CONTEXT FOR AMBIENT INTELLIGENCE ENVIRONMENT USING DYNAMIC BAYESIAN NETWORK

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**Abstract:** Recently, mobile devices became essential mediums in order to implement ambient intelligence. Since people can always keep these mobile devices, it is easy for them to collect diverse user information. Therefore, many research groups have attempted to provide useful services based on this ubiquitous information. This paper proposes a method to predict user activity in the sequence of mobile context. In order to conduct accurate prediction of activity among various patterns, we have considered user activity, place, time and day of week as mobile context. We have used dynamic Bayesian network to model the user activity patterns with this context, and learned the model of each individual to obtain better model. For experiments, we have collected the mobile logs of undergraduate students, and confirmed that the proposed method produced good performance.

## 1 INTRODUCTION

Ubiquitous sensors, devices, networks and information are essential infrastructure to implement ambient intelligence to provide diverse and relevant services to people (Cai *et al.*, 2009). Recently, Mobile devices such as smart phone and PDA became essential mediums in order to provide intelligent services in these ambient intelligence environments because people always keep them. Besides, it becomes so popularized that most people can have and use them. Since most of them have several functions and sensors including camera, GPS and MP3 players, it also can provide a lot of user information. Accordingly, many research groups attempt to store and manage users' information of daily life or provide diverse smart services to users in real world (Silva *et al.*, 2005, Gemmell *et al.*, 2009).

The most basic mobile log information is a user location from GPS, and LBS (Location-based Services) based on this information has been a promising research topic (Bellavista *et al.*, 2008). It also includes commercial services although they use very simple method like rule-based system. In addition to the user location, various context information including time, environment, user and

device has been used to infer higher-level context (Korpijaa *et al.*, 2003). Some of them analyze these mobile logs and show them to users as an interesting way, and AniDiary, which provided a cartoon-style summarization of users' daily life, can be a representative example (Cho *et al.*, 2007).

This paper attempts to predict user activity using mobile life log. If we can predict the activities in the future accurately, it is possible to provide information that user requires. One of the hardest difficulties in predicting user activity is that there are so many possible activities that we cannot conduct the accurate prediction. Only recognizing current activities has been a popular research topic (Ermes, *et al.*, 2008), and predicting trajectory not activities was conducted in a campus domain (Han *et al.*, 2006).

This paper learned the sequence of user activity pattern using dynamic Bayesian network. To solve the problem mentioned before in the learning process, we have considered information such as place, time, day of week, call record, MP3, SMS and photo in addition to activity. Also, we learned the prediction model with an individual user's data as well as integrated data for all users since each one can have a different activity pattern.

## 2 BACKGROUNDS

### 2.1 Bayesian Networks and Mobile Context

Normally, context is closely related to user activities. For example, place restricts the possible range of activities. 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 (Dey, 2001). Recently, the word "mobile context" has started to be used as a popularization of the mobile devices. Since mobile environment is under uncertainty, the mobile context includes much uncertain information.

Bayesian networks have been used as methods to model context, and they provide reliable performance with uncertain and incomplete information (Kleiter, 1996). It can be modeled using the data and can be designed using expert knowledge, and has been used to classify and infer the mobile context based on these strengths. Korpipaa et al. in VTT research center utilized naive Bayes classifier to learn and classify the user's context in mobile environment (Korpipaa *et al.*, 2003). Microsoft Research proposed the system that inferred what the user concentrated in a certain time in an uncertain mobile environment (Horvitz *et al.*, 2003). Dynamic Bayesian networks extend Bayesian networks to model problem in a sequential domain.

### 2.2 Classification of Activity and Place

Before predicting activities, it is important to classify main variables such as activity and place with the proper criterion. In this paper, we have referred GSS (General Social Survey on Time Use) for activity classification (<http://www.statcan.ca/>) and NHAPS (National Human Activity Pattern Survey) for place classification (Klepeis *et al.*, 2001).

GSS, a survey conducted by Statistics Canada, was to gather data on social trends to monitor changes in the living conditions over time, and the classification was conducted in a practical perspective. It divides all activities into ten categories first, and each category is subdivided into several subcategories as the characteristics. It has 3-level hierarchy, and the total number of activity is 177. Ten main categories are "Paid work and related activities," "Household work and related activities," "Social support, civic and voluntary activity,"

"Education and related activities," "Socializing," "Television, reading and other passive leisure," "Sports, movies and other entertainment events," "Active leisure," and "Residual."

NHAPS is a survey conducted on 1992 ~ 1994. It contains the patterns of human activity and place during 24 hours (Klepeis *et al.*, 2001). We used the place classification in this survey, and they are eight including "Traveling/Near vehicle (Outdoor)," "School/Church/Hospital/Public building," "Residence (Indoor)," "Traveling inside vehicle," "Bar or Restaurant," "Mall/Grocery store/Other store," "Other outdoor," and "Other indoor." It also provides the activity classification, but we do not use it because it is too out-dated.

## 3 PROPOSED METHOD

This paper has used the sequence of context collected from mobile device as input to predict the user activity. Fig. 1 illustrates an overview of the proposed prediction method. There are two phases: Prediction and modeling. The flow in the left side is for prediction, and the other one is for modeling.

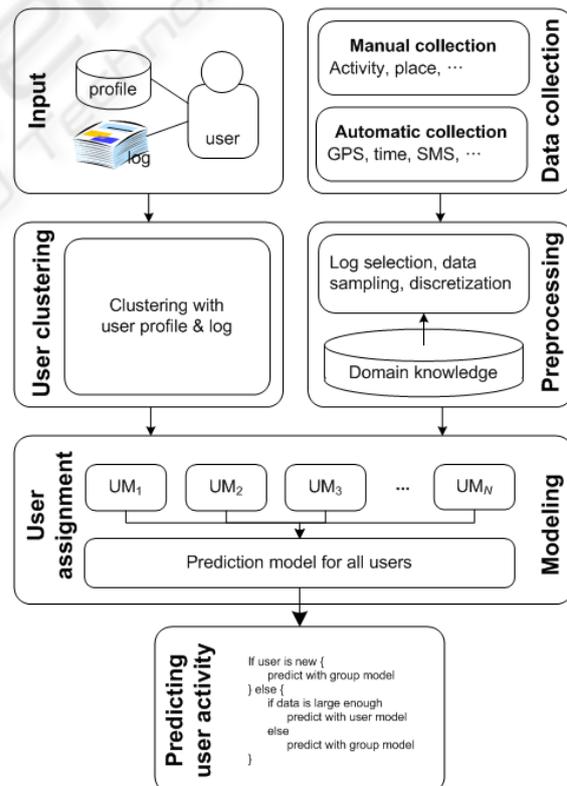


Figure 1: An overview of the proposed prediction method.

For modeling, we, first, collected the mobile context of activity, place, time, day of week, call record, MP3, SMS and photo. Activity and place are manually annotated by user, and call record, MP3, SMS and photo are binary attributes which have a state of "Yes" or "No." In a preprocessing step, we preprocessed the collected data, which included attribute selection, data sampling and attribute discretization. After that, we learned the prediction model (dynamic Bayesian network) of each user, and the model of all users was also modeled for a new user.

In prediction phase, after mobile context (log) of user is input, the system clustered the users together with contexts and profiles of other users. In the assigned group model, the prediction is conducted. In this paper, we assumed one group (cluster) because the data were collected from a group of college students, not several groups of users.

### 3.1 Data Preprocessing

Preprocessing step includes data sampling, attribute selection and attribute discretization. As explained, we used seven mobile contexts of activity, place, time, day of week, call record, MP3, SMS and photo. We called them an attribute of context. They were collected on every minute, and we call these stored contexts of sequence data of context.

Data stored on every minute were sampled on every hour. Since most of the activities last more than an hour, data stored on a minute or several minutes are outliers. If there were more than one activity in an hour, one occupied the most time was selected as an activity for that hour.

Among seven attributes, we selected activity, place, time and day (of week) considering their influence to the next activity. It can be checked with the data using maximum likelihood estimation method. Fig. 2 shows the influence of each attribute to the activity to be predicted according to the number of sequence. Thicker edge means more significant influence, and the number of sequence means the number of time point including the activity to be predicted. In this figure, we can find out that four activities of activity, place, time and day are more significant than others, and recent attributes are more significant than old ones.

Since Bayesian network requires discretized input, we discretized the context attributes. To discretize an activity, we modified the GSS hierarchy described in section 2.2. Original GSS is for general people, but we modified it to specific user groups. Figure 3 demonstrates this concept. We

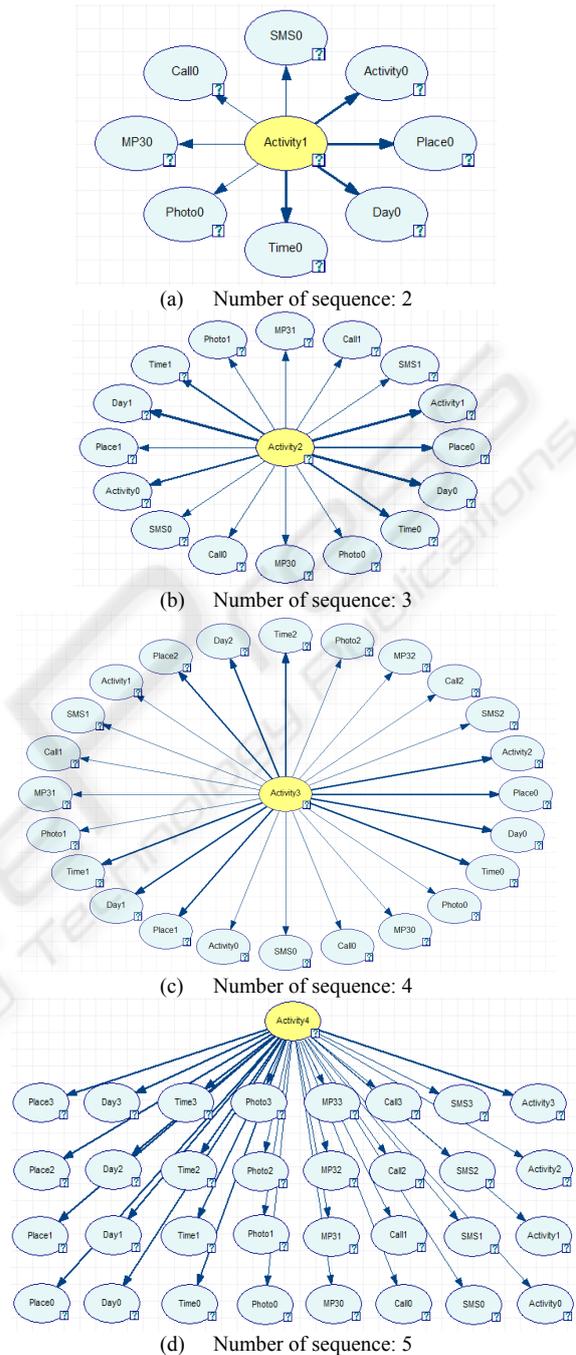


Figure 2: Influence of attributes to the activity to be predicted according to the number of sequences (the number following attribute name means the sequential order: 0 represents the first).

used 10 main categories of original GSS as shown in the left in Fig. 3, but modified the second hierarchical categories and activities in the last hierarchy for college students because one in original GSS is sometimes classified too much for

general users but sometimes classified not enough for specific user group like college students. Analyzing the collected data and survey from college students, we modified the right side in Fig. 3 of GSS. Fig. 3 illustrates an example. The category “Socializing” is divided into “Restaurant meals,” “Socializing at home,” and “Other socializing,” and “Restaurant meals” is subdivided into five activities.

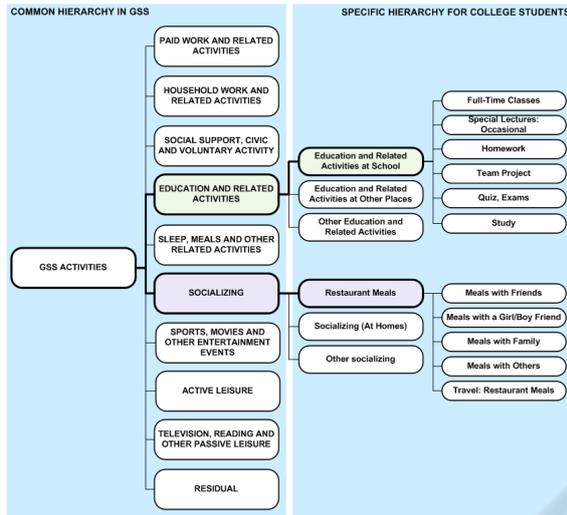


Figure 3: Modified GSS.

### 3.2 Learning Activity Prediction Model with Dynamic Bayesian Network

A Bayesian network (BN), associated with a set of random variables  $Z = (Z_1, Z_2, \dots, Z_N)$ , is a pair:  $B = (G, \theta)$  where  $G$  is a structure and  $\theta$  represents the parameters encoding conditional probabilities. The structure of BN is represented as a directed acyclic graph (DAG) where the nodes correspond to the variables  $Z_i$  in  $Z$  and edges between nodes correspond to the conditional dependencies. The parameters of BN are represented as the conditional probability table when nodes are discrete (Kleiter, 1996). Conditional probability distribution of each variable in BN is calculated as Eq. (1).

$$P(Z_1, \dots, Z_N) = \prod_{i=1}^N P(Z_i | Pa(Z_i)) \quad (1)$$

where  $Pa(Z_i)$  denotes the parents of  $Z_i$ .

Dynamic Bayesian network is an extension of Bayesian network to model probability distributions over sequential random variables (Murphy, 2002). Normally, dynamic Bayesian network assumes that the parameters of the conditional probability distributions are time-invariant; the model is homogeneous in time. It also assumes Markov

property where the conditional probability distribution of future states depends only on the present state and not on any past states given the present state and all past states. That is, the current probabilistic variable depends only on previous  $N$  and more recent steps. In inference, therefore, with the new network, which is “unrolled” by  $N$  steps, the conditional probability distribution of each variable is calculated as Eq. (1).

The user status inference is to infer user status from mobile contextual information by Bayesian network probability model. It is similar to the method in (Kiripipaa *et al.*, 2003) which focused on simplification and modularization of the complex Bayesian network model. We referred to context hierarchy and activity classification of GSS (General Social Survey) for the design of Bayesian network probability model. This structure increases the scalability of the model and permits tradeoff between precision and recall by manipulating conditional probability of virtual nodes.

$$P(Z_1, \dots, Z_T) = \prod_{t=1}^T \prod_{i=1}^N P(Z_i^t | Pa(Z_i^t)) \quad (2)$$

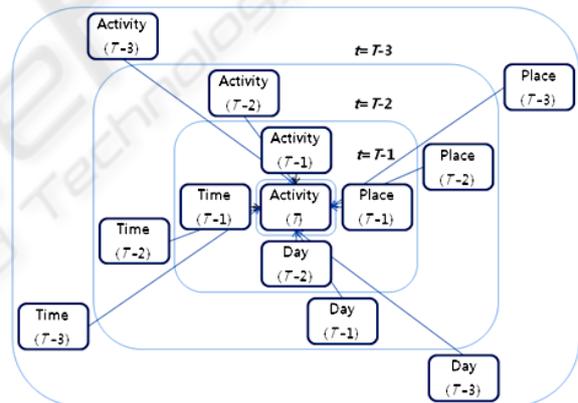


Figure 4: A structure of dynamic Bayesian network to predict user activity.

Since the user activity can depend on his/her previous activity, place, time and day of week we modeled this dependence according to time using dynamic Bayesian network, and attempted to predict the user activity. Dynamic Bayesian network used in this paper has a structure like naïve Bayes, which all evidence nodes in the past is connected to the query node. For parameter learning, MLE (maximum likelihood estimation) was used. Fig. 4 is an example of dynamic Bayesian network used in this paper to predict an activity. To predict an activity at  $t=T$ , we made dynamic Bayesian network model with the attributes of activity, place, day and time from  $t=T-1$  to  $t=T-3$ .

### 3.3 Predicting Activities

Learning of prediction model was conducted by user, and the prediction model of all users (group model) was also learned. This group model was used for new users until his/her data were stored enough to provide reliable performance. After enough data were obtained, individual user models were learned, and they were used for activity prediction. If activities can be predicted correctly, useful service like information recommendation for that activity can be provided.

## 4 EXPERIMENTS

We evaluated the proposed prediction model with the data collected from twelve users (college students) in ambient intelligence environment. The accuracy, how correctly the proposed model predicted the following activity from the sequence of mobile context, was used as an evaluation measure.

### 4.1 Experimental Data



Figure 5: Smartphone (a) and portable GPS (b) used for data collection.

Data for experiments were collected for 30 days by twelve college students. Fig. 5 provides mobile devices used for data collection. Samsung smart phone m-4650 was used for context collection, and portable GPS of BT-335 was used to obtain location information. Context information includes automatically collected one such as call record, GPS, MP3, time, day of week, SMS, photo and manually annotated user activity and place (from GPS).

### 4.2 Performance

In order to evaluate the proposed prediction model, we performed the experiments for calculating

prediction accuracy of user activities in the sequence of mobile context with collected data. As explained in preprocessing step, we selected four attributes of activity, place, time and day of week for modeling considering the influence to the next activity. We performed the experiments as changing the number of sequence, and compared the accuracy with the same dynamic Bayesian network model using all collected contexts.

Table 1: Prediction accuracy as the number of sequence (#: Number, Acc.: Accuracy).

Sequence size \ User #	2	3	4	5	6	7	8	9	10
1	45.6	43.1	42.6	41.9	<b>46.2</b>	<b>47.4</b>	41.5	42.8	37.1
2	<b>74.6</b>	<b>72.9</b>	68.6	65.0	61.0	56.7	52.1	49.0	51.1
3	<b>84.0</b>	<b>81.6</b>	79.8	78.8	78.1	78.2	76.9	76.0	74.9
4	<b>60.6</b>	<b>57.3</b>	54.7	51.6	49.6	45.6	41.9	38.0	36.5
5	73.2	72.2	69.1	62.6	63.9	64.8	66.6	<b>76.5</b>	<b>81.7</b>
6	<b>74.8</b>	69.1	69.5	<b>70.3</b>	65.3	63.0	53.8	51.2	53.3
7	69.3	76.6	77.0	76.0	<b>79.7</b>	77.8	<b>80.1</b>	76.5	75.7
8	<b>52.6</b>	<b>50.0</b>	45.3	48.6	44.8	43.4	40.0	26.9	29.4
9	<b>57.0</b>	51.9	50.5	51.2	53.8	<b>57.7</b>	53.8	48.1	42.1
10	85.8	<b>86.4</b>	85.0	84.6	84.4	85.5	<b>85.9</b>	83.4	84.9
11	<b>66.8</b>	<b>66.8</b>	65.7	62.0	56.0	51.9	49.6	47.4	45.3
12	<b>59.7</b>	<b>55.1</b>	51.6	46.3	44.7	40.6	36.6	34.2	33.3
Avg.	69.0	67.2	65.3	63.6	62.6	61.4	58.6	56.2	55.8
All users	69.3	67.2	64.1	61.6	58.2	56.2	53.4	51.2	49.1

Table 1 summarizes the prediction accuracy of each user according to the number of sequence. The pattern of each user is not the same. Half of them provided the highest accuracy when the number of sequence is 2 (when model considered the context of only 1 hour ago). The other half, however, showed the highest accuracy at different numbers of sequence. The accuracies are also different one another now ranging from about 40% to 86%. It means that the patterns of user activity and context depend on users, so individual model for each user is required. The model of all users and average of each user model also support this result. The latter have to provide better accuracy because the former learned the data of all users even though their patterns were different. Since the number of data for each user was different, the average was calculated considering the number of data from each user as weight.

Fig. 6 compares this result in Table 1 with the result using all attributes, and the model with selected four attributes provides better accuracy than one with all attributes for most users. It can be

thought that the preprocessing part, which excludes insignificant attributes, is effective.

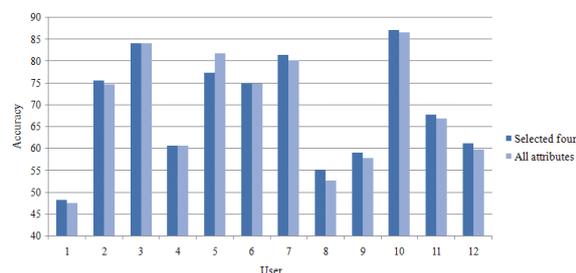


Figure 6: Prediction accuracy comparison with one using all attributes.

## 5 CONCLUDING REMARKS

This paper proposed the prediction method of user activity in the sequence of mobile context for ambient intelligence environment. We collected user activity, place, time, day of week, call record, MP3, SMS and photo as mobile context, and modeled the patterns in the context sequence to predict the user's next activity. For better modelling, we used the activity classification method in GSS and modified it to college students, which provided context data in this paper, and used the place classification method in NHAPS. We selected four attributes of activity, place, time and day of week among eight attributes considering the significance, and learned dynamic Bayesian network model with collected data. We also made models both for individual users and all users for new users. In experiments, we evaluated the proposed prediction method with the collected data, and confirmed the proposed method provided good performance.

For future work, we are planning to cover two more issues. One is user clustering and the other is recommendation. To deal with general users' context and activity patterns, user clustering is required before prediction modeling. It is also useful for recommender service from perspective of marketing. After prediction, it will be interesting to provide useful information to each user based on predicted user activity. For example, the system can recommend restaurant information if the model predicts the following activity is restaurant meals with friends. A service like this will make ambient intelligence a smarter one.

## ACKNOWLEDGEMENTS

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