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Predicting Customer Models Using Behavior-based Features in Shops

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AbstractRecent sensor technologies have enabled the capture of users' behavior data. Given the large amount of data currently available from sensor-equipped environments, it is important to attempt characterization of the sensor data for automatically modeling users in a ubiquitous and mobile computing environment. As described herein, we propose a method that predicts a customer model using features based on customers' behavior in a shop. We capture the customers' behavior using various sensors in the form of the time duration and the sequence between blocks in the shop. Based on behavior data from the sensors, we design features that characterize the behavior pattern of a customer in the shop. We employ those features using a machine learning approach to predict customer attributes such as age, gender, occupation, and interest. Our results show that our designed behavior-based features perform with F-values of 70–90% for prediction. We also discuss the potential applications of our method in user modeling.

1 Introduction Modeling the context for adapting to users is increasingly garnering interest in studies of user modeling and adaptive hypermedia. Numerous studies have addressed recognition and modeling of a user's external context, for example one's location, physical environment, and social environment, to provide context-aware information. Although "context" is a slippery notion [4], it is promising if we can recognize and adapt to aspects of users such as their activities, general interests, and current information needs [8]. Such user models are useful for adaptive context-aware information services in ubiquitous and mobile computing.

Recently, location information has become widely available in both commercial systems and research systems. The development of recent sensor devices such as Wi-Fi, Bluetooth, low-cost radio-frequency tags, and associated RFID enable us to obtain location-based information support in various situations and environments. One early and famous project was Active Badge [18]. Since that work, numerous studies of users' activity recognition and location-aware applications have been developed using location and other sensory information in the context of ubiquitous and mobile systems [20, 12, 5, 15, 16].

Although user models are sometimes assumed implicitly in these studies, several studies in recent years have proposed user models for ubiquitous computing. Heckmann proposes the concept of *ubiquitous user modeling* [6]. He proposes a general user model and context ontology GUMO and a user model and context markup language *UserML* that lay the foundation for interoperability using Semantic Web technology. Carmichael et al. proposes a user-modeling representation to model people, places, and things for ubiquitous computing, which supports different spatial and temporal granularity [2]. Automatically obtaining such ubiquitous user models from currently available location and other sensory information will help realize adaptive context-aware information services in ubiquitous and mobile environments. As discussed in [13], user modeling and behavior recognition are mutually complementary: given a more precise user model, we can more precisely guess the user behavior, and vice versa.

As described in this paper, we propose a method to predict user attributes from location information. In particular, we specifically examine the location information of customers in a shop. We conducted an experiment to obtain empirical data from an actual shop with more than 100 users. We capture customers' behavior in the form of time duration in a block and the sequence between blocks in the shop using sensors of various types. Based on the behavior data, we design several features that characterize the behavior pattern of a customer in the shop. We employ those features with a machine learning approach to learn customer attributes such as age, gender, occupation, and interests. Consequently, our method can automatically predict a user model of a new user coming to the environment. We show that some attributes are likely to be predicted using behavior-based features with F-values of 70–90%. The method is useful in ubiquitous and mobile environments for adaptive context-aware information services because it obtains user models automatically from location information.

This paper is organized as follows. In the next section, we describe related work. We introduce our sensors and describe sensor data in Section 3. The proposed method to predict user attributes from location information is explained in Section 4. Analyses of the results are made in Section 5. Finally, we discuss potential applications of our method in user modeling and conclude the paper in Section 6.

2 Related Work With recent advancements of sensor devices, numerous studies have addressed the use of location and other sensory information. Although most studies have specifically examined recognition of users' activity [18, 20, 12], some studies have recently addressed the issue of user modeling with location information [5, 16, 15]. Most of these studies have employed knowledge-related features for modeling a user, which require an explicit and a-priori built representation of the domain knowledge. In contrast, some studies have investigated modeling a user with features obtained non-intrusively such as observation of the behavior history and patterns [21, 1] using statistical user modeling techniques [19, 22]. Matsuo et al. proposed a similar method to predict user attributes using sensor information [13]. However, they employed only simple location history as the feature from sensors, whereas we design and combine several features to characterize behavior patterns, which in turn improves the performance for prediction.

Several studies in recent years have sought to model users for development of ubiquitous computing [6, 2, 14]. Heckmann proposes the concept of *ubiquitous user modeling* [6] including a general user model and context ontology GUMO and a user model, and a context markup language *UserML* that lay the foundation for interoperability using Semantic Web technology. Carmichael et al. proposes a user-modeling representation to model people, places, and things for ubiquitous computing. That mode of representation supports different spatial and temporal granularity [2]. Among various user-modeling dimensions, we mainly focus on long-term attributes such as age, gender, occupation, and interests. Kobsa lists frequently found services of user-modeling, some of which use users' long-term characteristics such as knowledge, preference, and abilities [11]. Jameson discusses how different types of information about a user, ranging from current context information to the user's long-term attributes, can contribute simultaneously to user adaptive mechanisms [7]. In the ontology GUMO, long-term user model dimensions are categorized as demographic information such as age group and gender, personality and characteristics, profession and proficiency, or interests such as music or sports. Some are basic and are therefore domain-independent, although others are domain-dependent. Our method contributes to the population of such existing user models by obtaining user attributes automatically.

3 Behavior Data from Sensors This section presents a description of our sensors and experiments to collect sensor and user data for designing useful features to predict user models. In our experiment, we obtain the location information of customers in a shop using sensors of various types. The shop is virtually divided into multiple blocks. We represent the behavior data of a customer in the form of the time duration in each block and the sequence from one block to another.

3.1 Sensors In our experiment, we use the following sensors of four types as shown in Fig. 1 to capture location information of customers in the shop:

- **IC card**: each participant in the experiment is delivered an Integrated Circuit card (IC card). The IC card readers are attached to the shelves in the shop. The participants can hold the IC card over the reader on the shelf if they would like to record their checking the goods on the shelf.

- **RFID and Wireless**: each participant also receives a mobile device that includes active Radio Frequency Identification (RFID) and wireless functions. The device is sufficiently compact that the participant can dangle it around the neck. Active RFID readers and wireless access points are installed in the shop to detect signals from the devices.

- **Video camera**: Video cameras are also installed in the shop to record participants' motions. The system identifies each participant by analyzing participants' facial images in the record video data.

Data from these sensors are integrated to estimate the time duration in each block and the sequence from one block to another in the shop. Using the integrated sensor data, we can capture users' locations and transitions between blocks with accuracy of 90%. For our research, we assume that users' location information is estimated properly with our sensors.

3.2 Data acquisition and Representation To collect the sensor data, we conducted an experiment at a general shop in a city area that is visited by a wide range of people from youth to seniors. We installed five IC card readers, three active RFID readers, nine RFID reference tags, three wireless access points, and five video cameras in the shop. In all, 109 men and women participants from their late teens to their forties were enrolled in the experiment. Each participant was provided an IC card and a mobile device. The participants were instructed to walk around the shop freely according to their personal interests towards the goods.

The shop is divided into several virtual blocks of about a meter square, as shown in Fig. 2. In our experiment, the granularity of the blocks are decided so that each block represents a certain kind of goods in the shop. We had seventeen blocks in total. Based on customers' location information from the sensors, we represent their behavior data as the time duration in each block and the sequence from one block to another. To estimate the time duration and the sequence, we integrate the location information captured from individual sensors. Then, we obtain behavior data of each participant as shown in Fig. 3. The time duration is counted by seconds.

3.3 Online system We provided the participants with an online system during the experiment. The online system automatically generates a personalized Blog template that includes points of interest from one's record of a IC card and one's location history from the sensor data (Fig. 4). The participant can freely edit the Blog template and create a Blog during the experiment. We obtained participants' subjective sentiment related to the shop or its goods on this Blog system.

4 Predicting a Customer Model In this section, we propose our method to predict a customer model consisting of several user attributes. The customer model is predicted using a machine learning approach with features based on customers' behavior in the shop. We first describe our customer model to be predicted. Then, we explain the design of customers' behavior-based features to be used for our machine learning method.

4.1 Customer Model Table 1 shows that we define our customer model using four attributes (*age*, *gender*, *occupation*, and *interest*). The attributes of *age*, *gender*, and *occupation* were obtained from the questionnaire that each participant filled out before the experiment.

The final attribute *interest* was obtained from the Blog

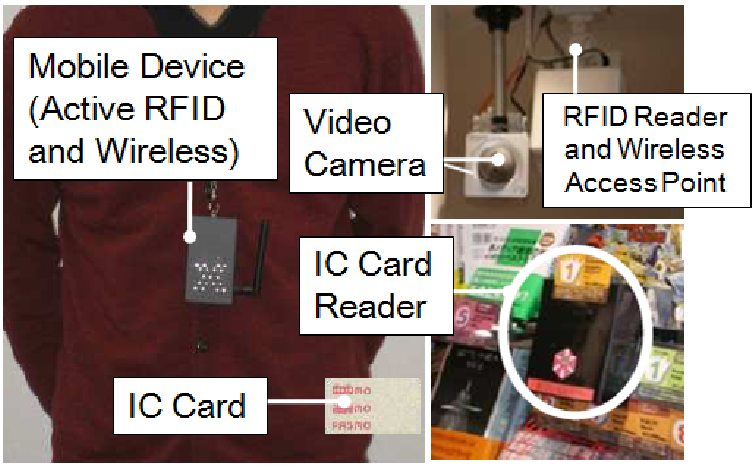

Figure 1: Sensors to capture location information of customers in the shop

Figure 2: Outline view and virtual blocks in the shop where sensor data are collected

Table 1: List of user attributes and their values in a customer model.

attribute	value (ratio)
age	10s (1.8%), 20s (43.1%), 30s (37.6%), 40s (17.4%)
gender	men (54.1%), women (45.9%)
occupation	office worker (58.7%), student (24.8%), housekeeper (10.1%), other (6.4%)
interest	interested (45.8%), disinterested (54.2%))

system that we provided for participants during the experiment. The Blog contains each participant's subjective sentiment related to the shop or its goods. We manually checked the Blog contents and counted both positive comments and negative comments for each participant. According to the sums of respective positive comments and negative comments, we classified each participant according to whether he or she was interested in the shop and its goods, which then defined that participant's *interest*.

4.2 Behavior-based Features We now describe our feature design for predicting our customer model. In the shop, a customer was able to take behavior patterns of several types. Although some customers might remain in places which interest them, others might stroll around the shop seeking something interesting for them. Our sensor data capture such different behavior patterns of individual customers in the form of the time duration in each block in the shop and the sequence between blocks. We can design several features that characterize customers' behaviors in the shop given the sensor data. In our research, we specifically examine the following intuitive features based on customers' behaviors.

- **binary**: whether a customer visits a block or not.
- **frequency**: how many times a customer visits a block.
- **duration**: how long a customer is in a block †.
- **sequence**: how often a customer moves from one block to another.

Matsuo proposed a method to infer user properties from sensor data as a text categorization problem by con-

† if a customer comes back to a block, we count this stay as another time of duration.

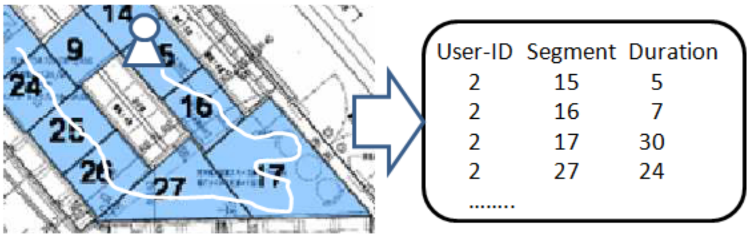

Figure 3: Customers' behavior data based on their location information

Figure 4: Interface of the system that enables users to create their Blog based on their location history in the shop

verting the sensor data into a sensor-user matrix, which resembles a document-by-word matrix. In line with this approach, we build the following matrices of two types: a user-block matrix (left) and a user-block transition matrix (right).

	b_1	...	b_j	...	b_m
u_1	v_{11}	...	v_{1j}	...	v_{1m}
...	...	...	...	...	...
u_i	v_{i1}	...	v_{ij}	...	v_{im}
...	...	...	...	...	...
u_n	v_{n1}	...	v_{nj}	...	v_{nm}

	$t_1 : b_1 \rightarrow b_2$	...	$t_l : b_s \rightarrow b_m$
u_1	w_{11}	...	w_{1l}
...	...	...	...
u_i	w_{i1}	...	w_{il}
...	...	...	...
u_n	w_{n1}	...	w_{nl}

Denoting the number of users as n and the number of blocks as m, the user-block matrix is an $n \times m$ matrix $U \times B$ and the user-block transition matrix is an $n \times l$ matrix $U \times T$ where l is the number of combination of bordering blocks. We denote v_{ij} as the element of $U \times B$ and w_{ij} as the element of $U \times T$. Furthermore, **binary**, **frequency**, and **duration** are derived from $U \times B$ and **sequence** derived from $U \times T$ by defining v_{ij} and w_{ij} as follows:

- **frequency**: $v_{ij} = freq(u_i, b_j)$ where $freq(u_i, b_j)$ is the number of visits of a user u_i at a block b_j.
- **binary**: $v_{ij} = \begin{cases} 1 & \text{if } freq(u_i, b_j) > 0 \\ 0 & \text{otherwise} \end{cases}$
- **duration**: $v_{ij} = dur(u_i, b_j)$ where $dur(u_i, b_j)$ is the time of stays of users u_i at blocks b_j.
- **sequence**: $w_{ij} = seq(u_i, t_j : b_o \rightarrow b_p)$ where $seq(u_i, t_j : b_o \rightarrow b_p)$ is the number of transitions of a user u_i from a block b_o to a block b_p.

For **frequency**, **duration**, and **sequence**, we normalized the weight for each feature by cosine normalization so that the feature weights fall in the [0,1] interval and the feature vectors become equal in length.

The normalization is defined as $weight_{ij}^{normalized} = weight_{ij}/\sqrt{\sum_{i=1}^{m}(weight_{ij})^2}$. Thereby, we generated three other features that we call **n-frequency**, **n-duration**, and **n-sequence**.

4.3 Prediction Given the customer model and the feature set, our task is now to predict each attribute in the customer model using the feature set. For each attribute in the customer model, we trained a learner that predicts the attribute given a set of training examples that includes a set of feature values corresponding to the certain value of the attribute. Although some attributes take multiple values, we solve the two-class problem for every attribute because the distribution of each value of some attribute is biased. For example, for *occupation*, 58.7% of subjects are classiable as "office workers". Thereby, we train the learner for *occupation* using the training examples of positive and negative classes and solve the two-class problem of classifying people into those who are office workers and those who are not. Similarly, we train the learner for *age* to classify people into those who are in their teens and 20s or 30s and 40s. Regarding *gender* and *interest*, they are also solved as two-class problems because they originally have two classes.

We employ a support vector machine (SVM) as a learner, which creates a hyperplane that separates the data into two classes with the maximum-margin [17]. The SVMs tend to be fairly robust to overfitting. In addition, there is a theoretically motivated "default" choice of parameter setting [9]. The SVM is often used to learn the categorization problem that is our case reduced from our user modeling problem. We employ a radius basis function (RBF) kernel, which performs well in our preliminary experiments. The SVM performance is evaluated using five-fold cross validation.

5 Evaluation and Results

5.1 Attribute Prediction Performance of the learner for each attribute are shown with Recall, Precision, and F-value in Table 2. The F-value is a geometric average of recall and precision, defined as F-value $= (2 \times \text{Recall} \times \text{Precision})/(\text{Recall} + \text{Precision})$. For example, if we use **frequency** as a feature to predict the *age* of a customer, the recall is 0.74, meaning that we can classify 74% of people with the *age* having a certain value.

On average, the F-value is about 62%, precision is about 60%, and recall is about 70%. However, the performance of the learner varies depending on the attribute to be predicted. For *age*, *gender*, *occupation*, and *interest*, the F-values are as high as 0.67, 0.71, 0.79, and 0.62, respectively, with about 0.44–0.98 recall and 0.51–0.74 precision. Depending on the attribute, the performance varies as much as 0.2 points, which indicates that some attributes are predicted and others are difficult to predict. We claim that we must carefully select the attribute to be applied for personalized information services if we use the automatically obtained user model from location information in ubiquitous and mobile environments.

The learner performance also varies depending on the feature. For *age*, **n-duration** has the highest F-value and **frequency** is the second best. Regarding *gender*, **n-sequence** is the best and **frequency** is the second. For *occupation*, **frequency** is the best and **n-duration** is the second. Finally, teh **n-sequence** is the best and **frequency** is the second for *interest*. Overall, normalization seems to function effectively for **duration** and **sequence**. The learner based on **frequency** performs well for every attribute. However, some features are useful for predicting particular attributes. Our results show that attributes such as *age* and *occupation* can be predicted effectively using features such as **frequency** and **n-duration** whereas *gender* can be predicted effectively with **n-sequence**. Selecting appropriate behavior features depending on the attribute to be predicted is important to obtain a user model from location information. Although *interest* seems difficult to predict compared with other attributes, the combination and selection of features improve the performance, as described in the following section.

5.2 Feature Selection The results show that behavior-based features are effective to predict some attributes. We were able to further assume that combining features such that they represent behavior patterns in a more detailed way would improve the performance. Although it is difficult to represent overall behavior patterns using only our simple features, combining those features represents customers' behavior more precisely than any single feature. For example, combination of the duration and the sequence can represent a user moving and stopping. The **frequency & duration & sequence** in Table 2 shows the performance of a learner with combined features. For *age*, *gender*, and *occupation*, a learner with the combined features does not perform better than using the best performance feature. On the other hand, the combined features improve the performance of a learner for *interest* as much as 0.08 points from the best performance feature and 0.14 points from average performance. Moreover, *interest*, which shows a customer's positive or negative attitude towards the shop or its goods seems affected by overall behavior patterns rather than partial behavior patterns. Some attributes are clearly better predicted by the combined behavior-based features.

In addition to our behavior-based features, we were able to design various features using other information sources. For example, if we were able to know user demographic data such as *age*, *gender*, and *occupation* beforehand, we could use those attributes as features to predict *interest*. In our experiment, each participant filled out a questionnaire that enabled us to derive user profile data such as age, gender, marriage, occupation, and PC proficiency. Based on the profile data, we design the profile-based features for predicting *interest*. As presented in Table 3, a learner with profile-based features performs better than the combined features. The combination of profile-based features and behavior-based features does not perform better than the profile-based features. The features from the user profile are clearly effective to predict *interest*. However, behavior-based features can pre-

Table 2: Performances of prediction for respective attributes depending on the feature

age

Feature	F-value	Precision	Recall
frequency	0.62	0.55	0.74
n-freq	0.46	0.50	0.50
bin	0.56	0.61	0.54
duration	0.60	0.61	0.60
n-duration	0.67	0.61	0.78
sequence	0.59	0.55	0.68
n-sequence	0.60	0.54	0.72
average	0.58	0.55	0.65
frequency & **duration** & **sequence**	0.58	0.60	0.58

occupation

Feature	F-value	Precision	Recall
frequency	0.79	0.69	0.98
n-frequency	0.69	0.66	0.80
binary	0.68	0.57	0.86
duration	0.78	0.74	0.83
n-duration	0.78	0.72	0.89
sequence	0.76	0.70	0.91
n-sequence	0.73	0.67	0.87
average	0.74	0.67	0.87
frequency & **duration** & **sequence**	0.75	0.69	0.94

gender

Feature	F-value	Precision	Recall
frequency	0.68	0.69	0.70
n-frequency	0.66	0.56	0.84
binary	0.50	0.52	0.54
duration	0.44	0.51	0.44
n-duration	0.52	0.58	0.54
sequence	0.67	0.66	0.76
n-sequence	0.71	0.71	0.78
average	0.59	0.60	0.65
frequency & **duration** & **sequence**	0.69	0.64	0.8

interest

Feature	F-value	Precision	Recall
frequency	0.59	0.58	0.62
n-frequency	0.58	0.58	0.62
binary	0.55	0.55	0.60
duration	0.48	0.51	0.50
n-duration	0.57	0.54	0.64
sequence	0.55	0.56	0.60
n-sequence	0.62	0.59	0.74
average	0.56	0.55	0.61
frequency & **duration** & **sequence**	0.70	0.67	0.78

dict *interest* with comparable performance of the user-model based features. This is important for modeling a user in a ubiquitous and mobile environment, where it is often difficult to obtain user information beforehand. Our behavior-based features, which are obtainable from the sensors in the environment, are useful to predict some user attributes like *interest* without knowing the user information.

For this purpose, several feature selection strategies to determine a proper set of features among many features have been proposed [3]. As portrayed in Table 3, the performance of a learner with selected features is better than the combination of all possible features. It is also comparable with the performance of profile-based features. Feature selection provides a set of weighted behavior-based features; consequently the weighted features give information about which behavior on a certain location is for the prediction. This information can be used for installing sensors so that the important location, the particular block in our case, is properly detected. From a practical perspective, such information is useful for arranging displays in a shop or for controlling customers' flow in the shop.

6 Discussion and Conclusion Although we focused on predicting a customer model using features based on customers' behavior in a shop, our method is not limited in such environment. Our method is applicable to a sensor-equipped environment which could provide a user's simple behavior history as described in this paper. By predicting a user model of a new visitor to the environment such as a shop and museum, we can offer personalized information services to the visitor. In particular, many researchers have examined systems using the user model from location information to improve a museum visitor's experience by recommending points of interest and personalizing the delivered content [15, 16]. Our method can be adopted easily to such existing systems by providing the user model from location information. Some studies use the user model ontology to provide such context-aware services [5]. Importantly, our method contributes to the population of existing user modeling ontologies for ubiquitous computing such as those of GUMO [6].

Because we provide an online system that helps a user create a Blog based on his or her behavior data during our experiment, our method can facilitate creation of a user-adaptive "Lifelog" by predicting whether the user liked a certain point in one's behavior history or not. Lifelog is fundamentally a dataset composed of one or more media forms that record the same individual's daily activities [10]. A main challenging issue is how to extract meaningful information from the huge and complex data which are captured continuously and accumulated from multiple

Table 3: Performance of prediction for *interest* depending on feature selection

interest Feature	F-value	Precision	Recall
frequency & **duration** & **sequence**	0.70	0.67	0.78
profile (age, gender, occupation, marriage, etc.)	0.74	0.74	0.73
frequency & **duration** & **sequence** + **profile**	0.70	0.72	0.74
selected features	0.72	0.72	0.74

sensors. Our method can tackle the issue by predicting what events, states, or places are interesting or important for a user and summarizing the useful records.

This paper has presented a proposal of a method to predict user attributes from location information. In particular, we described our specific examination of the location information of customers in a shop. We designed several features that characterize the behavior pattern of a customer in the shop. Machine learning techniques were applied to learn the pattern between the features and customer's attributes such as age, gender, occupation, and interests. Our results show that some user attributes are well predictable with behavior-based features. The results also show that the selection and the combination of features are important to predict some attributes. In future work, we will employ more complicated features that characterize various types of behavior patterns for predicting user models.

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