# Examining a Bayesian Approach to Personalizing Context Awareness in Ubiquitous Computing Environments

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**Abstract.** There is a growing interest in the use of context-aware systems, which can recognize user's situational context and accordingly provide a desirable interaction with the user. However, the design, development, evaluation and deployment of context-aware systems are still at its infancy. In this paper, we propose an operational mechanism approach to context acquisition driven by the relevant dependency between users' ongoing activities and context in ubiquitous computing environments. We present a Bayesian model to classify and predict users' activities and associated context that offers more interactive and construed context awareness to users. The model performance is examined in terms of its classification accuracy in predicting users' activities and the associated context trends. The results demonstrate that such probabilistic models can provide an effective and feasible approach to learning and predicting users' context that can yield further the development of deployable context-aware systems.

**Keywords:** Context-aware computing, mobile and ubiquitous computing, context modeling, context inference, context history, machine learning, Bayesian networks.

## 1 Introduction

Proliferation of ubiquitous computing in humans' everyday life combined with the significant advancement of mobile technologies and wireless networks have taken Human Computer Interaction (HCI) beyond desktop computers level. Amid this evolving trend, context-aware computing that aims at sensing clues about user's context to enable desired interaction with the users has gained increasing recognition as one of the emerging technologies for the next generation of personal computing. However, the design, development, evaluation and deployment of context-aware systems are still facing many challenges.

While much of the literature on the context and context awareness has broadly focused on the context extraction from users' surrounding environment and interpretation, the discrepancy between real world context perceived by humans and context aware systems poses a big challenge. For example, attuning a system to a

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limited set of real contextual circumstances might contain irrelevant inputs that are unintentionally included in the context-aware service trained context, leading to a mismatch between user anticipation and the context-aware system actions. Such unresolved mismatch, or so called "ambiguity" in both sensed and interpreted context, has received some attention. For example, Bellotti et al. [1] argued that traditional HCI fundamentals and Human-Human-Interface (HHI) "do not fare well", and urged for the need of real collaboration between social science and HCI researchers to provide a systematic framework for the design of sensing-based systems. Some researchers [2-4] also questioned the viability of the conventional notion of context awareness as a representational problem that is mainly focused on encoding and presenting the environmental surroundings in a software system. They suggested to rethink context awareness as an interactional problem, rather than a representational problem, of users' ongoing activities to directly build their relevant information.

In this article, we discuss some of the unresolved issues in this field and propose some solutions. We first introduce fundamental concepts of context and context awareness. Then, we present a user-centered context awareness approach, in which we propose an operational mechanism of context acquisition based on the relevant dependency between users' activities and ongoing tasks with their context. Finally, we examine the performance of our proposed model and conclude the paper with future work.

## 2 Related Work

The dynamic nature of context has granted the definition of context a "slippery" characteristic that keeps the context schema subject to researchers' context of interest and their intention of context utilization [3]. Among many context definitions [5-8], we adopt the one proposed by Dey and Abowd [5]: *"Any information that can characterize the situation to an entity that is considered relevant to the interaction between the user and the application. An entity is a person, place, or object that is considered relevant to the interaction between user and the application, including the user and applications themselves (p.3)."* The unconstrained boundaries of context have led to a taxonomy approach to context categorization in the literature, context is broadly classified into user context (e.g., activity, identity, etc.), and physical context (e.g., location, lighting, noise level, etc.) [9-11]. Much of the context awareness research has broadly separated the synthesis of the physical context (also called sensor-based context) from the user context [12, 13]. While most of the context-aware applications considered a few types of sensed context by and large location and time; interestingly, few have captured the user activity as part of their addressed context of interest domain. Similar findings were compiled in earlier literature surveys of context-aware applications [5, 6, 14]. Remarkably, [6] voiced a motivating concern about whether other contexts are difficult to be sensed or are viewed to be not useful.

Of the many schemes that have been proposed to categorize context-aware systems, context-aware systems can be broadly classified into explicit and implicit systems. Explicit systems normally behave based on users' direct input and setting commands, while implicit systems proactively provide users with certain awareness behaviors over time and place [5, 15, 16]. While the former approach leaves the definition of the context scope exclusively to the user interface (UI) that is usually predefined by users, this approach ignores the intelligent adaptive characteristics that are mainly sought for by context-aware systems. Alternatively, the latter approach ignores the natural dialogue between users and context-aware systems to uphold users' aspect in the context-awareness process. In this work, we attempt to take a different stance in addressing these limitations from the following aspects:

- The need for integration of implicit and explicit means of context-awareness. Such integration will bring users and context-aware systems closer and define a common awareness background based on the users' needs and tasks. This idea has been proposed in personalized information systems and goal-driven theories for information-related-activity in context user-modeling [9, 17].
- Context-awareness needs to be interpreted or abstracted from a user's perspective to extend context-aware systems' ability of parsing user context. This will enable a context-aware system to incorporate some of the contextual information already abstracted by users, rather than solely relying on the system's inference of user's actual context. We draw such an analogy from "embodied action" view of context in interaction [3].

A number of research efforts have been made to resolve the discrepancy between context-aware systems' synthesis and users' understanding of their surrounding context, mainly by integrating the users' cognizance into context-aware systems' intention of conduct [13, 18, 19]. Some researchers proposed a user-mediation approach to resolving the ambiguity of the sensor-based physical context [14, 20, 21]. Although those approaches aimed at bridging the gap between the physical context and user context, their scope was broadly limited to the user's input as a filtering criterion mainly to reduce the ambiguity of the sensor-based context acquisition. Of significant importance to our work is the Artificial Intelligence (AI) research on collaboration of users' interaction information with decision support systems to enable such systems to draw better conclusions and recommend appropriate courses of actions. Of these efforts are the initiatives that aimed at extending the functionality of interpersonal communication tools, such as Instant Messaging (IM) and Groupware Calendar Systems (GCS's) with users' presence and availability [22-25]. Other initiatives proposed probabilistic models to predict users' decisions based on historical information about their interaction with their daily calendaring events [26, 27]. For example, Horvitz et al. [28, 29] examined the potential cost of users' interruption of incoming messages based on users' availability and business status. While the aforementioned initiatives have broadly attempted to address the collaboration between users and their computing systems to infer some form of user context in very specific computer tasks, many questions related to the inference of the users' social situations beyond the computer activity domain remain not answered.

This work also touches on some of the key challenges for achieving the utility purpose of context awareness, highlighted by Abowd and Mynatt [30] who identified the following challenges of providing an augmented context information to couple users' natural interactions with their surrounding context in all, the failure of context-aware systems to 1) incorporate users' interpretation or input of their activities for the "what" part of context information; 2) incorporate user identity information in dealing with the "who" part of user context; 3) associate the "who" and "what" with the other

"W's" of context information, such as "when" and "where"; 4) go beyond using time as an index of records' capturing rather than an indicator of a general task or user interest for the "when" part of context information; and finally, 5) explore "why" users are interested in the context beyond the "what" part of context information. These and other issues presented earlier led us to propose a user-centered context awareness approach, in which we view user's daily activities and tasks as natural sensors of user context. The approach aims at enriching the context acquisition with user's ongoing social situations. The theoretical basis of our work comes from the theory of informal communication between users and personal computing artifacts [31], which aims to capture some of the abstracted information defined by users themselves rather than solely relying on the computing systems' deduction of users' actual intentions.

## 3 User-Centered Context Awareness

We propose a user context awareness model that inherits the uncertainty of users' context in their daily recurring activities. We apply Bayesian networks for learning and predicting user context based on users' daily interactions with system applications running on their ubiquitous computing devices, like calendaring and tasks management tools currently available on most mobile and handheld devices. This approach complies with Dey and Abowd [5]'s definition of context, in which they characterized context information according to its relevance with the interaction between the user and an application.

### 3.1 A Bayesian User Context Model

Bayesian networks are directed graphs of joint probability distributions over certain problem domain variables with some conditional independence relationships among those variables. One of the primary advantages of Bayesian networks, among many probabilistic models and inference techniques, is their ability of modeling causal relationships under uncertainty [32, 33]. Given the continuous updates to the joint probability distributions within their structure, Bayesian networks have been successfully deployed for inferring users' activity patterns [26, 27, 34]. Simply put, a Bayesian network $N = (X, G, P)$ consists of an acyclic, directed graph $G(V, E)$ with nodes $V$ and a set of directed links $E$, over a set of mutually exclusive and exhaustive variables $X \in V$, with a set of conditional probability distributions $P$ [35]. For each variable $X$, there is a conditional probability distribution $P(X_{child} \mid P(X_{parent}))$, which satisfies the Markov Model condition that the likelihood of a certain variable occurrence depends on previously occurred ones. Applying the chain rule of probability to repetitively decompose the conditional distribution over the network $N$, with a set of variables $X_i$ for $i = 1,...,n$ and $Pa_i$ to present the parents of $X_i$ yields the generalized probability distribution function for $X$, given all possible observations:

$$P(X) = \prod_{i=1}^{n} P(X_i \mid Pa_i). \tag{1}$$

Learning Bayesian networks becomes a task of identifying the problem domain within an acyclic, directed graph $G$, with nodes $V = (V_1,...V_n)$, that captures the skeleton of directed links $E$, between the network nodes for each variable $X \in V$. Applying the chain rule of probability rule to all the conditional probability distributions over V when $G(V, E)$ yields:

$$P(V) = \prod_{X \in V} P(X \mid Pa(X)). \tag{2}$$

Once the network structure is built with the complete joint probability distributions (JPD) between its node variables, one can perform probabilistic reasoning analyses for all possible inference queries of interest.

### 3.2 Building and Training the Model

To construct the network structure of our model, we conducted a series of informal interviews with a group of five graduate students within an academic department at an east-coast university of the United States. The goal of the interviews was to solicit and collect the factors considered by the interviewees in defining the naming convention of the context of their ongoing daily activities. With this in mind, the interviewees were asked to objectively define their activities' context domain, such as locations or places, activity types and attendees, as well as to define the relationship among the defined activities' context domain. In particular, the interviewees were asked to define the relationship between place and activity, activity and attending personnel or accompany, accompany and place, etc. The next step was to define a context profile that characterized the users' defined activities. To reflect the relevance of the context to the users' activities, as well as to provide context presentation decisions that better match the user's activity needs, we classified the context profiles according to the cognitive states, the interviewees thought to be normally associated with their defined activities. More specifically, we distinguished between the following context profiles, high-attention activity, medium-attention activity, and low-attention activity.

Fig. 1 illustrates the network nodes that represent the identified variables in the model, namely user activity, time of the day, place, weekday, accompany, activity recurring frequency, duration, and user context. The directed links between the nodes represent the causal relationships between the nodes. The model nodes consist of mutually exclusive and exhaustive variables that inherent the likelihood of the user context of a certain activity based on the influencing variables influencing the user activity. More specifically, time of the day (e.g., 8am-10am, 10am-12pm etc.); place (e.g., home, work, outdoor, etc.); accompany (e.g., individual, coworkers, family, friends, etc.); day of the week (e.g., weekday, weekend); duration of the user activity (e.g., 1 hour, 2 hours, 4 hours, etc.); and recurring types of the activity (e.g., daily, weekly, biweekly, monthly, etc.). The user activity is defined as busy, free, tentative,

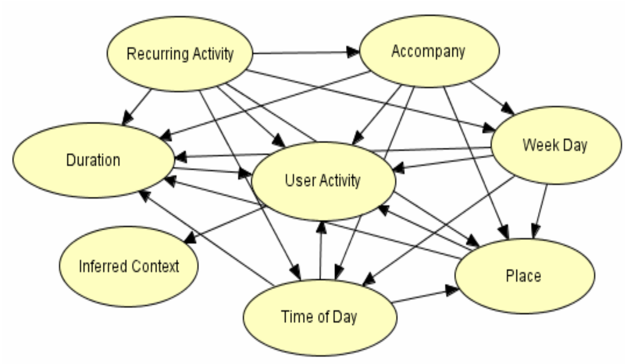
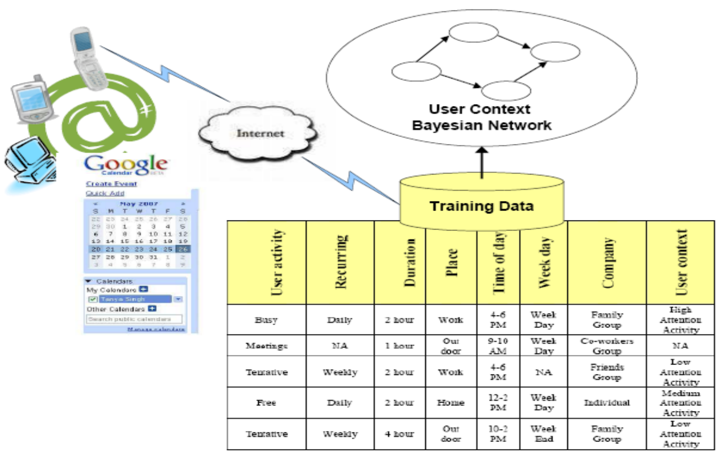



**Fig. 1.** A Bayesian network for user context inference

office, meetings, etc. As stated earlier, the users' context profiles associated with their activities are defined as high-attention activity, medium-attention activity, and low-attention activity. The model was constructed using Hugin Developer decision support systems software package [36].

We trained the model on three months worth of daily activities of a single user, with approximately 400 individual and group activities (382 observations). Previous research found that applying personalized Bayesian models derived from one or more user to another would yield poor performance [34]. To enable a realistic set-up, we chose Google calendar for mobile devices to observe and log the user daily activities and the causal influential variables defined in the model network structure, as shown in Fig. 2. In addition to its free shared calendaring web-based anytime anywhere service, Google calendar events format (i.e. events creation properties mainly centered around: what, who, where, and when type of questions), complied with our model structure data compilation requirements. Like any learning system, given the




| User activity | Recurring | Duration | Place | Time of day | Week day | Company | User context |
|---|---|---|---|---|---|---|---|
| Busy | Daily | 2 hour | Work | 4-6 PM | Week Day | Family Group | High Attention Activity |
| Meetings | NA | 1 hour | Out door | 9-10 AM | Week Day | Co-workers Group | NA |
| Tentative | Weekly | 2 hour | Work | 4-6 PM | NA | Friends Group | Low Attention Activity |
| Free | Daily | 2 hour | Home | 12-2 PM | Week Day | Individual | Medium Attention Activity |
| Tentative | Weekly | 4 hour | Out door | 10-2 PM | Week End | Family Group | Low Attention Activity |

**Fig. 2.** A user context awareness data compilation diagram

user context association sensitiveness to the user activity influencing variables, the user context likelihood is propagated to provide a context profile that best matches the user activity influencing variables. As new findings are obtained, the probability distribution of each relevant node in the network will be updated, and thus the network beliefs about the user context likelihood will be adjusted accordingly.

# 4 Evaluation of Model Performance

To examine the model performance, we used the general cross-validation evaluation technique to test the model power of accuracy of the user activity and associated context. The collected data were divided into 90% of training data, and the remaining 10% for testing. Table 1 presents the confusion matrix of user context inference accuracy, in pursuit of the model influential variables. The rows present the generated case values and the columns present the predicted values. The un-shaded diagonal cells present the correctly predicted cases, and the sum of these correctly predicted percentages present the overall classification accuracy of the model. The model showed a classification accuracy of 92% of user context inference with an average Euclidian distance of 0.007. Euclidian distance ranges from 0 for the perfect classifier and sqrt(2) for incorrect classification.

**Table 1.** Confusion matrix for user context inference

| | | **Predicted User Context** | | |
|---|---|---|---|---|
| | | High-attention Activity | Medium-attention Activity | Low-attention Activity |
| **Actual User Context** | High-attention Activity | 30% | 1% | 1% |
| | Medium-attention Activity | 1% | 31% | 1% |
| | Low-attention Activity | 1% | 1 % | 33% |

To assess the benefits of the model in support of decision making from a user satisfaction with respect to his/her context of interest; we used Multi-attribute utility theory (MAUT) evaluation process that is normally used to evaluate a user's consent when estimating his/her interests [37]. We defined a set of mutually exclusive and exhaustive variables of context awareness decisions corresponding to the earlier defined user situational context profiles (high-attention, medium-attention, and low-attention activity). The context presentation decision variable state, $Di$, is associated with a utility outcome, $u(Di, Cj)$, corresponding to the model context inference state $Cj$. The utility function is weighed over a 0 to 100 scale, representing the user satisfaction with the context awareness decisions. That being said, the expected utility

(EU) of the inferred context presentation decision obtained from the cumulative contribution to the total utility function outcomes is,

$$EU(Di) = \sum_{j} u(Di, Cj) P(Cj | \varepsilon). \tag{3}$$

Where $P(Cj \mid \varepsilon)$ is the probability of each context inference state $Cj$ conditioned on the given observations at hand $\varepsilon$. To enable a context presentation decision that couples the user situational context at hand with his/her tolerance of interruption of the earlier defined context profiles, we defined two context presentation states associated with the user's context profiles namely, interruptible or not interruptible context preference. The network belief about the user context likelihood was then evaluated based on the interrupting presentation decision that is weighed by the utility function outcome. The results showed that the model decision classifier performed fairly well in predicting the user cognitive situational context related to a given activity. For example, for the "meeting" activity of high-attention context profile, the model provided a utility value of 20% for an interrupting presentation decision, and 80% for a non-interrupting presentation decision. In contrast, for the "free" activity case of low-attention context profile, the model showed an equal utility weight of 20% for providing an interrupting or a non- interrupting presentation decision. The equal-weight decision indicated that neither decision has effect on the user satisfaction with respect to his/her current situational context.

In addition to studying the model classification accuracy, we are also interested in investigating the model sensitivity to the competing combinations of the network structure influencing variables (e.g. place, accompany, time, and duration). Examining the variables with higher contribution value to the overall context awareness value can lead to defining a base model with sets of variables in order to enhance the model accuracy and shorten the model learning time. A key feature of Bayesian models is their capability of computing the power degree of each variable over the remaining set of variables in the network using entropy reduction metrics [36], by calculating the posterior probability, in a form of a likelihood distribution over the remaining set of variables in the network, also known as the evidence function. Interested readers are encouraged to refer to any machine learning text, such as [38]. Using Hugin software, we reproduced multiple trials of the model learning association features from the earlier collected training data. For most theoretical probability distributions, simulation can be used to generate many observations, thereby reproducing population-like distributions [39]. Moreover, according to the central limit theorem, empirical measurements will tend to move toward a normal distribution asymptotically as the sample size increases [40]. That being said, we examined the model's classification accuracy given a distinct evidence function for each of the model influential variables at a time. We used the computed classification accuracy values to address the following question and hypothesis:

**Question:** Which competing approach (place, accompany, time, duration, etc.) provides the best context awareness value?

**Hypothesis:** There is a difference in the context awareness value provided by the competing influencing variables.

To examine the significance of each influential variable on the overall context awareness value, we used Analysis of Variance (ANOVA) parametric test. The results partially confirmed our hypothesis. The results showed that both place ($P=0.0018$) and accompany ($P=0.0013$) evidence variables performed significantly better ($P<0.01$) in determining the overall context awareness value. While weekday showed to be significant ($P=0.0461<0.05$), the activity duration showed insignificant ($P=0.0756$, $P>0.05$), and the recurring activity was noticeably not significant ($P=0.4992$) to the overall context awareness value. The significance of both place and accompany in determining the user context value also indicated their importance in enhancing the model classification accuracy at early stages of the model training.

## 5 Conclusion and Future Work

Looking back to Weiser's [41] view where people daily lives will become augmented with invisible computational resources to provide information and services when and where desired, in a way that such computational systems are interwoven into people life. In this article, we have presented a user-centered approach to context awareness, in which we perceive users' daily activities and tasks as natural sensors of their situational context. Our goal is to facilitate a simple yet practical approach to context awareness directly based on users' crafting of their personal activities and ongoing tasks. We have created a Bayesian model that inherits the uncertainty of users' context of their daily recurring activities, and provides context awareness inference driven by users' context of interest. We have demonstrated the model through developing an informed personal user context profile drawn from user's daily informal communication with the built-in calendar on his/her mobile handheld device. We have also assessed the potential value of our model in providing a context presentation decisions that better match user's situational context or context of interest for a given activity, such as users' defined tolerance of interruption of their situational context.

We found our preliminary evaluation results promising as a step forward towards building context inference and making context presentation decisions that are more relevant to users' context. Although we believe that the demonstrated model network variables and scenarios do not cover all users' social and mental states that might occur in reality, we think that the model will help in developing more deployable context awareness features relevant to the users' needs in reality. In contrast to the earlier work of Horvitz et al. [28, 29] and Mynatt et al. [26, 27] who examined models of users' availability and attendance mainly to facilitate and support users' scheduling activities and potential interruptibility, our proposed model intended to provide to mobile users a mechanism for developing an informed context-aware service beyond those normally dealt with in desktop applications.

Given the results presented in this paper, we have identified some potential future research to further validate and extend our proposed user context model. One issue of particular interest is to assess the overall context awareness value of incorporating both the sensor-based and user-centered context inputs. From a decision making perspective, we believe that the sensor-based approach and the user-centered contribute different measures to the overall context awareness value. In particular, we are interested in comparing our model context awareness prediction with the context detection of a sensor-based context determined value. A popular methodology that facilitates such analysis falls within the framework of Multiple criteria decision making (MCDM) [42], we are currently exploring to determine the context awareness value of incorporating the competing approaches of context acquisition, as well as to explore the measures that most contribute to context awareness from each competing approach.

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