Capturing and Modeling Human Cognition for Context-Aware Software

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Keywords: context-aware computing; context modeling.

Introduction

As computing becomes ubiquitous, it is possible for systems to sense their context of use and adapt their behavior accordingly. Using an appropriate context model that relates the users' cognitive contexts with specific activities can make ubiquitous computing systems more convenient and effective for their users. Recent work has explored the use of structural models for representing, sharing and reasoning complicated, dynamic and interrelated context information, e.g. Context Toolkit (Dey, Salber, & Abowd, 2001) , extended Object Role Model(ORM) (Henricksen, Indulska, & Rakotonirainy, 2003), and ontology-based context models (Strang, Linnhoff-Popien, & Frank, 2003; Serrano, Serrat, & Galis, 2006). However, human activities and preferences tend to be diverse and dynamically changing, depending upon material and social circumstances. Current context models usually concentrate on the computational representations of contexts which can be tracked and recorded, but ignore cognitive properties that are essential to human activities and decisions.

Theories from sociology and philosophy, especially ethnomethodology and phenomenology, suggest that user experience, such as subjective perception of system features and past experience of similar contexts, may influence current activity (Dourish, 2004). Ignoring human cognition in context analysis is therefore likely to frustrate and disorient users. In this paper, we present a cognitive context modeling framework that analyzes the diversity and dynamics of context-aware behavior by capturing and representing human cognition of context information, from objective settings, explicit user activities, to implicit user preferences, for a given task.

The Cognitive Context Modeling Framework

Context, according to Dewey (Dewey, 1960), has two components: 1) background, which is both spatial and temporal and is ubiquitous in all thinking; 2) selective interest, which conditions the subject matter of thinking. Computational tasks operate in a set of contexts, and the selection of contexts for monitoring and sensing is subject to computational, technical, and social constraints. Therefore, we classify the context information of a task into two major categories: *Objective Context(ObjCt)* and *Cognitive Context(CogCt)*. *ObjCt* refers to the contemporary settings within which a course of action emerges or the objective state of an activity, e.g., who, what, when, and where, which can be automatically sensed with a certain level of accuracy; while *CogCt* refers to a set of beliefs belonging to an individual or a community, e.g., purposes and preferences, which answers "*why*" a piece of information should be considered as "context" and "*how*" it affects the result.

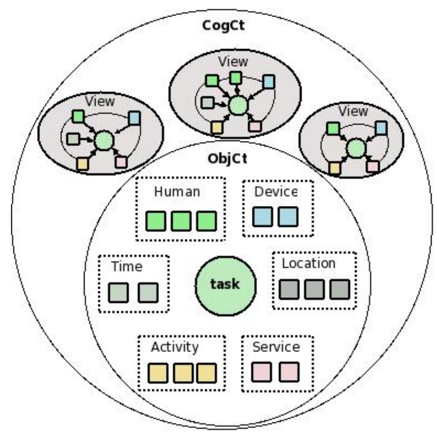

Figure 1: The Framework of Cognitive Context Model

Figure 1 shows our framework for modeling human cognition on a context-aware task. There are three key components in this framework: *task*, *objective context(ObjCt)* and *cognitive context(CogCt)*. An *task* can be interpreted as a flow of operations for transforming the object into an outcome. The process of the transformation, e.g., when and where to execute which operation, is affected by the state of a set of *ObjCt*s. The *ObjCt*s for a task are the detectable surroundings during the task process, e.g., time, location, device, etc. The cognitive selection of "interesting" $ObjCt$s of a task is specified in the *CogCt* component by context *views* drawn from end-users or communities. Each *view* contains a set of $ObjCt$s, which are relatively ranked according to their relevance to the $task$.

Case Study: Power Saving Schedule

The cognitive context model structures the representation of task and its contexts from end-users' perspective. We conducted case study on a power saving task to illustrate the use of cognitive context model for context identification and analysis.

Shutting down the computer when it is not in use contributes to energy saving. Figure 2 shows a cognitive context model for the power saving task, in which each plot line represents one context view, and for each view, the x-axis represents the time contexts and the y-axis represents their relevance to the power-off state. The model is built by moni-

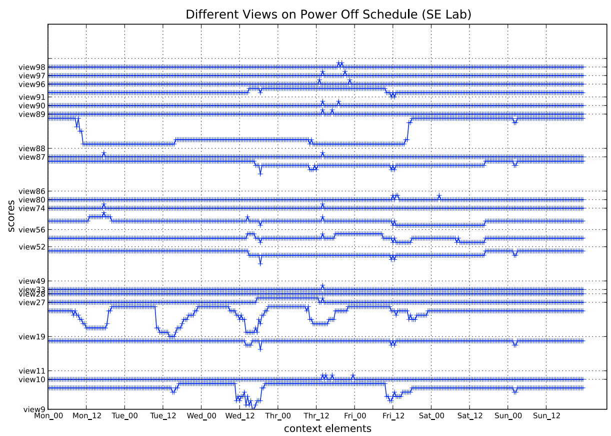

Figure 2: The diversity of context views on power saving

toring the power state of desktop computers used by staff and graduate students in our department, and the score is calculated by the power-off ratio (the total number of power-offs divided by the total number of observations).

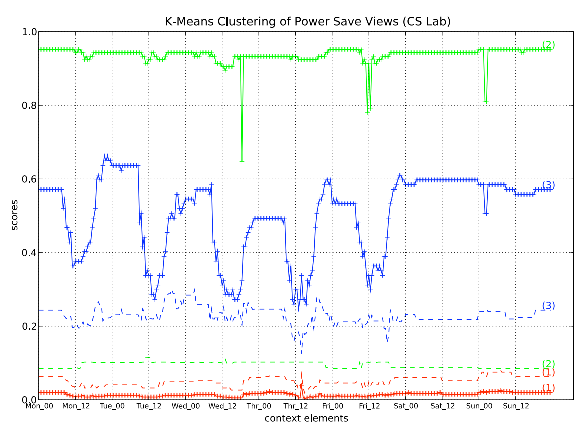

Figure 3: K-means clustering on context views (k=3)

The model exhibits the diversity of context views on the power saving task, i.e., the power state varies with time and views. The structure and data provided by this model also allow numerical analysis on the variance of human cognition and context-aware behavior. Figure 3 shows the result of K-means clustering we conducted on the context views in the model. With clustering, the context views are classified into three categories (the '+' lines): (1) almost never power-off, (2) always power-off, and (3) power state varies with time. The dashed lines in the figure represent the standard deviation values of each cluster. A low standard deviation value implies low diversity among context views in the cluster.

Since the context views in cluster(3) exhibit consciousness of power-saving activities, by assigning higher weights on these views, we generated an optimized context view for the power-saving task with AHP calculation (Saaty, 1994), as shown in Figure 4. The y-axis value indicates the relative

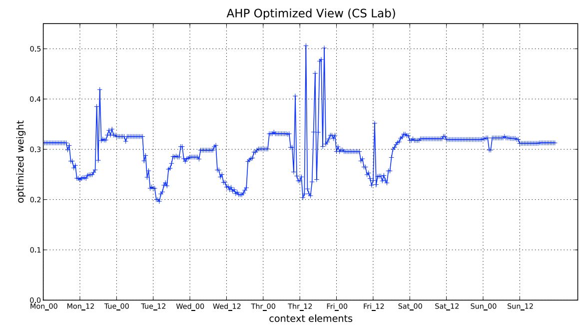

Figure 4: Optimized context view

importance/relevance of each time context to the power-off state. The optimized view integrates all the context views in cognitive context model and optimizes the relevance value of each context element, which can thus be used as an input to adaptation engine for context-aware task execution and reconfiguration.

Conclusions

This paper presents a cognitive context modeling framework for capturing and analyzing end-users' cognition of context-aware behavior. The performance of this framework is illustrated with a case study on computer power saving. It shows that with cognitive context modeling, various context views of a given task can be captured and visualized, which provides efficient support on checking the variance of human cognition and reducing bias in decision making.

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