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Context-prediction performance by a dynamic Bayesian network: Emphasis on location prediction in ubiquitous decision support environment ☆

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ABSTRACT

Ubiquitous decision support systems require more intelligent mechanism in which more timely and accurate decision support is available. However, conventional context-aware systems, which have been popular in the ubiquitous decision support systems field, cannot provide such agile and proactive decision support. To fill this research void, this paper proposes a new concept of context prediction mechanism by which the ubiquitous decision support devices are able to predict users' future contexts in advance, and provide more timely and proactive decision support that users would be satisfied much more. Especially, location prediction is useful because ubiquitous decision support systems could dynamically adapt their decision support contents for a user based on a user's future location. In this sense, as an alternative for the inference engine mechanism to be used in the ubiquitous decision support systems capable of context-prediction, we propose an inductive approach to recognizing a user's location by learning a dynamic Bayesian network model. The dynamic Bayesian network model has been evaluated with a set of contextual data from undergraduate students. The evaluation result suggests that a dynamic Bayesian network model offers significant predictive power in the location prediction. Besides, we found that the dynamic Bayesian network model has a great potential for the future types of ubiquitous decision support systems.

1. Introduction

As the ubiquity becomes perceived by users more easily in their daily lives, context-aware systems have received a lot of attention from both practitioners and researchers. World-wild excitement about smart phones is also representing people's passion about the context-aware devices. In this respect, context-awareness has been the subject of the growing attention in the area of ubiquitous computing over the years due to its usefulness for several application domains (Hong, Suh, & Kim, 2008). When computer systems are aware of the context in which they are used and are able to adapt to changes in context, they can engage in more efficient interaction with users.

Context awareness is concerned with enabling ubiquitous computing devices to be aware of changes in the environment, and to intelligently adapt themselves to provide more meaningful and timely decision support for decision-makers (Feng, Teng, & Tan, 2009). However, context-aware systems are limited by the fact that their target is the current context, and that the future context is not predicted by context-aware systems. Therefore, the quality of services provided by the context-aware systems is seriously restricted when future contexts change drastically. To this end, we need to consider the task of context prediction in order to proactively offer high-quality services for users in ubiquitous computing environments.

Context prediction opens a wide variety of possibilities of context-aware computing applications. A context-prediction application may infer the future location of an office owner and redirect incoming calls to the future location. A context-prediction application may also be useful for enhancing the quality of transportation systems. Based on the information about the current location and the future location of a particular user, transportation systems equipped with context prediction technology may be able to assist drivers more effectively by inferring possible preferred routes and by providing customized route suggestions for drivers, as well as warning the drivers about possible dangers by predicting their future context. Knowing the current location and current time, together with the user's calendar, could also allow application to have a good idea of the user's current social situation, such as if the user is in a meeting, in class, waiting in the airport, and so on.

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The list of applications listed here is limited and we believe that there is a great potential for context prediction to be used in a variety of ubiquitous computing applications. Especially, it becomes clear how much users would benefit from the ubiquitous decision support systems equipped with the context-prediction mechanism. As an alternative for the inference engine to be used in the ubiquitous decision support systems capable of providing context-prediction function, this paper proposes a dynamic Bayesian network (DBN) approach to location prediction for ubiquitous computing environments. DBN is an important technique because of its ability to represent the temporal properties of user context information. In fact, it is obvious that a user's current locations are influenced by their previous locations, and particular locations afford particular types of actions. Therefore, we adopted a DBN approach for recognizing the locations of users.

This paper is structured as follows. Section 2 discusses context prediction and various context prediction techniques in ubiquitous computing environments. The modeling techniques used to predict a user' locations are described in Section 3. The results of the experiment are presented and discussed in Section 4, followed by concluding remarks and directions for future work in Section 5.

2. Background

2.1. Context prediction

Context prediction focuses on inferring users' context based on analyzing the observed context history that users have shown so far. The observed context history is a series of context information showing how users are moving around in a certain ubiquitous computing environment. The context information is supplied by various types of sensors such as GPS, RFID, and a variety of wireless devices. These sensors may provide the context information about users' locations, users' actions, or the changes in a physical environment of the users. The purpose of context prediction is to predict the subsequent context that users will likely to enter (if the contexts are locations or situations) or perform (if the contexts are actions) based on a history of contexts which are compiled through various sensors. For ubiquitous computing environments, the ability to accurately predict a user's contexts would make it possible to provide context-aware services that are more natural and customized to people's needs. Accurately recognizing a user's contexts could provide more effective and personalized advices to a user, particularly in ubiquitous decision support systems.

2.2. Context prediction techniques

Several context prediction techniques have been proposed in the literature such as Bayesian networks (Hwang & Cho, 2009; Petzold, Pietzowski, Bagci, Trumler, & Ungerer, 2005), Markov models (Rashidi, Cook, Holder, & Schmitter-Edecombe, in press; Singla, Cook, & Schmitter-Edgecombe, 2010), Topic models (Huýnh, Fritz, & Schiele, 2008; Kim, Helal, & Cook, 2010) and neural network approaches (Petzold et al., 2005). Examples of context prediction are location prediction (Anagnostopoulos, Anagnostopoulos, Hadjiefthymiades, Kyriakakos, & Kalousis, 2009; Laasonen, Raento, & Toivonen, 2004; Petzold et al., 2005), movement prediction (Perl, 2004), action prediction (Brdiczka, Reignier, & Crowley, 2007; Davison & Hirsh, 1998; Singla et al., 2010), daily routine prediction (Huýnh et al., 2008; Kim et al., 2010).

Petzold et al. (2005) investigated Bayesian networks, neural networks, Markov and state predictors to predict the next location of the office owner in an office building. Their system predicted the next location of the office owner and switched over the phone call to the predicted location. Singla et al. (2010) proposed a Hidden Markov Model approach to recognizing activities performed by multiple residents in a single smart home environment. Sensor readings were collected in the smart home environment while participants were performing their activities. Hidden Markov Model was used to determine an activity that most likely corresponds to an observed sequence of sensor readings. Bayesian networks can be used to predict prominent activities of users. For example, Hwang and Cho (2009) proposed a modular Bayesian network model to infer landmarks of users from mobile log data such as GPS log, call log, SMS log, picture log, music-playing log and weather log.

A promising topic model approach to recognizing a user's daily routines has been proposed for ubiquitous computing environments. For example, Huýnh et al. (2008) adopted a topic model to predict a user's daily routine (such as office work, commuting, or lunch routine) from users' activity patterns. To evaluate the topic model, they collected the daily activities of one person over a period of sixteen days. For data collection, the subject wore two sensors in order to record low-level signals such as body movements or body posture. The subject was asked to annotate his activities in detail in order to model the relationship between user activities and low-level signals. In total, 34 activities were recorded in their dataset. Huýnh et al. first identified the user's activity patterns from low-level sensor data by using various classifiers such as Support Vector Machines, Hidden Markov Models, and a Naïve Bayesian network. The resulting user activity patterns that were identified were then given to the topic model as inputs to infer the user's daily routine.

As we have seen so far, there are many examples of context prediction in a variety of application domains. Several strategies can be employed to identify the future location of a user. One such technique is to adapt probabilistic models which predict a user's future location. Section 3 describes an inductive approach to generating location prediction models in ubiquitous computing environments.

3. Inducing location prediction models

Many types of location recognition models can be learned. We investigated probabilistic models such as dynamic Bayesian networks (DBNs), general Bayesian networks (GBNs), tree augmented Naïve Bayesian networks (TANs), and Naïve Bayesian networks (NBNs). Refer to appendix for more details about Bayesian networks that were considered in this study.

3.1. Bayesian models for location prediction

A Bayesian network approach is well suited for generating predictive models in a real-world domain because of its ability to deal with the uncertainty inherent in every facet of human life. Bayesian networks are probabilistic models in the form of directed acyclic graphs (Pearl, 2000). Nodes in Bayesian networks represent variables or propositions (e.g., the occurrence of an event or a feature of an object). Likewise, links represent causal or informational dependencies among variables, and are quantified by the conditional probability of a node, given its parents. If a node does not have parents, it is associated with a prior probability. Since Bayesian networks represent causal or informational dependencies among variables, variables that are not influenced by any other variables but do exert influence on other variables are positioned at the top layer of the network. Similarly, variables that are influenced by some variables and also influence other variables are positioned in the middle layers of a network, while variables that are influenced by some variables but do not influence any other variables are positioned at the bottom layer. In such a representa-