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Mobile context inference using two-layered Bayesian networks for smartphones

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ABSTRACT

Recently, mobile context inference becomes an important issue. Bayesian probabilistic model is one of the most popular probabilistic approaches for context inference. It efficiently represents and exploits the conditional independence of propositions. However, there are some limitations for probabilistic context inference in mobile devices. Mobile devices relatively lacks of sufficient memory. In this paper, we present a novel method for efficient Bayesian inference on a mobile phone. In order to overcome the constraints of the mobile environment, the method uses two-layered Bayesian networks with tree structure. In contrast to the conventional techniques, this method attempts to use probabilistic models with fixed tree structures and intermediate nodes. It can reduce the inference time by eliminating junction tree creation. To evaluate the performance of this method, an experiment is conducted with data collected over a month. The result shows the efficiency and effectiveness of the proposed method.

1. Introduction

One of the important issues in recent mobile computing is context-awareness. In next-generation mobile systems, novel solutions for user-centric service are crucial to provide personalized views of only the services of potential interest (Bellavista, Corradi, Montanari, & Toninelli, 2006). The service personalization should be based on user context and environment conditions. It requires high-level context inference from raw sensor data. Some researchers have tried to gather raw data from a mobile device and infer high-level context (Gemmell, Bell, & Lueder, 2006; Korpipaa, Mantyjarvi, Kela, Keranen, & Malm, 2003; Raento, Oulasvirta, Petit, & Toivonen, 2005; Siewiorek et al., 2003).

Models for context inference generate the desired target information (the high-level context) from existing information (low-level context). This leads to a kind of classification problem which determines "class" (state of the high-level context) from the combination of low-level information. Methods for context inference should be efficient, sound and complete according to Perttunen, Riekki, and Lassila (2009) and cope with imperfection of data (Bikakis, Patkos, Antoniou, & Plexousakis, 2008). Angermann, Robertson, and Strang (2005) specified the requirements further, suggesting means for fusion of several input sources and handling of possibly contradicting measurements, expressive modeling of situations, and adaptation to the needs of large-scale pervasive systems, i.e. distributed processing, personalization and adaptability to the system's dynamics.

Probabilistic approach for context inference deals with the uncertainty in measurements and propositions about various situations in real world by using probabilities that are encoding degrees of belief with values between 0 and 1. Bayesian network is one of the most popular probabilistic approaches. It efficiently represents and exploits the conditional independence of propositions. This model can be learnt from existing data, but also set manually by human experts as they can be interpreted easily. Also combinations of learnt and set probability models are possible. Some researchers used Bayesian techniques to recognize activities of daily life (Korpipää, Koskinen, Peltola, Mäkelä, & Seppänen, 2003) from sensor data.

However, there are some limitations for probabilistic context inference in mobile devices. Mobile devices contain relatively insufficient memory capacity, lower CPU power (data-processing speed), and limited battery when compared to desktop PCs. In addition, they have to operate in the changeable real world, which means that they require more active and effective adaptation functions (Dourish, 2004).

This paper adopts Bayesian probabilistic models to efficiently manage various uncertainties that can occur when working with mobile environments, including real-world irregularities, like uncertain causal factors. The proposed method presents a method to infer high-level context using a two-layered Bayesian network using mobile data. It constructs Bayesian network models with tree-like structures from low-level context. The models work more efficiently in mobile environments than standard Bayesian network models. Moreover, the models can be linked with hierarchical

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structure to provide more accurate and broad-coverage context. In order to show the feasibility of the proposed model, it was applied to several experiments using mobile log data collected from a smartphone for a month in the real world.

The rest of the paper is organized as follows. Section 2 introduces related work regarding mobile context inference. Section 3 describes Bayesian network design using tree structure and intermediate nodes to reduce the cost of context inference. In Section 4 we introduce a two-layered Bayesian model to infer high-level context. Section 5 shows experiments and the results to evaluate the approach. Finally, Section 6 summarizes this paper and presents future works.

2. Related work

2.1. Mobile context inference

There are many studies to infer high-level context such as a user's activities and emotions in mobile environment. Especially, human activity is very important context for ubiquitous computing applications (Yang, Lee, & Choi, 2011). Most of ubiquitous computing applications attempt to recognize activities from regular routines for daily life, personal preferences, and sensor information. We can divide previous work in mobile activity recognition into two types: probabilistic approach and non-probabilistic approach.

Probabilistic context inference includes various models like naïve Bayes classifier, hidden Markov model, Bayesian network, dynamic Bayesian network, Markov random field, conditional random field, and other methods. The probabilistic models are suitable to handle incomplete and uncertain sensor data and extract the most probable user state of high-level context. Yang et al. (2011) proposed a naïve Bayes-based method to recognize human activities using RFID object information. They also compared the cost of the naïve Bayes classifier with hidden Markov models and conditional random fields. Räsänen et al. used hidden Markov model as one of approaches to classify context from audio and acceleration data in mobile phone (Räsänen, Leppänen, Laine, & Saarinen, 2011). They recognized a user's transportation activities such as running, walking, bicycling, car/bus, etc. Zhu and Sheng proposed indoor human daily activity recognition by combining motion data and location information (Zhu & Sheng, 2011). They used hidden Markov model for real-time daily activity recognition. In order to fuse the motion data with the location information, Bayes' theorem is used to update the activities recognized from the motion data. Vinh et al. presented a novel implementation of the semi-Markov Conditional Random Fields (semi-CRF) for activity recognition (Vinh et al., 2011). They compared average precision and recall with other methods such as hidden Markov model and topic model.

The other methods for context inference have many kinds of variations such as logical approaches, neural network-based inference, and kernel machines-based approaches. Logic-based context inference deduces high-level context from the knowledge base. It is the most frequently applied approach for reasoning in context-aware systems (Bikakis et al., 2008). Ontology, fuzzy logic, and decision tree-based approaches belong to this type in context inference. Riboni and Bettini proposed a solution based on the use of ontologies and ontological reasoning combined with statistical inference (Riboni & Bettini, 2011). They used structured symbolic knowledge about the environment surrounding the user to infer the user's activities on Android smartphone. Weiss and Lockhart tried to identify the physical activity a user is performing from smartphone-based accelerometer data (Weiss & Lockhart, 2012). They mainly focused on evaluating the relative performance of impersonal and personal activity recognition models. WEKA is used for classification algorithms such as decision tree, random forest, and so on.

Neural network approaches simulate a brain's information processing. They consist of nodes, representing neurons, and weighted links (Haykin, 1998). Henpraserttae et al. investigated activity monitoring using accelerometer-embedded mobile phone (Henpraserttae, Thiemjarus, & Marukatat, 2011). They recognized six daily activities using neural network regardless of various different places and orientations. Lara et al. presented a system named Centinela that combines acceleration data with vital signs for activity recognition (Lara, Pérez, Labrador, & Posada, 2012). Many classification algorithms have been applied for activity recognition such as decision trees, Bayesian probabilistic methods, fuzzy logic, and neural networks.

Support vector machines (SVMs) are to find hyper-planes that linearly separate classes with a maximum margin to recognize context. Peng et al. presented a feature selection method for activity recognition in mobile devices (Peng, Ferguson, Rafferty, & Kelly, 2011). They used support vector machines to evaluate the performance of their proposed algorithm to recognize activities. Stewart et al. developed a simple application for mobile devices to recognize physical activity (Stewart, Ferguson, Jian-Xun, & Rafferty, 2012). They used support vector machine to classify activities.

2.2. Modular Bayesian probabilistic approaches

This paper uses Bayesian probabilistic models to handle uncertainties in mobile environments effectively. Bayesian network is a suitable means for context inference, but there are some problems because of the computational complexity of the probabilistic inference in mobile environment. Therefore, it is necessary to break BNs down into smaller modules.

Several researchers tried to divide large BNs into such BN modules for reduced inference time, re-usability and specification of networks. Xiang et al. proposed a method called multiply sectioned Bayesian networks for splitting Bayesian networks in 1993 (Xiang, Poole, & Beddoes, 1993). The core concept of the multiply sectioned Bayesian networks (MSBN) is the division of a Bayesian network into unchangeable and changeable Bayesian subnets. They used d-separation to divide a Bayesian network. Partitions in MSBNs have to form a tree structure, the partition tree. The partition tree is similar to a junction tree in PPTC.

A first step to the construction of the partition tree is the construction of junction trees of the identified partitions. The independence of the subnets allows partly independent modification and evaluation (Xiang & Jensen, 1999). Moreover, the subnets can run their inference processes asynchronously in parallel. MSBNs provide an effective approach for distributed inference but require the cost of constructing partition tree for context inference.

Laskey and Mahoney presented network fragments in 1997 for the domain of military situation (Laskey & Mahoney, 1997). A network fragment contains random variables and their conditional probabilities. Fragments distinguish between input and resident variables. Bayesian networks are divided into the available network fragments for a specific situation. The algorithm could combine the network fragments based on data association, hypothesis management, and pattern replication. Their inference yielded only approximate results through the combination of related network fragments. However, they did not consider the constraints for mobile devices.

Object oriented Bayesian networks (OOBN) was proposed by Koller and Pfeffer (1997). They applied concepts of object oriented programming into BNs. An OOBN consists of several object oriented network fragments that define its probabilistic properties. Also Bangso defined an OOBN-Framework in 2000 (Bangsø, 2004). The framework provides means for top-down modeling