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Abstract

The primary difference between mobile commerce (m-Commerce) and electronic commerce is its use in various contexts. Electronic commerce is mostly used in the predetermined environment of the Internet. Delivering relevant things to the right people at the right time in the right way becomes a key issue for m-Commerce: user information and context information are critical to the success of m-Commerce. However, few studies have been conducted to explore the relationship between the two and their influence on users' mobile commerce usage behaviour. It is far from clear the situations under which m-Commerce is used most frequently and the impact of context information on its users' m-Commerce usage behaviour.

This paper proposes a framework for studying the impact of user contexts on m-Commerce services consumption. Firstly, the Back-Propagation Neural Network (BPNN) is adopted to build a model to study the relationship between users' profile information and the context information. After that, a two-level Bayesian Metanetwork is employed for modelling the causal relationships between the user contexts and the user preferences in the mobile information environment. All special requirements of the mobile information environment have been taken into account for this framework building.

Keywords

Artificial Neural Network, Bayesian Metanetworks, Context, Profiling, Mobile Commerce

1 Introduction

Mobile commerce (m-Commerce) offers new mobile applications and services to assist users in performing time-critical and goal-driven tasks. It is believed that wireless mobile devices will replace stationary personal computers (PCs) as the medium of choice for electronic commerce (e-Commerce) users (Economist Intelligence Unit 2001), because of the anytime-anyplace characteristics of m-Commerce through wireless mobile devices. They allow information to be disseminated and transactions to be completed when users are in transit or away from their desks or home PC connections. Delivering relevant information to the right people at the right time in the right way thus becomes a key issue in mobile commerce. Hence, user information and context information, namely, the user's activity, location, preferences, and device capability are critical to the success of mobile commerce. It is crucial to provide personalized information based on users' context information and personal profile, due to the fact that wireless network traffic is busy and mobile terminal size is limited. However, m-Commerce is still dominated by relatively simple infotainment services. Moving beyond these simple services requires the inherent limitations of wireless mobile devices to be overcome, through higher degrees of automation and development of services that understand users more thoroughly.

Using knowledge about users' context information has the potential to overcome many of the problems of mobile commerce. Therefore, it is important to study the contexts in which people use m-Commerce and how they use them in each specific context. However, not much research has been conducted to define the numerous contexts of m-Commerce or to identify the key contexts in which people use m-Commerce most frequently. Many projects and initiatives are concerned with the elements of context and context awareness applications, but their focus is principally on sensor technology, smart environment, infrastructure, or other aspects (Chen and Kotz 2000). There are few developed applications that explicitly combine contexts in conjunction with user behaviour analysis. For example, both Forget-me-not (Lamming and Flynn 1994) and CyberMinder (Dey and Abowd 2000) systems capture current situational contexts but do not use any form of technology to interpret the user's interests or preferences. The GUIDE system (Cheverst *et al.* 2000) is the only exception. It incorporates the notion of a user model to interpret user's behaviour. However, the GUIDE system is concerned with current contexts applied to present information to users. This is another limitation of current context applications. The history of contexts provides far more information about the user. Some other researchers adopted predefined rules to interpret user's contexts (see Anhalt *et al.* 2001; Selker and Burleson 2000). However, predefined rules are not suitable for providing dynamic adaptations in the contextual environment. All the research studies mentioned above cannot offer sufficient support for interpreting multiple contexts. Utilising historic contexts together with data mining techniques offers an efficient approach to infer patterns from the mobile commerce user's behaviours and contexts.

In the research field of user behaviour, data mining technologies are actively investigated as a practical method to learn users' interests, preferences, knowledge, goals, habits, etc., in order to adapt the services to the users' individual characteristics (Mitchell *et al.* 1994; Pohl 1996; Billsus and Pazzani 1997; Ruvini and Fagot 1998). On the other hand, Lincoln and Skrzypek (1990) proposed clustering multiple back-propagation networks when Battiti and Colla (1994) suggested the concept of democracy to combine the outputs of different neural network classifiers. More recently, Gutta *et al.* (2000) suggested the use of hybrid models combining Radial Basis Function (RBF) networks and decision trees with FERET face image database for gender, ethnic origin and pose of face classification. These examples have shown that integration of the multiple data mining techniques could enhance the accuracy and generalization capacity. In our mobile commerce user's contexts research, two techniques are adopted, Artificial Neural Networks (ANNs) and Bayesian Networks (BNs) in mining our data.

ANNs have been used in many different kinds of applications with great success, including classification, pattern matching, pattern completion, noise removal, optimisation and control.

For example, ANNs have been used in the diagnosis and treatment of breast cancer (Bridgett *et al.* 1995), in forecasting the prices of the shares (Diamond *et al.* 1993), and in solving telecommunication routing problems (Rauch and Winarske 1988). Theoretical and experimental results support the use of ANNs in many behaviours applicative tasks. In particular, it has been shown that ANNs can perform sophisticated non-linear models to fit complex customer and market behaviours analysis better than traditional statistical analysis technologies (Haykin, 1999). Hence, utilizing ANNs in mobile commerce user's contexts analysis is likely to prove an efficient method.

A Bayesian Network (BN) consists of a directed acyclic graph (DAG) and a corresponding set of conditional probability distributions. The BN encodes all of the probabilistic conditional independencies satisfied by a particular joint distribution. Thus BNs have proven to be a valuable tool for encoding, learning and reasoning about probabilistic relationships (Patuwo *et al.* 1993, Heckerman 1995). Once learned, BNs can support any probabilistic inference task including prediction of user preferences. The utilization of BNs technology for user profiling in information retrieval was given in Wong (2000a). The idea of using probabilistic mixture models as a flexible framework for modelling users' preferences has been known and used (Cadez *et al.* 2001).

In our mobile commerce user's contexts research, both ANNs and BNs technologies are employed. This study attempts to identify individual users' contexts and the impact of each context on mobile commerce usage behaviour. We first propose a Back-Propagation Neural Network (BPNN) model for analysing context information and user profile information. Then a multi-level BN is proposed for modelling user preferences in mobile commerce environment. It can be used to predict m-Commerce users' preferences based on special characteristics of m-Commerce environment and their profiles. The aim of this research is to develop an appropriate context model of Bayesian Metanetworks with appropriate reasoning rules and to discuss the application of such networks for prediction of user preferences in mobile commerce environment.

2 Mobile Contexts

Much of the domain literature is devoted to the discussion of the elements of mobile contexts. For example, Schilit *et al.* (1994) and Rakotonirainy *et al.* (2000) listed three important aspects of contexts: where you are, whom you are with and what resources are near by. Pascoe *et al.* (1999) discussed four primary pieces of contexts: identity, location, time and activity in their work. Similarly, Ryan *et al.* (1997) suggested four context types, known as location, environment, identity and time. Other studies focus on the process of knowledge capture in contexts. Ozturk *et al.* (1998) built a context model for knowledge intensive reasoning. Akman and Surav (1996) used contexts in knowledge representation and reasoning, while Buvac *et al.* investigated the simple logical (1993) and semantic (1994) properties of contexts.

Although a number of studies have been conducted on m-Commerce context information, there is no common accepted definition about contexts. The definition and the use of context information are likely to vary on individuals or in different cultures. In this research, we regard mobile contexts as, "any personal and environmental information that may influence the person when he/she is using m-Commerce" (Kim 2002). The application area is moved from mobile Internet to mobile commerce. There are two reasons for adopting this definition. First, it focuses on the contextual information from the user's perspective. We are primarily interested in the information that may influence users' m-Commerce consumption behaviours because our study attempts to identify the relationships among the profiles of users in mobile commerce environments, the context information and their m-Commerce consumption behaviours. We focus on what is important to m-Commerce users, such as user tasks, user action, and the specific situations of the users. Second, this definition includes environmental contexts. In a broad definition, everything that can describe the characteristics of a user and the situations of his/her environments can be considered as context. So user's behaviours and interests are all considered as context factors. Based on our definition of the contexts, we propose a structure of m-Commerce contexts as shown in Figure 1.

In Figure 1, we divide contextual information into two categories: personal contexts and environmental contexts. The personal contexts refer to the information about the individuals who are currently using mobile commerce services (Künzer *et al.* 2001). The personal

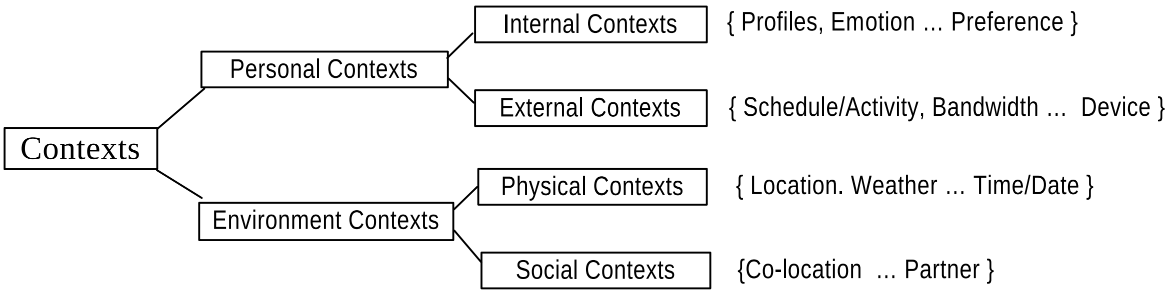

Figure 1: The Structure of Contexts of Mobile Commerce

contexts consist of the internal and external contexts (Schmidt *et al.* 1999). The internal contexts refer to the intrinsic aspect of a user, including personal profiles such as age and gender of the user (Profile), as well as usage patterns such as which kinds of m-Commerce services he/she preferred (Preference/Interests), and how he/she feels while using these services (Emotion). External contexts are data related to the activities or schedule of the day (Schedule/Activity), the tasks of activities (tasks), the type of devices he/she use (Device), the bandwidth available (Bandwidth), etc. On the other hand, the environmental contexts are composed of both the physical and the social environments surrounding the user while using m-Commerce services. The physical contexts describe the outer circumstances of the user, including the weather (Weather), time of the day (Time), date of the day (Date), where the user is staying (Location), etc. while using m-Commerce services. The social contexts refer to how many people are around the user (Co-location), with whom the user is staying (Friend), and other contexts while using m-Commerce services.

All of the above contexts are useful for studying m-Commerce users' behaviours. Among them, Location and Time, which are two pieces of information under special situation, are decisive for providing personalized m-Commerce services. The distinguishing features of m-Commerce is anywhere and anytime connection. Mobile network servers, and even wireless mobile devices, are able to determine the positions of the devices precisely. This capability provides the basis of location-based services. Location context and its applications have been discussed in numerous papers (Fielt *et al.* 2000; Van de Kar and Bouwman, 2001) and form an important aspect of emerging wireless e-commerce services. On the other hand, temporal patterns convey essential information about the time dependency of user's behaviour. The proper time to deliver proper information/services to mobile commerce users is a key parameter. However, little research in this area has been undertaken. One reason is that in e-

Commerce environment, it is general for services providers to push whatever information they have to whoever is on the mail lists whenever they want to. It is the users' decision when to open their email boxes or to connect to the Internet to browse the information. Mobile commerce services providers have simply copied this method. The other reason is that it is difficult to filter information based on m-Commerce environments, because m-Commerce usage, behaviour and preference change with time and location.

Therefore, one of the contributions of this work is to study the temporal context of users which would be derived from the investigation of the users' contexts denoted in figure1. There are two aspects to temporal context. One is the identification of the proper time to deliver necessary information to the right users based on their contexts. The other is the recurrent pattern of the users' mobile commerce usage behaviour. The influence and the utility of these features are the crucial gauge for the temporal context. One familiar temporal context based service is the reminder service. Since in many instances users may ignore important information received or even forget important events in their lives, mobile services providers can offer special reminder services to users. Shopping Assistant (Asthana *et al.* 1994), ComMotion (Marmasse and Schmandt 2000), and CyberMinder (Dey and Abowd 2000) all belong to this category of reminder-based context application. Combining the location of the user and time of day can develop powerful and flexible personal information services. Exploitation of the temporal pattern hidden in the users' m-Commerce consumption behaviour is expected to be important factor in client support.

After gathering context information, the next step is to build a model to understand and investigate the relationships among the contexts. One of the main goals of this study is to investigate the impact of diverse contexts on users' m-Commerce consumption behaviour. Each piece of context information may lead a user to decide which m-Commerce services to select. Context variation maybe a causal factor in different kinds of usage behaviour and the selection of m-Commerce services. In order to test the validity of this hypothesis, we need several comprehensive models to analyse the context information. In this study, we apply a framework of the BPNN model to represent those mobile contexts, and the Bayesian Matenetwork model to interpret and investigate them.

3 Artificial Neural Networks and Bayesian Networks

This section describes the application of Artificial Neural Networks and Bayesian Networks to the analysis of context information in m-Commerce. The ANN has been proven to be an effective algorithm to solve classification problems (Bishop 1995), while the BN is an effective algorithm in learning and reasoning probabilistic relationships (Jensen 2001). Therefore, it is appropriate to employ these two models to investigate this problem, because the use of m-Commerce is complex and dynamic.

3.1 Artificial Neural Network model for classification

The ANNs are made up of simple nodes or neurons interconnected to one another. Generally speaking, a node of a neural network can be regarded as a block that measures the similarity between the input vector and the parameter vector associated with the node, followed by another block that compute an activation function. The most widely used ANN is the BPNN, which is a feed-forward-back propagation model based on layers of neurons. Nodes of each layer are interconnected with all nodes of the following layer. Through supervised learning technique based on the minimization of a cost function, such as the Mean Square Error, the BPNN can effectively solve classification problems. It adopts the Error Back-propagation technique, which is one of the most diffused learning techniques. The Gradient Descent method (see Rumelhart *et al.*, 1986; Haykin, 1999) is employed in its learning function. In this way, BPNN offers non-linear performance.

The BPNN is well known for its capability of performing complex mappings between input and output data. It can often provide outputs of adequate accuracy over a limited range of input conditions, with the advantage of requiring a lot less computation than other models. Numerous previous studies have applied BPNN techniques to solve classification problems. For example, Wu and Jen (1996) proposed approaches that use the BPNN for work piece classification problems, Brooks & Etheridge (1994) solved financial classification problems with the aid of the BPNN, and Patuwo *et al.* (1993) investigated in detail with experimentation the two-group classification problem.

The non-linear behaviour of wireless mobile devices users can be automatically learned from data by a BPNN. Some features of context information in m-Commerce such as users' profiles and preferences can be used as input nodes. This classification analysis can examine whether the mobile commerce users' preferences or interests vary by the users' context features. The findings can derive which attributes influence m-Commerce users' behaviour. Thus, it can help to select effective context features for screening and targeting at more accurate m-Commerce users. Different groups are classified based on users' m-commerce consumption behaviour and similar profiles and preferences. By selection of effective context features and useful data with less noise, the BPNN can help us to build the cause-and-effect relationships among these attributes. This task requires a probabilistic algorithm as all these attributes are conditioned by uncertainty. Bayesian Networks will be adopted to fulfil the task in the next model.

3.2 Bayesian Network model for prediction

Bayesian Networks (BNs), also known as Belief Networks, are directed graphical models that allow representation of joint probability distributions of several random variables in a compact and efficient way (Duda *et al.* 2001). The nodes of a BN represent the random variables, and arcs between nodes represent conditional probabilistic dependencies. From a simplifying perspective, an arc pointing from node A to node B can be perceived as "A causing or influencing B". A BN is fully specified by the topology or structure of the graph, and the parameters of each conditional probability distribution. Learning the structure of BN is especially difficult when there is not prior knowledge of the BN's topology. However, once constructed for a domain, it can be used for probabilistic inference or reasoning about the domain; it can answer arbitrary questions about any conditional or joint probability of one or more of the random variables. In this study, the Bayesian Metanetwork (BM) is expected to be an effective tool for context information analysis in the mobile commerce environment (Terziyan 2002).

Terziyan (2002) provided an apt definition of BM:

> *"a set of Bayesian networks, which are put on each other in such a way that elements (nodes or conditional dependencies) of every previous probabilistic network depend on the local probability distributions associated with nodes of the next level network."*

Terziyan (2002)

A BM is a hierarchical set of standard BNs. Relations in each level reflect the relation of context objects to the next level. Such structure provides a solution to the derivation and interpretation of knowledge using all known levels of its context. A two-level conditional dependency BM is adopted in our model. The two levels are predictive network level and control network level. As personal contexts contain both predictive and contextual features of the users, the prediction features associated with the internal contexts, such as the users' preferences or interests, are put at the predictive network level, while external contexts, such as bandwidth and devices, are put at the control level. All items in the environment contexts are put at the control network level. The contextual features are used to predict the conditional dependencies between preference features of the users. It can be considered as a control level, a level higher to the level of network with predictive features. The nodes are labelled with directed arcs, which can lead to other arcs as well as nodes. Each node represents a type of contexts. This formulation is shown to be expressive enough to capture several aspects of contexts including reasoning and generalization in contexts.

The structure of BM is illustrated in Figure2.

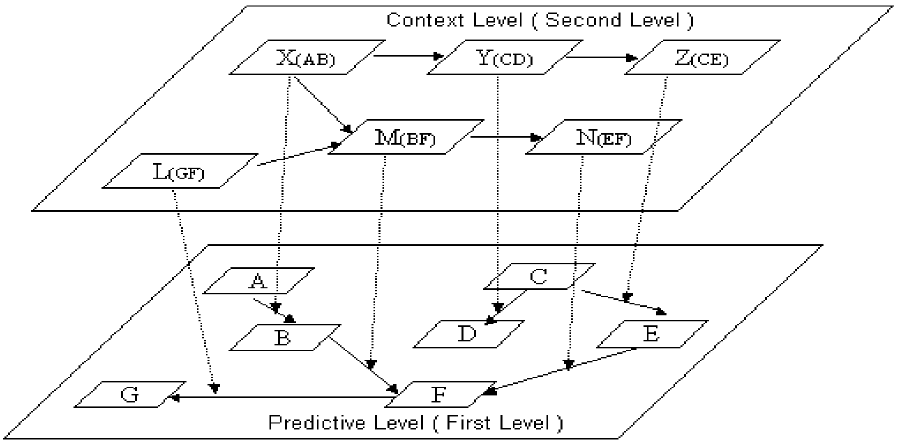

Figure2: Two-level Bayesian Metanetwork

The nodes of the contextual level network correspond to the arc of predictive level network, when their possibility correspond to the conditional probability of the predictive level network. The arc in the second level corresponds to the conditional probability of each node in the level. Standard Bayesian inference is applied in Bayesian Metanetwork at each level. An inference example of the Bayesian Metanetwork is shown in Figure 3.

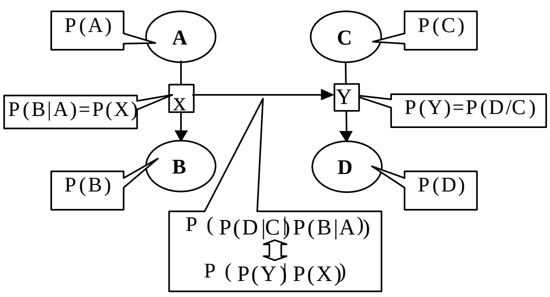

Figure3: The example of Bayesian Metanetwork

The inference is given in equation 1:

$$P(D) = P(C) * P(\frac{P(Y)}{P(X)}) * P(X) = P(C) * P(\frac{P(D \mid C)}{P(B \mid A)}) * P(B \mid A) \quad (1)$$

The nodes of second level network X and Y correspond to the conditional probabilities of the first level network P(B|A) and P(D|C). The arc in the second level network corresponds to the conditional probability P(P(D|C)/P(B|A)). The storage, training and learning of BNs are all conducted in relational databases (Cheng 1997, Wong 2000b). Bayesian model structure learning technology is employed to infer models from data and to identify key variables from the larger set of observations collected. There has been steady progress on methods for inferring BNs from data (Wong *et al.* 1995, 1997). Given a dataset, the methods typically perform heuristic search over a space of dependency models. A heuristic BN construction algorithm (Peng, Herskovits, and Davatzikos, 2001, 2002) can be used. There are many choices of the structure scoring function. In this study, we use Bayesian score (Cooper and Herskovits, 1992). When learning Bayesian networks from datasets, we use nodes to represent dataset attributes.

4 Conclusion

This paper proposes a framework to study m-commerce users' contexts information and the impacts of such information on their mobile commerce services behaviours. Users' contexts and profiles are combined together in our mobile commerce users' contexts in order to fully understand users' m-Commerce services usage pattern. Data mining techniques are adopted to explore advanced levels of context interpretation, both historic and current contexts information are included in our framework.

This study has several implications from both theoretical and practical perspectives. From the theoretical perspective, it provides a framework for modelling mobile commerce user contexts information using neural network and Bayesian Metanetworks. From the practical perspective, the results of the study will allow mobile commerce service providers to identify the appropriate audience for specific information resources. The main contribution of this work resides in integrating the personal contexts with the environment contexts with the aim of developing a model which describes users' behaviours and usage patterns.

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