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A Bayesian Network-Based Framework for Personalization in Mobile Commerce Applications

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A BAYESIAN NETWORK-BASED FRAMEWORK FOR PERSONALIZATION IN MOBILE COMMERCE APPLICATIONS

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ABSTRACT

Providing personalized services for mobile commerce (m-commerce) can improve user satisfaction and merchant profits, which are important to the success of m-commerce. This paper proposes a Bayesian network (BN)-based framework for personalization in m-commerce applications. The framework helps to identify the target mobile users and to deliver relevant information to them at the right time and in the right way. Under the framework, a personalization model is generated using a new method and the model is implemented in an m-commerce application for the food industry. The new method is based on function dependencies of a relational database and rough set operations. The framework can be applied to other industries such as movies, CDs, books, hotel booking, flight booking, and all manner of shopping settings.

Keywords: Bayesian network, personalization, mobile commerce, mobile users, rough set

I. INTRODUCTION

With the rapid progress in wireless technologies and handheld devices, m-commerce offers significant benefits and new opportunities to merchants and mobile users. The total number of worldwide wireless users is expected to exceed 2 billion by 2007[In-Stat/MDR, 2003]. Juniper Research predicted that global m-commerce market will turn into an $88 billion industry by 2009 [Juniper Research,2004].

A key factor for effective m-commerce is to deliver relevant information to the right people at the right time in the right way [Liao et al.,2004] because it is difficult for mobile users to access and browse much information over their mobile devices given their inherent constraints such as a small screen, little processing power, and low bandwidth. Hence, personalization is especially important to the success of m-commerce [Zhang, 2003].

To provide personalized products/services, an m-commerce application must be able to identify individual mobile users in an accurate way. To do so, requires effective representations of the relationships among several kinds of information and the ability to make inferences based on the representations. The information includes user demographic profiles, user preferences, and context and content information. Because many uncertainties exist among different kinds of information and their relationships, a probabilistic approach such as a Bayesian Network (BN) seems a promising solution to manage information for personalization of m-commerce.

This paper presents a BN-based framework for personalization in m-commerce applications. The framework helps to identify target mobile users and allows merchants to deliver relevant information to mobile users more effectively. Under the framework, a personalization model is constructed using a new method, and the model is implemented in an m-commerce application for the food industry. The new method is based on function dependencies of a relational database and rough set operations, where the rough set is used to discover function dependencies from data that are difficult to identify solely by semantics. The identified function dependencies are used to represent the relationships among information accurately, both qualitatively and quantitatively. The model provides personalized services for m-commerce applications from a new direction. That is, it makes use of the solid theoretical basis of relational database and data mining functionality.

II. A SCENARIO IN THE FOOD INDUSTRY

To illustrate the need for personalization in m-commerce and the way a personalization model is constructed, a sample scenario (use of m-coupons in the food industry) is set up as follows:

A fast food restaurant, CFC, wants to promote a newly created set lunch menu[1]. Rather than using paper coupons that proved not to be cost-effective, CFC decided to use m-coupons to market the lunch menu. A mobile operator, BBP, is chosen to deliver m-coupons to its mobile subscribers through a Multi-media Message System (MMS). If there is no personalization, the messages will be sent to all customers within a specified distance (e.g., 1 kilo-meter) around the restaurant during the lunchtime period. After receiving the promotion message, a mobile user can redeem the MMS m-coupon at CFC's Bluetooth-enabled counter for a discount with his/her mobile device. Under the current mobile business model, BBP charges CFC on the basis of usage, i.e., the more messages sent, the more CFC will be charged. The effectiveness of this new way of marketing, which is indicated by the ratio of number of people coming for the set lunch menu over the number of messages sent, will have a significant impact on CFC's business. Obviously, the ratio will be strongly influenced by users' interests in the received message. For those who have no interest, they may feel irritated and think it a waste of time to look at the message, and will simply delete it. In such cases, CFC's marketing efforts on those people will not be effective at all.

The scenario illustrates the importance of personalization to the success of m-commerce. If mobile users can receive relevant messages at the right time and in the right place, it will undoubtedly improve the merchants' business and the users' satisfaction.

III. BAYESIAN NETWORKS

A Bayesean Network (BN) is a directed acyclic graph in which each node represents a random variable, characterized by a set of mutually exclusive and collectively exhaustive propositions. Each set of arcs toward a node represents a probabilistic dependence between the node and its parents. A BN represents, through its structure, the conditional independence relations among the variables in the network. The conditional independences between variables render inference tractable in many real-world situations. Figure1 shows an example of a BN, where the variables

[1] A set lunch menu in Hong Kong is a western-style menu at a fixed price with no substitutions allowed.

of the problem are Fraud (F), Gas (G), Jewelry (J), Age (A), and Sex (S),respectively; arcs are drawn from cause to effect; the local probability distributions are partly shown adjacent to the node; an asterisk is a shorthand for “any state” [Heckerman, 1995].

The use of a BN is similar to that of expert system technologies. A BN represents beliefs and knowledge about a particular class of situations. Given a BN for a class of situations and evidence about a particular situation in that class, a prediction can be drawn with a degree of confidence [Fung and Favero, 1995].

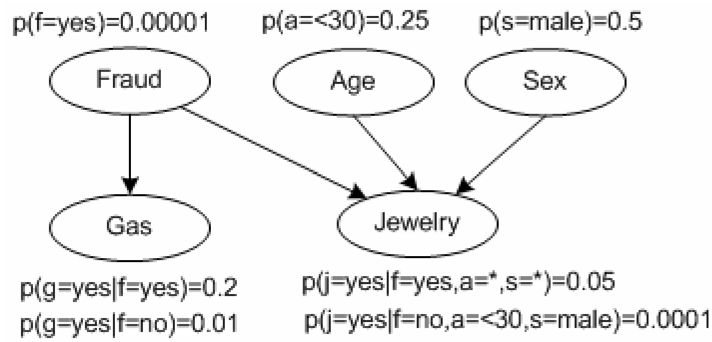

Figure 1. An Example of Bayesian Network

IV. PERSONALIZATION IN M-COMMERCE

M-COMMERCE

M-commerce is defined as the transactions of commodities, services, or information over the Internet through the use of mobile handheld devices [Mathew et al.,2004;Siau et al., 2001]. “Mobility” and “locatability” are two user-oriented core dimensions in which m-commerce has an advantage over e-commerce [Shi, 2004]. To help applications and technologies handle m-commerce, an integrated four-level framework for m-commerce is proposed by Varshney and others [Varshney et al., 2000; Varshney and Vetter, 2002]. The four levels are:

- m-commerce applications,
- user infrastructure,
- middleware, and
- network infrastructure.

The framework shows that the design of a mobile commerce application should take the following aspects into consideration:

- the general capabilities of user infrastructure (mobile devices);
- the middleware that provides a uniform and easy-to-use interface while hiding the underlying network’s details from the application;
- the network infrastructure that plays an important role because the user perceived service quality primarily depends on network resources and capabilities.

The framework also provides a developer-provider plan, which addresses the different needs and views of application developers, content providers and service providers.

PERSONALIZATION

Work on personalization is reported for e-business applications [Dogac and Tumer, 2002; Zhang, 2003; Toth, K. and S. R. Nagboth, 2003;Ozen et al., 2004]. Specifically, Zhang [2003] proposes a generic framework for delivering personalized and adaptive content to mobile users, which can also be applied to mobile commerce applications. Based on his framework, we define “personalization in m-commerce” as:

> *use of the mobile technologies and user, context, and content information to provide personalized products/services so as to meet the specific needs of the individuals.*

Individuals include both customers and merchants. Personalization covers two aspects:

1. From the customer point of view, it is designed to help them find the relevant services/products.
2. From the merchants’ perspective, it helps them identify potential customers, and then to provide the customers with customized services/products to improve the merchants’ business.

In essence, the personalization is a matching process between customers and merchants, based on their profiles and preferences, in conjunction with a changing environment including context factors such as time, location, and weather. The matching process requires effective representations of the relationships among types of information and the inferring abilities based on the representations.

V. A BAYESIAN NETWORK-BASED FRAMEWORK

OVERALL DESCRIPTION

Personalization in e-commerce is mainly meant to draw inferences about users’ preferences and activities (Section IV). However, in m-commerce, time and location factors, a kind of context information, are also important in personalization. Based on the analysis and information infrastructure for personalization presented by Instone [2000], and inspired by ideas in the frameworks proposed by Varshney and Zhang [Varshney et al., 2000; Varshney and Vetter, 2002; Zhang, 2003], a personalization framework for m-commerce is proposed in this paper. The framework provides a way to enable personalization with the following functionalities:

1. to create a personalization model that presents and integrates three kinds of information and their relationships: user information (e.g., user demographic profiles and preferences), context information (e.g., time, weather, location), and content information;
2. to provide inferencing ability for the personalization based on the different kinds of information and their relationships.

As shown in Figure 2, the proposed framework includes three layers,

1. the sources collection layer,
2. the relationship presentation layer, and
3. the inference layer.

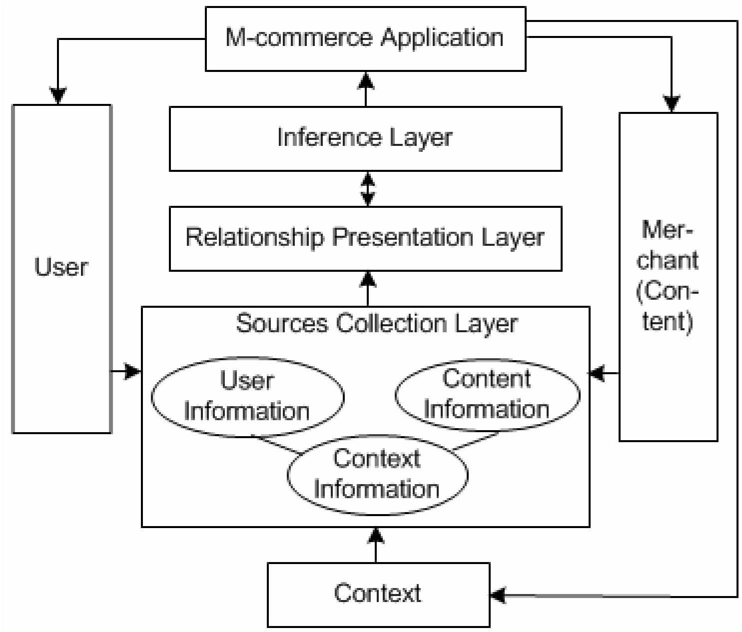

Figure 2. A Framework for Personalization in M-Commerce

In the relationship presentation layer, a personalization model is created to present the relationships among user information, context information, and content information in a format of qualitative and quantitative knowledge. More concretely, qualitative relationships are graphical representations of the dependencies between the information, while quantitative relationships determine how they depend on each other. In the inference layer, users and content are matched based on the relationships. For example, given a product promotion, the inference layer determines which user(s) should be selected and enables a merchant to send the matching services for a particular given user.

The proposed framework focuses on personalization modeling, and corresponds to the “mobile commerce applications” level presented in Varshney’s work [Varshney et al., 2000]. As mentioned in Varshney [2003b], personalization modeling will make m-commerce applications a reality when combined with such technologies as wireless networks, middleware, and mobile devices.

SOURCES COLLECTION LAYER

In this layer, several kinds of information such as user information (user demographic profiles and preference), context, and content information are collected and integrated into a central database, which prepares information for the construction of the personalization model.

Data Collection

From the data collection point of view, the following aspects are emphasized:

1. User demographic attributes such as income range, ethnicity, work experience, and education level are considered to be important because they represent the natural categories of customers [SBDC, 2002].
2. User preference, which is the user’s tendency toward selecting certain alternatives among others [Sun, 2003]. A survey by Londoneats [2004] showed that cuisine, recommendation, price, ambience, service, and location, in descending order, are the

most important factors to consumers in choosing a restaurant. Therefore, in the proposed model, cuisine preference, ambience, service, and price are included in the user preferences, and location is treated as a context factor.

3. The term ‘context’ can be defined as “any information that characterizes a situation related to the interaction between users, applications, and the surrounding environment” [Dey and Abowd, 2001]. Its use in mobile applications is receiving increasing attention [Gellersen et al., 2002]. Typical mobile context-aware applications are personal tour guide and mobile conference information systems. M-commerce is also unique in its context-aware capability compared with e-commerce. One of the difficulties of using context in mobile applications is that there is no common way to acquire and handle context [Zhang, 2003]. In the proposed framework, we only use simple and basic context information including time, user location, merchant location, weather, and simple activities.
4. Content information includes the product/service description, merchant brand, and promotion messages.

CONTEXT

User demographic profiles and user preferences are often obtained through web-based user interfaces and they are relatively stable. Content information is mainly uploaded by merchants through web-based merchant interfaces or collected by mobile agents from merchants’ websites. A piece of software called OceanSpray can help to obtain desired information from the website [OceanSpray, 2003]. Context information such as location and activity information can be obtained as follows:

1. The location information is collected by two major location positioning technologies, Global Positioning System (GPS) and Mobile Positioning System (MPS). These technologies differ in precision and actually supplement one another [Varshney,2001; Djuknic and Richton, 2001; Hightower and Borriello, 2001;Tarasewich et al., 2002; Barnes, 2002]. A detailed discussion of location management of various m-commerce applications can be found in Varshney [2003a]. In particular, GPS plays a large role in wireless communications. However, it does not work well indoors because it requires line-of-sight transmission between devices and satellites [Varshney, 2003a]. In our proposed framework, both GPS and MPS are used to provide user and merchant location information.

2. User activity information is more complex. In this research, we only consider simple activities. For example, in the food industry scenario, the activity status of a mobile user is either “free” or “busy”. The following process can be used to determine status.

   - From the user’s historical data, useful knowledge can be mined to provide the information about the user’s activities. For example, if time is about noon on a working day, a university staff member has no class or meeting at that time and he or she is on the university campus, then he/she is likely “free”. We may then link the user’s current location, the current time and his/her calendar information together to predict the user’s current activity based on the knowledge/ rules generated from the user’s historical data of activity. In our framework, a Bayesian network is used to mine the knowledge about the user’s activities since it is a promising technique to make predictions even if data are incomplete or inaccurate.

Thus, relevant information comes from different sources and usually in different formats. Therefore, it is necessary to represent the information in a unified format for further analysis. In modeling user and content information, attributes with numerical value are represented with an interval. For example, the value of Years of experience will be represented with intervals [2, 3], [3, 5]. This kind of attribute also includes Income and Budget. For attributes with discrete value, predefined discrete values are used to represent them (e.g., “male” and “female”). Education, Ambience, Brand, and Promotion attributes belong to this class. Discrete values are also used to represent the values of context information, for example, “hour” to represent a time, “busy” and “free” to represent an activity, and “sunny,” “rainy,” or “cloudy” to represent weather information. For location information, absolute coordinates are transformed into a relative distance description, such as “10KM,” “far,” or “near.”

Using these representation methods, all three types of information are represented by attribute-value pairs. In our framework, a relational database is used to store all the relevant information.

RELATIONSHIP PRESENTATION LAYER

A personalization model is constructed in this layer. That is, the model represents both qualitatively and quantitatively the relationships among the required information for personalization in m-commerce. The resulting model is the core of the whole framework.

Because of uncertainties in information and their relationships, and the information collected is often incomplete or even inaccurate. Therefore, model construction requires a tool that is capable of handling uncertain and incomplete data sets. We believe BN is a promising technique and thus was chosen to construct the personalization model. The following subsection describes the new construction method proposed in this paper.

Construction Method

A set of observations from the sources collection process that are considered relevant to the personalization of an m-commerce application are selected. The selected observations are organized into variables with mutually exclusive and collective states to construct a BN-based personalization model. Some guidance of the BN’s construction is given by decision analysts such as Howard and Matheson[1983]and statisticians such as Tukey [1977]. Based on their work, the tasks of a BN construction can be divided into the following two major steps [Heckerman, 1995]:

> Step 1. Build the network structure representing the relevant information, i.e., build a directed acyclic graph that encodes assertions of conditional independences.
>
> Step 2. Assess the local probability distributions (prior probabilities).

These two steps correspond to the relationship presentation layer of the proposed framework.

Step 1 is the most crucial step in using BNs to construct a personalization model. The proposed method is an extension of the method proposed by Liu and Song [2003]. Since function dependency is one of the most important data dependencies in a relational database, and it can be generally obtained from semantics among data. While it can sometimes be difficult to identify the dependencies between data solely from their semantics, data mining techniques (which can be used to mine interesting but previously unknown knowledge from data) provide an efficient way to solve the problem. Among many data mining techniques, rough set theory demonstrates a strong ability in data dependency analysis in real applications [Pawlak et al., 1995]. It is used to discover function dependencies from data in our framework. The function dependency contains conditional independence information that can be used to construct the structure of a BN. Compared with the existing BN structure learning method, our method is based on the solid foundation of a relational database. It is also more efficient since most function dependencies can be extracted from the corresponding Entity-Relationship (ER) diagrams. In the existing methods, the structure of a BN is constructed by performing complex calculations on an existing data set, which may lead to two problems:

1. In real applications, it is usually difficult to find sufficient data sets to construct the structure, and data are usually inaccurate.

2. This kind of calculation is usually time consuming. Our method is therefore a more suitable approach for m-commerce applications where it is difficult to collect a large amount of accurate data and the response speed is crucial. The three main processes of our method are:

Process 1. Identify Function Dependencies From Relational Data

For a given relational database, extract function dependencies from the corresponding ER diagrams. This extraction requires the participation of human experts who should be able to identify most function dependencies that are semantically “obvious”.

Use rough set theory to identify any possible missing function dependencies from the data. In rough set theory [Pawlak, 1991], a knowledge base is denoted as K=(U,R).

- U is a finite non-empty set, and elements of U are called objects.
- R is an equivalence relation over U.
- U/R refers to the family of all equivalence classes of R.

If P,Q $\subseteq$ R and P,Q $\neq \Phi$, the P-positive region of Q, denoted as POSP(Q), is the set of all objects of the universe U that can be properly classified to classes of U/Q employing knowledge expressed by the classification U/P. If the set POSP(Q) is equal to U, then we say that Q depends on P, and can be written P→Q.

The following example further explains the ideas in Process 1:

Suppose U={x1,x2,x3}, a group of mobile users in U are of different ages (young, old, middle), and different years of experience (short, long). Hence, U can be classified by age and years of experience. Assume users x1 and x2 are young , and with short years of experience, and user x3 is different from x1,x2 in age and years of experience. By the classification, two equivalence relations can be defined, namely, P and Q, having the following equivalence classes:

U/P = {{x1.x2},{x3}}, U/Q={{x1,x2},{x3}}

according to the above definition, POSP(Q)={x1,x2,x3}=U, which leads to a function dependency: years of experience depends on age.

Thus, Process 1, allows calculating the function dependency between P and Q by calculating POSP(Q).

Process 2. Construction of a BN Structure

The BN structure construction method is used to create one part of the personalization model, i.e., representing the qualitative relationships among the information.

Let R(U+P) be a probabilistic relational scheme, where U=A1,A2,…,An, P is a probabilistic attribute representing the joint probabilistic distribution of the tuple. According to the order (A1,A2,…,An), the following chain formula can be generated:

P(A1,A2,…,An)=P(A1)P(A2/A1)……P(An/A1,A2,…,An-1) (1).

Let S1=P(A1), S2= P(A2/A1),…,Sn= P(An/A1,A2,…,An-1).

Based on function dependencies obtained from Process 1, we can identify a set of minimal function dependencies F, for each Sk in Equation 1. If there exists F|= Xk→ •→ Ak, and Xk is a minimal set of (A1,A2,…,Ak-1), then we substitute Sk(k>2) denoted as p(Ak/A1A2…Ak-1) with p(Ak/Xk). Finally, a new chain formula is generated by this process and it can be used to construct the structure of a BN.

Process 3. Calculation of Prior Probabilities

After constructing the structure of a BN, we calculate the prior probabilities from the data. That is, we create the other part of the personalization model to represent the quantitative relationships among the information. Given that the data are already decomposed into 3rd Normal Form, the prior probabilities can be generated from the following process:

Given a set of instances r1,r2,…,rn, which are in 3rd Normal Form and the results obtained from Equation (1),

1. extract a set of probabilistic multi-valued dependency (PMVDs) from F;
2. for each factor in the chain formula, examine the schemas of the database and then select those whose union includes all attributes of the factor;
3. construct a decomposition tree in accordance with the PMVDs on the selected schemes;
4. join ri (i=1,2,…,m) according to an increasing order of the decompositions tree; take the node data that are needed to construct the BN from every join of instances.

INFERENCE LAYER

The task of this layer is to provide inferences based on the personalization model, i.e., to calculate the posterior probability. To accelerate the reasoning process, a widely adopted Bayesian software tool, a free Hugin Lite 6.4 [Hugin Expert A/S, 2004], was used to calculate the Bayesian network for our example.

The application in this research belongs to mobile advertising category. The detailed timing requirements of various m-commerce applications are discussed in Varshney [2001]. For mobile advertising, the timing requirements for location precision, response time and type of communications are: hundreds of meters, minutes, and asymmetric non real-time multicast, respectively. Therefore, the proposed framework provides personalization service within a few minutes after a request is received by capturing the location and activity information within a reasonable time interval. For location information, we only need approximate location information such as the distance between the user and the merchant. For activity information, we are only concerned about simple user activities such as whether they are “free” or “busy”.

VI. FRAMEWORK IMPLEMENTATION IN CONTEXT OF AN M-COMMERCE APPLICATION

To validate our proposed BN-based framework, we “implemented” it conceptually in the context of an m-commerce application. The application’s architecture is shown in Figure 3. The application consists of three layers: User Interface, Middleware, and Data Service. The User Interface Layer includes both a mobile phone interface and a web interface. The Data Service Layer includes a database storing customers’ and merchants’ data. The Middleware Layer, equipped with Java Servlets, Java Beans, and the BN-based framework, is the core component of the system. It processes and implements the business logic of the system.

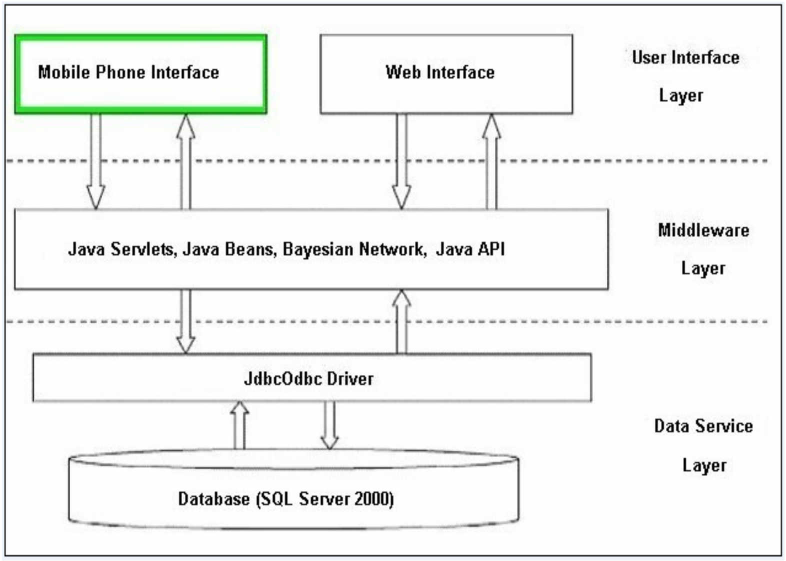

Figure 3. Mobile Application's Architecture

In the first stage of the implementation, we use survey methodology to gather user information such as demographics and preferences. We randomly select, say, 400 MBA, IMBA, and EMBA students (who come from various industries with E-Commerce or M-Commerce experience) from a Hong Kong-based university as the sample to conduct the survey. The user data collected are then imported into the database in the Data Service layer.

Upon receiving user requests from the Interface layer, the application tries to query the necessary information in the Data Service layer. If the needed information is not in place, the application collects data from various sources. For example:

- the distance is calculated by the location information (customer's and merchant's locations) specified by GPS or MPS,
- the time is provided by the computer system,
- the weather is obtained from the weather bureau website, and
- the information about the restaurant is either from the content model or the merchant's interfaces.

Similarly, the user information can also be obtained from the user interfaces. After the data collection is finished and the data is processed, a personalization model is created and populated with the support of the model construction method. The model enables the system to provide personalized services, i.e., to predict the target mobile users for a given m-coupon or to find a matched m-coupon for a given mobile user. The prediction is done through its reasoning capability, i.e., calculating the probability of the most matched m-coupons or mobile users. The personalization model is implemented in the Hugin software. The personalization information results are displayed through the User Interface.

VII. A SAMPLE DESIGN OF THE PERSONALIZATION MODEL

This section illustrates the steps described in Section V and demonstrates how to apply them to construct a personalization model in our proposed framework. The example is based on the m-coupon application.

SAMPLE PREPARATION DESCRIPTION

From the E-R diagrams of the m-coupon application, a set of function dependencies (FDs) were identified and denoted as:

F'={Education, Years of experience→Income
Brand,Time→Promotion;
Income, Education→Ambience;
Ethnicity→Cuisine;
Time→Activity;
Income, Cuisine,Ambience→Budget;
Time→userLocation;
Budget, Ambience,Cuisine→Brand;
Budget,Activity,Brand→Interest},

Another set of function dependencies, denoted as F''={mercLocation, Time→Weather; Brand→mercLocation}, was mined from data sets using the rough set operations (Process 1, step 1, Section V). Note that it is difficult to identify the second set of dependencies if the information is solely based on semantics. The minimal functional dependencies denoted as F can be identified from F' and F''.

In addition, several 3rd Normal Form tables were created. For example,

R1={Education Years of experience Income},	R2={Brand Time Promotion},
R3={Income Education Ambience},	R4={Ethnicity Cuisine},
R5={Time Activity},	R6={Income Cuisine Ambience Budget},
R7={mercLocation Time Weather},	R8={Brand mercLocation},
R9={Time userLocation},	R10={Budget Ambience Cuisine Brand},
R11={Education Years of experience Time Ethnicity},	R12={Budget Activity Brand Interest}.

Some sample instances are given as shown in Table 1, where Edu, Wo, Inc, Amb, Eth, Cui, and Bud stand for Education, Years of experience, Income, Ambience, Ethnicity, Cuisine, and Budget, respectively.

LEARNING QUALITATIVE RELATIONSHIPS

A partial joint distribution is used in this subsection to illustrate the construction method concretely.

Given a joint distribution p(Eth1 Edu1 Wo1 Inc1 Amb1 Cui1 Bud1) with an order: (Eth,Edu,Wo,Inc,Amb,Cui,Bud), (where Eth1=Chinese,

Table 1. Some Sample Instances of the Tables in the M-Coupon, M-Commerce Application

r1			
Edu	Wo	Inc	P
MBA	3-5	1-2	0.1
EMBA	2-3	2-3	0.1
…	…	…	…

r3			
Inc	Edu	Amb	P
1-2	MBA	General	0.1
2-3	EMBA	Good	0.1
…	…	…	…

r4		
Eth	Cui	P
Chinese	Fast food	0.1
American	Western	0.1
…	…	…

r6				
Inc	Cui	Amb	Bud	P
1-2	Fast food	General	50-100	0.1
2-3	Western	Good	200-300	0.1
…	…	…	…	…

r11				
Edu	Wo	Time	Eth	P
MBA	3-5	12:00	Chinese	0.1
EMBA	2-3	12:00	American	0.1
…	…	…	…	…

LEARNING QUALITATIVE RELATIONSHIPS

Edu1=EMBA, Wo1=2-3 year, Inc1=2-3 ten thousand$, Amb1=good, Cui1=Western, Bud1=200-300 $), the following chain formula is worked out:

P(Eth1 Edu1 Wo1 Inc1 Amb1 Cui1 Bud1) =P(Eth1)P(Edu1/Eth1)P(Wo1/Eth1 Edu1)P(Inc1/Eth1 Edu1 Wo1)P(Amb1/ Eth1 Edu1 Wo1 Inc1)P(Cui1/Eth1 Edu1 Wo1 Inc1 Amb1) P(Bud1/Eth1 Edu1 Wo1 Inc1 Amb1 Cui1).

Since F|= Edu Wo→ •→ Inc, as indicated by step 1 of the construction method, P(Inc1/Eth1 Edu1 Wo1) can be simplified to P(Inc1/ Edu1 Wo1). The same process is done for F|= Edu Inc→ •→ Amb; Eth→ •→ Cui; Inc Cui Amb→ •→ Bud.

Finally, a new chain formula,

P(Eth1 Edu1 Wo1 Inc1 Amb1 Cui1 Bud1) = P(Eth1)P(Edu1/Eth1)P(Wo1/Eth1 Edu1)P(Inc1/Edu1 Wo1)P(Amb1/Eth1 Inc1)P(Cui1/Eth1) P(Bud1/Inc1Cui1 Amb1),

will be generated and the structure of the corresponding BN will be as shown in Figure 4.

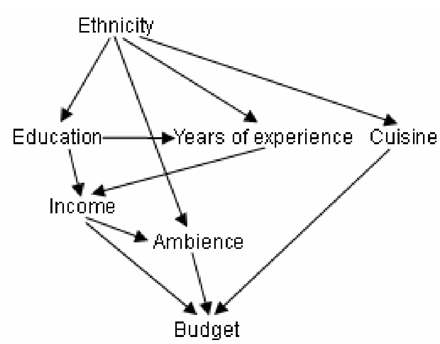

Figure 4. Partial BN Structure Constructed with Step 1

Figure 4 shows the relationships between user demographic attributes and user preferences. Similarly, the complete BN structure representing the relationships between user profiles, context, and content information can be built in the same way as shown in Figure 5.

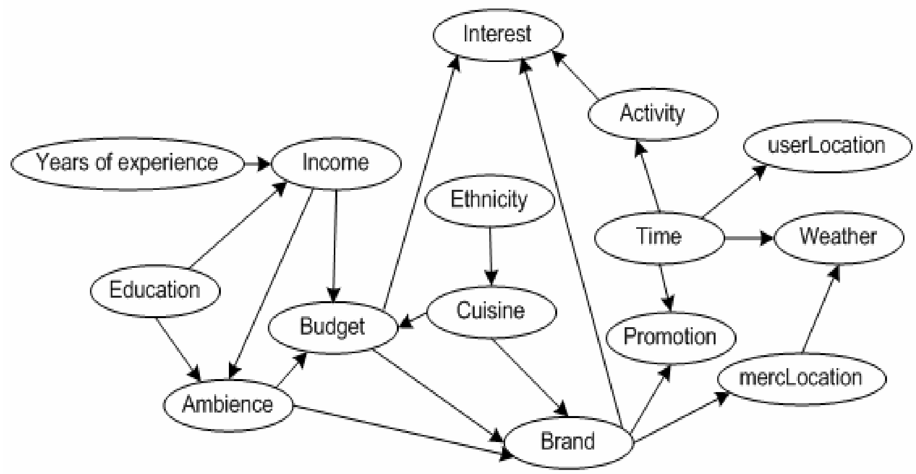

Figure 5. Complete Bayesian Structure Constructed with Step 1

It can be seen that the demographic data, user preferences, context information (such as time, weather, user location, merchant location) and content (product/service) information significantly influence the Interest status that determines whether a lunch coupon should be sent or not. For example, Years of experience and Education are the direct causes of Income, while Budget, Activity, and Brand directly impact Interest Status. With marketing research [Turban et al., 2000], it can be used to validate the correctness of the structure in Figure 5.

LEARNING QUANTITATIVE RELATIONSHIPS

A set of probabilistic multi-valued dependencies are implied by Function Dependencies such as:

Education, Years of experience→•→Income;
Brand,Time→•→Promotion;
Income, Education→•→Ambience;
Ethnicity→•→Cuisine;
Time→•→Activity;
Income, Cuisine,Ambience→•→Budget;
mercLocation,Time→•→Weather;
Brand→• →mercLocation;
Time→•→userLocation;
Budget,Ambience, Cuisine→•→ Brand;
Budget,Activity,Brand→•→Interest

Since R1∪R3∪R4∪R6∪R11={Eth Edu Wo Inc Amb Cui Bud Time}⊇{Eth Edu Wo Inc Amb Cui Bud}, only instances r1,r3,r4,r6,r11 then need to be considered. For P(Inc/Edu Wo), it can be found that R1 covers all of the attributes in it, namely, Inc, Edu, Wo. This searching process can be applied to finding each union including all attributes in the other chain factors. According to the probabilistic multi-valued dependencies, the decomposition tree shown in Figure 6 is constructed.

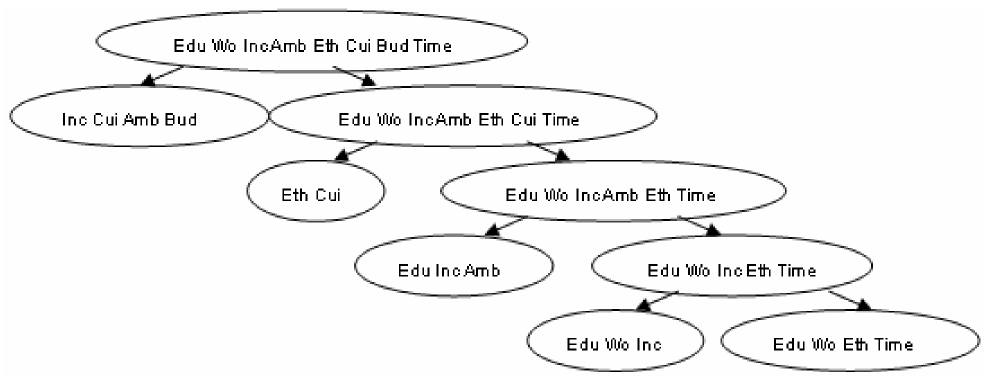

Figure 6. Decomposition Tree Constructed with Step 2

Based on the above process, the prior probabilities are worked out as:

From r4 and r11:
P(Eth1)=0.1, P(Edu1/Eth1)=P(Edu1 Eth1)/P(Eth1)=0.1/0.1=1,
P(Wo1/Eth1 Edu1)=1;
From r1:
P(Inc1/Edu1 Wo1)=1;
From (r11⊗r1) ⊗r3:
P(Amb1/Eth1 Inc1)=P(Amb1 Eth1 Inc1)/P(Eth1 Inc1)=1;
From r4 and r6:
P(Cui1/Eth1)=1; P(Bud1/Inc1Cui1 Amb1)=1.
Finally, P(Eth1 Edu1 Wo1 Inc1 Amb1 Cui1 Bud1)=0.1

INFERENCE BASED ON RELATIONSHIPS UNDER THE FRAMEWORK

By constructing the BN structure and its prior probabilities, we obtain both qualitative and quantitative representations of the relationships for the personalization model. Based on the framework, Hugin software is used in the next step to predict the correct mobile users for the lunch coupon, i.e., the model provides personalization services for CFC's marketing activities.

The prediction is made by calculating the posterior probability information for the given evidence, and using the result to support the personalization process. More concretely, what we are concerned with is the probability of Interest for the given observations of the other information. Consider P(Interest│Activity, Time,Promo, userLocation, Inc), denoted as p3, as an example. By Bayesian's reasoning, p3 can be computed as follows:

p3=p1/p2=P(Interest,Activity,Time,Promo,userLocation,Inc)/P(Activity,Time,Promo,userLocation,Inc)

where Activity, Time, Promo, userLocation, and Inc partly represent the context, content, and user information, and p1 and p2 can be calculated based on step 1 and step 2 of our method, respectively.

At the end, p3 can be used to make a prediction, i.e., users with high probability of being interested are regarded as the target users and the content information (an m-coupon) should be sent only to them.

INFERENCE RESULTS FOR THE M-COUPON APPLICATION

In the food industry, before the system is operational, both merchants and their mobile users must register, i.e., the user's profiles and preferences and the merchants' demographic data must already be collected. Once that is accomplished, the following is assumed: the time is noon, the user's location is near the CFC, e.g., he/she is within 1 kilometer of CFC, he/she is not busy with work, and CFC is promoting its newly created Western style lunch set meal.

Suppose CFC tries to identify the potential target users with support of the system. The system will generate a customers list, sorted in a descending order of probability indicating how likely the customers are interested in CFC's products/services. Based on the list, CFC can use a "push" method to send promotion messages to the potential customers more selectively. Figure 7 shows the top three user choices sorted by probability in a descending order. If the interest probability of a user exceeds CFC's threshold setting (e.g., 50.1%), the system signals "send," and the corresponding user (e.g., Xu Jing) together with other users with a higher probability (e.g.,Somic Wang, Anna Wu) are sent promotion information about CFC. If the recipient uses the coupon before the expiration date, the system will consider this case as a positive adaptation, otherwise a negative adaptation. Consequently, the system will learn from these experiences and update the personalization model for future calculations. Obviously, the more cases of positive adaptation, the more accurate the personalization model.

	Customer	Gender	Age	Education	Monthly Income	Match Ratio
1	Anna Wu	Female	16-30	Secondary	Below10000	65.5%
2	Somic Wang	Male	>30	Bachelor	10000-30000	52.4%
3	Xu Jing	Female	16-30	MasterAbove	Above30000	50.1%

F

igure 7. Merchant CFC Requesting Results

Conversely, Mobile users can use our model to ask mobile devices to identify which restaurants are nearby that best fit their profiles. For example, Somic Wang wants to find an appropriate restaurant for his lunch. After sending his request using his mobile phone, the system will send him the restaurant lists shown in Figure 8. Pizza Hut, CFC, and McDonald's turn out to be good choices for him.

Figure 8. User Somic Wang's Search Results

VIII. CONCLUSIONS

This paper presents a BN-based personalization framework and describes its implementation in the context of an m-commerce application in the food industry.

Although Bayesian networks were employed previously for user modeling [Zukerman, 2001; Jameson, 1995], recommendation-based systems [Jennings, 1992], adaptive information retrieval systems [Brajnik et al., 1990], and student modeling [Kay, 1995 and Elson-Cook, 1993] for studying personalization, are reported in the literature, the methods for learning the network from function dependency and 3rd Normal Form tables were rarely used in this context. Furthermore, few existing m-commerce applications employ a user model to support personalization.

Our proposed framework provides a way to integrate and present the various kinds of information and their relationships in the personalization process for an m-commerce application. It offers a means of handling uncertain and incomplete information, and provides a graphical representation for relationships among the three important kinds of information for m-commerce: user, context, and content.

In the proposed framework, we present a new method for constructing a BN. This method enables constructing the structure of a BN from functional dependencies and calculating the prior probabilistic from 3rd Normal Form tables. It also uses data mining on functional dependencies using rough set operations. The method fits the practical requirements of real applications in m-commerce as well as making a theoretical contribution.

We believe that the framework proposed in this paper can be applied to other industries such as movies, CDs, books, hotel booking, flight booking, and all manner of shopping settings.

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