Bayesian Metanetworks for Modelling User Preferences in Mobile Environment

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Abstract. The problem of profiling and filtering is important particularly for mobile information systems where wireless network traffic and mobile terminal's size are limited comparing to the Internet access from the PC. Dealing with uncertainty in this area is crucial and many researchers apply various probabilistic models. The main challenge of this paper is the multilevel probabilistic model (the Bayesian Metanetwork), which is an extension of traditional Bayesian networks. The extra level(s) in the Metanetwork is used to select the appropriate substructure from the basic network level based on contextual features from user's profile (e.g. user's location). Two models of the Metanetwork are considered: C-Metanetwork for managing conditional dependencies and R-Metanetwork for modelling feature selection. The Bayesian Metanetwork is considered as a useful tool to present the second order uncertainty and therefore to predict mobile user's preferences.

1 Introduction

Filtering the Web content is an emerging problem at the age of information overload. Delivering relevant information to a particular user is one of the key tasks in many information systems. The promising application area for the development of new filtering techniques is mobile information systems. The small secure mobile terminal is rapidly evolving into the Personal Trusted Device [20], which allows users to access mobile Internet services and run applications at any time and any place. Advances in wireless network technology and continuously increasing number of users of mobile terminals make the latter a possible channel for offering personalised services to mobile users and give space to the rapid development of the Mobile Electronic Commerce (m-commerce). As a result, the huge market for user profiling is open in the mobile communication environment.

Information filtering is the task of splitting a large-volume data stream into substreams according to some selection criterion [14]. Selection for a substream is based on criteria describing its profile, which might be "an interest to a given

user" or "a relation to a certain topic". The profile usually consists of a set of representative items, filter rules or description of the content of the stream in terms of items features. Whenever information is being filtered for a user, exploiting user's profile is important.

We consider profiling just as a data mining process for efficient and automated construction of the presentation of user's filtering preferences. Profiles are used to target the audience of particular products. Personal information that user provides on registration, his behaviour and history are combined to create user's personal profile. The profile is then used to target certain products or services for this user. XML-based and emerging Semantic Web technologies allow to present data in such a way that both the content and semantics of it including context descriptions are presented. Additionally, attributes allow us to provide metadata regarding that context.

Many filtering techniques have been developed in the last years. Generally filtering methods are divided into two main classes - content-based and collaborative filtering. In modern adaptive systems content-based and collaborative filtering are combined [6], [8].

Each filtering task has a set of variables (predictive attributes) that influence in some way the choice or the preference (target attribute) of a customer. It is evident that one cannot avoid dealing with uncertainty when predicting user's preferences. A Bayesian network has proved to be a valuable tool for encoding, learning and reasoning about probabilistic (casual) relationships. The Bayesian network for a set of variables $X = X_i, \ldots, X_n$ is a directed acyclic graph with the network structure S that encodes a set of conditional independence assertions about variables in X, and the set P of local probability distributions associated with each variable [10]. Bayesian networks as well as other probabilistic techniques are widely used for prediction of user's preferences. Once learned, the Bayesian network can support probabilistic inference including prediction of user's preferences.

The foundation for the use of Bayesian networks and Markov models for user profiling in the information retrieval was given by Wong and Butz in [23]. They implemented an idea of using probabilistic mixture models as a flexible framework for modelling user's preferences. In Cadez et al. [4] an application of probabilistic mixture models was studied for representing an individual's behaviour as a linear combination of his transactions. The works [2], [11] on probabilistic model-based collaborative filtering introduce a graphical model for probabilistic relationships - an alternative to the Bayesian network - called the dependency network. Kuenzer et al. [13] presented the empirical study of dynamic Bayesian Networks for user modelling. They evaluate six topologies of the dynamic BN for predicting the future user's behaviour: Markov Chain of order I, Hidden Markov Model (HMM), autoregressive HMM, factorial HMM, simple hierarchical HMM, and tree structured HMM. Hoffman [12] proposed an aspect model - a latent class statistical mixture models, and Popeskul et al. extended the aspect model to a three-way aspect model to incorporate three-way co-occurrence data among users, items and item content.

In [3] Butz exploited contextual independencies (see also Boutiler et al. [1]) for user profiling based on assumption that while conditional independence must exist in all contexts, a contextual independence need only exist in one particular context. He shows how contextual independencies can be modelled using multiple Bayesian networks.

A recursive Bayesian multinet was introduced by Pena et al. [15] as a decision tree with component Bayesian networks at the leaves and was applied to a geographical data-clustering problem. The key idea was to decompose the learning Bayesian network problem into learning component networks from incomplete data.

As our main goal in this paper, we are presenting another view to the Bayesian "multinets" towards making them to be really "metanetworks", i.e. by assuming that interoperability between component Bayesian networks can be also modelled by another Bayesian network. Such models suit well to user profiling applications where different probabilistic interrelations within predictive features from user's profile can be controlled by probabilistic interrelations among the contextual features.

As a new market for user profiling has appeared in the mobile communication systems, probabilistic models for modelling of user's preferences should take into account all the features of profiling in the mobile Internet.

Thus another goal of this work was to consider the use of sophisticated probabilistic networks in the context of prediction of user's preferences in mobile environment taking into account special features and constraints of mobile environment.

The rest of the paper is organised as follows. In Sect. 2 we first provide some features of the mobile information environment as an application area for advanced probabilistic modelling. In Sect. 3 we introduce the Bayesian Metanetwork to deal with modelling user's preferences in mobile environment. There we also provide two models of the Metanetwork. We conclude in Sect. 4.

2 Features and Constrains of Mobile Environment

Advances in wireless network technology and continuously increasing number of users of hand-held terminals make such Personal Trusted Devices (PTD) [20] a possible channel for offering personalised services to mobile users, and enables the rapid development of the mobile electronic commerce (m-commerce). The emergence of five different types of m-commerce can be identified: banking, Internet e-commerce over wireless access networks, location-based services, ticketing applications, and retail shopping [21]. The public commerce (p-commerce) in the mobile environment was introduced in [19]. P-commerce operates partially in a different environment than the traditional e-commerce due to the special characteristics and constraints of the terminals and wireless networks and due to the different context and circumstances where people use their PTDs. As a result the huge market for user profiling is open in mobile communication environment. The problem of profiling and filtering is urgent particularly for the

mobile information systems where wireless network traffic and terminal space are limited comparing to the Internet access from the PC.

The mobile environment imposes the set of constraints and requirements on a filtering technique, among which there are:

- restrictions on computational resources of a portable device;
- restrictions on time of a connection and amount of data transferred (a customer pays for every additional second or byte of information during a connection);
- limitations on size of a mobile terminal.

One of the most distinguishing features of mobile environment is *mobility*. The evaluation of mobility lies in satisfying the needs of immediacy and location [22]. The mobile network infrastructure is able now to determine the position of the terminal precisely enough. This gives the basis for the new class of services called the Location Based Services (LBS) [5]. If a user wants to go to the theatre, for example, he should be able to use the LBS to find a nearby show, to book a reservation, to get navigational directions to an event, to receive relevant traffic information and to use micro-payments to pay for all this [17].

Combining positional mechanisms with information about location of various objects can develop very powerful and flexible personal information services [16]. Suppose there is some geographical area that contains a certain number of objects (points of interests [9]). Each point of interest is assumed to have its virtual representation or, rather, a source of relevant information. A user of this information is expected to be mobile. The aim of the location-aware service is providing the user with information about the objects taking into account spatial relationships between him and the objects. One of the main input parameters is user's location. It is obvious that the system should have information about all objects with their spatial location and links to their information sources. If the system has this information, it is able to find the near objects. Note that for mobile objects the system has to update periodically the location information via the location service or to request it directly from the objects. The first could be done automatically if we have an access to the location service. In the second case, the user can input his location by himself, for instance the street address or the name of the region. After that, the service is able to provide a geographical description of his surroundings. These data act an auxiliary role of a navigator or a guide in order to connect real objects with their virtual representations. The next client's function is providing customers with the information from the sources associated with surrounding objects. The user can either directly receive the information from the chosen object or charge the server to find the needed information. In the last case, the server performs the whole work: it analyses information sources according to user's directives and sends the results of his query to him [24].

The attribute "location of mobile user" is constantly changing its values. We hardly can say that such an attribute is "predictive" in the full meaning of the word, although it has an influence on user's choice. Better to say that this is a "contextual" attribute. Location, among other highly dynamic attributes such

as e.g. time, forms a context in which a mobile customer makes his decisions. Filtering and profiling techniques for mobile environment should be specified to take into account the difference between predictive and contextual attributes. Thus we should require from our model to process separately predictive and contextual variables in order to improve performance of modelling and prediction tools for mobile information systems.

Taking into account the specifics of a mobile environment we suggest to distinguish several classes of attributes. Usually, when constructing the Bayesian network, every attribute is treated in a similar way. The typical task in learning Bayesian networks from data is model selection [10]. The set of models-candidates is evaluated according to some criterion that measures the degree to which the network structure fits the prior knowledge and data. Then the best structure (model) is selected or several good structures are processed in model averaging. Each attribute in ordinary Bayesian network has the same status, so they are just combined in possible models-candidates to encode possible conditional dependencies.

We propose the following classes and their inclusions into probabilistic model for modelling user's preferences:

Class 1. Target attributes. Possible members: best offering, type of goods, relevant information, user's cluster (user group to which he belongs), user's next transaction, etc. Characteristics: ordinary target nodes of the Bayesian network.

Class 2. Predictive attributes. Possible members: personal data about user (age, occupation, gender, etc.), observations of user's behavior (what he/she has bought before). Characteristics: ordinary nodes of the Bayesian network, which can form some structure according to casual dependencies among them. We call them "predictive" because of task definition - prediction of user's desires.

Class 3. Contextual attributes. Possible members: user's current location, time, weather, current user's mood, etc. Mobile user's coordinates together with the knowledge of the surrounding area can produce several location variables (e.g. distance to the nearest hotel, settlement scale - city, town or village, etc.). Depending on user's location different sets of predictive attributes will form user's preference. Characteristics: these attributes are conditionally independent of predictive attributes. They influence the dependencies in the predictive model, influence relevance of predictive attributes. But the knowledge of the state of variables at the predictive level doesn't have impact on the belief of the contextual variables. Contextual attributes can be dependent of other contextual variables.

Class 4. Metacontextual attributes. Possible members: parameters that define weakness or strength of some casual relationships between predictive and target attributes, relevance of location or time variables, etc. Characteristics: these attributes are independent of predictive and contextual attributes. They influence the conditional dependencies in the contextual model or influence relevances of contextual attributes.

Conceptual model of the domain should be build after the domain analysis is done and available variables are classified as target, predictive, contextual or even

metacontextual. There might be a situation, when some attributes belong to the predictive class in one case (one context) and to the contextual class in another case (another context). The parameters, which define the class membership, can be classified as metacontextual attributes.

3 The Bayesian Metanetwork and its Modifications

We define the Bayesian Metanetwork implementing the basic intuition we had while defining a Semantic Metanetwork few years ago. The Semantic Metanetwork [17], [18] was defined as a set of semantic networks, which are put on each other in such a way that the links of every previous semantic network are at the same time the nodes of the next network. In the Semantic Metanetwork every higher level controls the semantic structure of the lower level. Controlling rule might be, for example, as such: in what contexts certain link of the semantic structure can exist and in what context it should be deleted from the semantic structure.

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

The Bayesian Metanetwork is a triplet:

$$MBN = (BN, R, P), \tag{1}$$

where $BN = \{BN_1, BN_2, \ldots BN_n\}$ is a set of Bayesian networks representing a set of levels; $R = \{R_{1,2}, R_{2,3}, \ldots R_{n-1,n}\}$ is a set of sets of interlevel links; P is a joint probability distribution over the Metanetwork.

Each $R_{i,i+1}$ is a set of interlevel links between i and $i+1$ levels. We have defined 2 types of links:

- R_{v-e} is a link "vertex-edge" meaning that stochastic values of vertex $v_{i,k}$ in the network BN_i correspond to the different conditional probability tables $P_k(v_{i-1,j}|v_{i-1,pj})$ in the network BN_{i-1};
- R_{v-v} is a link "vertex-vertex" meaning that stochastic values of vertex $v_{i,r}$ in the network BN_i correspond to the different relevance values of vertex $v_{i-1,r}$ in the network BN_{i-1}.

According to the introduced two types of interlevel links we consider two models of the Bayesian Metanetwork:

- C-Metanetwork having interlevel links of R_{v-e} type – for managing conditional dependencies (Conditional dependencies Metanetwork);
- R-Metanetwork having interlevel links of R_{v-v} type – for modelling relevant feature selection (Relevances Metanetwork).

3.1 C-Metanetwork – the Bayesian Metanetwork for Managing Conditional Dependencies

First consider the two-level Bayesian C-Metanetwork with interlevel links of R_{v-e} type (Fig. 1). Context variables in it are considered to be on the second (contextual) level to control the conditional probabilities associated with the predictive level of the network.

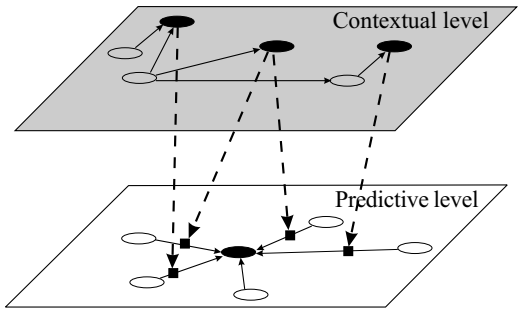

Fig. 1. The two-level Bayesian C-Metanetwork for managing conditional dependencies

We will consider each arc separately. The possible dependence between causal influences of two parents is processed on the second level of Metanetwork. Each arc in the ordinary Bayesian network corresponds to the conditional dependence between two variables. Standard Bayesian inference is applied in the Bayesian network of each level. The samples of C-Metanetwork (for simplicity projected to 2-D space) are presented in Fig. 2, Fig. 3.

The C-Metanetwork in Fig. 2 has the following parameters:

- the attributes on the predictive level: A, B, X, Y with their possibble values;
- the probabilities on the predictive level: $P(A)$, $P(X)$;
- the conditional probabilities on the predictive level (and at the same time attributes on the contextual level):
  - $P(B|A)$ which is a random variable with the set of values $\{p_k(B|A)\}$. It's important to note that this parameter serves as an ordinary conditional probability in the predictive level of the Bayesian Metanetwork and in the same time it is an attribute node on the contextual level of it;
  - $P(Y|X)$ which is a random variable with the possible values $\{p_r(Y|X)\}$ and is also considered as an attribute node on the contextual level of the Bayesian Metanetwork;
- the conditional probability on the contextual level: $P(P(Y|X), P(B|A))$, which defines Bayesian conditional probability between two contextual attributes $P(B|A)$ and $P(Y|X)$.

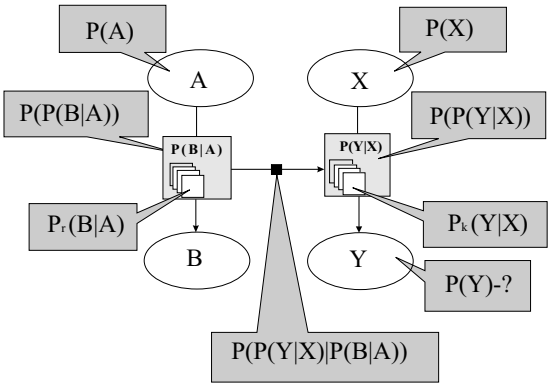

Fig. 2. The example of the Bayesian C-Metanetwork. The nodes of the 2nd-level network correspond to the conditional probabilities of the 1st-level network $P(B|A)$ and $P(Y|X)$. The directed arc in the 2nd-level network corresponds to the conditional probability $P(P(Y|X)|P(B|A))$. The inference is given in equation (2)

The probability of the target attribute $P(Y)$ can be computed by applying basic Bayesian inference on both levels of the C-Metanetwork as follows:

$$\begin{aligned} P(Y = y_j) = \textstyle\sum_i \sum_k (p_k(Y = y_j|X = x_i) \cdot P(X = x_i) \cdot \\ \textstyle\sum_r (P(P(Y|X) = p_k(Y|X)|P(P(B|A) = p_r(Y|X)) \cdot \\ \cdot P(P(B|A) = p_r(B|A))))). \end{aligned} \tag{2}$$

Such model of the Bayesian Metanetwork can be implemented for predicting mobile user's preferences in the following way. Mobile user's profile has some predictive and contextual features. Predictive features (learned or defined within user's preferences) will be placed on the basic predictive network level and they will be used to predict user's behaviour to be able to push him carefully selected and wanted filtered products and services. Contextual features will be placed on the control network level. They will be used to predict appropriate conditional dependencies between preference features of user's profile (the basic network level) regarding the current context.

In the location-based services the main contextual feature will be current mobile user's location. When the user changes his location some conditional dependencies between his preferences are probably also changed and after applying the Bayesian inference technique a mobile service provider is able to suggest and deliver the most preferable products/services regarding current location context.

The two-level Metanetwork can be easily extended for the multilevel (multicontext) Metanetwork [18]. In principle we can assume that the Bayesian Metanetwork might have as many levels as necessary. Fig. 4 shows an example of the three-level Bayesian C-Metanetwork.

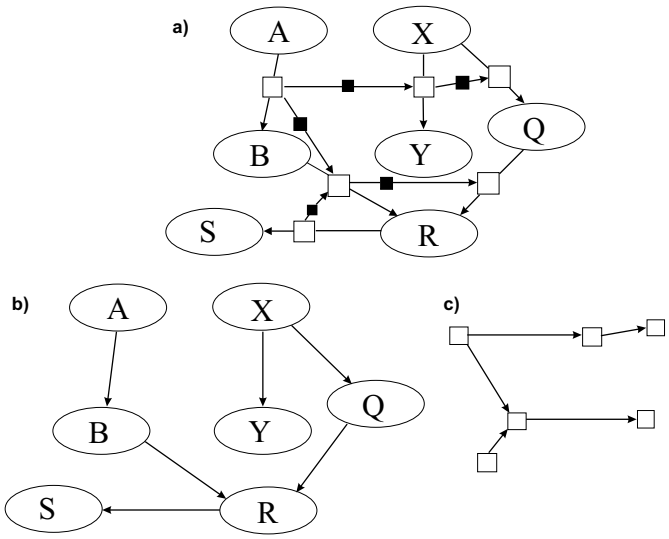

Fig. 3. The example of the Bayesian C-Metanetwork. The Metanetwork (a) actually consists of two Bayesian networks (b) and (c), and nodes of the network (c) correspond to the arcs of the network (b). The network (b) is the 1st-level predictive network, and it is controlled by the 2nd-level contextual network (c)

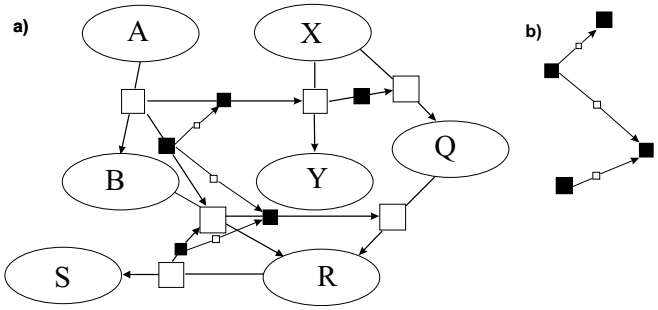

Fig. 4. The example of the three-level Bayesian C-Metanetwork. The 3rd level network (b) controls the conditional dependencies of the 2nd level network, which controls the conditional dependencies of the 1st level as shown in (a)

3.2 R-Metanetwork – the Bayesian Metanetwork for Modelling Relevant Feature Selection

Feature selection methods try to pick a subset of features that are relevant to the target concept. Each of these methods has its strengths and weaknesses based on data types and domain characteristics. It is well known that there is no single feature selection method that can be applied to all applications. The choice of the feature selection method depends on various data set characteristics: data types, data size, and noise. In [7] some guidelines were given to a potential user which method to select for a particular application based on different criteria. The Bayesian Metanetwork can be also used as a tool for modelling of relevant feature selection. Let's consider the two-level Bayesian R-Metanetwork with interlevel links of R_{v-v} type. Context variables are considered again as the control higher level to the level of network with predictive variables. Values of context variables influence the relevances of the variables on the predictive level as shown in Fig. 5.

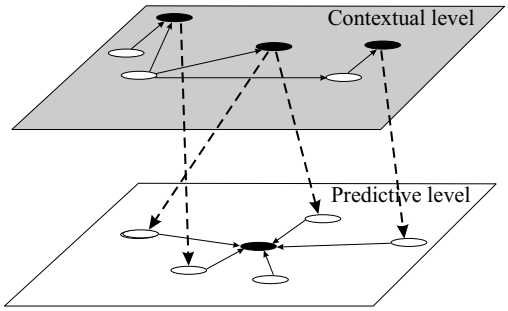

Fig. 5. The two-level Bayesian R-Metanetwork for modelling relevant feature selection

We consider relevance value as a probability of importance of the variable to the inference of target attribute in the given context (see Fig. 6).

The Bayesian R-Metanetwork in Fig. 6 has the following parameters:

- the attributes: X and with the values $\{x_1, x_2, \ldots x_n\}$; Y with the values $\{y_1, y2, \ldots y_m\}$;
- the probabilities: $P(X)$, $P(Y|X)$;
- the relevance predicate: $\Psi(X) =$ "yes", if parameter X is relevant; $\Psi(X) =$ "no", if parameter X is not relevant;
- the relevance value: $\Psi_X = P(\Psi(X) =$ "yes").

The conditional probability of Y given X and $\Psi(X)$ will be the following:

$$P(Y|X, \Psi(X)) = \begin{cases} P(Y|X); \Psi(X) = \text{“}yes'' \\ P_0(Y); \Psi(X) = \text{“}no'' \end{cases}, \tag{3}$$

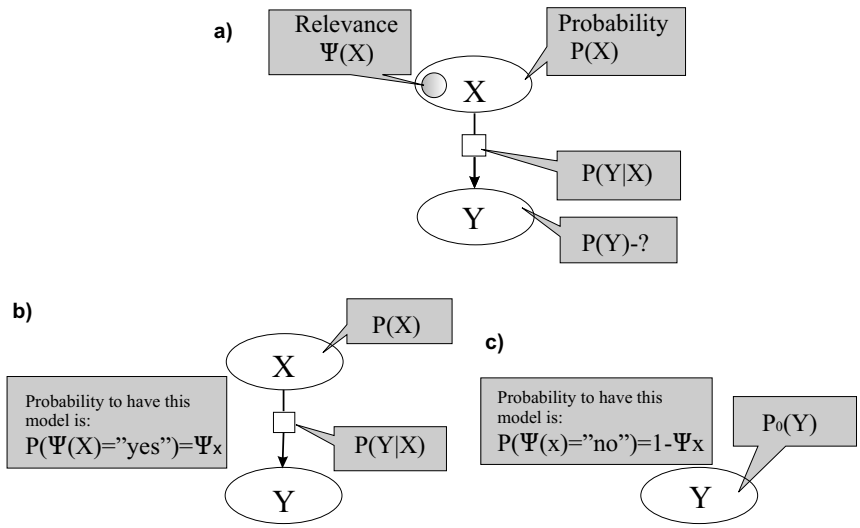

Fig. 6. The relevance definition for Bayesian R-Metanetwork. Bayesian inference is shown in equations (3), (4) and (5)

where $P_0(Y)$ is the prior probability distribution of Y. The possible way to calculate $P_0(Y)$ is:

$$P_0(Y = y_j) = \frac{1}{n} \cdot \sum_{i=1}^{n} P(Y = y_j | X = x_i), \tag{4}$$

where n is the number of values of X. So, the probability of the target attribute Y can be estimated as follows:

$$P(Y) = \frac{1}{n} \cdot \sum_{X} (P(Y|X) \cdot (n \cdot \Psi_X \cdot P(X) + (1 - \Psi_X))). \tag{5}$$

Contextual relevance network can be defined over the given predictive probabilistic network as it shown in Fig. 7. It encodes the conditional dependencies over the relevances.

In the relevance network the relevances are considered as random variables between which the conditional dependencies can be learned. The probability of target attribute Y can be computed as follows:

$$P(Y) = \frac{1}{n} \cdot \sum_{X} (P(Y|X) \cdot (n \cdot P(X) \cdot \sum_{\Psi_A} (P(\Psi_X | \Psi_A) \cdot P(\Psi_A) + (1 - \Psi_X))). \tag{6}$$

Considering such definition of the relevance network over the predictive network one can see that the strict correspondence between nodes of both networks exists but the arcs do not need to correspond. Relevances of two variables can be

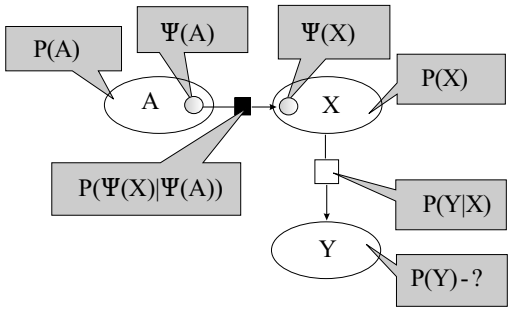

Fig. 7. The simple relevance network with attributes $\Psi(A)$, $\Psi(X)$ and conditional probability $P(\Psi(X)|\Psi(A))$ defined over the predictive network with attributes A, X, Y and conditional probability $P(Y|X)$. Inference of the target attribute is shown in equation (6)

dependent, although their values are conditionally independent and vice versa (as it is shown in Fig. 8). More complicated example of the Bayesian R-Metanetwork completed from the predictive and relevance networks is shown in Fig. 8.

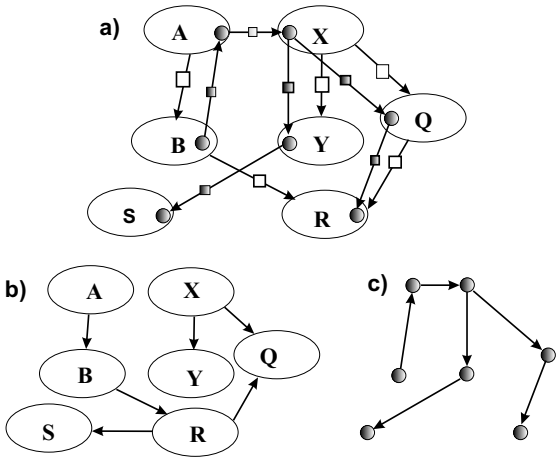

Fig. 8. The example of the Bayesian R-Metanetwork (a), consisting of the predictive network (b) and relevance network (c). The predictive and relevance networks have corresponding nodes, but different topologies

Modelling the relevant features selection with Bayesian R-Metanetwork can be implemented also in mobile applications, where applications should process only relevant information because of system resource restrictions. Mobile user's profile has predictive (user's preferences) and contextual features (user's location etc.). Contextual features will be used to decide which subset of predictive

features is relevant in the recent context. Evidence about some contextual features should give us hints to extract appropriate Bayesian substructure with the limited amount of attributes from the basic level. In location-based services the main contextual feature will be the current mobile user's location. When some user changes his location probably some preferences become probabilistically irrelevant and we can extract smaller subnetwork from basic level and process it. In such effective way a mobile service provider is able to suggest and deliver the most preferable products/services regarding current location context.

4 Conclusion

Filtering the Web content is an emerging technology at the age of information overload. The problem of profiling and filtering is important particularly for mobile information systems where wireless network traffic and mobile terminal's size are limited comparing to the Internet access from the PC. Mobile user modelling accounts not only user's profile features and collected user's experiences but also user's location, which can be tracked. Dealing with uncertainty in this area is crucial and many researchers apply various probabilistic models.

The main challenge of this paper is the multilevel probabilistic model (the Bayesian Metanetwork), which is the extension of traditional Bayesian networks and is also considered as a useful tool to predict a mobile user's preferences. The extra level(s) in the Metanetwork is used to select the appropriate substructure from the basic network level based on contextual features from user's profile (e.g. location). Two models of the Metanetwork are considered. C-Metanetwork considers conditional dependencies of the Bayesian network as random variables and assumes conditional dependencies between conditional dependencies. R-Metanetwork assumes that the relevances of predictive variables in the Bayesian network might be random variables themselves and provides a tool to reason based not only on probabilities of predictive variables but also on their relevances. The advantages of proposed multilevel models comparing with the ordinary Bayesian networks are:

- flexibility (you don't need to relearn the whole model when some changes occur, it can be enough to relearn the one level);
- reduction of computational complexity (in the case when complex one-level model can be decomposed on two or more easy structures, Naive Bayes for instance) and increase of processing speed;
- the accuracy of the Metanetwork will be higher than the accuracy of the traditional Bayesian network when the environment indirectly affects the probabilistic process, which is modelled by predictive network. We gain in the accuracy because use more precise models in every context and do not use averaging through all the contexts.

The Bayesian Metanetwork is considered as a useful tool to present the second order uncertainty and therefore to predict mobile user's preferences. The general formalism of the Bayesian Metanetwork can be applied for such modelling task

formulations: modelling conditional dependencies in the user's profile (by C-Metanetwork) and modelling relevant feature selection (by R-Metanetwork). As location of mobile user is being considered as a very important determinative attribute in modelling of user's decision making, the applications of Bayesian Metanetworks for mobile location-based systems and particularly to mobile and public commerce location aware services are viewed as relevant.

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