ONTOLOGY BASED KNOWLEDGE MODELING FOR THE TWO-STEP PERSONALIZED SERVICES IN NEXT GENERATION NETWORKS

Aekyung Moon, Yoo-mi Park and Young-il Choi
Convergent Service Platform Research Department, ETRI, Korea

Keywords: Recommendation, Personalization, Network Knowledge.

Abstract: We propose ontology based knowledge modeling (OKM) that can support to provide the two-step personalized services for the end users using network knowledge. The two-step personalization services are consisted of service recommendation step and contents recommendation step. To achieve this, in this paper, we classify network knowledge and build ontology to represent them including user profiles and user's preferences. Furthermore, we propose the efficient functions of learner and recommender. Learner makes the user service usage model which consists of {context, services} pairs. Recommender is consisted of service recommender and contents recommender for supporting two-step personalization.

1 INTRODUCTION

The significance of the personalization services increases by the user requirement of differentiated services. What is more, various attempts for providing the personalized services considering a situation and preference of a user are leading a new paradigm of the next generation networks (WWRF, 2005), (Mihovska et al., 2007).

Taking this into consideration, we propose ontology based knowledge modeling (OKM) to recommend personalized services by two-step. First, for handling network knowledge efficiently in OKM, we classify user information on the networks to three categories: context, profile, and preference. We build ontology to represent network knowledge including user profiles and user's preference. Especially we define preference ontology to recommend two-step personalized services.

The two-step personalized services are consisted of service recommendation step and contents recommendation step. To achieve this, user's preference ontology of OKM is consisted of service preference model and contents preference model. The former is to recommend a weighted list of useful service categories. The latter is to set up a weighted list of specific contents according to the service selected by a user. As a result, if user selected TV service among service categories to be recommended at the first step, it should match a user's desired TV programs and recommend TV programs with high user preference at the second step.

The remainder of this paper is organized as follows. Section 2 presents related works. In Section 3, we describe network knowledge and build ontology model. Section 4 proposes the system architecture and operations to provide two-step personalized services. Section 5 concludes this paper with further issues.

2 RELATED WORK

Recently, the requirement on personalized services using user behavior patterns and contexts has been increased (MobiLife, 2004). Personalized services have a role to identify the usefulness of service categories in a given situation, and then proactively discover and recommend services to the end-user (MobiLife, 2004). Generally, the recommendation approaches for service personalization are classified into the following categories, based on how recommendations are made (Adomavicus et al., 2005):

- Content-based recommendations: The user will be recommended items similar to the ones the user preferred in the past;
- Collaborative recommendations: The user will be recommended items that people with similar tastes and preferences liked in the past;
- Hybrid approaches: These methods combine

Moon A., Park Y. and Choi Y. (2009).
ONTOLOGY BASED KNOWLEDGE MODELING FOR THE TWO-STEP PERSONALIZED SERVICES IN NEXT GENERATION NETWORKS.
In *Proceedings of the 4th International Conference on Software and Data Technologies*, pages 332-337
DOI: 10.5220/0002280903320337
Copyright © SciTePress

collaborative and content-based methods

The studies of the vision of the personalized services and the development of prototypes to verify feasibility of the technologies have been performed in some of European projects.

WWRF proposed the vision of the future telecommunications services labeled as the I-Centric Service (WWRF, 2005). According to the concept of this service, the individual user, "I," has to be put in the center of service provisioning. WWRF offered the reference network model and described the requirements for providing this service. However, they didn't consider the modeling of the knowledge that can be used for future service platform architecture.

MobiLife proposed service architecture of I-Centric Communications and made the outstanding results which were next-generation mobile communications service scenarios and requirements (Mrohs et al., 2006). In the MobiLife, the activities on service recommendation for user "I" include the setup and maintenance of the decision policies for the service recommendation. Especially, the learning mechanism mainly extracts behavior patterns in the same situation of the user or similar users.

3 KNOWLEDGE MODELING

To understand the proposed two-step personalized services recommendation, we first illustrate a scenario that is likely to occur in NGN. Figure 1 shows the flow of two-step recommendation.

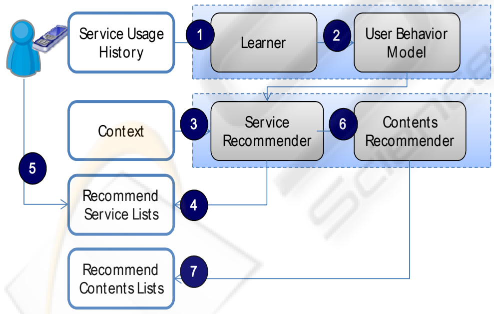

Figure 1: The flow of two-step recommendation.

Example 1. Suppose that a user usually watches TV when he enters living room and sits on the sofa after work. The Learner can make a user behavior model with behavior pattern extracted from the usage history (①-②). When the usage pattern became mature and service recommender catch his current situation that he enters home after work (③), Service recommender computes the preferred service lists using user behavior model (④). When received service lists, the user can select the TV service among service lists (⑤-⑥). And then, the contents recommender recommends the user's interest TV program lists (⑦). At this time, the feedback is stored in the service usage history.

To complete this scenario, we classify user information on the networks to three categories: context, profile, and preference. We build ontology to represent network knowledge including user profiles and user's preference.

3.1 Network Knowledge

Fig. 2 shows how to get the network information from the underlying network or environment and the classification of network knowledge. All network information is classified into three concepts: profile, preference, and context.

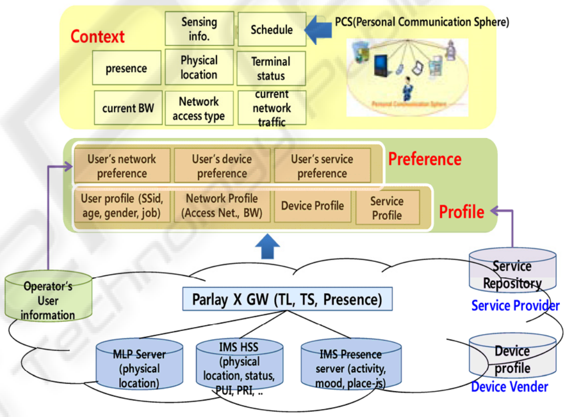

Figure 2: Classification of network knowledge.

Profiles are a collection of structured data that describe the static properties of an object. Table 1 shows the types of profile and example considered in network knowledge. Preferences are user's conditional choices of service characteristics of an object depending on context and ambient information.

Table 1: Definition of Profile in Network Knowledge.

Type	Definition
User Profile	User-related information. social security id, name, age, gender, job, etc
Device profile	Device-related information generated by manufacturer. device model, type, capabilities (input/output modality), etc
Network profile	Network capabilities information. operator, coverage, bandwidth, access technologies, etc
Service profile	Service-related information. service category, service fees, service provider, location where the service is available, etc

User preference consists of a set of policies {condition, actions} in order to apply that it can be dynamically changed according to the user's situation. User has three basic types of preference shown in Fig 3. Specially, we focused on service preference, which is a set of information related to user's preferred services, and service usage preference acquired by learning mechanism.

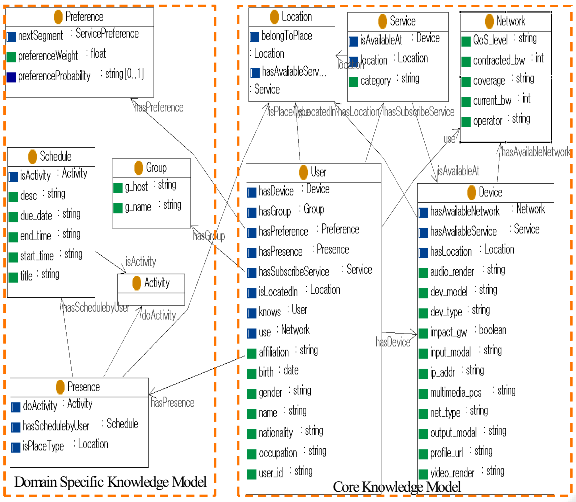

Figure 3: Ontology modeling of network knowledge.

Based on the definition of context by Dey et al. (Dey, 2001), context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves. We consider that sensed information from PCS (personal communication Sphere), current network bandwidth and user's current location, etc.

3.2 Ontology Modeling

3.2.1 Core Knowledge Modeling

In this section, we describe the results of ontology modeling in OKM. Fig. 3 shows the ontology modeling of network knowledge. As shown in Fig. 3, we made 10 classes (*User, Preference, Group, Network, Device, Service, Location, Activity, Schedule,* and *Presence*) and 13 major object properties from the relationship between classes. In addition to, there are *knows* for the relationship among users, *belongToPlace* for the relationship between location and 39 data-type properties for predefined classes such as user_id and user_name for User class. Actually, *User*, *Device*, *Network* and *Service* class represents profiles as previous mentioned in Table 1.

Our ontology model is consisted of core and domain-specific parts of the network knowledge. The core parts are comprised of the *Device*, *Service*, *User*, *Network* and *Location* classes, which represent contexts and profiles. The domain specific parts are comprised of *Preference*, *Group*, *Activity*, *Schedule*, and *Presence*, which are to provide personalized services according to application domains. The information of this part will be gathered from a variety of data sources.

3.2.2 Domain Specific Knowledge Modeling

Service ontology is consisted of service profile and service category. The service main categories at the topmost level describe in general what services are for. The subsequent sub-categories clearly specify the functionality of services.

Fig. 4 shows the example of *Service* Ontology for user's *Preference* which represents four service categories: commerce, information, entertainment, communication. The subclass of each category is shown in Fig. 4. For example, TV class is modeled as subclass of Entertainment. TV class includes user's preferred TV genre related to IPTV domain. The instance of TV class related to genre is made reference to TV-anytime forum (S-3 On: Metadata, 2001).

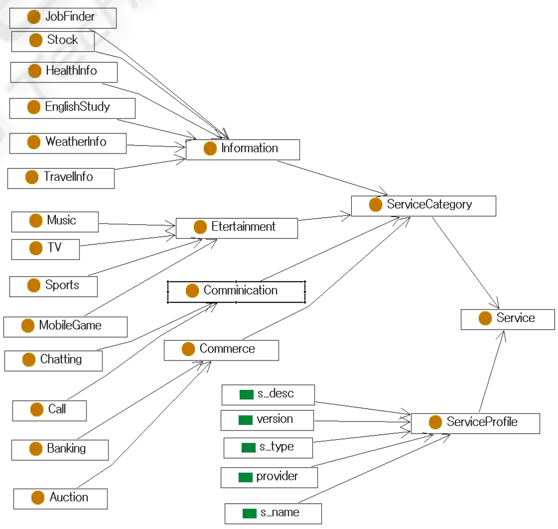

Figure 4: Example of service domain ontology.

The user preference model is to store user's service preference. This model is represented by ontology while referencing *Service* ontology shown in Fig 4. Fig. 5 represents the example the preference model of user "hong", which uses n-ary relation in OWL.

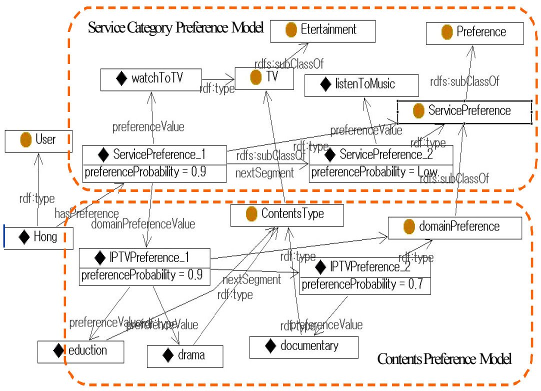

Figure 5: Example of user preference ontology.

4 KNOWLEDGE MANAGEMENT PLATFORM

This section describes the system architecture and operations of two-step Personalized Services and describes the results of simulation.

4.1 System Architecture

The system architecture is shown in Fig. 6. This platform consists of profile manager and knowledge manager. The profile manager is consisted of a user profile, user preference model and user service usage model. In the case of user profile is represented by *User* class of ontology model shown in Fig. 3. The user preference model is represented by service preference and contents preference model shown in Fig. 5.

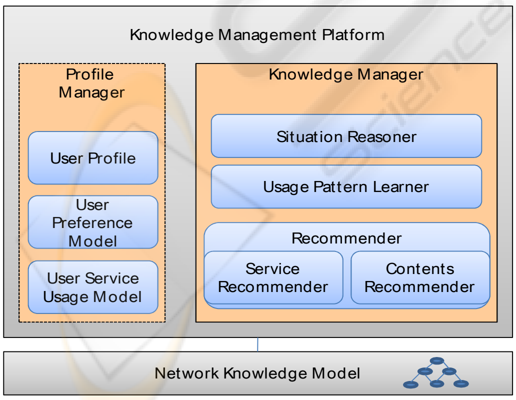

Figure 6: System Architecture of Knowledge Management Platform.

User service usage model sets up and maintains service usage behavior model using learning mechanism. In particular, the context information influences user behavior model because it contains a pair of user behavior (service usage) and a user situation consisted of contexts. The user service usage model is updated by user pattern learner that analyzes user behavior history. The proposed user service usage which consists of {context, service} pair can be acquired by the context and the service usage of a user; it then can be used to recommend personalized services according to user's situation. The detailed learner algorithm is shown in section 4.2. Situation reasoner has the capability deducing new information from available information using a predefined schema and interprets the situation based on the contextual information.

4.2 Learner

Learner makes the user service usage which consists of {context, services} pairs, called by C-TBL. Since that the state S is defined as three elements of [user activity, place, time], three C-TBL are needed. If user wakes up early morning, then he request "NewsInfo". The value of the C-TBL [morning][news] is calculated by a following algorithm. The detailed algorithm of the learning phase is as follows. In the Step 1, reward value R may be defined according to user feedback.

Step 1 is initialization phase for new context c_k. Initialize new C-TBL for c_k, set 0 to C-TBL[$a_{k,j}$][ac_k], for each $a_{k,j} \in$ Attributes(c_k), $ac_k \in$Action Classes. Initialize value of R for $R \in \{r_s, r_p, r_n\}$. R is reward value.

Step 2 repeats the following learning steps.

Step 2-1. Input current situation $s^{(t)}$, $s^{(t)}$ is consisted of $\{a_{1,i}{}^{(t)},\ldots,a_{n,j}{}^{(t)}\}$, where $a_{k,i}{}^{(t)} \in$ Attributes(c_k). If $a_{k,i}{}^{(t)}$ is continuous value, min-max normalization performs a linear transformation on the original data. Suppose that $\min_a$ and $\max_a$ are the minimum and the maximum values of $a_{k,i}{}^{(t)}$.

$$a_{k,i}^{(t)} = a'_{k,i} = \frac{a_{k,i}\ \min_a}{\max_a - \min_a}(new\_max_a - new\_min_a) + new\_min_a$$

Step 2-2. Input an current action ac(t) by user selection. Determine R(t) according to user behavior information. Update the C-TBL as following rules:

for each c_i in C-TBL[$a_{i,k}{}^{(t)}$][$ac^{(t)}$] do
C-TBL[$a_{i,k}$][$ac^{(t)}$] ← C-TBL[$a_{i,k}{}^{(t)}$][$ac^{(t)}$]+γ$R^{(t)}$,
where γ is the discount factor and $c_i \in$ *States*.

4.3 Recommender

We propose two types recommender for providing two-step personalized services. Service recommender is responsible for service recommendation; hence, it is to set up a weighted list of useful services according to user behavior patterns in the current situation and user's service preference shown in Fig. 5. Equation (1) shows user's preference for service recommender. That is to say, for user *u*, the preference value of service *i* is computed by equation (1). Contents recommender is responsible for contents recommendation according to selected service domain. As previous mentioned in Fig. 5, IPTV is included in this case.

$$Preference^{u,i}=\alpha\times Preference_{(Up)}{}^{u,i}+\beta\times Preference_{(Us)}{}^{u,i} \quad (1)$$

u : user, i : services
Preference ^{u,i}: The preference value of user u about item i
$\text{Preference}_{(Up)}{}^{u,i}$: The preference of user preference model
$\text{Preference}_{(Us)}{}^{u,i}$: The preference of user service usage model
α : The weight of user preference model
β : The weight of user service usage model

4.3.1 Service Recommendation Function

The service recommender fuction is as following equation (2). Equation (2) is applied to learner and preference ontology modeling.

$$Preference^{u,j}=\alpha\times preferenceProbalility(u, S_j)+\beta\times(w_k\times C\text{-}TBL[a_{k,i}][S_j]) \quad (2)$$

u : user, S_j: j^{th} services item
$\text{Preference}^{u,j}$: The preference value of user *u* about service item S_j
preferenceProbalility(u, S_j): The preference of user preference model by ontology shown in Fig. 5.
C-TBL[$a_{k,i}$][S_j]: The preference of user service usage model by learner
$a_{k,i}$: the attribute value of C_k
w_k : the weight of context C_k
α : The weight of user preference model
β : The weight of user service usage model

According to Equation (2), weighted list of preferred services is to set up and notifies to user. Suppose that "watch TV" service is recommended. If user selected TV service among service categories to be recommended at the first step, it should match a user's desired TV programs and recommend TV programs with high user preference by contents recommender according to information of shown in Fig. 5.

4.3.2 Contents Recommendation Function

For contents recommendation of TV domain, we choose content-based approaches in order that sparsity and cold-start (Papagelis et al., 2005) problems are solved. The sparsity problem has a major negative impact on the effectiveness of a collaborative filtering approach. Because of sparsity, it is impossible that the similarity between two users cannot be defined, rendering collaborative filtering useless. Even when the evaluation of similarity is possible, it may not be very reliable, because of insufficient information processed. Cold-start refers that it cannot be recommended unless it has been rated by a substantial number of users.

This is preference model for TV application domain. The content of TV programs can be represented in these items: identification information (ID/title), category information (genres/subgenres), broadcast information (channel/the starting time and ending time of the program), content ratings and keywords. To compute user preference, the TV model is divided into three types of information about TV content: "genre", "channel" and "companion".

Companion: with whom the TV was seen (alone, with friends, with family). It is possible to be included in common model.

To collect this information about the user's interests, the system can ask a user manually indicate his/her interests by giving GUI. The function of TV specific model consists of computing the preference of genre, channel and person, and multiplying the each result by weights as equation (3). The previous mentioned Fig. 6 shows the example of ontology model of TV genre preferences.

$$P^{u,i}=W_g\times P_{genre}{}^{u,p}+W_c\times P_{channel}{}^{u,p}+W_c\times P_{companion}{}^{u,p} \quad (3)$$

u : user, i : items p: TV broadcasting program
W_g: weight of genre, W_c: weight of channel,
W_c : weight of companion

4.4 Performance of Functions

To evaluate function, we chose the following the data set; Create Approval, Balance and balloon in UCI depository. In the case of the *create approval* of UCI data, this consists of 15 contexts which has 9 categorical attributes and 6 continuous attributes), and two action classes as show in Table 2.

Table 2: Example of UCI data for simulation.

Data	Instance	Attr.(Categorical)	ActionClass
Create Approval	665	15(9)	2
Balloons	20	4(4)	2
Balance	625	4(4)	3

And also, we chose machine learning algorithms from the Weka tool-kit (http://www.cs.waikato.ac.nz/ml/weka/): J48, ZeroR, NaiveBayes (Louis and Shankar, 2004).The performance evaluation metric in this experiment is the accuracy (precision). When R is being the number recommended as a user and the RP (Recommended Preference) is being the number which a user actually prefers, precision is calculated as the RP / R and showed by the %. The k-fold cross validation is used in order to raise the confidence of experiments. However, when computing by equation (2), the user preference by the ontology and contents preferences was not considered in order to experiment in same condition with the comparison algorithm. w_k is calculated by the entropy of context through the information gain (Mitchell, 1997).

Fig. 7 shows the precision of each algorithm according to categorical context only. Our approch is better than other algorithms in the aspect of Create Approval. The precision of our approach is 86.8% at create approval. All experiments our approach is better than ZeroR with 1.5times.

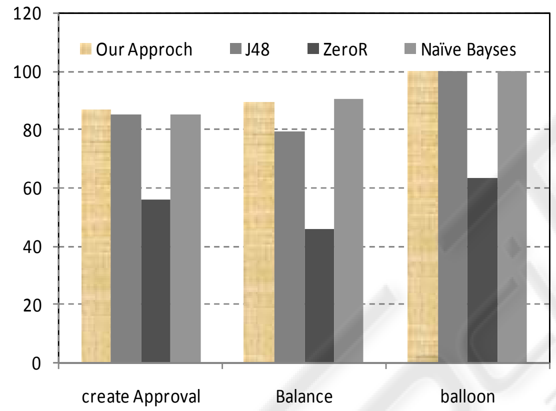

Figure 7: Results of evaluation.

5 CONCLUSIONS

In this paper, we propose ontology based knowledge modeling (OKM) that can support to provide the two-step personalized services for the end users by means of evolving network knowledge. To achieve this, OKM is consisted of service category preference model and contents preference model. Moreover, we propose knowledge management platform that can support to provide two-step personalized services. Proposed platform has two major functions: leaner and recommender. Learner makes the user service usage model which consists of {context, services} pairs. Recommender is consisted of service recommender and contents recommender.

We evaluated the learner and service recommender functions in proposed platform using UCI depository and Weka tool-kit. Our approach is better than other algorithms in the most of experiments. As a result, we expect that the platform will be an essential component in next generation networks. For further study, we have a plan to provide wholly implementation for providing two-step personalized services includes exposure layer.

ACKNOWLEDGEMENTS

This research is supported by the IT R&D program of MKE/IITA of South Korea. (2009-F-048-01, Development of Customer Oriented Convergent Service Common Platform Technology based on Network).

REFERENCES

WWRF, 2005. *Technologies for the Wireless Future: Wireless World Research Forum (WWRF),* John Wiley&Son.

Albena Mihovska *et al.*, 2007. "Towards the Wireless 2010 Vision: a Technology Roadmap," *Wireless Personal Communications*, vol.42, 2007, pp.303-336.

Yoo-mi Park, Aekyung Moon, Young-il Choi, and Sangha Kim, 2009. "Value-added Knowledge layer for the Context-aware Personalized Services in the Next Generation Networks," *The 3rd Intl. Conference on Knowledge Generation, Communication and Management,* in press.

IST-2004-511607, MobiLife D27b (D4.1b) v1.0, 2004.

G. Adomavicus, R. Sankaranarayanan, S. Sen and A. Tuzhilin, 2005. "Incorporating Contextual Information in Recommender Systems Using a Multidimensional Approach", ACM Transactions on Information Systems, 23(1), pp. 103-145.

Bernd Mrohs et al., 2006. "MobiLife Service Infrastructure and SPICE Architecture Principles," In Proc. of *IEEE Vehicular Technology Conf.*, Montreal, Canada, pp. 3047-3051.

Dey AK, 2001. "Understanding and Using Context," *Journal of Personal and Ubiquitous Computing*, Vol.5, No.1, pp.4-7.

The TV-Anytime Forum, Specification Series: S-3 On: Metadata, 2001.

M. Papagelis, D. Plexousakis and T. Kutsuras, 2005. "Alleviating the Sparsity Problem of Collaborative Filtering Using Thrust Inferences," iTrust, LNCS, pp. 224-239.

S. Louis, A. Shankar, 2004. "Context Learning Can Improve User Interaction, Information Reuse and Integration," *IEEE conf. IRI,* pp. 115-120.

Mitchell*,* 1997. *Machine Learning*, McGraw-Hill.