Short Paper: Situation-Awareness Model for Higher Order Network Knowledge Management Platform

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Abstract. In this paper, we propose the situation-awareness model for HKMP(Higher order Knowledge Management Platform) that has a capability to offer context-aware personalized services to user. HKMP is a platform that provides the higher order knowledge from the contextual information of the network and user ambient sensors through the knowledge processing techniques including reasoning and learning. This paper presents the system architecture of HKMP and classifies contextual information as lower order and higher order knowledge. The proposed situation-awareness model for providing context-aware personalized services recognizes the situation of the users and recommends personalized services based on the information. The main idea on this paper is how to evolve the awareness model without using personal information causing privacy issues and how to draw an inference effectively current situation of users. We continuously evolve our model to achieve this requirement by the learning mechanism using the interaction between users and mobile devices. As a result, we can make the user behavior pattern which can be learned in situation and the situation is captured by union of sensors under the current environments. In order to apply our model to new environments, we simply need to define the sensor profiles without any change of model itself. So, the proposed model consists of the pairs of context-action and deduce current situation of users inference through the ontology model. At the end, we evaluate the precision of the proposed approach through the use of Weka3 data mining software with data sets of UCI machine learning depository. In the result of evaluation, we expect HKMP to be an essential component to provide the personalized services in the next generation networks.

Keywords: Network Knowledge, Ontology, Learning, Reasoning, Recommender

1 Introduction

Since Mark Weiser proposed the concept of ubiquitous computing, a significant amount of work has been devoted to context-aware [1-3]. Recently, various attempts for providing the context-aware personalized services considering a situation as well as preference of a user are leading a new service paradigm of the next generation networks. We therefore have developed the higher order knowledge management platform (HKMP). The HKMP handles the network knowledge of the user surrounding to provide context-aware personalized services that can be dynamically adapted to a user's current situation. To do this, HKMP gathers contextual information from network as well as various sensors and classifies collected contextual information as two categories: lower order and higher order knowledge for handling efficiently it. Furthermore, HKMP provides higher order knowledge derived from contextual information, which is helpful to create context-aware personalized services according to user's context or situation.

In this paper, we propose learner and ontology model for situation-awareness in HKMP. To begin with, the proposed ontology model for situation-awareness defines user centric lower order knowledge and their relationships including profiles, context, and preferences of the user. Then, it derives user's current situation using ontology reasoning in order to providing users with context-aware personalized services. For applying it to different domains, it consists of two types of ontologies; core part for generic purpose and domain-specific part. We expect that it makes possible to recommend personalized services at any given domain for the end users by deducing simply user's current situation using the proposed model.

Another key point is learner for situation-awareness. Our learner makes user behavior patterns for recommending a weighted list of services to be preferred according to user's current situation. A several approaches have been proposed for context-aware personalized services [4-6]. However, most of previous approach assume static environment or fixed sets of context to determine user's situation. To overcome this problem, proposed model consists of context-action pairs and sensor profile that can applicable to a variety of environment flexibly. For applying the proposed model to new environment, we simply need to define the sensor profiles without any changes of model itself. Moreover, it is important that learner is to evolve model without the previous knowledge on a user. Therefore, we use reinforcement learning that does not require external supervision. As a result, the HKMP learns user behavior through both interaction with the user and user's situation captured by context. For the efficient normalization of context having continuous attributes, we adopt minimal set of interval approach [7, 8]. We evaluate the precision of proposed approach with data sets of UCI machine learning repository [9] to compare other algorithms using Weka3 data mining software [10].

The remainder of this paper is organized as follows. Section 2 presents related works. Section 3 discusses knowledge classification and system architecture of HKMP. Section 4 proposes ontology and learning approach for situation-awareness model of HKMP. Finally, section 5 summarizes this study.

2. Related Work

Personalization has become an important research area since the appearance of the first papers on collaborative filtering in the mid-1990s [11]. There has been much work done both in the industry and academia on developing new approaches to personalized recommender systems over the last decade. In the previous researches, it has concentrated on contents recommendation associated with information retrieval and filtering from the web. However, the current generation of personalization requires further improvements to make advanced methods more effective and applicable to an even broader range of real-life applications. Therefore, recent personalization system deals with contextual information, user's situation and behavior patterns to improve user experiences [12]. However, existing models aren't sufficient to support situation-awareness. For example, CC/PP [13] as well as UAProf [14] does not consider such information about the user's behavior in case a specific context or situation exists.

Although numerous definitions of situation-awareness have been proposed, Endsley's definition [15] is firmly established and widely accepted. Situation-awareness involves being aware of what is happening around users. In this respect, situation-awareness model contains information about the user's behavior pattern and user's situations. This is to provide users with useful services now and in the near future. There are several approaches for situation-awareness model, which assume static environment or fixed sets of context to determine user's situation [5,6]

The SPE (Secure Persona Exchange) [16] framework provides personalized services to users in ubiquitous computing environments based on user preferences stored on mobile devices; it does not fully include dynamic context information. Daidalos [17] proposed four case of personalization in call redirection. Unlikely SPE, Daidalos consider context, however, it use specific context defined in advance only.

MobiLife uses the learning mechanism to extract behavior patterns in the same situation of the user or similar users [12]. In the neural network house, it is able to predict occupancy of rooms and hot water usage using feedforward neural networks [18]. Additionally, there are several approaches using learning [5,19]. Krause focused on how machine learning techniques can identify typical user's situation and modify his mobile device's settings based on experience [5]. Feki suggested the service recommendation of robotics domain using Q-learning on user behavior [19].

3. Higher Order Knowledge Management Platform

3.1 Network Knowledge Classification

Lower Order Network Knowledge. The lower order knowledge includes all information directly acquired from the underlying network. As shown in the Fig. 1, the lower order knowledge consisted of information regarding the user and resources (network, device, and service) that he/she could access, use, and are offered. We defined profile as a collection of structured data that describes the static properties of an object. Preferences are user's conditional value of an object depending on context and ambient information. 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. Based on the definition of context by Dey et al. [1], context is any information that can be used to characterize the situation of an entity.

We consider that sensed information from PCS (personal communication sphere), current network bandwidth and user's current location, etc.

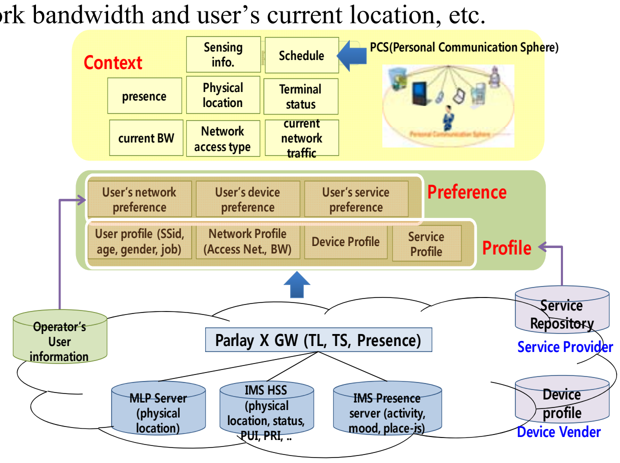

Fig. 1 Network Knowledge Classification

Higher Order Network Knowledge. Higher order network knowledge could be generated from lower order network knowledge using knowledge processing technologies such as context reasoner, learner, and predictor in the Fig. 2. Those were situation, intention, and pattern. Context reasoner has role to infer his/her situation based on contextual information. The type of an actual situation, for example "Waiting for bus", can be recognized based on given contextual information. Predictor is capable of predicting the services which the user is likely to want to use in the near future. Suppose that he and his family arrive to international airport. And they are on holiday, then predictor infers that their intention will "travel" and needs "travel-related information" when arriving at the destination. Leaner has a capability to extract rules and patterns out of massive usage history. Behavior pattern of a user can be used in preferentially recommendation of service when the user is in the specific situation. Recommender is to automatically identify the service categories to be preferred in a given situation, user intention and user behavior pattern, etc**.**

3.2 System Architecture of HKMP

The system architecture of HKMP is shown in Fig. 3. Among these capabilities, the core functions of HKMP for situation-awareness are context reasoner and learner. Proposed context reasoner for situation-awareness has a capability to deduce user's current situation from available contextual information using ontology reasoning with a predefined TBox schema. Leaner sets up and maintains service usage behavior model using learning mechanism. In particular, the contextual 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 model 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. We call these functions to SAM (Situation-Awareness Model) which is organized by context reasoner and leaner for situation-awareness. The detailed these algorithms are shown in section 4.

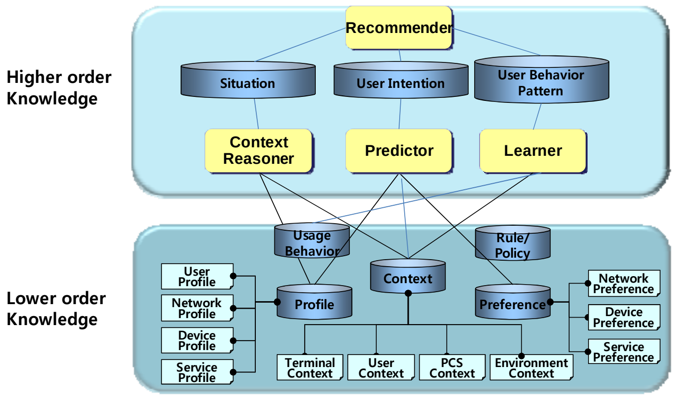

Fig. 2 Conceptual Architecture for HKMP

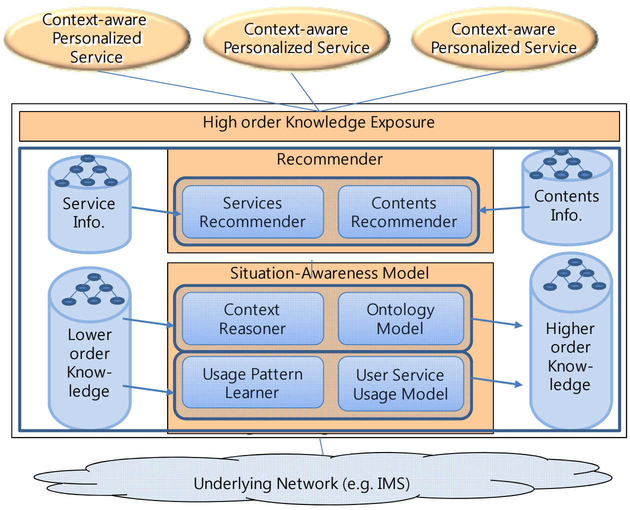

Fig. 3 System Architecture of HKMP

4. Situation-Awareness Model

4.1 Situation-Awareness Ontology Model for Context Reasoner

Ontology Structuring. First of all, we drew competency question (CQ) lists which could be asked for situation-awareness. After generalization of CQ, they were refined in the form of 4W (who, when, where, what) and 1H (how). Our basic CQ is "Which service/device/network (what) is best when the user (who) is at (where) location or situation".

Based on the generalized CQ, we extracted the keywords such as user, service, device, network, location, time, activity, and people. We found that every keyword was closely related to the user. The user's situation includes location of the user, current time, schedule, location's place type, etc. Therefore, we built user-centric core ontology by representing a user and objects to be related the user as shown in Fig. 4. Since situation and preference is domain-specific and especially situation is characterized by derived contexts, we divide user-centric core and domain specific parts for applying flexibly to different domains according to their purpose.

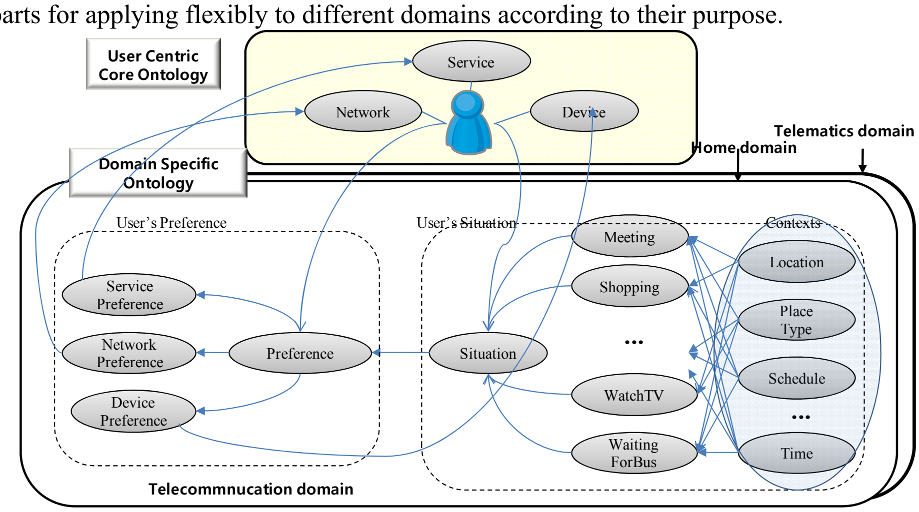

Fig. 4 Conceptual model for Situation-aware Ontology Structuring

Ontology Modeling. We depicted ontology model using OWL-DL in Figure 5. Ontology model consisted of a user-centric core and domain-specific parts. The core part is comprised of the Device, Service, User, Network, and Location classes. They represent generic contexts to meet basic requirements of modeling for situation-awareness. The domain specific part consisted of Preference, Group, Activity, Schedule, and Presence. It was designed to provide personalized services in any given domains. Preference is consisted of service preference and domain preference modeled by N-ary relations of W3C.

In our ontology model, user's situation is deduced from available information using TBox predefined rules. We defined four cases of situation for telecommunication domain as high-order knowledge; *PersonInMeeting*, *PersonInShopping*, *PersonInWatingForBus*, and *PersonInWatchingTV* as shown in Fig. 5. For example, '*PersonInMeeting*' can be recognized based on the given context such as location, role, schedule, and device status. Service ontology represents classes for four service categories; Commerce, Information, Entertainment, Communication. TV class is modeled as subclass of Entertainment and includes TV program genre referenced by TV-anytime forum [19].

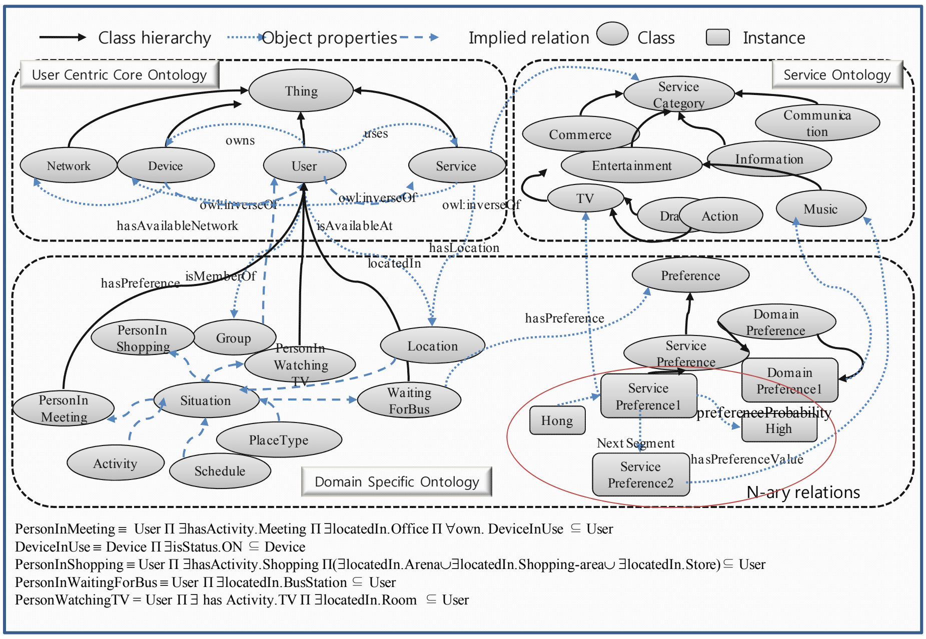

Fig. 5 Situation-aware Ontology Model for Context Reasoner of HKMP

4.2 Learner for Situation-Awareness

4.2.1 Basic Idea

Learner has the capability of keeping the situation model as patterns extracted from the history of usage behavior. It can help to evolve user's preference based on his usage behavior patterns. Our learner analyzes user behavior history using feature of reinforcement learning. The reinforcement learning method can proceed only through interactions between each user and mobile devices without previously known information. The representative studies using reinforcement learning are [20] and [21]. Our learner makes the user model by learning mechanism similar to reinforcement learning, but has more advanced features. In order that our user model applies to new environment, only sensor profiles are required to be defined without any modification to model. Table 1 shows data structures of sensor profile. It defines that a set of states *s* consists of contextual information as mentioned above. The user can perform any of a set of possible action classes *ac*. The agent then receives a real-valued reward *R*.

Table 1 Data Structure of Sensor Profile

$States\ =\ \{c_1,\ ...,\ c_n\},\ 1\leq n,\ c_k : k^{th}\ context\ in\ the\ State$
$Attributes(c_i)\ =\ \{a_{\ i,1},\ ...\ a_{\ i,k}\},\ 1\leq k\ and\ 1\ \leq i\ \leq n$
$Action\ Classes\ =\ \{ac_1,\ ...\ ac_m\},\ 1\leq m$
$Reward\ R=\{\ Selection\text{-}r_s,\ Positive\ Feedback\ \text{-}r_p,\ Negative\ Feedback\text{-}r_n\ \}$

Our learner has to two tables: context-aware user model (C-TBL) and a prediction table (P-TBL). Suppose that the user's current state s is comprised of three contexts [user activity, location, time]. For each context, three C-TBL are needed. For example, if a user gets up in the morning and listens to news (ac_1) in his or her bedroom, this becomes the [c_1: wakeup, c_2: bedroom, c_3: morning] situation. C-TBL[c_1][ac_1], C-TBL[c_2][ac_1] and C-TBL[c_3][ac_1] are updated by learner. P-TBL is designed to predict and recommend. To recommend user action in current situation, P-TBL is computed by recommender using the C-TBL. The action classes are the services provided by the service provider. That is, the value stored in the P-TBL[cs][ac_k] shows the preference of action ac_k in the corresponding current situation(cs). The user directly chooses an action and the next state is determined according to the selected action. Therefore, in the proposed scheme, we modify the rule (1), because the reward value for a recommendation is affected by the behavior information between the system and user. The learning equation is given as:

$$Q(s,a) \leftarrow Q(s,a) + \gamma R, R \in \{r_s, r_p, r_n\} \quad (1)$$

The detailed algorithm of the learning phase is as follows. In the **Step 1**, If C-TBL for c_k(c_k $\in$ States) doesn't exist, create C-TBL for context c_k using context profiles. The context profile is required to register attribute values which each context has. Refer sensor profile information in the Table 1. If C-TBL for c_k ($c_k \in$ States) doesn't exist, create C-TBL for context c_k using sensor profiles.

Step 2 is initialization phase for new context c_k. Initialize new C-TBL for c_k, set 0 to C-TBL[$a_{k,i}$][ac_j], for each $a_{k,i}$ $\in$ Attributes(c_k), ac_j $\in$ Action Classes. Initialize value of R for R $\in$ {r_s, r_p, r_n}.

Step 3 repeats the following steps.

Step 3-1: Input current situation s(t), s(t) is consisted of sum of $a_{k,i}(t)$, where $a_{k,i}(t)$ $\in$ Attributes(c_k) and k $\in$ {1, ..., n}. The relationship among state, current state and current situation is as follows:

$\forall c_k$, c_k $\in$ Current States $\Rightarrow$ c_k $\in$ States

Situation(s(t), x) $\Leftrightarrow$ $\forall$x, x $\in$ Attribute (c_k), and c_k $\in$ Current States

Step 3-2: if $a_{i,k}^{(t)}$ is continuous value, it needs to be normalization. We adopt simple normalization approach and minimal set of interval approach for discretization of context with continuous attributes.

Case 1. min-max normalization performs a linear transformation on the original data and makes fixed intervals. Suppose that $\min_a$ and $\max_a$ are the minimum and the maximum values of $a_{i,k}^{(t)}$.

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

Case 2. we quantize continuous value into k intervals, where k is the minimal constant depending on the range of particular feature. In order to discretize feature A into k intervals, we use basic heuristic [7] to find a minimal set of intervals. Context data sets with continuous values will fall into an appropriate space

Step3-3: 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_k in C-TBL[$a_{k,i}(t)$][ac(t)] do

C-TBL[$a_{k,i}$][ac(t)]$\leftarrow$ C-TBL[$a_{k,i}(t)$][ac(t)]+αR(t), where α is the discount factor and $c_k \in$ States.

To provide the individualized and active services by using the learned C-TBL tables, P-TBL can determine whether it is a best to recommend any kind of action and recommends the action to a user in the particular state.

$$P-TBL[c_i][ac_k] = M(cs)\sum_{a_i \in cs} w_i \times C-TBL[a_i][ac_k] \quad (2),$$

where M(*cs*) is a normalization term, w_i represents the weight of c_i, and *cs* is user's current situation. w_i represents the weight of c_i and can be set identically. However, the significance of each context can vary with a user. For example, there is a sensitive user on the illumination sensor compared to other peoples. In order to differentiate the significance of each contexts interpreted by sensors, the entropy of a context is calculated through the method that is proposed in [8]. Then, preference for an action ac_k, $Pref(ac_k)$ can be estimated by the following rule using P-TBL:

$$\Pr ef(ac_k) = \sum_{a_i \in cs} P-TBL[a_i][ac_k]$$

4.3. Evaluation

Learner must be evaluated by real users in the ubiquitous environments. However, it is difficult to acquire behavior pattern of the real user; because of some critical problems related to the privacy issue of individuals. Keskustalo [22] noted that experiments on the effectiveness of relevance feedback with real users are time-consuming and expensive; therefore, leaner has been tested on several sets of data in UCI depository. To evaluate operation of leaner, we chose the following the data set; Iris, Wine, Create Approval, Balance and balloon in UCI repository. For example, Iris is perhaps the best known database to be found in the pattern recognition literature. In the case of the create approval in UCI machine learning repository datasets [9], 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 Datasets for Simulation

Data	Instance	Attr.(Categorical)	ActionClass
Create Approval	665	15(9)	2
Balloons	20	4(4)	2
Balance	625	4(4)	3
Iris	150	4(0)	3
Wine	178	13(0)	3

And also, we chose machine learning algorithms from the Weka3 data mining software [10]: J48, ZeroR, NaiveBayes [23] and SMOSupport Vector Machine. J48 builds a C4.5 decision tree Naïve Bayses selects the most likely classification based on a set of attribute values using prior probabilities and conditional densities of individual features. ZeroR simply predicts the majority class in categorical or average class if the class is numeric [23]. The k-fold cross validation is used in order to raise the confidence of experiments. 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 %. In order to raise the confidence of experiments, k-fold cross validation is used. K-fold cross validation is one way to improve over the holdout method. The data set is divided into k subsets, and the holdout method is repeated k times. However, when computing by equation (2), the user preference by the ontology was not considered in order to experiment in same condition with the comparison algorithm. w_i is calculated by the entropy of context through the information gain [8]. We implemented two algorithms: Learner-S and Learner-Q. Learner-S uses the min-max normalization and quantizes continuous value into 10 fixed intervals. On the other hand, Learner –Q quantize continuous value into minimal k intervals. And we only consider r_S because that it is difficult for deciding the reward value without explicit user feedback.

The left side of Fig. 6 shows the precision of each algorithm according to categorical context only. Learner is better than other algorithms in the aspect of Create Approval. The precision of our learner is 86.8% at create approval. And in all data sets, our learner is better than ZeroR with 1.5 times. The right side of Fig. 6 shows the precision of each algorithm according to continuous context only. Learner-Q is better than other algorithms in the aspect of Iris and Wine data sets. In the case of Wine data sets, Learner-Q improves 2.4times compared to ZeroR even though improves slightly compared to J48. Fig. 5 shows that Learner-Q is better than Learner-S. In the case of Wine data sets, Learner-Q improves with 1.2 times compared to Learner-S.

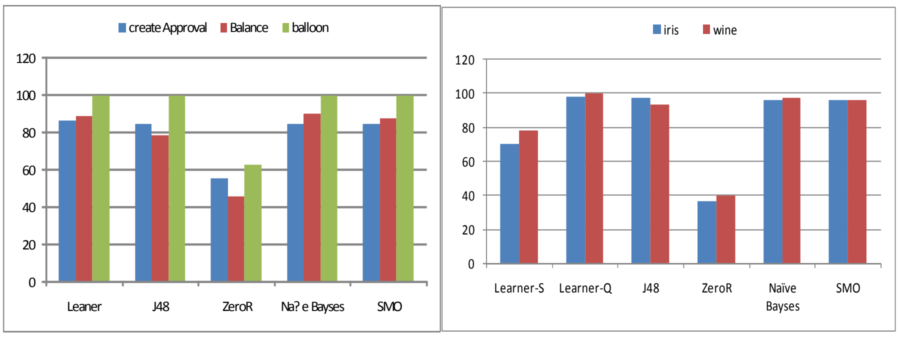

Fig. 6 Results of Evaluation

5. Conclusions

We propose the situation-awareness model for HKMP(Higher order Knowledge Management Platform) that has a capability to offer context-aware personalized services to user. This paper presents the system architecture of HKMP and classifies contextual information as lower order and higher order knowledge. The Proposed situation-awareness model is aware of user's situation and recommends personalized services based on this information. The main idea on this paper is how to evolve the awareness model without using personal information causing privacy issues and how to draw an inference effectively current situation of users. To achieve this requirement, we evolve our model through interactions between users and mobile devices using learning mechanism. And it derives user's current situation using ontology reasoning. Moreover, we adopt minimal set of interval approach for improving performance about discretization of context having continuous attributes.

We evaluated the precision of proposed approach using Weka3 software with data sets of UCI machine learning depository. The precision of our learner is 86.8% at create approval data set. And in all data sets, our learner is better than ZeroR algorithm with 1.5 times. Learner-Q is better than other algorithms in the aspect of Iris and Wine data sets. In the case of Wine data sets, Learner-Q improves 2.4times compared to ZeroR even though improves slightly compared to J48. In the case of Wine data sets, Learner-Q improves with 1.2 times compared to Learner-S. For further study, we have a plan to provide wholly implementation of HKMP approaches includes higher order knowledge exposure layer.

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References

1. A. Dey, G. Abowd and D. Salber, "A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-aware Applications," Human Computer Interaction, 16, (2001)
2. H. Kranenburg, M. Bargh, S. Lacob and A. Peddemors, "A Context Management Framework for Supporting Context-Aware Distributed Applications," IEEE Communications Magazine, pp. 67-74, (2006)
3. A. Moon, H. Kim, H. Kim and S. Lee, "Context-Aware Active Services in Ubiquitous Computing Environments," ETRI Journal vol. 29, no. 2, pp. 169-178, (2007)
4. M. Sutter, O. Droegehorn and K. David, "User Profile Management on Service Platforms for Ubiquitous Computing Environment," IEEE Vehicular Technology Conf., pp. 287-291, (2007)
5. A. Krause and A. Smailagic, "Context-Aware Mobile Computing: Learning Context-Dependent Personal Preferences from a Wearable Sensor Array," IEEE Trans. On Mobile Computing, 5(2), pp. 113-127, (2006)
6. J. Fogarty et al., "Predicting Human Interruptibility with Sensors," ACM Trans. On Compute-Human Interaction, 12(1), 119-146, (2005)
7. S. Nguyen and A. Skowron, "Quantization of Real Value Attributes," Joint Annual Conf. Information on Sciences, pp. 34-37, (1995)
8. K.Jearanaitanakij and O. Pinngern, "An Information Gain Technique for Acceleration of Convergence of Artificial Neural Networks," ICICS, pp. 349-352, (2005)
9. UCI Machine Learning Repository, "http://archive.ics.uci.edu/ml/"
10. Weka3 Data mining Software, http://www.cs.waikato.ac.nz/ml/weka/

11. G. Adomavicius, “Towards the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions,” IEEE trans. On Knowledge and Data Engineering, 17(6), pp. 734-749, (2005)
12. IST-2004-511607, MobiLife D27b (D4.1b) v1.0, (2004)
13. W3C, Composite Capabilities/Preference Profiles (CC/PP), (2004)
14. OMA, Use Agent Profile (UAProf) v2.0, (2003)
15. M. Endsley, “Toward a theory of situation awareness in dynamic systems,. Human Factors 37(1), pp. 32-64, (1995)
16. A. Brar and J. Kay, “Privacy and Security in Ubiquitous Personalized Applications,” User Modelimg Workshop on Privacy-Enhanced Personalization, (2005)
17. S. McBurney, M. Williams, N. Taylor and E. Papadopoulou, “Managing User Preference for Personalization in a Pervasive Service Environment,” IEEE Conf. on Telecommunications (AICT'07), (2007)
18. M. C. Mozer, “The Neural Network House: An Environment that Adapts to Its Inhabitants,” AAAI, pp. 110–114, (1998)
19. M. Feki, S. Lee, Z. Bien and M. Mokhtai, “Context Aware Life Pattern Prediction Using Fuzzy-State Q-Learning,” LNCS 4541, pp.185-195, (2007)
20. The TV-Anytime Forum, Specification Series: S-3 On: Metadata, (2001)
21. F. Herndex, E. Gaudioso and J. Boticario, “A Reinforcement Learning Approach to Achieve Unobtrusive and Interactive Recommendation Systems for Web-Based Communities,” AH 2004, LNCS3137, pp. 409-412, (2004)
22. H.Keskustalo, Kalervo and A. Prikola, “The Effects of Relevance Feedback Quallity and Quantity in Interactive Relevance Feedback: A Simulation Based on User Modeling,” ECIR 2006, LNCS 3936, 2006, pp. 191-204, (2006)
23. S. Louis, A.Shankar, “Context Learning Can Improve User Interaction, Information Reuse and Integration,” IEEE conf. IRI, pp. 115-120, (2004)