Context-aware Mobile Recommendation System Based on Context History

Qihua Liu
School of Information Technology, Jiangxi University of Finance and Economics,
Nanchang 330013, China, 86-079183983891
email: qh_liu@163.com

Abstract
Recommendation systems for the mobile Web have focused on endorsing specificr content based on user preferences. But, user preferences vary in different contexts, such as at different times of day and in different locations. Therefore, in a mobile networking setting, providing proactive personalized service is more likely to depend on actual user context. This paper proposed a context-aware mobile recommendation system framework based on user models utilizing the context history. The approach was validated in the tourism domain. From our experiment and evaluation, the proposed framework is a promising approach to provider proactive personalized services to mobile users. Moreover, this research offers the personalized services to new users analyzing between the new user's information and the stored association rules.

Keywords: mobile web, recommendation system, context-aware, context history, mobile tourism

1. Introduction

Recommendation systems for the mobile Web have focused on endorsing particular types of content based on user preferences. However, mobile devices can be used anywhere at any time and in any context to connect to the mobile Web. User preferences vary in different contexts, such as at different times of day and in different locations [1]. So, user context data are potentially useful for identifying the user's current needs in a sense that the contextual situating can be a crucial factor affecting user models. In a mobile networking setting, providing proactive personalized service is more likely to depend on actual user context [2]. Moreover, advances in mobile technologies have made the collection of customers' context information feasible.

To manage these context-sensitive situations, recently, context-aware computing has been considered to automatically acquire and utilize context data in order to run the services that are appropriate for the particular people, place, time and events [2-3]. Many researchers have been interested in context-aware computing [1-15]. Context is any information that can be used to characterize the situation of an entity where an entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including location, time, activities, and the preferences of each entity [13]. Context awareness is about capturing a broad range of contextual attributes to better understand what the user is trying to accomplish, and what services the user might be interested [11]. So, using the context-aware technology to estimate user models are crucial for mobile networking applications.

There were some previous researches for the personalized services using the users' preferences on context-aware computing. However, most research only consider the current user' context while ignoring the context history. As the collection of the past context and users' actions for the past context, context history has been used for the prediction of future context, selection of devices and adaptation [8, 13]. So, the user's context history should be taken into account in order to model and infer their needs in the present situation. Byun and Cheverst (2004) used Decision tree based on context history to infer the preferences of the user [8]. But, it is difficult to predict new user's preferences in this research because individual preferences were extracted and saved. There is also lack of specific method to infer user's preferences. Hong et al (2009) have suggested the basic direction for provision of the personalized services on context-aware computing and utilization of context history [13]. They assume that the high-level context is already inferred in their research, and extract the preferences of users using the

survey about the preferred services when the high-level context is given. However, there are some limitations like these: (1) First, accurate high-level context inference is notoriously difficult as dimensions of context may be dynamically updated, which makes it more complicated to handle the change of the user's dynamic models than the change of static user models. (2) Second, this research did not provide the common formal and reusable representation format of user preference and preferred services, which tends to lead to some semantic problems such as synonymy and polysemy.

This paper proposed a context-aware mobile recommendation system framework based on user models utilizing the context history. Based on the proposed framework, we presented a system called CAMTRS, which was a context-aware mobile tourism recommender system. From our experiment and evaluation, the proposed framework is a promising approach to provider proactive personalized services to mobile users. Moreover, this research offers the personalized services to new users analyzing between the new user's information and the stored association rules.

2. System Framework

Context history is the collection of the past context and users' actions for the past context. The history of contexts could be extremely valuable in enabling the current level of context interpretation to be significantly enhanced [8]. For example, by using histories of context (such as user location, calendar information, etc.), it may be possible to determine that a certain user has a regular meeting schedule. A proactive system could then take the proactive step of reminding the user of the meeting at an appropriate time before each meeting [13].

Figure 1 decribes the context-aware mobile recommendation system framework based on user models utilizing the context history. It has four phases: context history acquisition, context history inference, preference prediction and user modelling, and recommender.
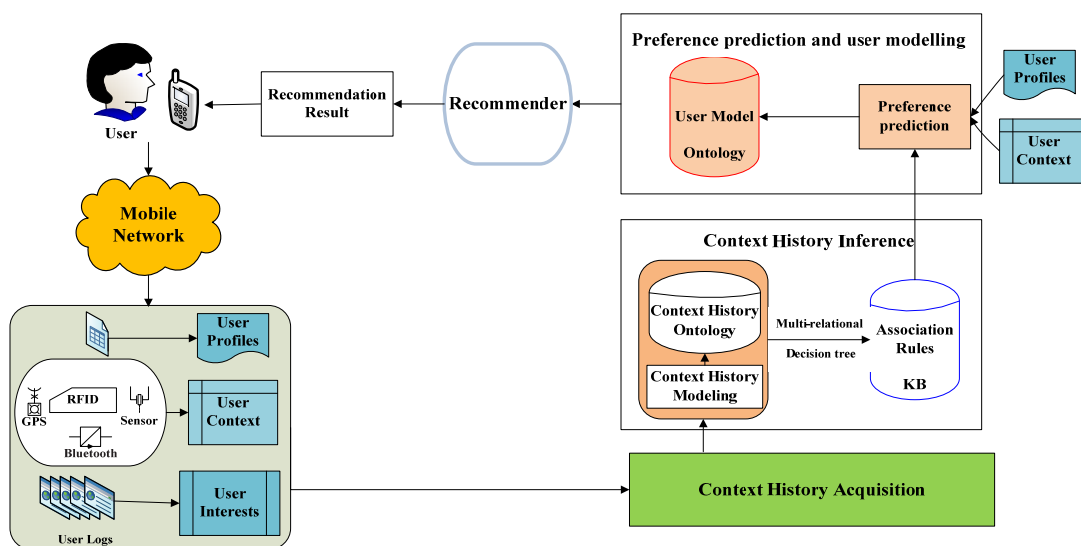

Figure 1. Context-aware System Framework for Proactive Personalized Mobile Networking Applications

Mobile agents are software agents that are capable of transmitting themselves (including their program and their state) across a computer network and recommencing execution at a remote site [11]. Mobile agents have been proposed to solve problems of networked application domains, for example, electronic commerce [16], network management [17], and information retrieval [18].

As the mobile applications are generally operated in an open environment in which resources and repositories are distributed in different machines and the network connection is

unreliable, the multi-agent design methodology thus provides an appropriate solution to the deployment of such type of application services [11]. So, this framework consists of seven mobile agents: user profiles agent, user context agent, user interest agent, context history agent, association rules agent, user modeling agent, and recommender agent.

2.1. Context History Acquisition
The acquisition of context history information depends on three sources: user profiles, user context and user interests [19].

Users' profiles refer to the users' personal information such as gender, age, nationality, educational level and available income. User profiles agent uses the form-filling approach to collect the information about the users' profiles. In the form-filling approach, information is acquired directly from users' inputs.

User context is the central dimension in contextualized mobile applications and the most widely one addressed in the research area. User contexts considered in this paper are: location, time, weather and device. Although, there are no limits of number of contextual dimensions in the context-aware applications, only four dimensions were used for the simplicity. These four dimensions were selected since location, time, weather, device and network have been the most widely used context dimensions so far. User context agent uses various advanced mobile and ubiquitous technologies such as Sensor, RFID, Bluetooth, and GPS to collect four user contexts: location, time, weather and device.

User interests may be described by the user behavior for the past context. User behavior, seen as set of implicit feedback indicators such as past click history, clickthrough data, browsing features and eye-tracking [20]. HUNC (Hierarchical Unsupervised Niche Clustering) [21] is a hierarchical version of the unsupervised niche clustering algorithm, which has been effectively applied in web usage mining and personalized service applications. So, User interest agent applies HUNC algorithm on web log data to analyze the prevalent online activity patterns and build user interests ontology based on domain ontology as Figure 2. Use interests are represented using domain ontology based on Semantic Web technology and ontology markup language.
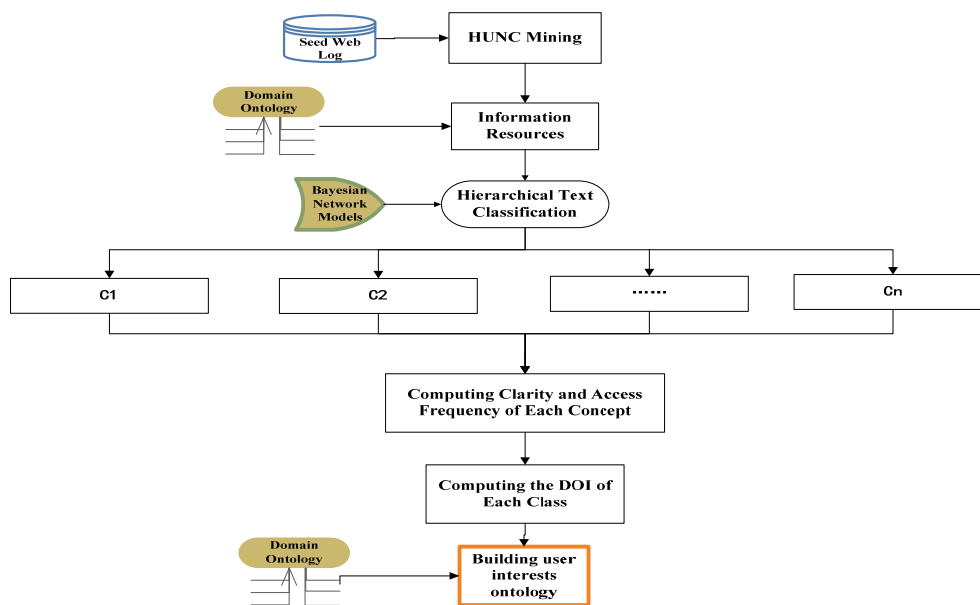

Figure 2. Building user interests ontology based on domain ontology

(1) Applie HUNC algorithm on web log data to acquire relevant web pages,
(2) Use the method which, given a web page to be classified, automatically generates an ordered set of appropriate descriptors extracted from the domain ontology based on [22],

(3) Compute the clarity of each concept $Clarity(C)$ with the following property:

$$Clarity(C) = \frac{NumAttribute(C) + 1}{NumSubConcepts(C)} + 1 \tag{1}$$

$NumAttribute(C)$ is the number of attributes of the concept C, $NumSubConcepts(C)$ is the number of the each leaf class of the concept C,

(4) Compute the access frequency of each concept $RFrequency(C)$ with the following formula:

$$RFrequency\ (C) = \sum_{i=1}^{j} RFrequency\ (URL_i) = \sum_{i-1}^{j} \frac{Q(URL_i)}{Q} \tag{2}$$

$RFrequency(URL_i)$ is the access frequency of the web page *I*, $Q(URL_i)$ is the access number of the web page *I*, *Q* is the access number of the all pages,

(5) Compute the DOI of each concept $Interest(C)$ with the following formula:

$$Interest(C) = RFrequency(C) \bullet Clarity(C) \tag{3}$$

(6) Build user interests ontology based on domain ontology. User interest ontology stores the degrees of interest for each instance and for each class refereed to the user interest preferences. The degrees of interest (DOI) of each class belong to the range [0, 1] and can be computed by considering the sum of DOI for each leaf class.

2.2. Context History Inference

Context history inference layer include two mobile agents: context history agent and association rules agent.

Ontology is a formal explicit specification of a shared conceptualization. It is a widely accepted approach for context history modeling with the benefits of: (1) sharing and reusing context knowledge, (2) giving formal semantics to context element which enable formal analysis and reasoning, and (3) independence of programming language [12]. Context history agent uses ontology based on OWL to represent context history information. Because to manage and process lots of context information on context-aware computing is difficult and the amount of context information, we use the hierarchical approach to build context history ontology. Context history ontology consists of common ontology and domain ontology in this research as Figure 3.

Mitchell et al. (1994) argued that learning based on a decision tree is suitable because the rules generated may be intelligible to humans, whereas, learning based on the neural network approach is less suitable because the weights produced by this approach are difficult to interpret by human users [23]. However, Setiono and Liu (1996) suggest a method of symbolic rule representation from the weights obtained from a neural network and empirically showed that the rules generated by the augmented neural network and the rules extracted by a decision tree are remarkably similar [24]. However, he also recommended that when the time for learning must be as short as possible, the decision tree approach is most appropriate because it takes considerably longer to learn a rule set by a neural network than by a decision tree.

Leiva (2002) developed a multi-relational decision tree learning algorithm (MRDTL) [25]. Experiments reported by Leiva (2002) have shown that decision trees constructed using MRDTL have accuracies that are comparable to that obtained using other algorithms on several multi-relational data sets. However, MRDTL has two significant limitations from the standpoint of multi-relational data mining from large, real-world data sets: slow running time and inability to handle missing attribute values [26]. Against this background, Atramentov (2003) describes MRDTL-2 which attempts to overcome these limitations and has achieved better experiment results.

So, association rules agent uses multi-relational decision tree induction MRDTL-2 to min context history for building association rules knowledge base.

Step 1: Storing context history ontology in relational databases;

Relational database systems are very mature and scale very well, and they have the additional advantage that in a relational database, ontology data and the traditional structured data can co-exist making it possible to build applications that involve both kinds of data. In this paper, we apply a novel approach to transformation of context history ontology to relational databases, which is proposed by [27].

Step 2: Using MRDTL-2 to build the multi-relational decision tree;

Step 3: Converting the multi-relational decision tree into IF-THEN rules, and building association rules knowledge base. Accroding the study of Mollestad and Skowron (1996) [28], we pre-set a threshold u ($0<u<1$), and delete some rules with a smaller credibility.
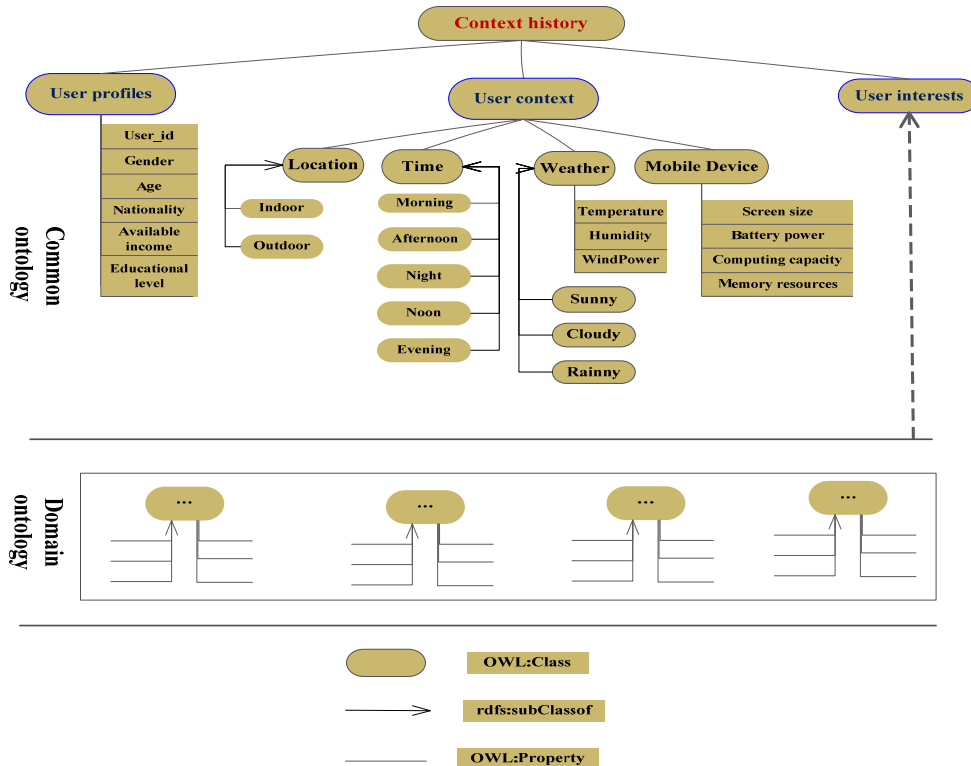

Figure 3. Context History Ontology

2.3. Preference Prediction and User Modeling

The development of personal networked mobile computing devices and environmental sensors mean that personal and context information is potentially available for the personalized applications. According to users' current context and personal information, user modeling agent infers users' interest preferences in specific situation as Figure 4, and builds the user model.
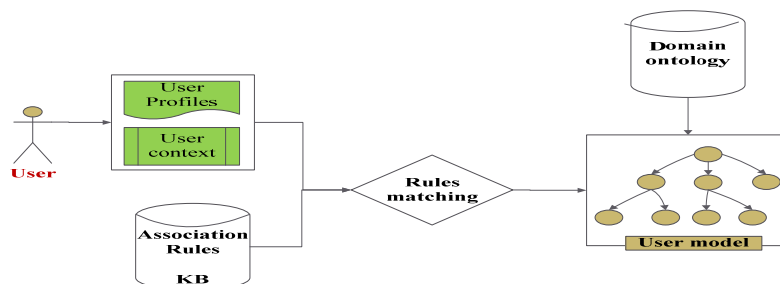

Figure 4. Preference prediction and user modeling

Step 1: Using user profiles agent and user context agent to collect user's personal and contextual information in the present situation;

Step 2: Using association rules KB to infer users' interest preferences;

Step 3: Building the personalized user model based on domain-specific ontology.

2.4. Recommender

We use the content-based filtering approach to proactive provide personalized information to mobile users. In this paper, the User model is described by the Semantic Vector based on ontology: $U = \{u_1, u_2, ..., u_k\}$. C_k indicates the specific concept of User model, and u_k indicates the DOI of C_k to user u. The web pages are described by the Semantic Vector based on ontology: $R = \{R_1, R_2, ...R_k\}$. R_k indicates the importance of C_k to the page R, can be determined with the TF-IDF (Term Frequency-Inverse Document Frequency) measure method. Then, the cosine similarity measure is used to compute the similarity between U and R. The formula could be seen in the following equation:

$$Sim(U, R) = \frac{U \bullet R}{|U| \times |R|} = \frac{\sum_{i=1}^{k} u_i R_i}{\sqrt{\sum_{i=1}^{k} u_i^2 \sum_{i=1}^{k} R_i^2}} \tag{4}$$

3. Application to Mobile Tourism

The tourism industry has always been open to new technologies; even more so to the mobile networking, giving rises to the field of mobile tourism (m-tourism). M-tourism represents a recent trend in the field of tourism that involves the use of tourist applications offering services and tours with multimedia content executed on electronic mobile devices, e.g., mobile phones, personal digital assistants (PDA), palmtops, i-pods and psp consoles [29].

Because the number of possible travel options and sources of available information is growing at a staggering rate, it has become more difficult to provide support to travellers at any time during their trip: when they build their pre-travel plan, during their move to, or their stay in, the selected destination, and possibly when the trip finishes. In a mobile setting, the characteristics of the tourist recommendation services are [30]:

a) The relevant information to support the decision is distributed.
b) The information sources are specialized.
c) The information is updated frequently and in an asynchronous way.
d) The query is done in real time and the result needs to be efficient.

So, personalization has been recognized by researchers as a critical factor of effectiveness, added value and commercial success in tourism. In mobile tourism, personalization has mainly been addressed in the context of guides, providing content recommendations that match user preferences, typically consolidated in user models.

According to the proposed context-aware system framework, this paper proposed the CAMTRS-Context-Aware Mobile Tourism Recommender System. CAMTRS is an mobile networking application that serves a tourist with information needed in his specific context that are interesting to him given his goal for that moment.

CAMTRS is composed of three sub modules: Tourist Information Collection Module, User Modelling Module and Personalized Recommendation Module as Figure 5. The User Modelling Module consists of Context History Acquisiting Wrapper, Context History Inference Wrapper and Preference Prediction Wrapper.

Tourist Information Collection Module collects tourist information based on some tourist web sites. The Weblech crawler (http://weblech.sourceforge.net) is employed to crawl web pages. The seed URL is the web site"www.51yala.com", and the predefine topic is"Travel". In this paper, we collected 28954 Chinese web pages as the data set.

User Modelling Module use MRDTL-2 to min context history for building user model based on e-Tourism ontology (http://e-tourism.deri.at/ont/docu2004). This e-Tourism ontology describes the domain of tourism and it focuses on attractions, accommodation and activities. It

is based on an international standard: the Thesaurus on Tourism and Leisure Activities of the World Tourism Organization.

Personalized Recommendation Module uses the content-based filtering approach to proactive provide personalized tourist information to mobile users.
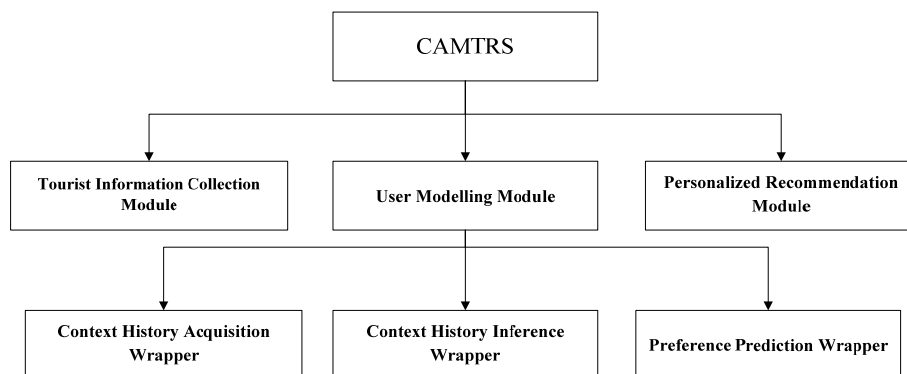

Figure 5. Program Structure for CAMTRS

4. Implementation and Evaluation

The CAMTRS was implemented using Java under JDK1.6 and experimented on a HP ProLiant DL388 G7 Server platform with the LINUX operating system. Context history ontology was stored in Microsoft SQLServer 2005.

To collect users' context history, we studied 200 China mobile web users. The statistical information of the users is presented in Table 1.

Table 1. The Statistical Information of the Users

Demographic characteristic	n	Percentage of the total
Age		
18 and under	8	4%
19-30	114	57%
31-45	50	25%
46-60	24	12%
Over 60	4	2%
Gender		
Male	116	58%
Femal	84	42%
Gducational level		
Bachelor's degree	122	61%
Master's degree	48	24%
Doctorate	16	8%
Post-doctorate	4	2%
Others	10	5%
Available income (CNY)		
500 and under	5	2.5%
500-2000	109	54.5%
2000-10000	46	23%
10000-50000	28	14%
Over 50000	12	6%

First, we obtained the users' personal and contextual information using the form-filling approach in mobile site of CAMTRS; only the form-filling approach was used for the simplicity. Second, we obtained the user interest from user logs between July and September 2012. At

last, the data of context history more than 38,000 records of 200 users in this experiment. During the context history inference, 368 association rules are generated.

In this paper, we use the predictive accuracy metrics to evaluate the CAMTRS. Measuring predictive accuracy are necessarily limited to a metric that computes the difference between the predicted rating and true rating such as MAE(Mean Absolute Error). But, MAE may be less appropriate for mobile networking application. An inconvenient user interface (small devices with small screens and slow onscreen keyboards) may constitute a barrier to browsing the mobile Web; therefore a ranked result is returned to the user, who then only views items at the top of the ranking. In a mobile setting, users may only care about errors in items that are ranked high, or that should be ranked high. It may be unimportant how accurate predictions are for items that the system correctly knows the user will have no interest in.

This paper uses the MAE (N) to measure the predictive accuracy of recommender system in the mobile networking applications. The formula could be seen in the following equation:

$$\text{MAE}(\text{N}) = \frac{\sum_{i=1}^{N}|P_i - U_i|}{N} \tag{5}$$

In this equation, MAE (N) represents the mean absolute error of N items that are ranked high in the result set; P_i indicates a predicted rating; U_i indicates the user's true rating.

The threshold u is either known information must be fixed to facilitate the evaluation of results. We randomly selected 10 users, and computed the MAE (10) for u values of 0.1, 0.2, 0.3, 0.2, 0.5, 0.6, 0.7, 0.8, and 0.9. The results are shown in Figure 6. The MAE (10) initially decreases as a function of K, reaches a peak at u=0.6, and then increases thereafter, so data are best accounted at the point of u=0.6. Therefore, we choose the threshold is u=0.6.
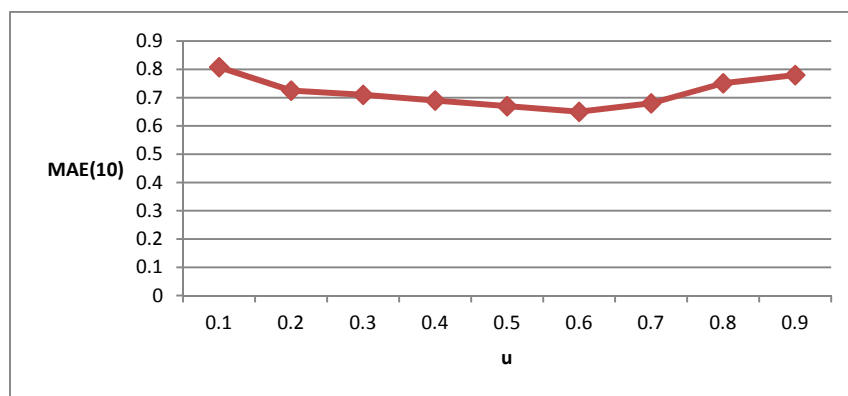

Figure 6. The Value of MAE (10) for Different u

Table 2. Architecture of the Measured Models

Model	User profile	User context	User interests	Context history
Model 1	No	No	Yes	No
Model 2	No	Yes	Yes	No
Model 3	No	Yes	Yes	Yes
CAMTRS	Yes	Yes	Yes	Yes

To evaluate the performance of CAMTRS, we have tested four different methods (Table 2). The first one uses only the user's interests, which applies HUNC algorithm on web log data to analyze the prevalent online activity patterns. The second one builds the user model based on the user's interests and his current context [7]. The third one collects and accumulates user contexts as a context history, and infers the users' perferences using Decision tree algorithm

[8]. The fourth one is the CAMTRS, which integrated three main elements into context history: users' profiles, user context, and user interests.

It is difficult for the previous researches (Model 1, Model 2 and Model 3) to provide new user with the personalized services due to the deficiency of their history or information. So, we investigated the performance of different methods by performing a survey amongst 50 registered users (42% females and 58% males). In this experiment, we computed the MAE (N) of four methods for N values of 5, 10, 20 and 50. The obtained results were depicted in Figure 7.
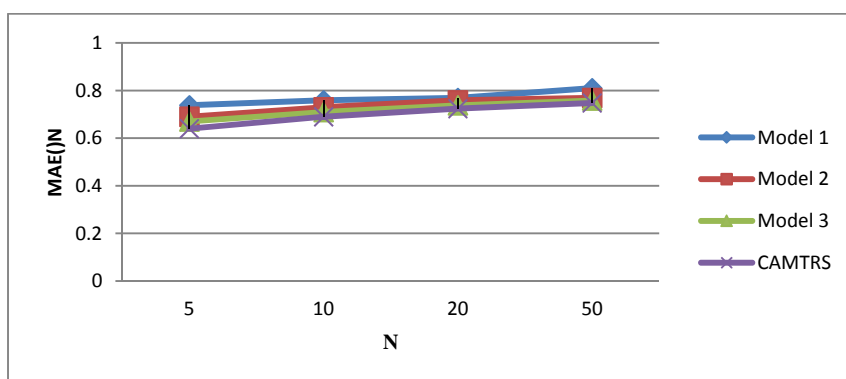

Figure 7. Results Obtained with the Different Models as Shown in Table 2

As can be seen in Figure 7, the CAMTRS has the lowest MAE. So, CAMTRS has a better predictive performance than the other methods. Moreover, CAMTRS can offer the personalized services to new users analyzing between the new user's information (user's profiles and contexts) and the stored association rules.

5. Conclusion

This paper proposed a context-aware mobile recommendation system framework based on user models utilizing the context history. The approach was validated in the tourism domain. From our experiment and evaluation, the proposed framework is a promising approach to provider proactive personalized services to mobile users.

Some limitations of this research should be mentioned. First, CAMTRS uses the form-filling approach to collects users' contexts for the simplicity. Second, CAMTRS uses the content-based filtering approach to recommend tourist information to mobile users. But, it is necessary to verify whether the recommendation technique is reasonable or not. Most recommendation techniques fall into three categories, namely content-based filtering, collaborative filtering, and hybrid filtering approach. Future research can try to use different recommendation algorithms to observe whether the predictive performance of CAMTRS can be improved.

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