Effective Context-aware Recommendation on the Semantic Web

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Summary
Semantic web is the driving technology of today's Internet as it can provide valuable information on-the-fly to users everywhere. The semantic web is well recognized as an effective infrastructure to enhance visibility of knowledge on the web. The core of the semantic web is ontology, which is used to explicitly represent our conceptualizations. Since the information overload, recommendation systems are facing new challenges for effective recommendation. With semantic web technology, information can be given well-defined meaning which can be understood and processed by machines. It provides new possibilities for effective recommendation. The main contribution of this paper is to provide a recommendation mechanism based on the semantic web. In addition, this paper presents and discusses some experiments that are based on quantitative and qualitative evaluations.

Key words:
recommendation, context-aware, semantic web, ontology

1. Introduction

Context-aware computing is a new paradigm in which applications can discover and take advantage of contextual information, such as user location, time of day, nearby people and devices, and user activity. In context-aware computing environment, computers will be everywhere around us and we will not be aware that we are using a computer. The emergence of context-aware computing opens up radical new possibilities for acquiring and sharing contextual information.

The emergence of context-aware computing opens up radical new possibilities for recommending contextual information. The context-aware recommender systems used to provide users with relevant information and/or services; the first based on the user's context; the second based on the user's interests [2,10,13].

The semantic web is well recognized as an effective infrastructure to enhance visibility of knowledge on the web. The core of the semantic web is ontology, which is used to explicitly represent our conceptualizations [5,9]. Ontologies expressed in the semantic web languages provide a means for independently developed context-aware systems to share context knowledge, minimizing the cost of and redundancy in sensing [1]. Ontologies play an important role in context-aware systems, because ontologies are envisioned as key elements to represent knowledge that can be understood, used and shared among distributed applications. There are some context-aware recommendation systems, which benefit from the use of ontologies [3].

The recommendation methods using ontologies manage the most detailed information overload by helping a user choose from among an overwhelming number of possibilities. Moreover, the detailed information far exceeds that which is needed or could ever be used.

For effective context-aware recommendation, our method first provides the information for the current context. After identifying a concept of interest in the recommended information, the user changes the current context to the context of the concept of interest. More detailed information is then provided for the new context. This method can thereby produce more effective recommendation.

The paper is organized as follows. We start giving an overview of the related works, then effective context-aware recommendation. Finally, we present some experiments, showing the benefits of our system and discuss the results and conclusions of our work.

2. Related Works

Recently, many researchers have actively tried to leverage a semantic web in support of context-aware recommendation. There are ongoing researches aimed at leveraging a semantic web in support of context-aware recommendation system. myCampus (Carnegie Mellon's Context-Aware Mobile Campus Services) and CoolAgentRS (Cool Agent Recommendation Service) are recommendation systems in which the user's context is modeled as ontologies [2,12]. myCampus is a Semantic Web environment for context-aware mobile services aimed at enhancing everyday campus life at Carnegie Mellon University. CoolAgentRS demonstrates the ability to allow contextual information to be freely distributed among agents so that the meaning of that information can be shared and understood. Both of the systems take into account contextual parameters, such as location, calendar, social context, and personal preferences. While the modeling of the contextual information as ontologies is an essential first step, the real benefit can be seen when the

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ontologies are shared between systems, which then reason over the information.

In CRUMPET(CReating of User-friendly Mobile services Personalised for Tourism), the user can ask for recommendations for sites near the user's current location [11]. This provides new information delivery services and service integration systems for a far more heterogeneous tourist population than any system in the past. Information and services accessible from any location using different devices and different connectivity allow the user to prepare a journey and plan activities during that journey, or at the destination.

COMPASS (COntext-aware Mobile Personal ASSistant) is a context-aware recommendation application that provides tourists with information and services for a specific context relevant to their goals for that moment [14]. This can reuse already existing ontologies for the modeling of context and for intelligent reasoning of the context.

In contrast, most previous related works provide information that does not depend on the required level of information for each context. Instead, they provide an abundance of useless information that the user is unlikely to need or want.

3. Effective Context-aware Recommendation

The previous researches based on ontologies provide an abundance of useless information that does not depend on the required level of information for each context. In our method, ontologies enable an effective recommendation using concept.

In this paper, we developed an ontology model for grocery store. Our ontology is categorized into four distinctive but related themes: (i)ontology about product, (ii)ontology about location, (iii)ontology about the record, and (iv)consumer. The "Product" ontology specifies the products that are recommended by our method, and the "Location" ontology specifies the contextual information, especially the location context. The "Consumer" and "Record" ontology are used to model the consumer records and the shopping records.

The proposed method conceptually comprises three main steps. The first step is to extract a consumer's preferred items on the basis of the consumer's shopping records. To extract these items, instances and classes with the preferred item score above a given threshold are selected in product ontology. The preferred item score, $PS_{i,u}$, for a product item, *i*, with respect to a consumer, *u*, is defined as follows:

Instance: $$PS_{i,u} = \frac{\text{the total number of } i \text{ in } u\text{'s shopping records}}{\text{the total number of } u\text{'s shopping records}}$$

Class: $$PS_{i,u} = \sum_{j=0}^{j=max} PS_{j,u} \text{ X } \frac{|H_i|}{|H|} \quad (1)$$

where max is the number of child items for *i* with respect to *u*: Hi is the position of the component in ontology hierarchy, H (where the uppermost class has a value of 1 and the bottommost instance has the value of |H|) and |H| is the total height of the ontology hierarchy.

In the second step, the level of information to be provided to the consumer is determined. Instead of simply providing the most detailed information regarding the consumer's preferred items for each context, we use an ontology with concept hierarchy. The concept hierarchy contains a large number of concepts organized into multiple levels, where the concepts at a higher level have a broader meaning than those at a lower level. In general, a child concept is more specific in meaning than its parent concept. Our method first provides the information at a higher level for the current context. After a consumer identifies a concept of interest in the recommended information, the consumer changes the current context to the context of the concept of interest. The method then provides information at lower levels according to the new context. It rapidly recommends information that is more accurate for the target context.

In this step, we consider how many items the consumer prefers for each context and the maximum number of items to be included in the recommendation. When the number preferred items is greater than the maximum number of items to be recommended in the consumer's mobile device, the level of information is higher.

In the final step, the recommendation information in the second step is refined in relation to the consumer's attention. Attention is defined as focused mental engagement on a particular message or piece of information [4]. We adopt the parameter of attention weight, AW, as found in [8]. The degree of attention, which is used as a weighting factor for a recommendation, is based on the context preferences and behavior of the consumer. In the recommendation, the amount of information needed for a context with a high weight is larger than that needed for a context with a low weight.

For faster and more accurate recommendation, we use a caching and prefetching method. We prefetch recommendation information to be retrieved in the near future. When attention to the current context is high, the method estimates which other contexts that are contained by the context are likely to be visited in the near future. The prefetch weight is used to prefetch the information in the recommendation. If the prefetch weight for a context is low, there is a low possibility that the recommended information for the context will be accessed in the near future. Moreover, consideration is only given to contexts in which the prefetch weight is greater than a certain threshold.

The prefetch weight, $PW_{k,u}$, for a context, k, to be contained by the current context, c, with respect to a consumer, u, is defined as

$$PW_{k,u} = \frac{AW_c}{\text{the length of ontology path from context c to k}} \quad (2)$$

The total amount of recommended information that a consumer can obtain is restricted to a limited amount of information, called R_{max}. This restriction means that the amount of the information in the recommendation does not exceed R_{max}. Thus, the amount of information to be prefetched is set to R_{max} multiplied by $PW_{k,u}$.

4. Experiments

In experimenting with a consumer's PDA application and a grocery server, we considered both the proposed method, called *System1*, and the existing method, called *System2*.

In the experiments, the number of instances in the product is 420. In the location ontology, the number of instances is 1 in the top level zone, 10 in the mid-level zone, and 33 in the selling zone. The stores that share the ontologies in Figure 1 are called store1(store2 ... store10), and the largest store, store10 has all instances in the product ontology. We varied the number of items for sale in each store varied by 10%; that is, from 10% of the number of the largest store's items for sale to 100%.

We also varied the number of preferred items for each selling zone by 10% from 20% to 50%. The score for the preferred items was randomly generated. In addition, we matched the number of items purchased with the number of preferred items. Of the items purchased, 80% were preferred items and 20% were non-preferred items.

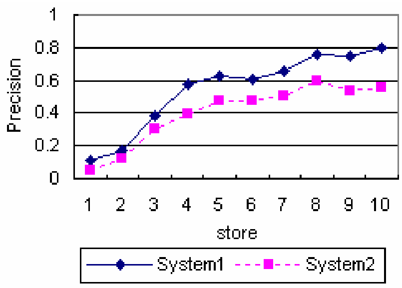
The attention weight was set to 0.5 in the top level zone. If a consumer purchased items in a selling zone, the attention weight of the selling zone as well as that of the middle level zone that contained the selling zone was set to 1. Otherwise, the attention weights were set to 0.2. The maximum number of items to be recommended in the consumer's PDA was set to 5. For the performance evaluation, we conducted the experiment 100 times.

4.1 Experiment 1: Precision and Recall

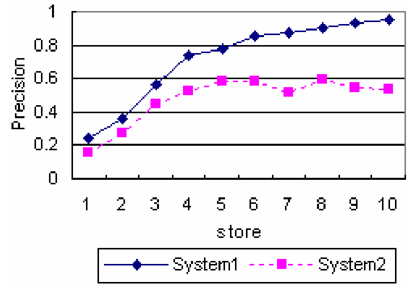
To evaluate the accuracy of recommended information, we used the precision and recall. Precision is measured as the proportion of information retrieved which are relevant, whereas recall is the proportion of the available relevant information that has been retrieved. In the following equation, R is the information recommended to a consumer, P is the set of items purchased by the consumer, and |S| is the cardinality of a set S. The precision and recall are usually defined as shown below.

$$\text{Precision} = \frac{|R \cap P|}{|R|} \qquad \text{Recall} = \frac{|R \cap P|}{|P|}$$

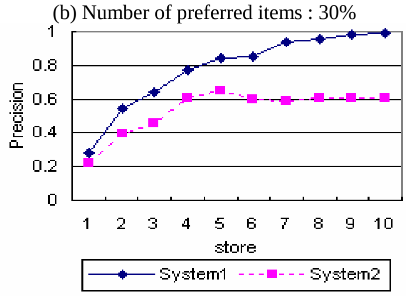
In the equation, R is the information recommended to a consumer, P is the set of items purchased by the consumer, and |S| is the cardinality of a set S.



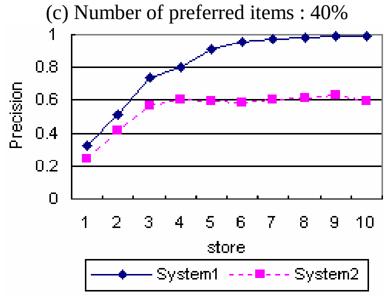
(a) Number of preferred items : 20%



(b) Number of preferred items : 30%

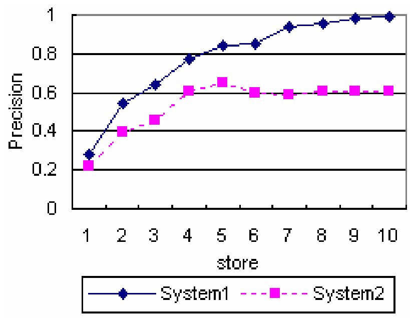


(c) Number of preferred items : 40%

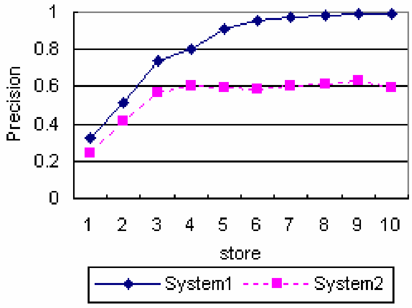


(d) Number of preferred items : 50%

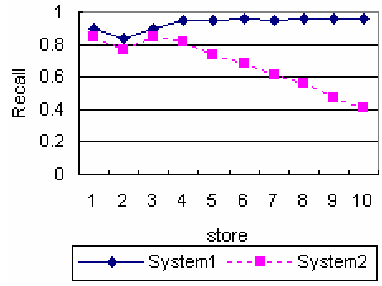
Fig. 1. Average precision



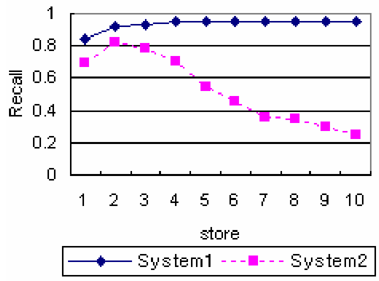
(a) Number of preferred items : 20%



(b) Number of preferred items : 30%



(c) Number of preferred items : 40%



(d) Number of preferred items : 50%

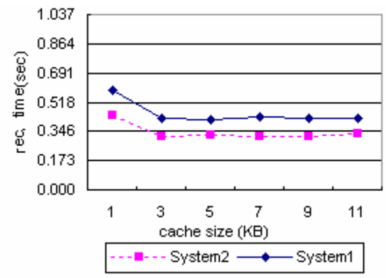
Fig. 2. Average recall

Figure 1 and Figure 2 show the average precision and recall of the recommended information for each context. Several of the same observations are found in these results. First, the average values of the precision and recall in *System1* are consistently better than those of *System2*. Second, as the number of preferred items increases, the difference in values of precision and recall between *System1* and *System2* increases. This phenomenon is due to the fact that when the number of preferred items is greater than the maximum number of recommended items the level of information is higher and the information has a broader meaning.

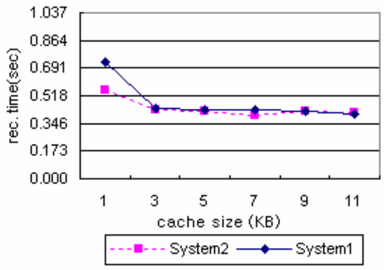
Significantly, when the number of preferred items increases, the difference between *System1* and *System2* is higher in Figure 2 than in Figure 1. As the number of preferred items increase, the number of items purchased increases. *System2* recommends the top five items at the lowest level, regardless of the number of preferred items. In *System1*, on the other hand, as the number of recommended items increases, the level of recommended items rises. Thus, when the number of preferred items increases, the average recall of *System2* is near 0 and the average recall of *System1* is near 1

4.2 Experiment 2: Recommendation Time

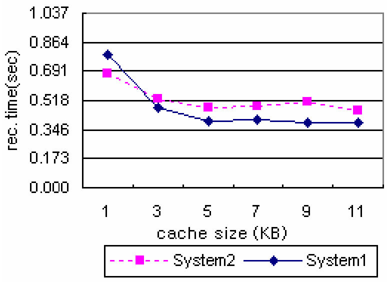
To evaluate the recommendation speed, we tested the average recommendation time for each context whenever the consumer's cache varied in size. For comparison, we varied the cache size by 2Kb from 1Kb to 11Kb.



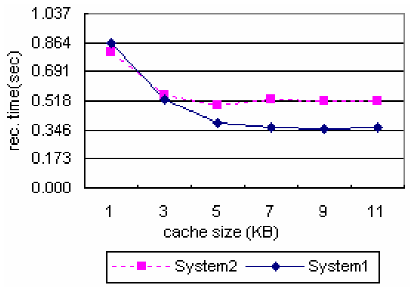
(a) Number of preferred items : 20%



(b) Number of preferred items : 30%



(c) Number of preferred items : 40%



(d) Number of preferred items : 50%

Fig. 3. Average recommendation time

Figure 3 shows the average recommendation time whenever the consumer's cache varies in size. When the cache increases in size, recommendation time decreases. Significantly, when the cache increases in size and the number of preferred items increases, *System1* performs better than that of *System2* and the performance difference between *System1* and *System2* is higher. This phenomenon is due to two things: firstly, that the amount of recommended information in System1, is reduced when the attention weight is low; and, secondly, that the amount of prefetched information increases when the cache size and the number of preferred items increase.

5. Conclusion

The semantic web technologies promote an efficient and intelligent access to the information. At the core of semantic web, ontologies are envisioned as key elements to represent knowledge that can be understood, used and shared among distributed applications. And recommender systems have been developed as a solution to the abundance of choice people face in many situations today.

Our work shows that the newly recommendation method is suitable for effective recommendation on the semantic web. We present a new procedure for improving the effective recommendation by using the multi-level characteristic of ontology. Our method involves three steps. First, a consumer's preferred items are extracted from the consumer's records. Second, the level of information to be provided to the consumer is determined. Finally, the information recommended in the second step is refined in response to the consumer's attention. Our experimental results also confirm that our method has greater accuracy and speed in terms of precision, recall, and recommendation time. They can be generalized to fit other domains.

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