Providing Context-Aware Personalization through Cross-Context Reasoning of User Modeling Data

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Abstract. Existing personalization systems base their services on user models that typically disregard the issue of context-awareness. This work focuses on developing mechanisms for cross-context reasoning, i.e., inferences linking user model data in two different contexts. That reasoning process can augment the typically sparse user models, by inferring the missing information from other contextual conditions, and can better support context-aware personalization. Thus, the proposed approach improves existing personalization systems and facilitates provision of more accurate context-aware personalized services.

1 Introduction

During the years, personalization research yielded a number of techniques that facilitate adapting the services provided to the user to his/her interests, needs and constraints. Those are expressed by the User Models (UMs) [7] that constitute an essential input for every personalization technique. Current personalization techniques suffer from a severe limitation. User preferences represented by the UMs are generally valid only in a specific application and in a specific context, which is typically disregarded by the state-of-the-art personalization systems. However, considering various contextual conditions can prove essential for providing accurate personalization.

For example, consider a task of recommending radio music for a user during his/her daily driving from home to work. Although the user's music preferences are quite steady, different types of music may be recommended as a function of his/her mood, presence of other people, or traffic and weather conditions. Hence, there is an emergent need for *slicing* the general preferences represented by the UM according to various contextual conditions. This will allow considering the contextual aspects and providing the user with context-aware personalization.

On the one hand, context-aware personalization may significantly improve the accuracy and the usefulness of the provided service. On the other hand, the information stored in the UMs may not suffice for providing accurate context-aware personalization. This deficiency follows from the above slicing of the general UMs that splits the available user information according to the appropriate contextual conditions. Hence, any attempt of inserting the context-awareness dimension into the state-of-the-art personalization systems implies developing a reasoning mechanism, which will facilitate inferring the essential parts of the UMs across various contextual conditions.

This work focuses on developing mechanisms for cross-context reasoning for UMs, which can be applied for the purposes of the subsequent context-aware personalization. The core element of these mechanisms is referred to as user *experience*. By experience we denote an explicit or implicit feedback provided by a user as a result of consuming (i.e., using, purchasing, viewing, reading, listening, browsing and so forth) a certain item in a certain context. Figure 1 schematically illustrates the experience components. For example, a user may rate a pop-music radio program listened when driving alone on a rainy morning by assigning it *4* stars on a *5*-stars scale. In this case, the experience relates for the user, *4* stars to the content of the pop-music radio program in the context of a rainy weather and being alone. The overall collection of such experiences is regarded as the UM. Given such UM, the goal of the cross-context reasoning mechanism is inferring the essential parts of the UM for the purposes of generating context-aware personalization for future user experiences.

Our approach is based on semantically-enriched descriptions of the experiences. This means that all the components of the experience (users, items and contexts), are described using semantic schemata. These schemata facilitate applying various cross-context reasoning mechanisms, that augment the sparse parts of the UM by inferring the missing information from past experiences in other contextual conditions. The inferred UM data is further used for providing context-aware personalization services.

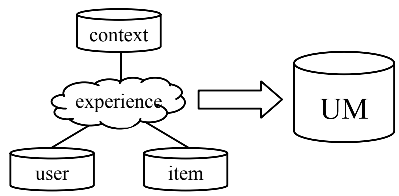

Fig. 1. Representation of Users Experiences and UM

Hence, context-aware personalization can be represented as a two-stage process. First, context-aware UMs are being inferred from past experiences, and then personalized services are provided to the users. This separation improves the flexibility of the personalization process, as each stage can be implemented using a wide variety of techniques. The decision regarding the concrete technique to be used depends on various factors, such as availability of data, dynamicity of the application domain, data pre-processing capabilities and others. In this paper we sketch a number of illustrative techniques, focusing on the UMs inference, rather than on the personalization stage.

The contribution of our work is three-fold. First, we provide a high-level framework for semantic representation of context-aware user experiences. Second, we exploit this framework for defining extensible reasoning mechanisms for inferring the essential parts of context-aware UMs. This upgrades the capabilities of personalization systems and facilitates provision of accurate context-aware personalization. Third, we describe two evaluations within running projects, studying the cross-context reasoning aspects.

2 Related Work

Rich context models are of special value for supporting activities, in which the user is confronted with diverse and probably unexpected situations. For instance, when guiding a user during a sightseeing tour, an assistant may adapt its personalization with respect to contextual information such as available time, financial limitations, mobility constraints, and local weather conditions (see [3] and [1]). Here, the user stays within a single coarse-grain tour context. Other scenarios combine rich context models adapted to diverse tasks. For instance, [8] describes a context-aware assistant for avoiding nursing accidents in hospitals. It distinguishes between diverse context models of various nursing tasks and predicts actions before their actual occurrence.

The above works exploit UMs, providing information about the user in diverse contexts. Such contextualized user modeling is a research area on its own. As pointed out in [4] and [6], context-based user modeling may be performed on the level of sensor data. Our work aims at a higher level of abstraction, in particular, at a UM built from semantic structures. Along this approach, [9] proposed the use of a common ontology-based user-context model as a basis for the exchange of UMs across applications. Here, the context is modeled as an extensible set of facets representing the characteristics of the user and his current context. Ubiquitous user modeling [5] extends this idea by continuously modeling the user by means of situational statements, which enable modeling the user in (ideally) any context. However, if the user is currently in a context not encountered before, which information from previous contexts could be exploited for user support? Therefore, we propose a reasoning mechanism allowing to assemble a UM for a given situation based on a collection of previous experiences.

3 Example Scenario

Everyday life is composed of various events where users request information suited to the individual characteristics of the users and the contexts. For example, let us consider two scenarios: one is defined for a work day and the other for a vacation day.

Let us imagine a traveler, who is married with two kids, likes music, nature, outdoor and water sports, and Italian cuisine. Contextual information implies a summer day with a nice weather and driving a private car. In the following scenarios we highlight the context-aware personalization services provided in form of recommendations.

1. Working day: Traveling for about an hour to a city nearby for a business meeting. The meeting is planned to start at 10:00 and end at 12:00, and the traveler is expected to return at 14:30 for another meeting.
2. Vacation day: Traveling to the same city for a daily vacation. During the day, the traveler will go to a lake, spend some time there, and return home afternoon after enjoying preferred water sports and lunch.

In the first scenario, the recommendation for traveling is to leave home at 08:30 (after rush hour), allowing some time for traffic congestions and planning to arrive early. In addition to the above contextual details, the context implies that the traveler travels alone, time is morning, season is summer, and travel goal is work. Recommendations are required about the road and parking place next to the meeting place. During the trip, another recommendation task arises: music selection. Our traveler drives on the highway, listening to a favorite singer, gets to the meeting place early, parks in walking distance from the meeting place. There are 15 minutes to wait, so the system recommends having coffee at a nearby bar.

In the second scenario, there are no time constraints, so the system suggests leaving at 09:00 to avoid traffic, taking a scenic road to the lake, parking in a free parking area far from the city, but where surfing equipment can be rented and some restaurants are available. During the trip to the lake, the system suggests a favored country CD.

These scenarios detail two possible flows of very similar activities for the same user in two different contexts: work and leisure. They clearly demonstrate the effect of context-awareness on the recommendations generated by the system.

4 Data Representation

The fundamental problem related to data representation is "how can this heterogeneous situational information be represented in a uniform and semantically-enriched fashion"? We addressed it by basing our approach on so-called s*ituational statements* [5] that serve as integrating data structures for user modeling and context-awareness.

The basic idea behind situational statements is to apply predefined meta-level information in an extended RDF representation with OWL ontologies. These ontologies provide a shared and common understanding of a domain allowing communication between heterogeneous widely spread systems. The recently defined general UM ontology GUMO [5] is collecting the user's dimensions modeled within user-adaptive systems, e.g., the user's age, and occupation. Furthermore, it also facilitates representing the user's interests and preferences.

In a similar manner, GUMO also facilitates modeling various dimensions of contexts (e.g., for the traveling scenario: day-time, season, companions, motivation and others) and items. Hence, we updated GUMO and inserted there several intuitive contextual dimensions. In general, we assume that the modeling of context is a one-time task that can be conducted by domain experts. Figure 2 illustrates partial representation of context in GUMO.

Fig.2. GUMO Context Representation

5 Reasoning Model

The above representation of UM data in RDF/OWL format facilitates provision of context-aware personalization. To explain cross-context inference mechanism, we need to consider the UM data in more detail. User experience was defined as the feedback a user provided for a certain item in a certain context. For capturing this context, we use (in a simplified syntax) situational descriptions, such as:

```
context.time=afternoon
```

For example, consider experience *E* representing a situation, an item, and a rating:

```
context.motivation=work
context.time=afternoon
item.meal.price=moderate
rating=0.8
```

One possible approach for the inference task is defining reasoning rules (over the RDF representation) that reflect the relations between various contextual aspects. This approach is referred to as a *rule-based inference*. For example, rule-based inference can be done by abstraction rules deriving knowledge about more generic situations from more specific ones by discarding some contextual information. Consider a rule:

```
context.motivation AND context.time => context.time
```

It allows aggregating detailed knowledge referring to `context.motivation` and `context.time` into coarse-grained knowledge that refers to `context.time` only.

As such, abstraction rules define the factors that are more important for the context-awareness and help to deal with general situations, such as

```
context.time=afternoon
```

by inferring that for this situation, experience *E* can be used as a basis for recommendation. They allow inferring the missing parts of the UMs, even if no past experiences have been recorded for the very specific situation.

Another type of reasoning rules exploits knowledge about the relations between the values of certain contextual aspects. For example, consider a contextual situation *S*:

```
context.motivation=work
context.time=4PM
```

The experience *E* and the rule

```
4PM => afternoon
```

allow inferring the UM data also for the new situation *S*. So, the first type of rules is associated with the presence of certain semantical context aspects (the generality of the situations), whereas the second type is associated with the semantical structure of the domains and the domain knowledge. Needless to say that it is possible to define rules combining the above two types.

We would like to stress the fact that the above examples relate to the same user and item in a different context, i.e., new situation and previous experiences of the same user on the same item. Hence, these are examples of pure cross-context reasoning. Also, we can include the items in the rules, yielding cross-context cross-item reasoning from past experiences on other items in other contexts. Instead, including the users in the rules yields cross-context collaborative (cross-user) reasoning from past experiences of other users in other contexts. Currently, we only point out these possibilities, without exploring them in depth.

Another alternative approach for the inference task is adapting past experiences of similar users on similar items in similar contexts. This approach, usually applied in Case-Based personalization systems, is referred to as *similarity-based reasoning*. In this case, the reasoning process should determine the re-using (adaptation) mechanism of past experiences, that in turn can also based on rules.

In this type of reasoning, to infer the missing part of a context-aware UM for a new experience, this experience is compared against previously recorded experiences. Then, a set of most similar experiences (the *K* most similar ones, or all those with a similarity over a threshold) are retrieved. Finally, the retrieved experiences and their ratings are re-used to infer UM data for the new experience.

Applying similarity-based reasoning requires defining a stable similarity metric for the experiences. We propose to base the similarity metric on the above RDF representation of the experiences, which guarantees that the experiences will be represented in a semi-structured form (despite a predefined structure, values of some slots may be unavailable). The similarity metric will facilitate retrieving similar experiences, and then aggregating them.

When we compare the above rule-based and similarity-based reasoning approaches, we see that on the one hand, rule-based reasoning may produce more accurate UM data, as in the typical scenario the rules are defined by domain experts. On the other hand, manual definition of inference rules may hamper scalability and flexibility. Conversely, the typical scenario for similarity-based reasoning is fully autonomous and gives, therefore, a more flexible process. However, to achieve this there is a need for a large number of past experiences to bootstrap the reasoning process. For this, other machine learning and reasoning approaches can be considered.

Once the required parts of the UM are inferred the reasoning stage is completed. The following stage of the context-aware personalization process deals with generating the recommendations. Any state-of-the-art recommendation technique may be exploited here. Separating reasoning and recommendation stages in the personalization allows higher flexibility, as higher computational effort may be put on either stage, independently of the other stage.

6 Evaluation Scenarios

We have conducted a number of initial valuations of the proposed approach in context-dependent scenarios within the *Passepartout* [1] project. The prototype illustrates typical search, browse and viewing activities with a personalized digital TV program guide. Users normally appear individually or in groups, and are switching between different daily, weekly, monthly or yearly contexts, with the same or similar preferences and interests. Hence, it is important to identify the right granularity for the cross-context reasoning. Performing comparative studies with predefined granularity settings for spatio-temporal aspects, context, and UM characteristics allows finding the most efficient setting for gathering experiences in different contexts.

We tested how our semantics-driven techniques improve the search for TV content in terms of increasing the recall by broadening the search, as well as the precision by finding the most relevant content. As test set we used real TV programs metadata collected dynamically daily over the Web. User profiles for six test users were constructed and given various interests and contexts. The results show that applying domain ontologies for finding concepts that (semantically) correspond to the keywords (i.e. synonyms, related terms, background, and context) dramatically improves the shortcomings described for using keywords only. We apply the user model concepts in the post-processing of results, as opposed to the ontology models which are used in the pre-processing of the search query before a call to the metadata service is made. As the employment of ontology models improves our search by making it broader, the user model is used to narrow the results and arrange the presented results in a personalized order. The more advanced effects occur when values in the user model are connected to a context. Without the notion of context, the interest values in the user models can only provide general recommendations, whereas in reality people may have very different TV interests in for example the morning and the evening, as we have discussed earlier.

Our test results illustrate two different aspects in which context: (1) restricting an interest expression to be valid only in a particular context; and (2) automatic inclusion of the user's current context data itself, in addition to the context-based interest that may be valid, with the aim of reducing the input that the user has to give (i.e. automatic inclusion of the geographical location and the current time of the user). We also plan to use the geographical data in the filtering of results instead of adding it as a search term.

We have also planned further evaluations within the *SharedLife* [10] project. It is a multi-user shopping scenario, completed by other everyday activities. A positive experience observed in a certain situation is exploited for recommendations in other situations. However, this should be justified by a sufficient overlapping between the situations, since the positive feedback might actually relate to several context elements. Another rich field for experimenting is the configuration of the UM sharing behavior. For instance, a user might be more willing to deal with incoming sharing requests during a relaxed shopping trip than during cooking. Since such sharing can be treated as experiences, similarity between experiences and context reasoning rules provide a means to extracting information on when requests should be presented to the user, and when the system should try to handle them automatically.

In both projects, the evaluations assess the use of rich semantic information (e.g. GEO/TIME ontologies and contextualized UMs), to find proper settings to include in the reasoning, and the metadata and the semantic structures to present to the user. In both, users are collecting and exchanging experiences across various contexts, allowing evaluating of various cross-context reasoning approaches.

7 Conclusions and Future Work

This paper motivates the need for context-aware personalization and suggests an initial model for it. The model is based on cross-context reasoning, applied over semantically enhanced descriptions of user experiences. Note that the proposed cross-context reasoning model is extensible. It may be integrated with other personalization approaches, e.g., cross-user and cross-item reasoning. Hence, it integrates with the ideas adapted from the state-of-the art personalization techniques in order to provide a complete framework for provision of context-aware personalization services.

Future research will focus on formalizing the model, integrating it with known representation and reasoning techniques, demonstrating it in a real-life scenario as proof of concept and evaluating various reasoning mechanisms.

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