Interactive User Modeling for Personalized Access to Museum Collections: The Rijksmuseum Case Study

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Abstract. In this paper we present an approach for personalized access to museum collections. We use a RDF/OWL specification of the Rijksmuseum Amsterdam collections as a driver for an interactive dialog. The user gives his/her judgment on the artefacts, indicating likes or dislikes. The elicited user model is further used for generating recommendations of artefacts and topics. In this way we support exploration and discovery of information in museum collections. A user study provided insights in characteristics of our target user group, and showed how novice and expert users employ their background knowledge and implicit interest in order to elicit their art preference in the museum collections.

Keywords: CHIP (Cultural Heritage Information Presentation), user study, adaptive system, personalization, RDF/OWL, recommendations, user modeling.

1 Introduction

The CHIP[1] project is part of the Dutch Science Foundation funded program CATCH for Continuous Access to Cultural Heritage. Since early 2005 the CHIP research team has been working at the Rijksmuseum Amsterdam and interviewed curators and collection managers in order to perform detailed analysis of the museum domain, target users and museum web applications. As a result of this extensive domain and context analysis requirements were obtained for the development of several low-fidelity prototypes [1]. The prototypes focused on eliciting information from domain experts about novel personalization functions for the visitors on the museum web site. We proposed an approach based on an interactive semantics-driven dialog for

[1] CHIP project: http://www.chip-project.org

eliciting user knowledge, inspired from previous work on the adaptive learning content management system SWALE [2].

In this paper, we present the results of a user study with real users evaluating our first functional prototype. The results show that novices need support in externalizing their implicit art preferences and thus profit from the CHIP adaptive dialog. The experts, on the other hand, have prior knowledge and use the interactive dialog in order to discover new insights and semantic relationships in particular collections. The ultimate goal for our research is to realize ‘the Virtual New Rijksmuseum” where different types of users can easily find their ways in the Rijksmuseum and access information which is tailored to their needs, personal interests and competency level.

2 Personalization in Museum Collections

In the last few years, dedicated recommender systems have gained popularity and become more and more established practice in online commerce, like purchasing of books, music, and organizing a travel. Museums also direct their efforts to provide personalized services to the general audience via their websites. There are various examples of museum websites attempting to meet the needs of individual users. A key problem here is the semantic vocabulary gap between the experts-created descriptions and the implicit and often not domain-related art preferences of end users. Moreover, museum collections maintain multiple perspectives for their information disclosure. These challenges lend themselves well to the application of recommender technology as explored in this work. Our goal is to bridge the vocabulary gap and provide a user-driven approach for eliciting user’s preferences and characteristics, and recommend known/new information from the collection in a coherent and comprehensive way. Studies show that understanding is stimulated when the systems use concepts familiar to the user (considering interests and knowledge level) [3]. In this paper, we capitalize on the non-obtrusive collection of users data as part of an active interaction with the museum collection (versus filling in static isolated preference forms).

3 Cultural Heritage Information Presentation

Fig. 1. CHIP interactive user modeling interface

We developed an interactive quiz to help users find artefacts and topics of their interests in the Rijksmuseum collection. Figure 1 gives a snapshot of its user interface. On the top-left artefacts to rate are presented as an interactive dialog. The ratings are stored in a user profile (top-right) and are used to filter the relevant artefacts (bottom-right) and topics (bottom-left). Each recommendation is accompanied with an explanation (‘why?’ option). The demo collects feedback about the recommended items by allowing users to rate also recommendations. In this way the system gradually builds the user profile to be used for personalized tours generation. The user profile we build is an extended overlay of the CHIP domain model depicted in Figure 2. It contains topics and artefacts of interest assessed in a five-star scale (respectively -1, -0.5, 0, 0.5 1), where 1 is maximum interest, -1 is maximum distaste and 0 is neutral. The topics are grouped in four main categories, i.e. artist, theme, period-location and style.

The rich semantic modeling of the domain with mappings to common vocabularies (Getty vocabularies[2] and Iconclass thesaurus[3]) and use of open standards (e.g. VRA, SKOS and OWL/RDF), allows us to maintain a light-weight user profile and efficiently perform the reasoning over the domain model. This allows for a dynamic and run-time calculation of the user’s interest, as well as a high-level of serendipity of the suggested items and explanations. We also store the skipped (not rated, but presented items), in order to optimize the presentation sequence. We use XSLT to convert the XML of the Rijksmuseum database into the RDF scheme we developed. Much of this transformation derives from the taxonomical merging resulting in two types of new triples: (1) equivalence - identifies concepts across taxonomies that are the same; (2) narrower and broader terms - defines local extensions within hierarchical taxonomies.

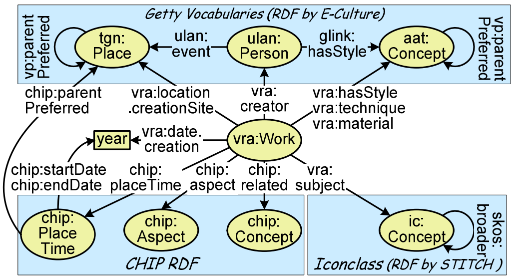

Fig. 2. CHIP RDF data model

Figure 2 shows our current RDF data model, representing these vocabularies/thesauruses. The initial RDF representation was provided by the E-Culture project (for Getty) [4] and the STITCH project (for IconClass) [5].

4 User Study at the Rijksmuseum Amsterdam

Based on our first recommender prototype, we did a first formative user study with two-fold focus: (1) to test with real users the effectiveness of the demo with respect to novices and experts; and (2) to gain insight in characteristics of the target group in order to elicit requirements for the user modeling scheme and approach. The rationale of this study[4] is illustrated in Figure 3. It contains five steps: Step 2–4 focus on testing the effectiveness of CHIP demo. Step 1 and 5 are two additional questionnaires about users’ background and usability issues of the CHIP demo.

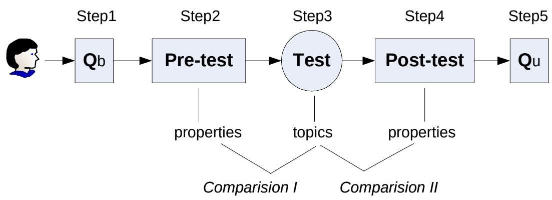

Fig. 3. Rationale of the user study

[2] Getty vocabularies: http://www.getty.edu/research/conducting_research/vocabularies/

[3] Iconclass thesauru: http://www.iconclass.nl/libertas/ic?style=index.xsl

[4] CHIP user study: http://www.chip-project.org:8091/demoUserStudy/

To test the demo, we designed a novel method to compare the process of rating and recommendation of experts and novices while using the demo. We claim that the CHIP recommender helps novices to elicit art preferences from their implicit knowledge/interest in museum collections. To test it, we let users rate their interest in art-related properties before and after using the demo. Here, it is called 'pre-test', 'test' and 'post-test', which refer to step 2 to 4 in Figure 3. In consultation with the Rijksmuseum domain experts, the demo used a selected data source which covered 37 properties from 4 popular artefacts. These properties are randomly divided into two questionnaires, pre-test and post-test, in a non-overlapping way. Users assess each property on a five-degree scale from 'not interested at all' to 'very interested'. The main idea was to measure whether the properties generated as recommended topics from the demo match the properties positively rated by the users in the pre-test and post-test questionnaires. This measure of discrepance is expressed in Comparision I and Comparision II, see buttom Figure 3.

To gain insight in our target users, we designed two additional questionnaires, one about the users' background (e.g. age, education, interest in art, etc.) and another about usability issues of the demo, see Qb and Qu in step 1 and 5 in Figure 3.

In total 39 users participated in this study that was held in a period of two weeks in August 2006 at the Rijksmuseum Amsterdam. 33 users were randomly selected from the actual visitors of the museum. In addition, we also asked 6 employees (no domain experts) of the Rijksmuseum to take part in the study.

5 Results and Analysis of the User Study

In the questionnaires, we collected user characteristics (e.g. age, gender, profession) and comments on the demo usability. Some dominant factors appeared as characteristics of the users:

- Small group with 2-4 persons and a male took the leading role (67%)
- Mid-age people in 30-60 years old and well educated (62%)
- No prior knowledge about the Rijksmuseum collections (62%)
- Visit the museum for education (98%) and strong interest in art (92%)
- Recommendations are useful (82%) and explanations is helpful (57%)

These findings guide our subsequent user-centered design of personalized adaptive systems: (1) consider community/social aspects in the user model, (2) enable collaborative tasks among users, (3) not explicitly test user's pre-knowledge, and (4) no need to motivate users but focus on providing art education in a pleasant way.

To distinguish within these 39 participants between novices and experts, we roughly defined an expert-value as a weighted sum of five factors: prior knowledge of the Rijksmuseum collection (v1), visiting frequency of Rijksmuseum (v2) and other museums (v3), interest in art (v4) and history (v5), calculated by:

$$\textit{expert-value} = V1*0.5 + (V2+V3)*0.15 + (V4+V5)*0.1$$

If the user's expert-value is higher than a particular threshold (2.5), then she will be idenitfied as an expert, otherwise as a novice. However, there is no sharp distinction between them. To establish the correspondence of properties collected from pre/post-test (Pp) and the actual test (Tp), we use a valuation function V to obtain values in the range of -1, 0 and 1, that we can compare (when both values have a similar sign there is a positive correspondence), as expressed in the formula: Cp = V(Pp)*V(Tp). For a particular user, we derive a combined positive correspondence, over all properties P, by applying: ΣC = ΣCp. At this point, we do not consider negative correspondences, as they seemed not to contain valuable information. By using this interpretation model, all data from the pre/post-test and test were processed.

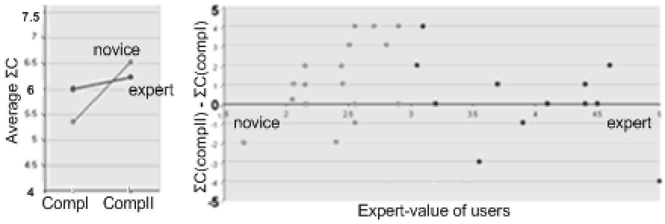

Fig. 4. ΣC in Comparison I and II according to user expert-value

In Figure 4 (left part), we show the comparison of ΣC based on two groups: novices and experts. A significant increase, 1.18, was found for novices when relating Comparison I and II. Besides, we found a very slight increase, 0.23, for the experts. Secondly, when we plot the difference of ΣC between comparison I and II on a continuous range of the expert-value, we may observe (right part, Figure 4), ignoring extreme values, a convergence as expert level increases. These results confirmed our hypothesis that the novices indeed profit from using demo to elicit their art preferences in the Rijksmuseum collections.

6 Conclusion

In this paper we have presented a user study of the CHIP demo, indicating that personalized adaptive systems have the potential to benefit users in various contexts. It is well integrated in the tasks users expect to perform on a museum website, and in the same time gathers necessary data about the users in order to provide personalized information access and presentation. It is geared towards user’s characteristics and behaviors, and it can make the active interaction more effective and fruitful.

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