CONSTRAINT-AWARE USER MODELLING AND PERSONALISATION IN PHYSICAL ENVIRONMENTS

Fabian Bohnert[1]

Abstract
The vast amounts of information presented in physical educational spaces such as museums are often overwhelming to a visitor, whose receptivity and time are typically limited. Hence, s/he might have difficulties selecting the personally interesting items to view within the available time. Mobile electronic guides can support a visitor in this selection process by identifying and recommending items that match his/her interests. However, recommendation generation in physical spaces has challenges of its own. Factors such as the spatial layout of the environment and suggested order of item access must be taken into account, as they constrain the recommendation process. This research investigates adaptive user modelling and personalisation approaches that consider such and other constraints.

Fabian Bohnert
Faculty of Information Technology, Monash University
Clayton, Victoria 3800, Australia
+61 3 9905 5207
`fabian.bohnert@infotech.monash.edu.au`
Advisors: Ingrid Zukerman and Liz Sonenberg

1. Problem Statement and Research Question

Educational leisure environments, such as galleries, museums and zoos, offer large amounts of information. However, a visitor's receptivity and time are typically limited, confronting the visitor with the challenge of selecting interesting items to view within the available time. A personal human guide could support the visitor in this selection process, but the provision of personal guides is generally impractical. Advances in pervasive computing and user modelling have made possible an alternative solution: personalised electronic handheld guides. Electronic guides have the potential to infer a visitor's interests non-intrusively by tracking his/her behaviour within the environment, and to store the acquired information in models of the user. A visitor's interests and activities can be predicted by consulting these user models, and recommendations about items of interest can be made based on these predictions. However, in physical educational environments, user modelling and personalisation have challenges of their own. As items have informational dependencies suggesting a certain order of access, careful thought is usually put into placing the items into the physical space to enable a coherent experience. Consequently, a visitor's behaviour is influenced by both the suggested order of item access and the spatial layout of the environment. Hence, these factors must be considered

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when modelling a visitor from non-intrusive observations of his/her movements through the space, and when generating recommendations. Further, these recommendations must consider a visitor's position and time limitations. That is, the personalisation process is constrained by the spatial layout, informational dependencies between items (and imposed order of access), and time constraints. To date, these factors have not been considered sufficiently.

This research investigates non-intrusive statistical user modelling and recommendation techniques that take the above constraints into account. It aims to reduce information overload and to improve a visitor's experience by means of

... **Personalised guidance:** Lead the visitor through both the physical space and informational space by finding and pointing to content pro-actively, matching the visitor's interests and needs.

... **Coherence:** Select the items sensibly as a coherent whole, i. e., spatially and informationally coherent, considering also the educational objectives of the provider (e. g., by including highlight displays).

From these objectives, the following research questions were derived.

1. How do constraints such as the spatial layout, informational dependencies between items and time constraints affect a visitor's behaviour?
2. How can these constraints be effectively considered when inferring a visitor's interests and predicting a visitor's activities from non-intrusive observations of his/her movements through the space?
3. How can these constraints be incorporated in the construction and recommendation of a suitable pathway for the continuation of a visit?

Our initial research focus has been the prediction of a visitor's interests and future pathway from his/her behaviour, partially addressing the first two questions. In the future, we propose to also address the third question. The adaptation of the content delivered for the recommended items is outside the scope of this work.

2. Approach and Methodology

Recent developments in the area of positioning technology have made possible the non-intrusive tracking of users equipped with a positioning device. Although a detailed assessment of such technologies is outside the scope of this work, the availability of techniques to infer a visitor's high-level activities from sensing data, e. g., [6], is crucial to this research. For our purposes, we assume to be given a visitor's pathway as a time-annotated sequence of visited items, where each *observation* comprises the tuple (item, visit duration). These observations are the only input to our system GECKO for the current visitor.

As depicted in Figure 1, GECKO's functional components are assigned to the following four layers [7]: sensor, semantic, control, and actuator. The decomposition of GECKO into modelling components (semantic layer) and a personalisation component (control layer) reflects the sequential nature of the recommendation process, i. e., first prediction, and then recommendation generation. Two modules comprise the semantic layer: space models and user models, both of which make use of *external data sources (knowledge base)*. Visitor observations (sensor layer) trigger updates within the *user*

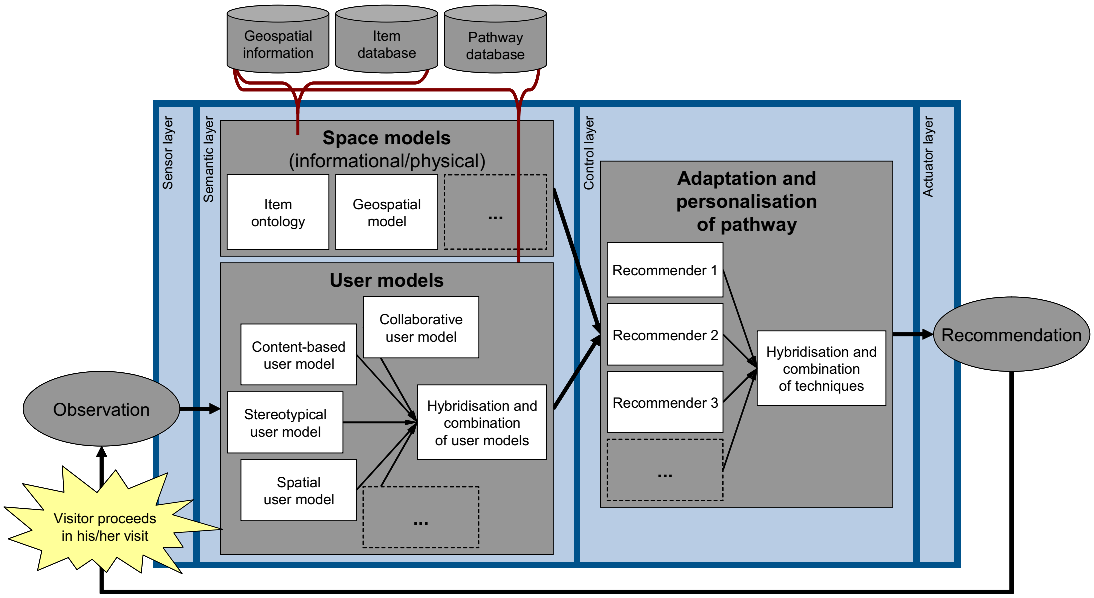

Figure 1. Conceptual architecture of Gecko

models, which capture the information required for predicting a visitor's activities and interests. We propose to combine different user modelling techniques, with the aim to overcome their respective drawbacks [10]. Our experiments include collaborative and content-based approaches to model a visitor's interests. Additionally, spatial user models capture the visitor's behaviour suggested by the organisation of the space. For example, we employ transition models based on visitor movements between items, and propose to use distance models based on the spatial arrangement of items. Further, we consider employing stereotypical user models to predict what type of visitor a user is (e. g., greedy or selective). The user models are consulted to predict a visitor's interests, movements, and visitor type. These predictions are then passed on to Gecko's personalisation component. However, as outlined above, spatial and informational constraints must be considered in the adaptation process. Hence, *space models* capturing informational and semantic dependencies between items (item ontology) and spatial layout (geospatial model) constitute further input. Within the personalisation component (control layer), a suitable pathway satisfying the above constraints is constructed, before Gecko delivers a *recommendation* to the visitor (actuator layer).

Physical educational environments are spaces where the physical layout is used to structure information. For instance, a museum space might be subdivided into galleries that are usually fairly heterogeneous with respect to the concepts presented, and these galleries might be further subdivided into exhibitions and collections of exhibits whose content is rather homogeneous. We call this hierarchical organisation *(physical) space taxonomy*. Different levels of the space taxonomy might require different prediction and recommendation mechanisms. In principle, this suggests the following research methodology, with the cell numbering 1 to 4 indicating the order of study.

Level of space taxonomy \ Step	**Prediction**	**Recommendation**
Micro (item, room)	1	3
Macro (subsection, section)	2	4

The validity of the developed prediction algorithms (cells 1 and 2) has been and will be evaluated experimentally using real-world datasets collected in Melbourne Museum, by measuring and comparing the predictive accuracy of the proposed techniques. The evaluation of our recommendation approaches (cells 3 and 4) will require user studies. We would appreciate guidance from the research community regarding the effective realisation of such studies.

3. Related Work

This research lies at the intersection of statistical user modelling [10] and personalised guide systems for physical educational environments. Personalised guide systems in physical domains have often employed adaptable user models, which require visitors to explicitly state their interests in some form. For example, the *GUIDE* project [5] developed a handheld tourist guide for visitors to the city of Lancaster, UK. It employed a user model obtained from explicit user input to generate a dynamic and user-adapted city tour, where the order of the visited items could be varied. In the museum domain, the *CHIP* project [1] investigates how Semantic Web technologies can be used to provide personalised access to digital museum collections both online and in the physical museum, based on explicitly initialised user models. Less attention has been paid to predicting preferences from non-intrusive observations, and to utilising adaptive user models that do not require explicit user input. In the museum domain, adaptive user models have usually been updated from the user's interactions with the system, with a focus on adapting content presentation rather than predicting or recommending exhibits to be viewed. For instance, *HyperAudio* [8] dynamically adapted the presentation content and hyperlinks to stereotypical assumptions about the user, and to what the user has already accessed and seems interested in. The *PEACH* project [9] developed a multimedia handheld guide, which adapted its user models both from explicit visitor feedback and implicit observations of a visitor's interactions with the device, and used the information stored in these user models to generate personalised multimedia presentations. These systems, like most systems in the museum domain, rely on knowledge-based user models, which require an explicit and a-priori built representation of the domain knowledge. In contrast, this research focuses on non-intrusive statistical user modelling and recommendation techniques that do not require this explicit representation. Additionally, although spatial constraints affect the movements of visitors in a physical space, and informational dependencies between items suggest a certain order of access, these factors have not been sufficiently considered to date. This research aims to take such factors into account.

4. Preliminary Results

To date, we have developed our system GECKO conceptually. The proposed architecture (Figure 1) has been validated as far as our research has progressed. Our research has focused on the prediction of a visitor's interests and future locations from non-intrusive observations at the item level (research methodology, cell 1). We have proposed two collaborative predictive models of visitor behaviour (*Interest* and *Transition*), and a hybrid model that combines their predictions [4]. The collaborative *Interest Model* is built by calculating the *Relative Interest* for all combinations of visitors and items that occurred.[2] Missing relative interest values for the current visitor are predicted from these values collaboratively. In contrast, the *Transition Model* models a visitor's behaviour based on visitor movements between items, and hence implicitly captures the spatial layout. These models are employed to predict the next K items to be viewed (we used $K = 1$ and $K = 3$), using two types of prediction approaches: set (unordered) and sequence (ordered). We evaluated the different model variants with a small dataset

[2]We devised a measure of *Relative Interest* to transform observations into implicit ratings, based on the assumption that visitors spend more time on relevant information than on irrelevant information in an information-seeking context [3].

collected at a rather homogeneous exhibition in Melbourne Museum. Our results show that the *Transition Model* generally outperforms the *Interest Model*, indicating that the layout of a physical space with homogeneous items is a main factor influencing visitor behaviour. However, the *Hybrid Model* yielded the best performance, which shows the importance of also considering a visitor's interests. Additionally, our results indicate that, when predicting the next three exhibits, a sequence-based model has a higher predictive accuracy than a model that predicts a set. Surprisingly, this is not the case when predicting a single item, where the performance of the simpler set-based model is comparable to the performance of the model that predicts the next item as the first item in a sequence.

5. Conclusions and Future Steps

In initial research, we have experimented with two collaborative predictive models and their hybrid (Section 4). Currently, we are extending this work by investigating a combination of collaborative user models with content-based models. We also intend to investigate stereotypical user models, which could be employed in the initial phase of a visit to address the cold-start problem of statistical user modelling techniques. The next challenge will be to apply these prediction techniques to higher levels of the space taxonomy (research methodology, cell 2), where the space is less prescribed and more heterogeneous. By evaluating our algorithms at different taxonomy levels, we hope to gain valuable insights about the influence of space prescriptiveness and item diversity on the performance of our models. For instance, we expect the relative performance of the *Interest Model* to improve in a less prescribed space with heterogeneous content. We are currently undertaking a manual data collection in Melbourne Museum covering the entire space, which will enable us to undertake this evaluation. The collection of visit trajectories is an expensive and time-consuming process in our scenario, both when done by human observers and by electronic equipment. We would appreciate advice regarding the feasibility of generating artificial but realistic visitor pathways from small samples in order to overcome this data bottleneck.

As yet, we have focused on the prediction of a visitor's interests and future activities. Accurate predictions will enable us to make recommendations about items to visit. However, in our domain, the transition from prediction to recommendation is not trivial. The second part of this thesis will investigate this step.

Recommendations that match a visitor's intentions build trust in the system. However, recommendations that are too detailed, or trivial recommendations, e. g., of items along a path prescribed by the spatial layout, may annoy the visitor. As this is likely to occur at the lower space taxonomy levels, where the space is homogeneous and prescribed, we propose to refrain from recommendations at these levels (cell 3). However, at the higher levels of the space taxonomy, where the space is less prescribed and content is heterogeneous, recommendation generation is reasonable (cell 4).

A number of competing factors must be considered in order to construct the pathway continuation that is most appropriate given a visitor's current situational context.

- **Content:** Include items matching a visitor's interests to enrich his/her knowledge of topics of interest (collaborative and content-based recommendations).
- **Serendipity and Surprise:** Surprise with recommendations which do not necessarily reflect a visitor's obvious interests, i. e., include out-of-the-box items (collaborative recommendations).
- **Intensity:** Choose the most appropriate number of items based on the user's visiting style (stereotypical recommendations).

- **Continuity and Coherence:** Take into account spatial layout, informational dependencies between items, and curator constraints such as must-see items.
- **Consistency and Detail:** Achieve consistency with previous recommendations, and consider consistency when determining the horizon and level of detail of a recommendation.
- **Time:** Take into account time constraints both of the visitor and the environment.

We propose to investigate utility-based recommendation generation strategies that balance these factors, e. g., Markov Decision Processes, which were recently proposed for decision-theoretic and user-adaptable planning in the shopping guide domain [2]. We would appreciate advice regarding the possibilities of evaluating our recommendation approach, both in offline experiments with collected datasets and real-world user studies.

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