Gaming and Cognitive Profiles for Recommendations in Museums

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Abstract

This paper presents an approach to enhance museum visitors experience through the use of Gaming, Social Networks and Recommendations. The originality of the dedicated social and mobile visit personalisation system is that it relies on the user's cognitive profile in addition to his interests, both inferred from a game on Facebook.

1. Introduction

A problem often faced by museum visitors is that they often do not fully profit from their visiting experience. That is, in the course of their visit, visitors may lose time viewing items that do not interest them and miss those that do, due to time restrictions or simply to the tiredness that inevitably occurs during visits. Missing important exhibits and viewing items that the visitor is not so much interested in may significantly lower visitors experience. Therefore, a need exists to improve the Quality of Experience (QoE) of museum visitors through intelligent recommendations that will route visitors inside the museum towards exhibits of interest. This is the target of the BLUE experiment of the EXPERIMEDIA project, which takes it from the particular angle of people cognitive profile and social networks.

The BLUE approach extends a conventional museum visit to the virtual world by offering to Facebook users a dedicated game allowing them to build their own virtual museum with objects they can win inside the game or brought back from actual museum visits, which they can report and share with friends. Through playing the game, their cognitive styles and personal preferences related to museum topics are first determined. Both are then used to provide them a personalised guided tour inside some museum including recommendations and personalised descriptions.

The personalisation of museum visits has been the subject of studies since several decades. The apparition of wireless technologies and mobile devices has opened new doors for advanced personalisation, targeting each particular visitor and offering a better experience not only inside museums but also on the virtual world provided through internet and social networks. Mobile guides providing personalised visits have been proposed in some works at least already fifteen years ago.

Oppermann *et al.* [1] proposes such a guide exploiting both user interests and his position inside the museum. User profiling is performed from a visit preparation phase, where the future visitor consults the system to collect information and content linked to future exhibits he plans to see. The social aspect is also considered since users can share comments and evaluation on museum exhibits in the developed system. Chou *et al.* [2] present a context-aware museum guide as an application of the eWallet concept, exploiting semantic web models of exhibits and also allowing visitors to share their experience with others. Explicit user profiling is used through a small questionnaire visitors have to fill when they are given the guide. The CHIP project (see e.g. [3]) has proposed semantics-driven recommendations for museums and semi-automatic generation of personalised museum visit based on visitor's profile. In [3], Aroyo *et al.* propose to detect user preferences and compute a personalised visit, optimised by walking distance and the art objects that each visitor perceives as interesting. They moreover maintain a dynamic user model and offer users to enrich the available palette of experiences by going online. Other approaches try to predict user behavior to help them optimise their visit through recommendations. In this case, user interests and prediction on user behavior are inferred from direct observation during the visit. In [4], collaborative models have been proposed to predict visitors location from the behavior of the visitors crowd.

While our approach is closed to those described above regarding goals, means and offered services, it relies on three innovative pillars. Getting users' profile for personalisation bears some difficulties, since it has to be build by explicitly asking the user or inferred from some learning phase where users are observed. As such implicit profiling is affected by the cold start effect, relevant personalisation is obtained only after a time laps until enough data has been collected. So far, proposed approaches to personalised museum visit fall into one of the two categories. An interesting alternative that moreover can increase user experience is to build an implicit profile through a game, which replaces the classical questionnaire used in explicit profiling and avoids the cold start effect faced by implicit profiling based on observations during visits only. This is the first pillar. Then, our proposition relies on the estimation of visitors cognitive profile, i.e. their specific way of thinking and behaving. To the best of our knowledge, this has never been exploited before. Finally, we link directly visitors' museum experience with social networks. None of the work reported here has exploited this direct link to extend experience sharing and foster socialisation through museum visits.

We present in this paper the approach we have designed to conduct an experiment in a museum in Athens. We present the developed concepts, tools and algorithms used for providing a personalised visit to visitors. In the remainder, we first present theoretical results showing the usefulness of recommendations for QoE enhancement. Then after a summary on the kind of personalisation we propose to visitors, we detail the profiling and the recommendation approaches. Conclusions and perspectives are then given.

2. Theoretical effects of using recommendations in museums

In order to assess our postulate that personalising museums visits increases the visitor's Quality of Experience (QoE), we have designed a simulator system

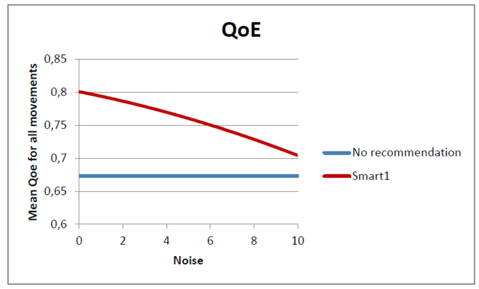

Figure 1. Theoretical QoE evolution with recommendations of decreasing accuracy (i.e. noise increase).

to observe theoretical effects of different variables on the latter. This simulator models a museum settings, simulates crowd movement inside and measures QoE metrics like interests for exhibits viewed, walking time and congestions found during the visit (see [5]).

Museums are modelled as a set of n exhibits $E = \{e_1, ..., e_n\}$, where each exhibit has a maximum crowd capacity M_i. Exhibits are clustered in $m <= n$ rooms $R = \{r_1, ..., r_m\}$ where all exhibits belonging to a same room r are connected together through a path p: $\forall e_i, e_j, \exists p(e_i, e_j) \iff \exists r \in R \mid e_i, e_j \in r$. It is assumed that there is a single path from one room to another, modelled by a connection between the unique exhibits attached to each room's entrance: $\forall r_i, r_j, \exists! e_i \in r_i, \exists! e_j \in r_j \mid \exists p(e_i, e_j)$. The simulator receives as input two $|E| \times |E|$ matrices: a positioning matrix, which is used to find the connections between items of the same room and between rooms; and a distance matrix, which is used to calculate the path distances. Visitors are modelled as a tuple $v = \langle I, CT, t_{max}, ws \rangle$, where the vectors I and CT represent respectively the interest of the visitor and its crowd tolerance for each exhibit of a museum. t_{max} is the time that the visitor can spend inside the museum, and ws stands for the visitor walking speed.

The QoE is measured by the simulator as a function of the visitor's interests and of the time needed to reach each exhibit:

$$QoE = \sum_{i=1}^{n} (\alpha_1 . I_{e_i} + \frac{\alpha_2}{wt_i}), \tag{1}$$

where $\alpha_1, \alpha_2 \in [0, 1]$ are calibration weights and $wt = d_i k / ws$ is the distance between exhibits e_i and e_k, the latter being the exhibit where the visitor was before reaching exhibit e_i.

The effect of recommendations on the average QoE of visitors can be analysed by observing the differences between visitors walking randomly in the museum and visitors driven by recommendations. Figure 1 shows the theoretical QoE obtained with a basic recommendation algorithm that optimizes suggestions according to interests and minimum walking time. Compared to random walk that gives a constant QoE of 0.675, perfect recommendations lead to a QoE of 0.8 on a $[0, 1]$ scale, which decreases obviously with the recommendations accuracy. The latter is modelled by the addition of random noise on the same $[0, 10]$ scale as weights on visitors interests: the simulated recommender estimates the visitor interests with a deviation of $\pm noise$ from the real interests weight.

Simulations we have conducted have shown that recommendations have an impact on visitors QoE. More realistic experiments have been conducted taking into account the different movement patterns people can have during a visit, i.e. their visiting style. We have observed that recommendations effects are different for each visiting style and that some styles are more affected than others, suggesting that recommendations are useful only for specific categories of visitors [5].

3. Personalising a visit

To enrich user experience in the museum, BLUE offers both personalisation and recommendation. While the latter is also a form of personalisation, we refer to personalisation as the adaptation of something, in the form of an alteration, specifically for the user. Recommendation consists in offering suggestions to the user, tailored to his profile, usually including interests or needs. Both, personalisation and recommendation require user profiling. The latter, can be done explicitly by asking the user, or implicitly by observing their behaviour and recommendation consumption (in case of recommendation). In BLUE, the part of the user profile that will be exploited is mainly related to the nature of the cognitive style of the museum visitor.

Personalisation in BLUE concerns the following elements which are personalised according to the cognitive profile and, where applicable, to the visitors personal interests and preferences: (1) language used in applications tailored to the user's origin; (2) written exhibition descriptions, specialised for each combination of the cognitive style dimensions.

Recommendations in BLUE are computed according to three main elements: (1) the visitors' cognitive style together with a set of corresponding stereotypical rules; (2) personal interests (in relation with the museum exhibition topics); (3) a set of rules related to the current context/situation (i.e. time constraints, visitors current and previous activity, position of the visitor). Then, they can comprise the following elements:

- Exhibitions to visit, respectively points of interest (POI) to go to. POIs are additional areas inside the museum like shops or restaurants. They can moreover include more specific things like, e.g., places where to take photos or messages left by friends in specific locations.
- Type of ticket that matches user preferences and his time constraints.
- Path to follow inside the museum, i.e., the sequence of exhibitions and points of interests to see to complete the visit.
- Spontaneous actions to perform (e.g. take a picture, rest, write a comment, etc.).

4. Visitor profiling

Museum visitors are modelled as a tuple:

$$U = < CP_U, PI_U, UD_U, LOC_U, ACT_U, T_U > \quad (2)$$

The resulting profiles are composed of three elements representing visitor's characteristics and three other elements representing his situation. In the first group, CP_U stands for the cognitive profile, PI_U the personal interests and UD_U the personal profile. Situation-related elements are: LOC_U, the visitor's location; ACT_U, his current activity and T_U, his time constraints. CP_U is obtained for each visitor after he has fulfilled a minimum number of steps through gaming. Cognitive profiles are predefined as a combination of cognitive style dimensions, where each possible combination constitutes a stereotype to which visitors having the corresponding behaviour will be affected (see details in section 4.1). PI_U is a list of topics linked to museum exhibitions, obtained from the gaming session. UD_U includes some demographic data (e.g. age, gender and linguistic background), extracted from Facebook visitor accounts or deduced from the mobile device settings. LOC_U is obtained from a geolocalisation system. ACT_U is determined from actions performed or estimated from the visitor's position. Last, T_U consists in time constraints regarding the availability of the user for a visit.

Figure 2. The virtual museum in the MMS Facebook game.

4.1.User profiling by gaming

The purpose of the developed Facebook game, named *My Museum Story*[1], is to allow users building their personal museum and share their museum experience (virtual or real) with friends. The choices that a user makes during the game are used in the estimation of his cognitive profile and personal interests.

The cognitive profile is estimated through an initialisation phase, performed only once. In this phase, the user has to choose different things from the multiple choices he is proposed for each: an avatar, a tool, a pet and an organisational template for his museum. Each possible choice is mapped to a cognitive style dimension [6]: extroversion (E), introversion (I), sensing (S), intuition (N), thinking (T), feeling (F), judging (J), perceiving (P). This mapping has been established from a studying the in-game behaviour of a set of students from which the cognitive profile was first evaluated with a short version of the Myers-Briggs Type Indicator (MBTI) questionnaire, a reference psychometric tool. Accounting that cognitive style dimensions are regrouped in 4 pairs of opposite elements, there are 16 possible combinations of cognitive styles dimensions, representing each one possible cognitive profile. We have thus $CP = \{abcd;\ a \in \{E, I\}, b \in \{S, N\}, c \in \{T, F\}, d \in \{J, P\}\}$. A set of behaviour rules and generic interests is linked to each cognitive profile, pre-determined according to state of the art knowledge and previous studies. Common to each person belonging to a cognitive profile, the rules are mainly used for content presentation (personalisation using the cognitive style).

1. https://apps.facebook.com/mymuseumstory

After the initialisation phase is completed, the user can navigate inside his virtual museum (see Fig. 2). The latter is designed from the decoration and organisational styles the user has chosen and comprises a set of emplacements where objects can be exposed. The user can populate his museum by playing small games (like e.g. solving puzzles, playing tic-tac-toe or gambling), from which he is able to win objects to expose. Those objects are related to real museums exhibitions topics (e.g. an ancient vase is linked to exhibitions related to ancient civilisations) and allow determining user's personal interests from their choices.

User interests, POIs of a museum and game objects are all related to a set of topics. These topics are preferably related to exhibitions in real museums, and for the sake of simplicity it is predetermined. At this stage of our work, we do not exploit relationships between topics or their semantics, although it is considered as an interesting option for the future. Let this topic set be represented by a vector: $\mathbf{topics} = (topic_1, ...topic_n)$. Game objects and POIs are represented each by a vector, respectively, $\mathbf{top}_{obj} = \mathbf{w}_{obj} \times \mathbf{topics}$ and $\mathbf{top}_{POI} = \mathbf{w}_{POI} \times \mathbf{topics}$, where $\mathbf{w}_x$ is a weight vector whose elements are in $\{0, 1\}$. User interests comprise both personal interests (PI) and generic interests attached to their cognitive profile. They are represented by a vector $\mathbf{I}_U = (\mathbf{I}_{CP_U}\ \mathbf{I}_{PI_U})$, where $\mathbf{I}_{CP_U} = \mathbf{w}_{CP} \times \mathbf{topics}$ and $\mathbf{I}_{PI_U} = \mathbf{w}_{PI} \times \mathbf{topics}$. Weights of interests verify respectively $w_{CP_i} \in \{0, 1\}$ and $w_{PI_i} \in [0, 1]$. Contrary to generic interests which correspond or not to a cognitive profile (i.e. weight is 0 or 1), personal interests can be given a weight with a real number reflecting the number of times the corresponding topic has appeared in the objects chosen during the game.

5. Personalisation system

When visitors enter the museum, they are given our mobile application, *My Museum Guide* (MMG). MMG allows users to log into their Facebook account, tying their experience into their Facebook account if they choose to. Upon logging in, personalised recommendations are retrieved from the server. Once computed, the personalised visit, which is a sequence of POI recommendations, will be kept up to date and relevant to the visitor's current activity and location. For each POI, the visitor has the possibility to comment and attach pictures, hence building its own visit diary. He may also indicate when he has visited an exhibition or completed a recommended action. In that case, they are removed from the recommended sequence. At the end of his visit, the visitor may choose to upload his visit diary, i.e. posting their itinerary and pictures, including comments, as Facebook status and gallery.

5.1. Recommendation approach

The items recommended can be either *POIs* or *Actions*. Each POI is represented by a list of descriptions comprising one description for each possible cognitive profile (see section 4.1), a list of topics attached to it and time constraints. We write $POI =< DESC_{POI}, TOPICS_{POI}, T_{POI} >$. Both POIs and actions have been built by analysing the available museum exhibitions and typical actions undertaken in a museum or on social media. The number of recommendable POIs depends on the museum. In our case we identified twelve POIs including all operational exhibitions and other points of interests such as the gift shop or coffee bar. We specified seven actions ranging from taking a picture over enjoying a meal to leaving a comment using the MMG.

The computation of recommendations is done in two phases. First, all POIs are ranked according to their suitability for the given visitor, thus establishing their *matching*. After the ranking, the sequence of personalised recommendations is computed by taking into account the schedule (i.e. time constraints) of each POI. The objective is to offer to the visitor a complete tour of the museum's POIs while maximising the matching of the recommended sequence with the visitor profile, preferences and context. Personalisation is added by applying the matching description, out of the sixteen possible descriptions, to each POI in the sequence. It is dependent solely on the cognitive profile CP_U of a visitor. Some user profile elements like, in particular the visitor's age, could be used in to make some refinement. However as we focus on the use of cognitive style, we did not use it at this stage. The matching between POIs and a user is computed using the classical Cosine similarity on the topic vectors linked to the user's cognitive profile ($\mathbf{I}_{CP_U}$) and personal interests ($\mathbf{I}_{PI_U}$), and to each POI ($\mathbf{top}_{POI}$):

$$\begin{aligned} M_{POI}(U) &= \max(cos(\theta_{CP_U}), cos(\theta_{PI_U})), \\ \theta &= \frac{\mathbf{x} \cdot \mathbf{top}_{POI}}{\parallel \mathbf{x} \parallel \parallel \mathbf{top}_{POI} \parallel}, \end{aligned} \tag{3}$$

where $\mathbf{x} = \mathbf{I}_{CP_U}$ for $\theta = \theta_{CP_U}$ and $\mathbf{x} = \mathbf{I}_{PI_U}$ for $\theta = \theta_{PI_U}$.

After this step, each POI has a matching value in the range $[0, 1]$. Although the matching from the cognitive profile and the one from the personal interests could have been combined to give the final matching value, the $\max$ function is used to increase recommendation diversity. In our dataset we note which one of the $\mathbf{I}_{CP_U}$ or $\mathbf{I}_{PI_U}$ resulted in the maximum matching. It will allow us to draw conclusions of the usability and accuracy of the mapping between cognitive styles and interests. Once the final matching has been determined, the next step involves building the sequence of recommendation items.

Two objectives are targeted to build the initial sequence of POIs: (1) include as many POIs as possible in the time frame of the visit, taking into account exhibitions schedule, meaning that T_U and T_{POI} are used; (2) maximise the global matching of the sequence, which is computed by:

$$M_{Seq}(U) = \sum_{i=1}^{|Seq|} \frac{Matching(U, POI_i)}{i} / \sum_{i=1}^{|Seq|} \frac{1}{i}. \tag{4}$$

Due to the sequencing being determined by the possibility to recommend a POI in regard to its availability in time, part of the sequencing is static. Some exhibitions are only available once during the day and only on well defined times. The sequencing of the recommendation takes these into account and either inserts or attaches, depending on the spacing between scheduled exhibitions, permanently available POIs. Out of all possible sequences, only those satisfying our first objective are retained. The best sequence is then determined by looking at $\max_{i=1}^{n}(M_{Seq}(U))$, where n is the number of retained sequences.

5.2. The mobile guide

The MMG mobile guide presents the sequence to the visitor as a list of POIs scheduled on the visit time line as illustrated in Fig. 3. Under each POI's image, stars represent the computed matching of the recommendation. Each short description beside a POI or a detailed one the user can access by clicking the image, is personalised according to the visitor's cognitive profile.

Once the best fitting sequence of POIs has been chosen, it will be immutable. However, actions may be inserted into the sequence triggered by a change of location LOC_U or the starting of an activity ACT_U. For example, after exiting an exhibition, the visitor may see a recommendation to comment on his latest

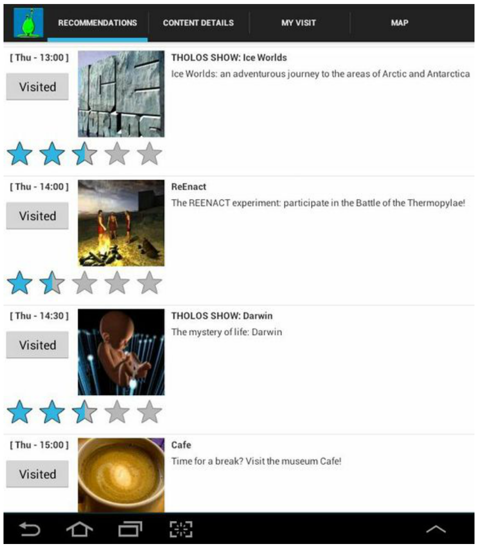

Figure 3. The recommendation screen in MMG.

consumed recommendation item. With each switch of the location context or the switching of activity, obsolete Actions are removed while new actions may be recommended.

6. Conclusion and future work

We have presented here the approach to IT-driven museum visit personalisation developed in the BLUE Experimedia project, which relies on visitors' cognitive profile estimation and gaming through Facebook. The social dimension is essential as it provides the inputs for profiling and allow users to discuss and share their museum visits with others. They also have the possibility to invite people to visit the virtual museum they build.

During the trials we have scheduled in a museum in Athens, Greece, we observe the interactions of visitors both with the MMS game and with the MMG during their visits. Additionally we ask them to fill in a questionnaire in order to gather feedback on their QoE and the usefulness of the different personalisation and recommendation functions they are provided. With these observations and feedbacks, we intend to assess both the usefulness of cognitive profile for personalisation and the suitability of the couple social gaming / personalisation to enhance visitors' QoE. At the time we write this articles, trials are not finished and the analysis of results has not started. However, the first feedbacks gathered from users during the first trial tends to confirm the usefulness of personalising exhibits descriptions from the cognitive profile. Each user was satisfied of descriptions provided to him and found the suitable level of details inside.

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