Towards Personalized Storytelling for Museum Visits

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ABSTRACT
Storytelling is a new way to guide museum visitors, where the traditional set of exhibit-centric descriptions is replaced by story-centric cohesive narrations with carefully-designed references to the exhibits. Personalized storytelling customizes the narrations according to different user characteristics, either statically or dynamically during the visit. In this paper, we describe the basic elements of an effort towards achieving personalized storytelling for museum visits in the context of the CHESS project. We outline the user and story models employed, we detail the main tools and mechanisms to bootstrap personalization for first-time visitors, and we describe the overall system architecture. The results of some very preliminary experiments with actual visitors are encouraging and show several directions for future work.

1. INTRODUCTION
CHESS (Cultural Heritage Experiences through Socio-personal interactions and Storytelling) is a system that aims to enrich museum visits through personalized interactive *storytelling*. It uses a) personalized information about cultural artefacts to create customized stories that guide individuals or groups through a museum and b) aspires to (re-)inject the sense of discovery and wonder in the visitor experience. The CHESS system employs mixed reality and pervasive games techniques, ranging from narrations to augmented reality on smart phones. Two museums participate in the effort, each with a different scope and end user requirements: the Acropolis Museum, focused on the archaeological site of the Acropolis of Athens, Greece, and the Cité de l'Espace (City of Space) in Toulouse, France, a science museum focused on space and its conquest.

Storytelling is a new way to guide museum visitors, where the traditional set of exhibit-centric, often disconnected descriptions is replaced with story-centric cohesive narrations with carefully-designed references to the exhibits. Personalized storytelling takes into account different user characteristics, e.g., age, language, education level, learning style, and past knowledge to choose the appropriate story to tell. Adaptive storytelling further customizes the initial story during the visitor's interaction, by attempting to emulate a human guide who *listens* to and *understands* the visitor's needs. CHESS is following a hybrid, plot-based approach with pre-defined content, where *story authors* (curators, museum staff, script writers) write stories around pre-selected museum themes. This is done in a modular fashion (story elements) with conditional branching based on a variety of events or/and visitor characteristics. During the visit, story elements are mixed and matched (i.e., order in which events are presented, the point of view from which they are narrated, the amount of information provided in the story, and the narrative style and genre, narrative character) to tailor the visitor expectations.

To support the authoring process and address the personalization cold start problem, CHESS utilizes the notion of *personas*[1], a design tool from the marketing world. Personas are detailed descriptions of imaginary people constructed out of well-understood, highly specified data about real people [1]. On the authoring front, personas enable authors to have particular visitors in mind when creating and characterizing story elements. On the user experience front, the persona profile is employed at the beginning of the visit, while no significant data is yet provided for the user. The system leverages persona definition to match visitors to personas, essentially aligning visitor preferences to the author's understanding of the museum visitors. During the visit however, as the user interacts with the system and additional evidence is collected about him/her, the individual profile is gradually refined and emphasized.

The paper describes the overall personalization approach that has been designed for the CHESS environment, with a focus on the explicit profiling approach that has been implemented by leveraging user preferences to persona profiles.

1.1 Contributions of our work
The described approach is built on top of PAROS[2], a system under development at the Univ. of Athens, whose goal is to obtain an understanding for its users by maintaining profiles of their attitudes, so that it may offer them information and other services in a personalized and adaptive fashion. PAROS has been designed so as to provide rich relevant functionality at a generic level, on top of which particular applications may be built.

In this paper, we describe the implementation of a particular CHESS profiling approach on top of PAROS. Our work is summarized in the following main points:

1) Modeling of CHESS users and storytelling data model under PAROS modeling framework
2) Definition and modeling of appropriate personas for the target museum institutions. Personas are defined using a set of variables, which are modeled under the PAROS user model along with the CHESS storytelling data model.

[1] The correct Latin plural is *personae*, but popular usage in English has been *personas*; hence we will use the latter.

3) Design of visitor survey tool for obtaining visitor input and analysis of its results, which are interpreted into the PAROS modeling framework
4) Exploitation of personas profiles to address the cold-start problem during initial story selections.
5) Modeling and implementation of traditional cosine similarity into the generic profile interpretation paradigm of PAROS (using path propagation operators).

The exploitation of persona profiles for story selection is evaluated under the current Cité de l'Espace setting and preliminary evaluation results indicate that the proposed approach is very promising for initial story selection.

Our main contribution is that we have addressed a novel application setting, having a complex storytelling data model and imposing hard constraints and requirements. While the great majority of research on personalization systems focuses on efficiently modeling and profiling "repeated visitors", an important requirement for the CHESS environment is to also adequately deal with "unique visitors", providing them a personalized and adaptive experience during their first museum visit. We have addressed this requirement by defining persona profiles which are utilized for initial story selection. We have modeled the CHESS storytelling data model using the generic PAROS modeling framework and we have extended the PAROS system with components and algorithms that are capable of representing, analyzing and processing museum-specific knowledge about CHESS visitors, while at the same time following the generic profiling paradigm supported by PAROS.

2. OVERALL SYSTEM APPROACH

Figure 1 presents the key system components and their interactions under the CHESS application setting.

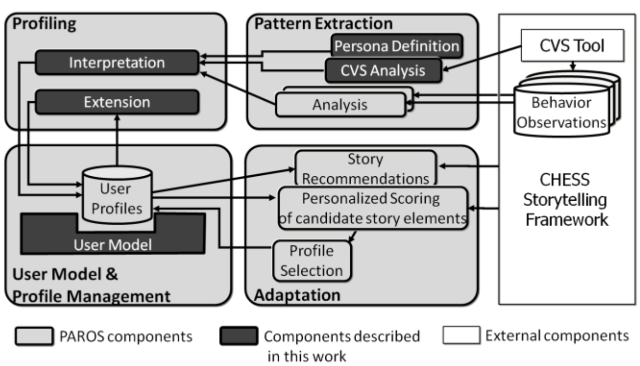

Figure 1. System Architecture

The *User Model and Profile Management* component serves as the foundation on top of which all other parts are built. It provides the basic functionality required by the PAROS user model, which captures several levels of user attitudes towards the relevant world entities and concepts.

The *Pattern Extraction* component is responsible for analyzing user actions and input to discover interesting behavioral patterns and other observations. Such data may be collected explicitly, by having users provide related input directly, or implicitly, by monitoring the users' interactions within particular application setting(s).

The *Profiling* component encompasses techniques for processing the extracted patterns and observations and appropriately interpreting them within the framework of the user model, to extract profile elements. Such profile elements are used to instantiate or enhance the user profiles by determining new attitudes between entities, or by altering existing ones. Furthermore, user profiles can be expanded with additional elements using profile extension algorithms that process further the available profiles to discover new, implicit, or hidden knowledge. Profile extension in PAROS is abstracted as an optimal path computation problem. Following path algebra formalism, a label is associated with each edge and each path in the graph. A path label is computed as a function called *CON*, of the sequence of labels of the edges in a path. A path set *P* is also associated with a label, which is computed as a function called *AGG*, of the labels of the paths in *P*. This formalism is not ideal in some cases, but serves extremely well in the process of providing different profiling services in a uniform way.

The *Adaptation* component represents the actual selection of the appropriate profiles and their use to adapt the behavior of and the content provided by information systems and other applications to the users' preferences and interests. To this end, PAROS provides a generic query mechanism that can be used to determine the attitudes of users towards specific entities. Under the CHESS Storytelling Framework, a dedicated component is responsible for obtaining personalized recommendations and rankings from PAROS. It then leverages them to make a variety of content-selection decisions, while also considering additional story coherency and contextual factors (purpose of visit, available time, environmental and technical parameters, etc).

The *CHESS Visitor Survey (CVS) Tool* is a configurable web application that enables visitors to reveal their preferences to the CHESS system, by answering a series of questions. The tool is generic and can be used to perform any desirable survey, provided it can use the constructs supported, such as single choice questions, multiple choice questions, ranking questions in a variety of presentation formats supported (textual, visual, single/multiple column layout, etc).

In the following sections we elaborate on the user modeling, pattern extraction and profiling techniques that have been designed and implemented in PAROS system for classifying CHESS visitors into visitor types. The corresponding PAROS components are highlighted in Figure 1. To address the particular requirements and characteristics of CHESS environment, PAROS platform has been extended with some CHESS-specific analysis components, implementing the Persona Definition and CVS Analysis techniques. Such approaches are particularly tied to the application environment, hence requiring significant adjustment for being re-applied in other settings. On the other hand, the employed PAROS modeling and profiling techniques are quite generic and they have been easily configured so as to be applied for CHESS environment.

3. USER MODEL AND PROFILE MANAGEMENT

The PAROS user model represents in a uniform way the entire universe of users and their attitudes. The model is a graph *GUM(UOF,DAA)*, where *UOF* is its set of nodes and *DAA* its set of edges. Nodes in the graph include among others, users of the system, objects being personalized, functions between the above, communities, and sets. Edges in the graph represent two kinds of relationships among the nodes: i) data relationships that capture object associations, structure and memberships, and ii) attitudinal relationships that capture user preferences, beliefs and actions. Each edge is potentially associated with a, simple or more complex, label vector that depends on the edge type. The aforementioned model is rather general, enabling to adequately capture a great variety of models which are managed in a uniform way under the same framework.

For the purposes of the CHESS project, a novel storytelling data model has been defined, representing a great variety of story-related entities that are interlinked with particular types of semantic and structural relationships (Figure 2). Stories are viewed under three main levels, namely, the *scenario*, the *staging* and the *plot level*. At the scenario level, each story is decomposed into story units. Story units have attributes, such as title, description, subject, suitable age groups, functional type, etc.

Moving on to the staging level, the story is placed into the physical world (wherever such a connection is feasible and desirable) with links to spaces and exhibits. Spaces are represented through pre-defined "hotspots" located within the museum environment. Hotspots and exhibits provide the two main staging entities in the storytelling data model. Hotspots may be related to exhibits, indicating the exhibits location within the museum space, or not, indicating important location points (such as the entrance or exit of a hall). Exhibits and hotspots are also connected to story units to represent the semantic relationships between them.

Finally, in the plot-level, the story is brought to life by specifying the multimedia resources employed for manifesting the story units. For each story unit, a set of digital assets is synchronized under the frame of an activity. Both activities and assets have their own i) multimedia attributes (mime type, duration information, length/size, resolution) and ii) conceptual attributes (subject, age groups, type). A variety of additional associations and relationships are defined between story units, hotspots, exhibits, activities and assets, so as to allow adaptation and alternate implementations of a story.

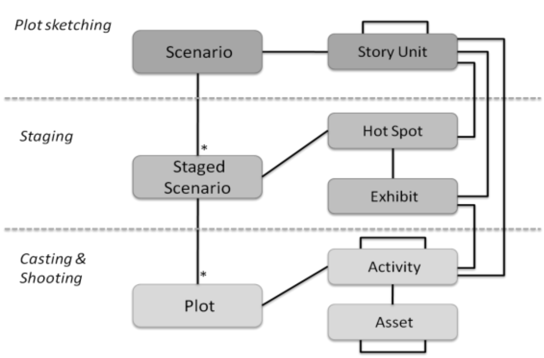

Figure 2. Storytelling Data Model

The described entities, attributes and relationships are represented following the PAROS user modeling framework. For instance, consider two types of entities: story units and subjects. An abstract object node is employed for each one (white circles in Figure 3), capturing the main object characteristics, and the two nodes are connected with a *has_subject* object node, denoting a particular function between them. All the concrete story units and subjects are represented with additional object nodes (black circles in Figure 3), which are connected with an *is_a* type of edge to the appropriate abstract object nodes, denoting the instantiation of such objects. Moreover, concrete story unit nodes are connected through *has_subject* function nodes to concrete subject nodes, denoting the subject of each story unit.

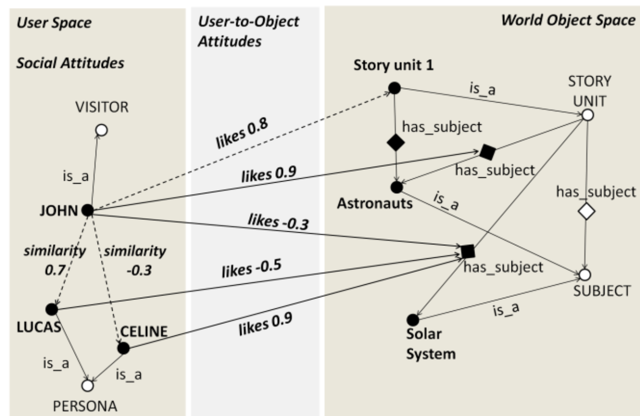

Figure 3. CHESS User Model

The user nodes represent individual visitors of the museums and a set of characteristics is stored for each user (name, gender, age). Moreover, a set of personas has been defined by museum experts, capturing visitor archetypes. Such personas are also represented through "persona nodes" (a special type of user node), having their own characteristics, similarly to real visitors.

For the time being, two types of attitudinal edges are considered in CHESS user model, namely: i) persona_similarity, a directed edge between user nodes and persona nodes, indicating the matching of a visitor to personas (if such a match is possible), and ii) preference, a directed edge between user nodes and object nodes indicating the visitor's level of preference over the particular object. Preference edges might also be between user nodes and function nodes, indicating that the user likes/dislikes an object node as part of a specific functional relationship. For instance, to express that a visitor likes in general story units having "Astronauts" as a subject, a preference edge is employed between the user and the functional node that connects the abstract story unit node and the concrete node denoting the subject "Astronauts" (Figure 3).

4. PATTERN EXTRACTION

Museum visitors perform a large number of actions during their visit and while interacting with CHESS system. Such actions may include the interruption or completion of an activity or story, entrance/departure from hotspots, requests for additional resources, user selections from a list of candidate resources, requests for changing story, etc. Typically, the analysis of recorded actions leads to interesting behavioral patterns that provide important insights in what visitors like and dislike. However, CHESS is an ongoing project and the resulting software framework will be heavily tested by real visitors towards the project completion, so no significant usage data will be provided until then. Therefore, the implementation and evaluation of traditional pattern extraction algorithms is not feasible yet.

Addressing the described requirements and constraints, we have proposed an explicit profiling approach that i) employs predefined persona profiles and ii) acquires and analyzes user input at the beginning of the visit through the CVS tool, for subsequently constructing initial user profiles that will enable to quickly conduct personalized selections.

4.1 Persona Definition

Interaction designers have argued that the best way to successfully accommodate a variety of users is to design for specific types of individuals with specific needs [3]. As Hacko and Redish [3] note, "good design happens only when designers understand who will be using their product and the personal characteristics, habits of mind, physical capabilities, and limitations those users bring to their tasks". A popular user modeling technique for communicating about different types of users and their needs is to build *personas,* i.e., user models that are represented as specific individual human beings.

The definition of personas for CHESS is a result of the synthesis of data from a variety of sources: primary sources (such as the museum data collected via questionnaires, the interviews with staff, the ethnographic observations of visitors and staff at work studies) and secondary sources (such as the study of related literature on museum visitors and visiting styles).

This data has been pieced together to define a set of 26 demographic and behavioral attributes, the CHESS variables. These form the essential set of user characteristics that relate to user needs and preferences during a museum visit. They can be used to describe each user and, consequently, each persona. Although personas cannot and do not need to be completely accurate [1], the point in filling up these variables is to ensure that they reflect the essential information about target users.

The values can be quantitative or qualitative, depending on the variable. The variables include demographic ones (age, gender, country of origin, language), skills and experience (educational level, educational background, profession, experience with the use of digital devices), possible disabilities and health issues, interests, either general or related to the museum topics, visit specific (visit duration, returning visit), preferences related to the visit (visiting style, part of collections to visit, preferred narration style, preferred level of interactivity, etc).

The defined CHESS variables are modeled under the employed user modeling framework and the predefined persona values are utilized for initializing the corresponding persona profiles.

The following section presents the design and analysis process of the user input that is provided through the CVS tool.

4.2 CVS Design and Analysis

The design of the CVS has undergone a detailed iterative approach according to the following steps:

1. Selecting the variables for which the CVS needs to record values. The questions included in the CVS have been defined according to a subset of the persona variables, relevant to each of the participating museums.
2. Designing the questions to be included in the initial CVS prototypes. In this case, an extensive literature review was performed and a psychologist was employed to identify the most suitable questions that could provide indications for specific variables. This process leads to the design of low fidelity prototypes which are validated with selected users.
3. Designing high-fidelity prototypes. Once the low-fidelity prototypes have been validated, high-fidelity design produces an experience as close as possible to the final CVS product.
4. Evaluation of the prototype. This process has identified user interface issues as well as question structure ones.

Regarding the analysis of the CVS-based input, each visitor's answer to a CVS question is viewed as one or more user actions. In particular, each answer is associated with: i) a specific value from the domain of a persona variable, ii) an intensity value indicating the strength of the preference, iii) an indication if the action shows positive or negative preference. For example, the question "What do you prefer to watch on TV?" has the following potential answers: 1. Scientific Documentaries, 2. Cooking Shows, 3. Sci-Fi/Fantasy, 4. Drama/Comedy.
Let's suppose that we want to express that the first answer shows a strong preference towards "Space Technology" and a somewhat milder preference towards "Space Missions". To express this, we need to link this answer to the following two user actions:

1. A strong positive intensity towards the value "Space Technology" of the Thematic Taxonomy variable we have defined.
2. A medium positive intensity towards the value "Space Missions" of the Thematic Taxonomy variable.

As a result, when the user chooses this answer, these two pieces of evidence will be generated regarding user's preferences.

Obviously, the described CVS analysis is closely tied to the characteristics of the particular application environment. For the purposes of CHESS, it is conducted by a team of museum members and cognitive experts. This team of experts is responsible for assigning the possible CVS answers to the appropriate variable values along with the appropriate preference evidences. The whole set of CVS-based evidence is subsequently exploited by the profiling algorithms to create user profiles.

5. PROFILING

To conform to the CHESS user model the following transformation is applied over the acquired CVS-based evidence: the intensity level and positive/negative indicator is transformed to a rating in [-1,1]. In particular, high positive corresponds to 1, medium positive to 0.6, and low positive to 0.3, while high negative to -1, medium negative to -0.6, and low negative to -0.3 (the exact numeric assignments are ad-hoc and may be easily reconfigured for different settings).

Such transformations apply when the user profile has no prior edge towards the value of the action and it results in the creation of a new edge along with the appropriate weight. If an edge already exists in the user profile, then the weight is updated to the average of the current weight and the intensity of the considered action.

Having the CVS evidence been interpreted into the CHESS user model, a *persona matching* procedure takes place, calculating the similarity of the user with the available persona profiles. As a first-step similarity measure, the cosine similarity is utilized; given the common liked objects a visitor and a persona share, a value between [-1, 1] is computed, where -1 denotes total dissimilarity and 1 complete similarity. The cosine similarity formula can be incorporated and produce a degenerate form of a path computation algorithm (one-step propagation). Among the various different labeled edges, we define the problem on the subset graph with nodes users (visitors and personas) and chess variables, while considering only edges labeled with "likes". We should note however, that in this section, when we refer to 'chess variables' we assume that they are represented as triplets (*chess_object*, *with_chess_variable*, *that_takes_value*) and a 'like' can be expressed on the triplet by an arc that starts from the user node and ends in the chess variable node.

We consider that a path (disregarding the direction of the arcs) is formulated between $User_A$, CV and $User_B$ nodes if there exists i) an edge from user node $User_A$ to a chess variable node CV, ii) an edge from user node $User_B$ to the same chess variable CV. As a result the two "like" labeled edges are concatenated and form a path $User_A \rightarrow CV \rightarrow User_B$, which results in a new edge $User_A \rightarrow User_B$ labeled "similar", with weight between [-1, 1] (Figure 4).

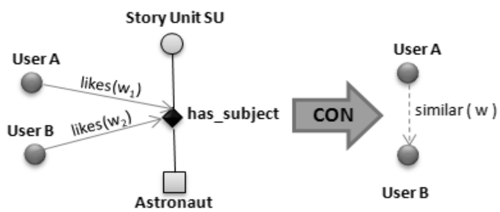

Figure 4. Visualization of *CON* operator

Having established that, we define the *CON* operator below:

$$CON(l_1, l_2) = sgn(l_1 \cdot l_2) = \begin{cases} -1, & if\ l_1 \cdot l_2 < 0 \\ 0, & if\ l_1 \cdot l_2 = 0 \\ 1, & if\ l_1 \cdot l_2 > 0 \end{cases}$$

$$where\ l_1\ weight\ of\ edge\ User_A \rightarrow CV, and$$
$$l_2\ weight\ of\ edge\ CV \rightarrow User_B$$

Figure 5. Definition of *CON* operator

When several paths between the two user nodes are found, the *AGG* operator must be applied to aggregate the similarity values into one (Figure 6).

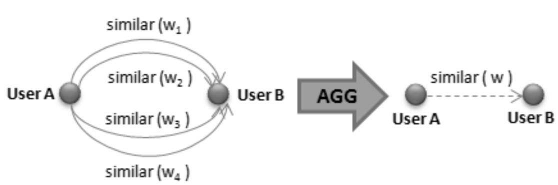

Figure 6. Visualization of *AGG* operator

AGG is defined as the weighted average of the calculated paths. The formula used is given in the following figure.

$$\underset{1 \le i \le N}{AGG(\{CONpath_i\})} = \frac{1}{\sqrt{A}} \cdot \frac{1}{\sqrt{B}} \cdot (\alpha_1 \cdot CONpath_1 + \alpha_2 \cdot CONpath_2 + \cdots + \alpha_N \cdot CONpath_N)$$

$$where\ A = \sum_i^N l_{Ai}^2,\ B = \sum_i^N l_{Bi}^2\ and\ \alpha_i = li_{A \rightarrow CV} \cdot li_{B \rightarrow CV}$$

Figure 7. Definition of *AGG* operator

It is denoted that (as part of the selected paths) l_{Ai} is the weight that starts from user node A, l_{Bi} is the weight that starts from user node B, and factors $a1, a2, \dots, aN$ are calculated as the multiplication of the weights of the labeled "like" edges that point to the same CV node.

For the effective calculation of *AGG* (e.g. for some *AGG* properties to hold) the information about A, B, and the factors $a1, a2, \dots, aN$, must be kept separately and updated gradually, as more paths are discovered and take part in the computation. In that front, each path created with *CON* should also hold (apart from its calculated weight) its factor $\alpha = w_i * w_j$, while user node A and B nodes, should hold and update A and B values respectively, as more paths are considered.

6. PRELIMINARY EVALUATION RESULTS

The CHESS system is currently being adapted to the needs of the Cité de l'Espace museum to offer personalized and adaptive story telling. One of the first results is the design of a CVS appropriate for the specific museum described in the following tables.

Table 1: Variables and their Values for Cité de l'Espace CVS

Variable	Values
Subject (S)	Human in space (HIS)
	Astronomy Basics (AB)
	Eating in Space (EIS)
	Living in Space (LIS)
	Technical Artifacts (TA)
	Astronauts (A)
	Space Missions (SM)
	Selection & Training (S&T)
	Activities in space (AIS)
	Solar System (SS)
Experience with the use of digital devices (XP)	Novice (N)
	Medium (M)
	Experienced (EXP)
Level of user control (UC)	above average (AV+)
	below average (AV-)

Answers A3.1-A3.5 are matched to an intensity level based on their rank. The top two answers get an intensity of Positive High, the next two of Positive Medium, and the last one of Positive Low. If the user doesn't rank an answer, it is considered as an indication of disinterest, and the corresponding intensity is Negative Medium.

Table 2: Questions and possible Answers

Question	Answer
Choose 2 of the following that you prefer to watch on TV the most (Q1)	Science and Technology
	Cooking (A1.2)
	Drama/Comedy (A1.3)
	Sci-Fi / Fantasy (A1.4)
Technology is... (Q2)	Awful! I hate anything digital
	Hard to understand (A2.2)
	Necessary (A2.3)
	Great! I love gadgets (A2.4)
Move to the right the topics you are interested in and put them in the right order (Q3)	Preparing an astronaut mission
	Everyday life in space (A3.2)
	Rockets and station tech (A3.3)
	The solar system (A3.4)

	Past missions to space (A3.5)
Choose what you prefer (Q4)	I prefer to do a lot of things at once
	I prefer to do one thing at a time
Choose what you prefer (Q5)	I want clear instructions (A5.1)
	I prefer to figure things out (A5.2)

Table 3: CVS Analysis Evidences

Answer	Value	Intensity
A1.1	HIS	Positive High
	AB	Positive High
A1.2	EIS	Positive High
	LIS	Positive Medium
A1.3	LIS	Positive Medium
A1.4	TA	Positive Medium
	A	Positive High
	SM	Positive High
A2.1	N	Positive High
	M	Negative High
	EXP	Negative High
A2.2	N	Positive High
	M	Negative Medium
	EXP	Negative Medium
A2.3	M	Positive Low
	EXP	Positive Low
	N	Negative Medium
A2.4	EXP	Positive High
	N	Negative High
A3.1	SM	Based on rank
	S&T	Based on rank
A3.2	AIS	Based on rank
A3.3	TA	Based on rank
A3.4	SS	Based on rank
A3.5	SM	Based on rank
A4.1	AV+	Positive Medium
	AV-	Negative Medium
A4.2	AV-	Positive Medium
	AV+	Negative Medium
A5.1	AV-	Positive Medium
	AV+	Negative Medium
A5.2	AV+	Positive Medium
	AV-	Negative Medium

With the collaboration of museum personnel, we identified two visitor personas: (a) Lucas, a tech-savvy young individual, experienced in and excited with the use of digital devices, gaming and interactive experiences, and very much interested in space technology and astronaut missions, and (b) Céline, a more relaxed person, with only a basic experience with digital devices, preference in more guided experiences in museums and interested more in the everyday life of astronauts and the history of space programs. To each persona we assigned one of the two possible starting stories, “Train to become an astronaut” (Lucas) and “A travel in space” (Céline).

Based on this setting, we conducted a study with ten users who were asked to perform the CVS and also to pick the starting story that interested them the most, independently from their answers to the survey. We counted as correct the cases where the starting story chosen by our system was the same as the one chosen by the user. Under this definition, our system gave a correct answer in all ten cases.

7. CONCLUSIONS & FUTURE WORK

Addressing the need for a personalized story selection step at the beginning of the visit while having no prior information about the visitor, we have implemented an explicit profiling approach that collects user input and leverages persona profiles for selecting the most promising story. The results of some very preliminary experiments with actual visitors are encouraging and large-scale experiments have been scheduled so as to evaluate the proposed approach in a systematic way.

An immediate extension of our work includes the implementation of profile expansion algorithms, taking advantage of the rich graph structure that links users with the storytelling data model and propagates knowledge on object nodes for which no prior interactions have been recorded.

Regarding the use of personas, as the users interact with the system and their profiles are enriched, the initial persona matching through the CVS may become deprecated. A user may change persona, or exhibit some attitudes that are unique and not covered by the defined personas. Efficient profile update techniques are required on that front, to enable efficient on-the-fly adaptation of CHESS functionality. Finally, when sufficient amount of usage data has been collected, the application of pattern extraction algorithms is expected to result in the identification of visitors clusters, whose representatives may reveal new or additional prominent visitor types and their profiles can be used similarly to the predefined persona profiles.

8. ACKNOWLEDGMENTS

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