A Multilevel Graph-Based Recommender System for Personalized Learning Paths in Archaeological Parks: Leveraging IoT and Situation Awareness

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Abstract: Enhancing Cultural Heritage relies on innovative technologies to improve user interaction with cultural assets. The advent of the Internet of Things (IoT) has made integrating smart devices with educational methodologies possible, enabling a combination of cultural engagement, heritage promotion, and learning. This study aims to introduce a Recommender System capable of suggesting personalized learning paths for users visiting archaeological parks, leveraging a multilevel graph-based approach. The method is grounded in Situation Awareness (SA) and structured into three main levels: perception, comprehension, and prediction. The perception level is ensured through data acquisition from sensors deployed in the field; the comprehension level utilizes semantic and contextual graph approaches for domain representation; and the prediction level is developed using predictive algorithms based on Bayesian Networks. A preliminary experimental campaign conducted across three archaeological parks allowed for testing the effectiveness of the proposed approach, demonstrating its predictive capabilities and potential in creating tailored cultural experiences. The findings highlight how advanced technologies can enrich users' educational experiences and significantly contribute to the valorization of cultural heritage.

1 INTRODUCTION

Enhancing cultural heritage requires employing novel technologies to support users' interactions with cultural assets. The capability of providing personalized experiences permits the improvement of enjoyment (Hong et al., 2024) by suggesting appropriate tours to users integrated with e-learning strategies. Therefore, identifying systems that filter and analyze data to understand user preferences is crucial (Casillo et al., 2023; Colace et al., 2023).

Then, this work introduces the MuG Approach (Casillo et al., 2024b), which is exploited as a Recommender System (RS) to suggest learning paths to users visiting archaeological parks. In recent decades, e-learning has been increasingly enriched with new tools to improve the educational process. The typical processes of the traditional education world, which are still valid today, are assisted by the advent of new technologies. The present era is characterized by new intelligent devices capable of exchanging information with each other, contributing to the Internet of Things (IoT) paradigm (Casillo et al., 2024a; Michalakis and Caridakis, 2022). How can we take advantage of such technologies to further enhance e-learning? Suggesting training activities in a cultural-historical center allows users to connect with historical assets, furthering the training process. However, this is not enough to obtain good training results. It is necessary to follow a well-structured educational path provided by an expert guide whose objective is not simply to describe the artifacts present as is typically done with tourists but to give a historical-cultural perspective with a formative character (Jin et al., 2022). This process is particularly complex. In this scenario, having a methodology that deals with the automatic design of educational paths could be interesting. This technology could employ smart mobile devices and the large amount of data they produce to build customized learning paths. These training paths could also be developed ad hoc concerning the archaeological sites visited, allowing the combination of two objectives: promoting learning and enhancing cultural heritage value.

The crucial point of the proposed work is achiev-

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ing Situation Awareness (SA). SA has emerged in the literature as a central theme since the 1980s and can be intuitively interpreted as awareness of what is happening in a given context around people (Endsley, 1995; Casillo et al., 2022; Stanton et al., 2001). There is no single definition of SA, as different scientific interpretations focus on distinct aspects: perception and understanding of the environment, interaction between humans and the environment, and mental models (Stanton et al., 2001). In general, SA is concerned with human interaction, which is identifiable through tools such as projection, cognition, mental models, perception and reflection, and the external environment.

Endsley's theory is based on a three-level approach (Endsley, 1995):

- Perception: acquisition of information about the surrounding environment.
- Comprehension: processing information to become aware of the environment.
- Prediction: using perceived and comprehension information to predict future actions and anticipate problems.

The degree of awareness increases as we move between levels, reaching a maximum in the ability to predict.

This work aims to achieve SA through three graph approaches: the Multilevel Graph (MuG) approach (Casillo et al., 2024b). Specifically, the level of perception is achieved through the use of data acquired through the IoT paradigm. Then, the Context Dimension Tree (CDT) and a Domain Ontology are exploited for the comprehension phase. Finally, the structure of a Bayesian rate is identified via structural learning algorithms, which enables the prediction phase.

Developing an experimental campaign for three archaeological parks permits testing the MuG approach to suggest suitable user cultural experiences. The campaign's aim was to evaluate its predictive capabilities.

The paper is structured as follows: Section 2 focuses on state-of-the-art analysis, Section 3 describes the proposed approach, Section 4 introduces the experimental campaign, and Section 5 presents conclusions and future developments.

2 RELATED WORKS

Enhancement of cultural heritage by improving user experiences is a topic of considerable interest in the literature.

There are many techniques aiming to improve the learning process. As Cicero liked to walk around memorizing by associating physical paths to narration, new systems are increasingly aware of the power of Digital Storytelling in e-learning. Digital Storytelling represents a traditional, modern take on oral Storytelling, combining the ancient tradition of oral Storytelling with today's technological tools. There are many studies in the literature regarding the application of Digital Storytelling techniques in educational pathways (Smeda et al., 2013; Weng et al., 2011). In (Smeda et al., 2010), guidelines are proposed to develop an advanced framework for e-learning that exploits the Digital Storytelling technique. This is primarily by exploiting the pedagogical-innovative capabilities of this approach that has the potential in engagement that promotes improvement in learning.

Moreover, solutions to offer training models based on Digital Storytelling to different groups of users with different backgrounds and levels of digital literacy are addressed in the literature to revive such learning models in developing countries (Ungerer, 2019). This technique has been evaluated in different learning domains, including foreign language learning in interdisciplinary projects obtaining exciting results (Yang et al., 2022). Another fascinating field where Storytelling is applied is in e-tourism and museums to enhance Cultural Heritage (Chen et al., 2014; Ioannidis et al., 2013).

Sometimes, Digital Storytelling approaches are complemented with gamification. In (Rossano and Roselli, 2018), a Content Management System for Digital Storytelling to support knowledge acquisition and fruition is proposed. This approach has obtained interesting results in young patients with particular health problems capable of influencing their emotional sphere. Many studies in the literature propose using e-learning systems that are able to use gamification approaches (Amriani et al., 2014; Sanina et al., 2020).

Such approaches aim to consolidate the training path, using the capacity of modern technological systems, which, if well exploited, can adapt to users' needs (Jianu and Vasilateanu, 2017). Based on this, an interesting application is to combine gamification with augmented reality to make the gaming experience more meaningful and enveloping (Bonsignore et al., 2012). This approach has been found in many areas, such as business production (Korn, 2012), social relations (Morschheuser et al., 2017), and e-learning (Saidin et al., 2015). In particular, in (Pombo et al., 2019) augmented reality has found excellent feedback in learning paths especially outdoor.

Believing that the use of techniques as such is valid in the e-learning field, another aspect to consider is the use of such methodologies to enhance cultural heritage. These methodologies are exploited to process and interpret personal user information and contextual information. To this end, context can be used to create applications (Dey, 2001; Raento et al., 2005) that can filter relevant data by providing the correct information at the right time and constantly updating (Jin et al., 2014). Modern applications, in addition to personal interests, can adapt to the user's profile (Fink and Kobsa, 2002), distinguishing, for example, between a child and an adult, and can learn from former choices and provide real-time updates concerning the context (Ghiani et al., 2009; Gavalas and Kenteris, 2011). Therefore, the need arises to create a methodology that combines the effectiveness of new technological devices to create training paths in the field. The innovation of the proposed methodology is to exploit the capabilities of the new devices, the amount of data they produce, and the REST services to automatically design context-sensitive training paths valid for different categories of users. These training paths, to be performed in archaeological sites, address education by collecting many innovative techniques in the field of e-learning such as digital Storytelling, augmented reality, and gamification.

This case study aims to use the MuG approach as a recommendation system to suggest educational paths exploiting a high degree of context awareness. This approach is able to combine several methodologies that underlie models working in different domains, such as smart cities and cultural heritage enhancement. In particular, in concurring with the prefixed objective, that is, to recommend the right educational path to the users according to the context, it is possible to refer to the proposed methodology. This method can bring semantic value to the available data to provide users with illustrated and augmented reality stories in proximity to the visited places and according to different factors able to influence the educational path such as available time, weather conditions, and user's attitudes.

3 THE PROPOSED APPROACH

This section describes the proposed approach to achieving situation awareness by employing three graphs. It also aims to describe how the proposed approach is applied to enhance cultural heritage. This task requires the definition of an architecture based on four functional layers to provide personalized services to users consisting of e-learning cultural paths chosen appropriately for users.

The section is divided into two subsections: the first describes the MuG approach, while the second contextualizes it for improving user experience.

3.1 The Multilevel Graph Approach

The Multilevel Graph (MuG) approach aims to make the architecture that will be described in subsection 3.2 achieve Situation Awareness. To do this, it is necessary to achieve the three levels described in the introductory section: perception, via data acquired from sensors and API Services, understanding, and prediction.

Underlying the proposed approach are three graphs: the Context Dimension Tree (CDT) and Domain Ontology that enable the comprehension stage, and the Bayesian Network (BN) that enables the prediction stage.

The CDT is a context representation model based on a graph

$$G_c = < r_c, N_c, E_c >, \qquad (1)$$

specifically a tree, with a set of nodes (N_c) and arcs (E_c) (Bolchini et al., 2009). The nodes are divided into:

- Dimension nodes: represent dimensions, shown in black.
- Concept nodes: represent dimension values, shown in white.
- Attribute nodes: represent attributes and are always leaves of the tree.

Specifically, the root node r_c is a concept node representing the most general context. Dimension nodes have only concept nodes as children, attribute nodes can have only dimension or concept nodes as their parents and cannot have children, and each attribute node is a unique child. Dimension nodes without concept children must have at least one attribute child.

The CDT alternates between dimension nodes and concept nodes, forming distinct generations. Each node is characterized by its type (dimension or concept) and a unique label determined by the path connecting it to the root. Finally, parameters can be associated with leaf nodes to further refine data selection.

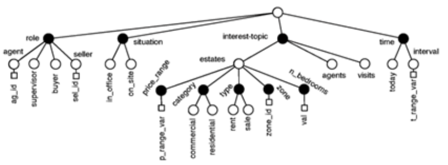

Figure 1: Example of Context Dimension Tree.

Ontology is a valuable tool for representing, sharing, and reusing information (Gruber, 1995). It reduces conceptual and terminological confusion through a shared vocabulary that includes precise definitions and semantic relationships between entities. This formalization enables clear communication between humans and machines, ensuring that each piece of information has a precise meaning related to its context. An ontology is a formal and explicit specification of a shared conceptualization. It includes concepts, attributes, and hierarchical and semantic relationships formalized to be machine-processable. Ontologies can be classified into lightweight (more straightforward, with essential relationships) and heavyweight (more complex, with additional axioms and constraints).

Let formalize the Ontology

$$O = < C, A, H, R^+, R^- >, \tag{2}$$

where C are the concepts, A the attributes, H the hierarchical relations, and R^+ and R^- dependency and independency relations. As with the CDT, the Ontology can be represented by a graph

$$G_0 = < r_0, N_0, E_0 >, \tag{3}$$

where the set of nodes N_O consists of the concepts nodes and the set of edges

$$E_0 = \left\{ (n_1, \lambda, n_2) : n_1, n_2 \in N_0, \lambda \in H \cup R^+ \cup R^- \right\} \tag{4}$$

presents labels that describe the typology of connections among concepts. In addition, dimensions and concepts nodes of the CDT are a subset of the concepts C of the Ontology and attribute nodes of the CDT are a subset of the attributes A of the Ontology.

The interaction between CDT and the Ontology allows the definition of constraints to improve the knowledge of the dependency and independency among nodes. These constraints permits to improve the construction of the structure of the BN. Specifically, the BN can be represented by the graph

$$G_B = < N_B, E_B >, \tag{5}$$

where the nodes N_B are a subset of the concepts of the Ontology and the edges represent the dependency connections among the nodes N_B.

Specifically, Algorithm 1 describe the structural learning procedure integrated with the constrains identified by the interaction between the Ontology and the CDT.

Specifically, the algorithm requires the nodes N_B of the BN, the dependency and independency constraints D and I, perspectively, and the definition of the order of nodes and a maximum number of parents u. In addition, the algorithm requires the definition of a function $g(\cdot,\cdot)$ that allows to evaluate the reliability level of identified BN (see (Casillo et al., 2024b)).

Algorithm 1: Algorithm of the MuG approach.

Data: N_B, dependency constraints D, independency constraints I, node order, max number of connections u.
Result: printout of the node's relatives for each node.
for $h = 1, \ldots, n$ **do**
  $\bar{\pi}_h \leftarrow \{(X, X_i) \in D\} \subseteq D$;
  $P_{\text{old}} \leftarrow g(h, \bar{\pi}_h)$;
  status ← True;
  while *status AND* $|\bar{\pi}_h| \leq u$ **do**
    Let be $z \in \text{Prec}(X_h)$ and $\bar{\pi}_h$ which maximizes $g(h, \bar{\pi}_h \cup \{z\})$;
    $P_{\text{new}} := g(h, \bar{\pi}_h \cup \{z\})$;
    if $P\text{new} > P_{\text{old}}$ **then**
      $P_{\text{old}} \leftarrow P_{\text{new}}$;
      $\bar{\pi}_h \leftarrow \bar{\pi}_h \cup \{z\}$;
    else
      status ← False;
    end
  end
  write: Node X_h - Parents $\bar{\pi}_h$
end

3.2 The Proposed Architecture

After describing the MuG approach, we want to describe the architecture enabling this methodology to enhance users' cultural experiences and cultural heritage.

The architecture, depicted in Figure 2, has four layers: the Acquisition Layer, the Knowledge-Base Layer, the Inference Engine Layer, and the Application Layer.

The first layer aims at data acquisition through sensors and API services. The central point of this layer is the IoT paradigm. The ability to manage devices that not only acquire data of interest but are also capable of sending this data via the Internet to centralizers that allow it to be managed and sent to Cloud platforms allows for data to be available that not only describes the context in which the system acts but also allows for the improvement of the suggestions made by acquiring data about both the users and the points of interest that constitute the paths that will be suggested. This layer exploits sensors capable of acquiring data related to meteorological conditions and user location. In addition, data acquired through external sources is integrated via API services.

After the data acquisition phase, the Knowledge-Base Layer comes into play. At this stage, the raw data needs a preprocessing and cleaning phase that allows storage in the database. The stored data pop-

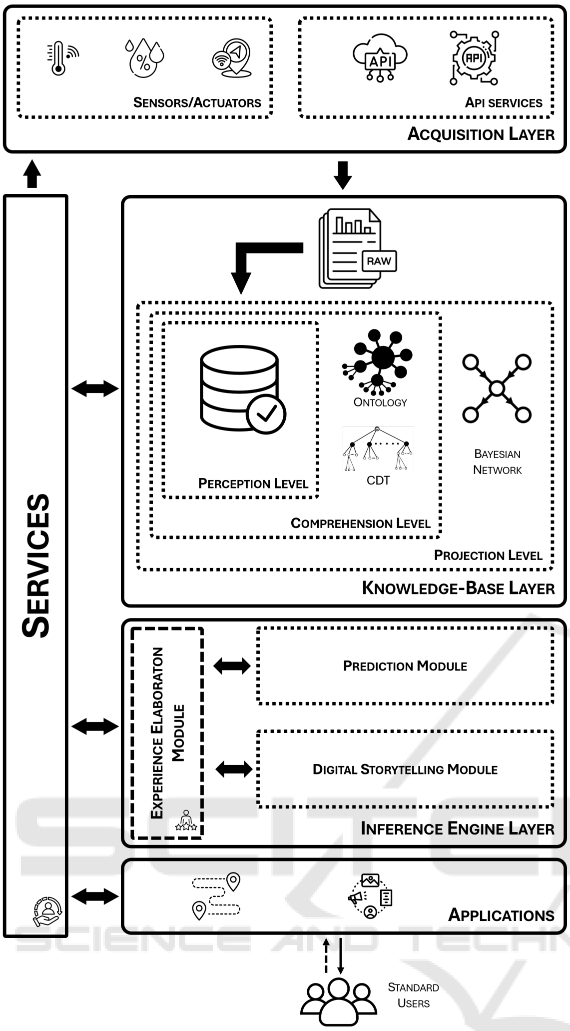

Figure 2: The proposed architecture for enhancing cultural heritage based on IoT and the MuG approach.

ulates the system, allowing it to move from the perception to the comprehension phase by employing CDT and Domain Ontology. The CDT allows us to understand the context in which the system is acting, while the Ontology allows us to gain knowledge about the data through the defined relationships. Using these two graphs completes the comprehension phase and allows for identifying the BN structure that will enable the prediction phase. Specifically, the Knowledge-Base Layer performs the online phase that enables training by integrating structural learning techniques with the constraints defined through the interaction between CDT and Ontology (Colace et al., 2019). In addition, this phase is reproduced periodically to allow the prediction capability to be improved periodically due to new data acquired from the architecture.

The Inference Engine Layer, on the other hand, exploits the online phase of the MuG approach through the Prediction Module to figure out the best path to suggest to the user. Similarly, the Digital Storytelling Module is leveraged to identify multimedia content that enables the implementation of storytelling strategies aimed at user engagement. Finally, the Experience Elaboration Module enables the integration of Prediction Module predictions with Digital Storytelling Module processing.

Finally, the Application Layer permits users to access elaborated services, which consist of suggested paths and related multimedia content.

4 EXPERIMENTAL RESULTS

The evaluation process of the proposed methodology, in this case study, was conducted through the development of a prototype based on the proposed architecture. The prototype consists of a server component and a hybrid mobile app. The technologies used were the Ibernate framework, based on Java, to build the Rest API server-side service; the Apache Cordova Framework for developing the mobile app.

The experimental phase was performed in three archaeological parks in southern Italy: The Archaeological Park of Paestum, the Archaeological Park of Herculaneum, and the Archaeological Park of Pompeii. Even if the proposed architecture allows the System to access several open data on the web, the prototype has been modeled with particular attention to the three archaeological sites in this first experimental phase. Several training modules related to the considered archaeological parks have been inserted inside the System, allowing the System to build the related educational paths. The different training modules have been inserted in order to collect the needs of different users (children, adults, and experts) during the training path.

A total of 230 users were involved, trying to divide them homogeneously by different age groups and characteristics, who were unaware of the purpose of the research. Each participant was equipped with the application prototype, and they enjoyed different training modules within the specific archaeological parks. Users were divided into three different groups composed as follows:

- Group 1: Archaeological Park of Pompeii (95 users)
- Group 2: Paestum Archaeological Park (65 users)
- Group 3: Archaeological Park of Herculaneum (70 users)

Following the experience of using the content, a questionnaire divided into the following sections was proposed to all users:

A. Presentation
   1. The information has been presented appropriately.
   2. The information provided was exhaustive.

B. Reliability
   1. The System provided path suggestions during the entire visit.
   2. The System was able to run adequately during the whole visit.

C. Recommendation
   1. The proposed services and contents have satisfied the needs of the user, based on personal preferences and the current context.
   2. The System has managed to adapt to context changes.

D. Performance
   1. The System was able to show smooth operation and without unexpected jumps.
   2. Response times are adequate.

E. Usability
   1. The system interface is user-friendly.
   2. The System is able to provide suggestions without being unwelcome

Based on the Likert scale, each section of the questionnaire had two assertions to which five possible responses were associated: totally disagree - TD, disagree - D, Undecided - U, agree - A, totally agree - TA. The responses were collected in Table 1

Table 1: Case of Study on paths recommender: Questionnaire answers.

Sections	**Answer**				
	TD	**D**	**U**	**A**	**TA**
A	18	21	89	187	145
B	20	27	55	230	128
C	18	3	26	239	174
D	11	65	82	203	99
E	37	28	46	205	144

In addition, a smaller number of participants were asked to participate in the experimental phase to evaluate the System's effectiveness in suggesting services. To this end, five training modules were selected for each archaeological park, and users were allowed to indicate whether such a proposed module was relevant according to their needs and context. The participants who took part in the experimental phase for the second time are divided as follows:

- Group 1: Archaeological Park of Pompeii (43 users)
- Group 2: Paestum Archaeological Park (32 users)
- Group 3: Archaeological Park of Herculaneum (34 users)

In this experimental phase, the System's knowledge base was augmented by the data that emerged from the experience of previous users. The results, expressing the relevance of the proposed training modules to the context and needs, were collected in the form of a confusion matrix (Figure 4(a), Figure 4(b), Figure 4(c)).

Table 1 shows the degree of satisfaction of the 230 participants. Users agree that the System is able to provide training modules that are tailored and in line with the context.

In Figure 3, the results obtained are shown graphically. Users are most satisfied with the ability to recommend the right training path concerning the context. The confusion matrices shown in Figure 4(a), Figure 4(b), Figure 4(c) show that the System was able to recommend suitable training modules to users based on the profile and time requirements of the users. All the confusion matrices report an overall accuracy greater than 70%, very encouraging data. Figure 4(a) brings back an overall accuracy advanced to 85%; this extraordinary result can be due to two factors. A factor could be the choice of the formative modules that turn out particularly adapted to the selected place. The second factor could be related to the size of the Archaeological Park of Paestum. Unlike other sites, due to its medium-large size and the layout of the archaeological finds, it is better suited to itinerant training and augmented reality. However, all the results obtained are very encouraging and could improve over time by the users' experiences.

The objective of this case study was to validate the proposed methodology in supporting users to choose training paths within archaeological parks. The aim was to provide tailored training content making the training experience adaptable to the context and the user's needs. This case study confirms that the proposed architecture could be declined in different contexts and mobile applications. The experimental results are promising and encouraging; they show that the System is able to design training paths effectively and that the developed prototype is efficient from several points of view. The degree of reliability the usability of the prototype have been evaluated very positively by the users involved in the experimental campaign. In addition, the recommendation ability of the System reached a high level of accuracy.

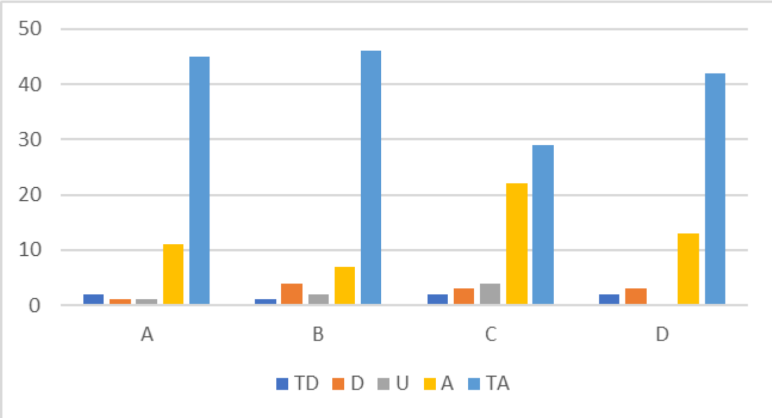

Figure 3: Case of Study on paths recommender: Trend of questionnaire answers.

Prediction \ Reference	M1	M2	M3	M4	M5
M1	75	5	4	0	2
M2	3	73	5	4	1
M3	1	7	69	6	3
M4	3	0	4	72	7
M5	0	2	5	2	77

Overall Accuracy : 85,12%

(a) Case of Study on E-Learning paths recommender: Confusion Matrix Group 1

Prediction \ Reference	M1	M2	M3	M4	M5
M1	75	5	4	0	2
M2	3	73	5	4	1
M3	1	7	69	6	3
M4	3	0	4	72	7
M5	0	2	5	2	77

Overall Accuracy : 85,12%

(b) Case of Study on E-Learning paths recommender: Confusion Matrix Group 2

Prediction \ Reference	M1	M2	M3	M4	M5
M1	75	5	4	0	2
M2	3	73	5	4	1
M3	1	7	69	6	3
M4	3	0	4	72	7
M5	0	2	5	2	77

Overall Accuracy : 85,12%

(c) Case of Study on E-Learning paths recommender: Confusion Matrix Group 3

Figure 4: Confusion matrices related to Group 1, Group 2, and Group 3.

5 CONCLUSIONS AND FUTURE WORKS

The article aims to exploit the MuG approach as a Recommendation System to improve the enjoyment of cultural heritage. Through the Internet of Things paradigm and using three graphs (CDT, Onotlogy, and Bayesian Network), it was possible to suggest personalized experiences to users while exploiting Digital Storytelling techniques to build e-learning paths. The experimental phase presented confirms the goodness of the proposed approach. Future developments concern the integration of XR strategies, such as Augmented Reality, Virtual Reality, or Mixed Reality, to better engage users in the cultural experience. In addition, further future evaluations will address the potential for generalization of the proposed approach through application to additional case studies outside the world of cultural heritage.

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