Improving Enjoyment of Cultural Heritage Through Recommender Systems, Virtual Tour, and Digital Storytelling

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Abstract: The integration of Information and Communication Technologies (ICT) within the world of cultural heritage has the role of added value for its enhancement. In particular, improving the enjoyment of cultural Points of Interest by suggesting personalized routes allows for better interaction between users and the cultural site. To this end, this paper aims to introduce an architecture that, by employing Recommendation Systems integrated with the Situation Awareness paradigm, allows for the identification of personalized paths for users through the acquisition of data through smart sensors, which is then processed through the proposed approach, defined as a Multilevel Graph (MuG) approach. This aims to filter through the data's context and ontological layers to its processing through the Bayesian network, which is identified through structural learning algorithms integrated with the domain's semantic knowledge. The architecture also incorporates physical and virtual experiences, exploiting the advantages of virtual tours and involving users more by employing digital storytelling techniques. Testing of the proposed architecture based on the MuG approach took place through an offline experiment aimed at evaluating the accuracy of the approach used and an online experiment to test the validity of the designed architecture.

1 INTRODUCTION

Enhancing artistic and cultural heritage involves strategies that enable both the preservation of the heritage and the improvement of visitor enjoyment (Brumana et al., 2023).

This task requires the support of new technologies, particularly in Information and Communication Technologies (ICT). In the case of preservation, these technologies must provide the necessary tools for monitoring. Through the data collected, it is essential to identify data processing strategies to prevent future damage (García-Valldecabres et al., 2021). Conversely, in the case of improving the interaction between artistic and cultural heritage and users, ICTs must provide the necessary data to enable users to adapt the cultural experience and develop personalization strategies to tailor the cultural experience to both the user and the environmental condition in which the visit takes place (Ruotsalo et al., 2013).

To improve the enjoyment of cultural visitors, analyzing and filtering data that will allow systems to understand user preferences and adapt the cultural experience accordingly is necessary. Specific tools called Recommendation Systems (Colace et al., 2022; Ricci et al., 2022), applied historically in tourism and particularly useful in the cultural heritage sector, are also exploited (Borràs et al., 2014). Understanding users' preferences makes it possible to suggest the most suitable points of interest (POIs) for the user. In this field, various strategies allow Recommendation Systems (RSs) to suggest the best content to cultural users. Historically, the main strategies are Content-Based, Collaborative Filtering, and Hybrid RSs (Ricci et al., 2022). Over time, these have hybridized with machine and deep learning techniques (Nikolakopoulos et al., 2022; Zhang et al., 2022), but they preserve the main features. Content-based aims to acquire data about users and the products, usually called items to be suggested. Thus, they aim to assess the affinity between users and items (Musto et al., 2022). In contrast, Collaborative Filtering exploits interactions be-

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tween users and items, usually ratings, to understand what users prefer to make predictions about items with which it has not interacted (Koren et al., 2022). Finally, hybrid approaches allow two or more strategies to be integrated to overcome the problems of individual recommendation approaches (Ricci et al., 2022).

These tools integrate additional data to improve their predictive ability in addition to recommendation strategies. This is the case with Context-Aware Recommendation Systems (CARSs), which use Context Awareness to adapt predictions to the conditions under which the system processes data and suggests the best POIs to users (Adomavicius et al., 2022; Colace et al., 2023). The integration of Context Awareness within RSs allows its acquisition in the perception phase, which directly links to the hint prediction phase. However, to enable the Recommendation System to integrate into the Situation Awareness paradigm, integrating an understanding phase before the prediction phase is necessary (Endsley, 1995). It is possible to incorporate ontological layers related to domain knowledge to acquire knowledge from data (Casillo et al., 2022; Musto et al., 2022).

This work aims to introduce an architecture for enhancing artistic and cultural heritage by improving the enjoyment of cultural users by defining a recommendation system that integrates the Situation Awareness paradigm within an RS. The recommendation approach used takes advantage of a Multilevel Graph approach that leverages three graph approaches: the Context Dimension Tree (CDT) that enables context management, a Domain Ontology that allows the acquisition of knowledge about the data through semantic data analysis, and finally, a Bayesian Network that enables the prediction phase (Casillo et al., 2024). The structure of the network is done through structural learning algorithms integrated with the filtering phase through CDT and Ontology, which allow for a more reliable construction of the Bayesian Network.

Coupled with the prediction phase via the Multilevel Graph (MuG) approach, it is necessary to integrate supporting techniques that aim to improve the user's cultural experience. To this end, the proposed architecture leverages Digital Storytelling to engage users through narratives centered on the path suggested to users through the RS (Podara et al., 2021; Selmanović et al., 2020). In addition, the proposed experiences will be hybrid through virtual tours based on 360° photos (Argyriou et al., 2020). Virtual tours using 360° photos allow users to create immersive experiences of physical spaces by enabling users to explore real environments through interactive panoramic images. Virtual 360° tours are created by taking a series of panoramic photographs with a 360° camera, thus requiring devices capable of capturing 360-degree images or video in all directions. Once the 360° images have been captured, they must be processed using software to create the interactive tour. The resulting virtual environment can be freely explored through navigation points, defined as hotspots, creating a continuous and fluid experience. The main advantages of using 360° Tours include providing an immersive and realistic experience that relies on a generally intuitive and easy-to-navigate interface. In addition, integrating virtual tours allows for improved accessibility of suggested POIs.

The paper is structured as follows: Section 2 describes the literature related to Recommender Systems and the use of Tour 360° aimed at application in the field of cultural heritage; Section 3 introduces the proposed architecture and describes the proposed approach leveraged as a Recommender System that integrates Situation Awareness to suggest cultural paths to users; Section 4 presents the experimental results aimed at evaluating the introduced recommender approach and analyzing the effectiveness of the proposed architecture through the development of a prototype; finally, Section 5 describes the conclusion and future work.

2 RELATED WORKS

Recommendation Systems employed in cultural heritage have a tradition stemming from using these tools in tourism (Casillo et al., 2023).

(Cramer et al., 2008) investigate the impact of transparency on user trust and acceptance of content-based recommender systems in the context of cultural heritage. The study explores whether providing explanations for recommendations or showing how confident the system is in its recommendations affects users' trust and acceptance. The authors experimented with several groups of 60 participants, who interacted with three versions of an artwork recommendation system. This system proposes works based on users' ratings of other works of art. The three versions tested were a non-transparent system that did not explain the recommendations, a transparent system that explained why a recommendation was made, and a system that showed how safe the system was in giving the recommendation. The results show that explaining the recommendations increased their acceptance but did not significantly improve confidence in the system. Showing the system's level of certainty influenced neither confidence nor acceptance. The study derives some guidelines for the design of recommendation systems in the cultural heritage domain.

In (De Gemmis et al., 2008), the authors explore the integration of tags within a content-based recommendation system. Combining static object descriptions with dynamic user-generated tags aims to improve content personalization, especially in the context of cultural heritage. The study uses natural language processing techniques to analyze and disambiguate tag meanings, transforming them into semantic concepts that can be used to create more accurate user profiles. These profiles are then used to improve the recommendations provided to users. The paper describes the recommendation process in three main steps: content analysis, user profile learning, and recommendation generation. It focuses mainly on how personal and social tags can improve the accuracy of recommendations. Preliminary results show that including tags increases recommendations' accuracy compared to using only static descriptions.

(Su et al., 2019) explore using artificial intelligence based on Edge Computing technologies to create an advanced recommendation system in the context of cultural heritage. The proposed system combines artificial intelligence techniques, Big Data, and personalized recommendations to improve visitors' experience of museums, archaeological sites, and other cultural spaces. The system is based on a multilevel architecture that uses Big Data infrastructure to manage a large amount of heterogeneous data from different sources, such as social media, digital libraries, and environmental sensors. A crucial part of the system is the Smart Search Museum mobile application, which provides personalized suggestions about museums and other cultural attractions based on contextual recommendation techniques and artificial intelligence built into users' devices. In addition, the authors describe how integrating different data sources can provide personalized tourist routes and recommendations of cultural objects, thereby optimizing the artistic experience.

In (Hong et al., 2017), the authors describe a social recommendation system for applications in cultural heritage. It focuses on using digital technologies and social services to improve people's interaction with cultural spaces, make them dynamic, and promote the discovery and sharing of new knowledge. The proposed system uses social affinity among users to provide personalized recommendations of artworks and cultural content based on the characteristics of the artworks and users' experiences. An architecture for managing group recommendations is also proposed, addressing issues such as the scarcity of data on user preferences and the sustainability of recommendations in cultural contexts. It also describes how using social networks and contextual information can improve recommendations and presents an innovative approach to calculating and exploiting social affinity among users for group recommendations.

In addition to techniques for personalizing services, 360° virtual tours have become an innovative tool for enjoying cultural heritage. Virtual tours can improve accessibility to historic sites, allowing remote and interactive explorations enhanced by multimedia content such as text and video.

In (Valtolina et al., 2006), the authors describe a system facilitating personalized access to cultural heritage distributed across multiple museums. The system meets the needs of two categories of users: visitors, who can access information tailored to their interests and interaction preferences, and domain experts, such as museum curators, who can create thematic pathways to provide a better understanding of artifacts. The approach relies on a semantic representation of cultural heritage to build customizable visual interfaces called "Virtual Wings" (VWs) that allow users to navigate through digital archives and thematic pathways, creating personalized virtual tours. A practical example includes integrating customized digital guides and 360° panoramic images.

The authors of (Gunawan and Lesmana, 2023) develop a 360° virtual tour of the Dharma Rakhita Temple in Jamblang village as an educational tool to promote heritage knowledge. The temple, which is more than 200 years old and rich in history, is little visited due to its isolated location and poor tourism promotion. The study proposes using 360° images captured with digital technologies to create a virtual tour accessible through web applications, allowing the public to explore the temple remotely. The main goal is to preserve the temple and use it as a source of cultural learning by enhancing storytelling and historical documentation through 360° filming techniques.

3 THE PROPOSED ARCHITECTURE

This section introduces the proposed architecture for enhancing artistic and cultural heritage through improving user enjoyment. The architecture aims to suggest personalized paths for users to tailor the cultural experience to visitors' preferences. For added value, the paths are integrated with digital storytelling techniques that enhance engagement through storytelling and exploit multimedia content. In addition, the proposed experiences are hybrid as, depending on the users' needs and the specific context, suggested routes integrate physical and virtual POI visits through 360° tours.

The proposed architecture, illustrated in Figure 1, consists of four functional layers: the Acquisition Layer, the Knowledge Base Layer, the Inference Engine Layer, and the Application Layer.

The acquisition layer consists of all the devices that enable the acquisition of environmental data and contextualize the suggestions that will be processed during the data processing phase (Michalakis and Caridakis, 2022). In this layer, through the Internet of Things paradigm, it is possible to exploit sensors that, once they have acquired the data, can communicate it via the Internet using the MQTT protocol. Specifically, the sensors used involve environmental monitoring. A weather station is installed to acquire temperature, humidity, air quality, pressure, and atmospheric precipitation data (Colace et al., 2018; Mitro et al., 2022). In addition, user location data must be acquired, and sensors must be installed to monitor the level of crowding at each POI. Data acquired through sensors should be integrated with API and open-source data services that allow both the integration of the acquired data and the acquisition of data beneficial for the architecture as multimedia content, in addition to the content built specifically for the case study and already used.

Once the data has been acquired, it must be stored through the Knowledge-Base Layer. The raw data collected via sensors and external services is initially cleaned to detect possible missing or anomalous data through a pre-processing module. Once cleansed, the data are stored within the database, which must handle structured and semi-structured data. In addition, the pre-processing module must also work as a filter for the data flow from the database to the Inference Engine Layer to do the cleaning and preparation work necessary for the actual processing of the data.

The third layer of the architecture, the Inference Engine Layer, represents the beating heart of the architecture. Here, data is processed to provide services to users to improve their cultural experience. Four modules are available here: the Experience Elaboration Module, the Recommendation Module, the Content Selection Module, and the Digital Storytelling Module.

The Recommendation Module leverages the Multilevel Graph (MuG) approach (Casillo et al., 2024), which will be described in more detail later, and aims to integrate the Situation Awareness paradigm within the recommendation engine. For this purpose, it is necessary to explain in detail how Endsley's three levels of awareness are obtained (Endsley, 1995).

The system achieves the perception stage from the data acquisition stage to data storage, including the pre-processing stages. Then, through the context filtering that takes place through the Context Dimension Tree (CDT) and the semantic filtering phase through the Domain Ontology, the comprehension phase is obtained (Kokar et al., 2009), which will allow the predictions to be adapted both based on the ontology's domain knowledge and based on the environmental conditions in which the system operates through the CDT. In addition, the understanding phase permits the integration of the application phase of the structural learning algorithm that allows for the Bayesian Network (BN) structure (Scanagatta et al., 2019). However, this is identified through the data, supplemented by the filter represented by the Ontology and the contextual analysis performed. As a result, the BN enables the prediction phase that aims to suggest cultural paths to users based on gold preferences and contextual conditions (Casillo et al., 2024; Scanagatta et al., 2019). The schematic of how the MuG approach falls within the Situation Awareness paradigm is described in Figure 2.

From the description given, it follows that the Recommendation Module initially requires an offline phase in which the BN is detected. In this phase, the acquired data filtered through the CDT and Domain Ontology are exploited. This allows for identifying constraints that force the identification of probabilistic dependencies among the BN nodes or avoid the identification of inconsistent dependencies. Such constraints complement the applied structural learning algorithm and enable the identification of a more reliable network structure. Once the offline phase is completed, the network allows predictions to be obtained during the online phase. In addition, new data can periodically update the network.

In addition to the Recommendation Module, the Inference Engine Layer exploits the Experience Elaboration Module, the Content Selection Module, and the Digital Storytelling Module. Once the path to be suggested to the user has been identified, the Experience Elaboration Module selects based on the context related to POI crowding and the time available to the user which POIs of the identified path are to present in virtual form and which ones are not. Then, based on this distinction, the Digital Storytelling Module composes the narrative by assembling the available textual content and linking them appropriately according to the strategy of non-linear Digital Storytelling. Once the narrative has been identified, the Content Selection Module identifies the multimedia content to be provided to the users, which is distinguished by whether the POI will be visited physically or virtually.

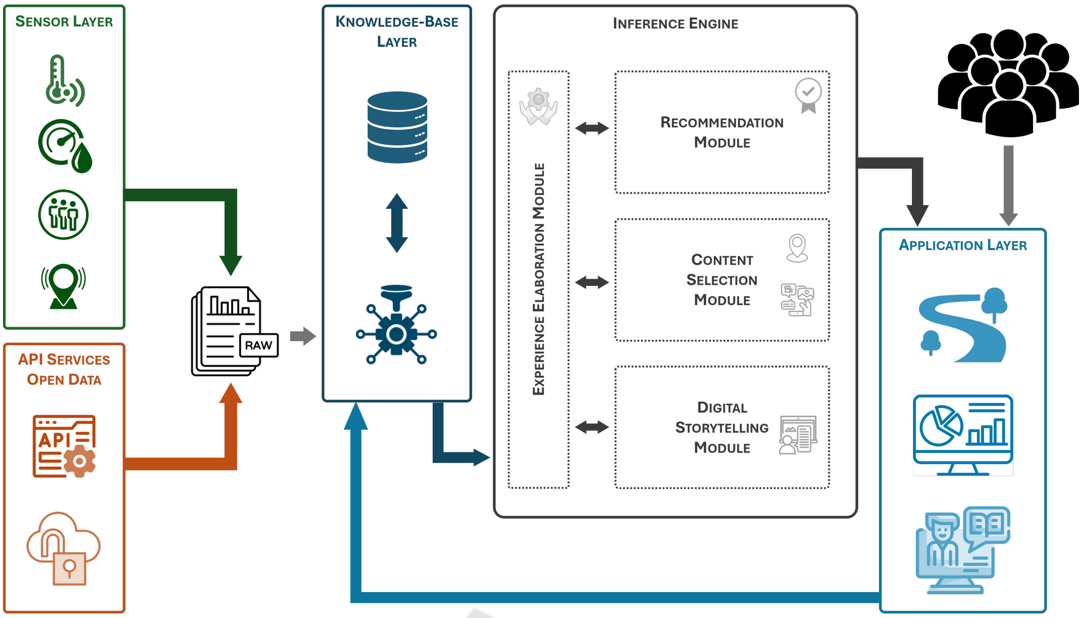


Figure 1: The proposed architecture designed to improve the cultural experience of users.

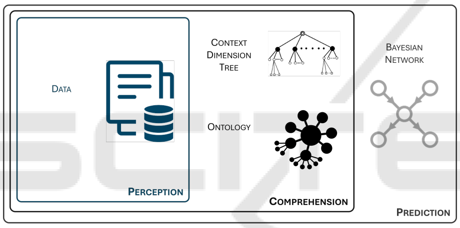


Figure 2: Scheme of the Multilevel Graph approach contextualized in the Situation Awareness paradigm.

Finally, the architecture presents the Application Layer, which provides services to the user. This layer allows access to the custom path elaborated for the user based on his preferences, integrating contextual analysis and semantic analysis. In addition, the service related to Digital Storytelling is also provided with the addition of being able to visit the site through the option of 360° Tours. The system selects these via the Experience Elaboration Module, but the user can change how individual POIs or parts of the route are visited. However, this requires modifying the history provided and the multimedia content associated with the POIs.

3.1 The MuG Approach as Recommender System

To provide personalized pathways to users to enhance their enjoyment of the arts and cultural heritage, it is necessary to have a recommendation system capable of filtering and analyzing data to understand their preferences. In addition, the recommendation system will need to exploit context and leverage semantic analysis to enable the system to gain situational awareness. To this end, the previously described architecture exploits the Multilevel Graph approach based on three graphs: the Context Dimension Tree (CDT), the Domain Ontology, and the Bayesian Network (BN) that enables predictions.

The CDT is a tree depictable by a graph

$$G_{\mathrm{CDT}} = < N_{\mathrm{CDT}}, E_{\mathrm{CDT}}, r_{\mathrm{CDT}} >, \qquad (1)$$

where N_{CDT} represents the nodes of the CDT, E_{CDT} contains the edges of the graph, and r_{CDT} is the root of the tree (Bolchini et al., 2006). The nodes in N_{CDT} are divided into dimension nodes, concepts nodes, and parameters. This structure allows context management through the 5W+1H paradigm (Jia et al., 2016), which represents the fundamental nodes among the dimension nodes and is represented graphically with black nodes. On the other hand, concept nodes specify the values assumed by a specific context domain represented by the dimension nodes and are graphically represented through white nodes. Finally, parameters provide additional information to the concept nodes and are represented graphically with triangles. The CDT graph starts from the root r_{CDT}, which connects to the dimension and concept nodes. Finally, the parameters are the children of the concept nodes.

The Ontology also consists of a graph structure

$$G_O = \{C, A, H, R^+, R^-\}, \qquad (2)$$

where C represents the concepts in the ontology to which A attributes are associated. Then, it also includes the hierarchical type relations H and the dependency and independence relations R^+ and R^-, respectively.

In particular, the CDT shares the graph nodes with the domain ontology. Specifically, dimension nodes are among the Ontology concepts, while concept nodes are among the associated attributes. This allows an interconnection between the two graphs and joint filtering through context and semantic analysis. The BN is also seen as a graph structure

$$G_{\mathcal{BN}} =< N_{\mathcal{BN}}, E_{\mathcal{BN}} >, \tag{3}$$

where N_{BN} contains the random variables of the BN and the set E_{BN} represents the edges that are the dependency relations of the random variables. In addition, the random variables considered in the Bayesian network (BN) also fall within the defined ontology structure. The defined dependency and independence relations can be identified among the random variables forced through the ontology and the independence relations. This makes it possible to determine the dependency $R^{(D)}$ constraint list and the independence $R^{(I)}$ constraint list (Casillo et al., 2024).

Through the definition of the function $g(h, \pi_h)$, which quantifies the connection between the node h and the relatives π_h within the graph, i.e., the dependency relationships to be identified (Cooper and Herskovits, 1992), the goal for the construction of the Bayesian network using the data is to maximize the Bayesian network bound function

$$\prod_{h=1}^{n} \max_{\pi_h} \mathrm{P}(\pi_i^s \longrightarrow B_i)\, g(h, \pi_h) \tag{4}$$

best suited to represent the data (Cooper and Herskovits, 1992), where n represents the number of random variables. In addition, at the stage of identifying the network B_i, it is necessary to integrate the constraints $R^{(D)}$ and $R^{(I)}$ identified following the algorithm 1.

Data: N_{BN}, $R^{(D)}$, $R^{(I)}$, u
Result: The structure of the BN
for $i = 1, \ldots, n$ **do**
  Add the dependency relation of $R^{(D)}$:
  $\bar{\pi}_i = \left\{ (X, x_i) \in R^{(D)} \right\}$;
  Calculate $\mathrm{P}_{\mathrm{old}} = g(x_i, \bar{\pi}_i)$;
  status = True;
  while *status* & $|\bar{\pi}_i| < u$ **do**
    Add the dependency to the node z;
    Calculate $\mathrm{P} = g(x_i, \bar{\pi}_i \cup \{z\})$;
    if $\mathrm{P} > \mathrm{P}_{\mathrm{old}}$ **then**
      $\mathrm{P}_{\mathrm{old}} = \mathrm{P}$;
      $\bar{\pi}_i = \bar{\pi}_i \cup \{z\}$;
    else
      status = False;
    end
  end
end

Algorithm 1: Multilevel Graph approach algorithm (Casillo et al., 2024).

4 EXPERIMENTAL PHASE

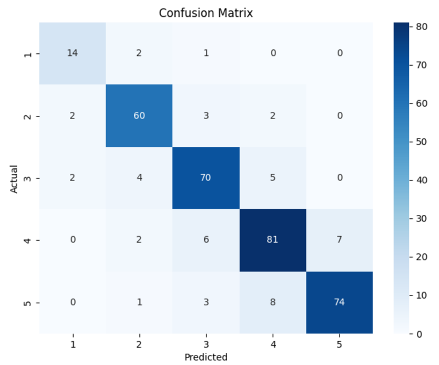
Once the architecture for enhancing artistic and cultural heritage has been introduced based on the Multilevel Graph (MuG) approach used as a recommender system, this section presents the experimental phase divided into two steps. In the first step, the accuracy of the recommendation approach is evaluated by testing how the classification using the Bayesian Network (BN) succeeds in suggesting individual Points of Interest (POIs) and identified paths. In the second step, the architecture's ability to improve the enjoyment of cultural aptitude is evaluated by exploiting an online experiment and developing a prototype.

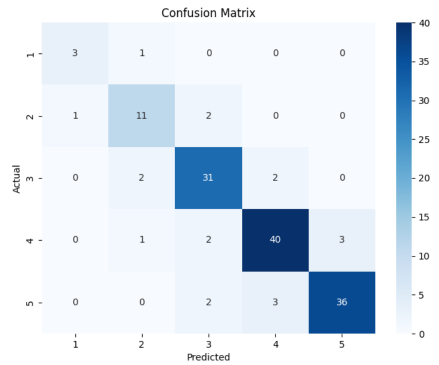
4.1 Accuracy Evaluation of MuG

The first step of the experimental phase aims to evaluate the proposed approach's accuracy through data collected about interactions between users and POIs and between users and identified routes.

Specifically, two datasets were collected: the first relating 81 POIs to 13 users for 347 identified interactions. These interactions represent the ratings provided by users about the POIs based on the environmental conditions in which the users were located. Specifically, the 347 available ratings are divided into five classes: 17 associated with the 1-star class, 67 with the 2-star class, 81 with the 3-star class, 96 with the 4-star class, and 86 with the 5-star class. The second dataset, conversely, contains interactions between 16 users and 27 possible paths for 140 available ratings. Again, the ratings are divided into five classes: 4 associated with the 1-star class, 14 with the 2-star class, 35 with the 3-star class, 46 with the 4-star class, and 41 with the 5-star class. The precision, recall, and f-score metrics for each class and the system's overall accuracy were used to evaluate the proposed approach's accuracy (Gunawardana and Shani, 2015; Rainio et al., 2024). In addition, k-fold cross-validation was used in the testing phase by dividing the datasets into five parts (Koren et al., 2022).

In the case of the first dataset, Figure 3a reports the confusion matrix obtained, while Figure 4a reports the precision, recall, and f-score results for each class considered. It can be seen from the figure how, for each class, the system achieves at least 80% precision,

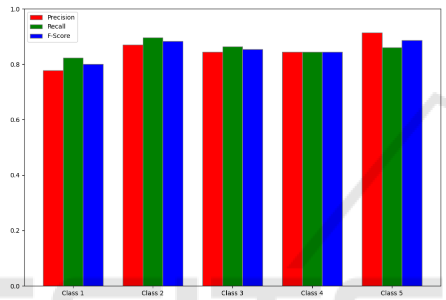


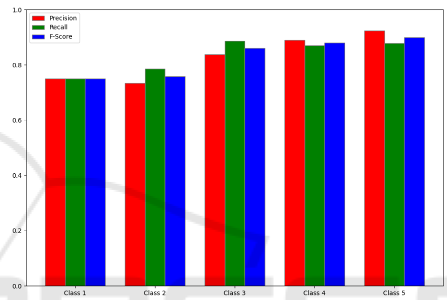


(a) Confusion matrix obtained on the first dataset of 347 ratings related to 13 users and 81 POIs.

(b) Confusion matrix obtained on the second dataset of 140 ratings related to 16 users and 27 routes.

Figure 3: Confusion matrices related to the two considered datasets.





(a) Precision, recall, f-score on the first dataset of 347 ratings related to 13 users and 81 POIs.

(b) Precision, recall, f-score on the second dataset of 140 ratings related to 16 users and 27 routes.

Figure 4: Precision, recall, f-score related to the two considered datasets.

which becomes higher than 85% in the case of the 2stars, 3stars, and 5stars classes. For recall, at least 80% is achieved for all classes except for the 1-star class, which contains the least available ratings. The results for the f-score, which is the harmonic mean between precision and recall, achieve at least 80% for each class considered. The accuracy obtained is 86.17%, which is satisfactory despite the imbalance of available ratings in the various classes.

Instead, in the case of the second dataset, Figure 3b reports the confusion matrix obtained, while Figure 4b reports the precision, recall, and f-score results for each class considered. The figure shows that the system overcomes the 86% precision for classes 3-stars, 4-stars, and 5-stars. For recall, the system overcomes the 83% for the 3-star class, the 85% for the 4-star class, and the 92% for the 5-star class. The accuracy obtained is 86.43%, which is adequate despite the more significant imbalance of available ratings in the various classes than in the previous dataset.

4.2 Online Experiment

Once the accuracy of the recommendation system had been assessed, it was necessary to develop a prototype for evaluating the effectiveness of the proposed architecture in enhancing artistic and cultural heritage. The development of the prototype also required the development of virtual tours based on 360° photos. The first step of elaborating the virtual tour involved collecting 360° images by preliminarily defining the hotspots associated with the POIs. Then, the photos are processed through software that allows the creation of the virtual tour and, thus, implements the hotspots that enable the user to move from one point to another on the tour. In addition, the prototype required the installation of a weather station and sensors to assess the crowding of individual POIs. The application enabling user interaction was also developed.

The experimental phase involved 41 users who, after using the services described in Section 3, evaluated their cultural experience by answering a questionnaire consisting of five sections:

- Section A aimed to assess the suggested route

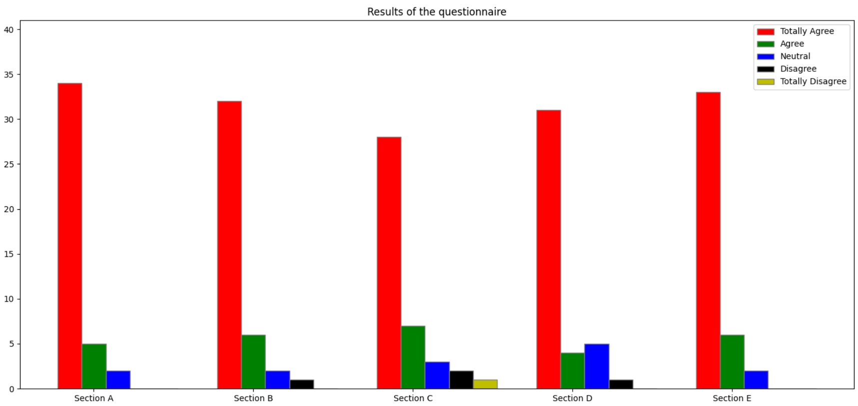


Figure 5: Results of the questionnaire related to the online experiment.

to understand whether the system could meet the users' preferences;

- Section B focuses on the Virtual Tour and its ability to engage the user through the virtual experience while considering the ease of interaction;
- Section C requires evaluating the digital storytelling techniques applied, which will assess whether the user felt engaged in the narrative presented;
- Section D aims to evaluate the hybrid experience, divided between POIs visited physically and POIs visited virtually overall;
- Finally, Section E seeks to assess the users' cultural experience overall.

Each section could be evaluated based on 5 possible responses: Totally Agree, Agree, Neutral, Disagree, and Totally Disagree.

It can be seen from Figure 5 that the results obtained are more than satisfactory as each evaluated section achieves excellent levels of evaluation.

5 CONCLUSIONS AND FUTURE WORKS

This work introduces an architecture that aims to enhance the artistic and cultural patrimony by using a recommendation system capable of integrating Situation Awareness, virtual tours based on 360° photos, and Digital Storytelling techniques. The design and implementation of the prototype require defining four layers that, starting from data acquisition and storage, enable the elaboration of services to be provided to users to improve the enjoyment of artistic and cultural heritage. During the experimental phase, the accuracy of the usage recommendation approach based on the Multilevel Graph approach through two datasets was evaluated on the one hand, and the ability of the proposed architecture to improve the user experience on the other hand. Possible future developments involve increasing the data collected so that a more meaningful sample of data can be used to evaluate the accuracy of the recommendation system. In addition, they want to improve the prototype further and continue the testing phase through the online experiment.

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