



CHAT-Bot: A cultural heritage aware teller-bot for supporting touristic experiences



Mario Casillo^a, Fabio Clarizia^a, Giuseppe D'Aniello^b, Massimo De Santo^a,
Marco Lombardi^{a,*}, Domenico Santaniello^a

^a Dipartimento di Ingegneria Industriale (DIIN), University of Salerno, Via Giovanni Paolo II 132, Fisciano (SA), 84084, Italy

^b Dipartimento di Ingegneria dell'Informazione ed Elettrica e Matematica Applicata (DIEM), University of Salerno, Via Giovanni Paolo II 132, Fisciano (SA), 84084, Italy

ARTICLE INFO

Article history:

Received 10 September 2019

Revised 20 December 2019

Accepted 6 January 2020

Available online 7 January 2020

Keywords:

Recommender system

Context-aware computing

Digital storytelling

Chatbot

Tourism

Cultural heritage

ABSTRACT

Cultural heritage is an important resource that allows us to know and promote a territory. In this respect, it is important to experiment with the enhancement of cultural heritage by adopting approaches that meet the dynamic needs of various types of users. The aim of this paper is to introduce a recommender system capable of developing adaptive tourist routes. In fact, the proposed system suggests points of interest and related services according to both the profile of the tourist and contextual aspects. In particular, the interaction of the user with the system occurs through a chatbot that allows to build a real dialog. In order to show the potential of the proposed approach, a prototype was developed to support the user in building a customized tourist route related to some of the most important cultural sites in Campania (a region in Southern Italy): Herculaneum, Paestum and Pompeii.

© 2020 Elsevier B.V. All rights reserved.

1. Introduction

The pervasiveness of digital technologies has led to the replacement of traditional data management and recommendation services with sophisticated systems. These systems can integrate data and services extracted from heterogeneous sources to provide value-added information. Nowadays a huge amount of information is used in mobile applications, even if there is the risk that this huge amount of data could generate confusion. The filtering of data and services, based on the context, arises to model possible usage scenarios.

The reason for this “information deluge” is due, in large part, to the proliferation of devices that have an active role (sensors and, in general, all those objects defined as “smart”). Those devices are able to communicate with each other creating a highly pervasive network, which is at the base of the new paradigm of the Internet of Things (IoT) [1], that represents an ecosystem thanks to which “context-aware” applications exist [2–6]. In fact, in information management, these systems are mainly dedicated in determining which part of the entire information is relevant with respect to environmental conditions, allowing us to offer to the user a wide range of services that could help him in everyday life, work

or private, in order to better manage the resources such as the time available. The parallel development of these paradigms (IoT and Context Aware) acquires fundamental importance in the design of smart environments capable of tailoring itself to users [7].

In addition, technological evolution has also been followed by a human beings' behavior evolution: we are faced with an ever-increasing number of “digital” and “social” users, who are accustomed to use several mobile devices to search and share every type of information in multiple situations [8]. In this scenario, e-Tourism is one of the most investigated application domains [9], in which a change of context causes a transformation of the experience even before being lived [10]. Thanks to new technologies, in fact, a tourist can use several services able to filter the huge amount of data present on the network in order to only provide relevant information according to the context [11].

1.1. Contributions

The aim of this paper is to introduce a chatbot based on a Context-Aware System able to recommend contents and services according to tourist profiles and context. This chatbot is capable to maintain, through the combination of Pattern Recognition and context recognition techniques, a logical conversation with the user and to supply to specific tourist needs. The proposed architecture would be able to control the evolution and presentation of infor-

* Corresponding author.

E-mail address: malombardi@unisa.it (M. Lombardi).

mation to the user based on different types of context. The chatbot could be seen as a modern tourist guide, which allows the dynamic delivery of several information, services, or narrative content (textual and multimedia) properly integrated and tailored to the needs and dynamic behavior of users.

2. Background

The concept of context does not have a rigorous definition, and, over the years, many different interpretations of its meaning have been given. In fact, this concept plays an important role in many different disciplines, such as psychology, linguistics and computer science, and in each of these can take on a different meaning, more fitting for its application.

2.1. Definition of the context

In the specific field of computer science, the first to have given a definition of “context” were Schilit and Theimer, within their work regarding “distributed mobile computing” [12]. Their interpretation was applied to the problem of “location awareness” in the office environment. This concept has been got again, among others, by Pascoe who considered environmental characteristics such as, for example, the description of current weather conditions [13]. This definition was later remarked by Schmidt et al. who presented the concept of context to include, in addition to environmental conditions, information on devices, users and their activities. Moreover, Chen and Kotz highlighted the importance of time parameters such as a timetable, a day of the week or a season of the year [14]. Finally, Dey and Abowd gave a definition of the more precise and widely used context in the field of information technology, as follows:

“Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves” [15].

The success of this definition is due to its clarity in explaining that if an information can be used to describe and characterize the situation in which one of the participants of the interaction is found, and then such information can be considered part of the context.

2.2. Classification of the context

The definition of the context of Dey and Abowd, given the strong abstraction, is difficult to develop in practice without a classification or without a modeling system. From this assumption, a modern approach is born of defining the context and its subdivision into main aspects which follows an informal method of gathering information mainly used by reporters to report the facts: “5 W + 1H method” (Who, What, Where, When, Why, How). For example:

- Who is it that we are trying to identify?
- What does the user do?
- Where is the user?
- When does the user perform specific action? How long?
- Why does the user perform a certain action? Why is the user here?

A deep understanding of the context is essential to choose or design the right model.

2.3. Representation of the context

Representing an abstract concept as effectively as the context can be almost as complicated as giving a precise definition. In

context-aware projects developed over the years, various models have been proposed and used, which try to quantitatively capture the relevant characteristics of the context to make them available for the subsequent processing phases.

A model widely used and of great interest, is the Context Dimension Tree: a tree composed of a triad $\langle r, N, A \rangle$ where, with r is indicated its stem, with N the set of nodes of which it is composed and with A is represented the set of arcs joining these nodes. The CDT is able to represent, in a graphic manner, all the possible contexts that can be had within an application. The current context, defined by the values assumed by the various dimensions, can be represented as a subgraph in which at each node size N_D (black circle) is combined at most a concept node N_C (white circle) or parametric node N_P (white square): it is defined as an AND between different “context elements”. The adoption of a hierarchical structure allows, in addition to orthogonally distinguish the several dimensions of the context, also to use different levels of abstraction to specify and represent all the possible and admissible contexts in a given application domain. In particular, the methodology consists of three main phases: design phase of the context tree, definition phase of partial views and composition phase of global views (contextual views) [16].

2.4. Context awareness and context-aware computing

As for the definition of context, context-aware computing was also treated and introduced for the first time by Schilit and Theimer in 1994:

“Context-aware software adapts according to the location of use, the collection of nearby people, hosts, and accessible devices, as well as to changes to such things over time” [17].

From this definition, there have been several attempts to define context-aware computing, but most of these have been too specific and even too difficult to use in practice. In this regard, Dey provides a more generic definition and is suitable for practical use:

“A system is context-aware if it uses context to provide relevant information and/or services to the user, where relevancy depends on the user’s task” [15].

The difference with respect to the previous definition lies in the fact that an application to be considered context-aware does not necessarily have to be able to perceive the whole context, but must be able to react to it, giving appropriate answers in terms of data and user services. Context-aware computing describes the development of technologies and applications capable of detecting data from the surrounding context and reacting accordingly with certain actions, reducing and simplifying the human-machine interaction process [18]. The context awareness must therefore be understood as a set of technical features capable of giving benefit to data and services in different application segments.

3. Related works

The importance of context in information technology has increased in recent decades as computers have become increasingly pervasive in everyday life. Context awareness, or the idea that these systems can detect and react to a user situation, is a popular research topic. While the computer community has initially considered the context as a question of user position, in the last few years this concept has been considered as part of the whole process in which users are involved. Sophisticated and general context models have been proposed to support context-aware applications, which use them for example to: adapt interfaces, tailor a series of data relevant to the application, increase the accuracy of infor-

mation retrieval, discover services, make user interaction implicit, create intelligent environments.

Consider the example of automated support for museum visitors, which are equipped with a mobile device that reacts to a change of context [19]. In this scenario the main feature provided by the system could be:

- adapting the user interface according to the visitor's different backgrounds;
- providing contents based on the different profiles and interests of visitors (students, journalists, archaeologists, etc.) and on the room in which they are currently located;
- learning, based on previous choices made by the visitor, what information will be interested in later;
- providing adequate services, for example to buy a ticket for a temporary exhibition or to reserve a seat for the next exhibition on the life of the favorite author;
- deriving information on the position from sensors that detect the user environment;
- providing active functions within the various areas of the museum, which indicate to visitors a series of suggestions and incitement on what is happening in each particular environment.

3.1. Context-aware technologies for tourism and the enhancement of cultural heritage

The cultural tourism market is evolving towards a dimension of complete satisfaction of the tourist's needs, enhancing on one hand the centrality of the cultural aspect within a 360° travel experience and on the other a greater attention in the choice of your own "holiday path", accompanied, according to the context, with all the necessary services (transport, catering, etc.). The tourist also shows a growing need to play an active and participatory role in the tourist experience, integrating the cultural contents of the visit with self-generated personal contents and sharing them with the "community".

The viral distribution of information, the radical changes in the traveler's decision-making process and the expansion of the knowledge tools available to all connected users are now more than ever the main levers of change. In this regard, the application of context-aware technologies allows us to offer services at the base of e-Tourism, able to support users, public institutions and sector operators, through automatic, adaptive and real-time recommendation. Dynamic of "core" and "ancillary" services for tourism promotion [20].

Italy, for example, has a cultural heritage that often fails to be fully exploited. The natural, artistic and cultural resources present in many cities, especially in the smallest ones, often remain hidden from tourists. This problem becomes even more relevant when the tourist has little time to visit a city. Think, for example, of some passengers on a cruise that in a few hours must visit a place unknown to them. The problem also arises for those people who, for work, live a temporary experience in a city. Where to eat? What see? How to move? These are the typical questions that a user of this kind arises when he is in a station, in an airport or in a port. If in the big cities there are pre-established itineraries that can be easily found by tourists, this is not always true in small or medium-sized cities which, even having an important cultural heritage, often risk not fully exploiting it [21].

3.2. Context-aware systems and digital storytelling for tourism

The use of the term "Cicero", as a synonym of tourist guide, was born when the Roman citizens, improvising as local guides, began to accompany the wealthy visitors of Rome among its archaeological wonders, demonstrating an oratory ability to remember the famous lawyer Roman Marco Tullio Cicerone. Using the Cicerones of

Rome as a reference model, a "Digital Cicerone" aims to simulate all those functions necessary to tell the territory that a potential tourist is visiting. The main objective is to encourage him to visit, through the story, pointing out new points of interest right when he moves.

A feature of this type explores the possibility of using digital storytelling techniques in combination with those at the base of context-aware computing to control the evolution and presentation of information to the user based on different types of context. In this way, a modern tourist guide can be implemented that allows the dynamic delivery of different narrative contents (textual and multimedia) appropriately integrated, not necessarily predetermined and adhering to the needs and dynamic behavior of users. The digital story can include: information on the place of visit (main features and historical information), for example the story told in the first person by the host (memories, autobiography, family traditions) and the stories lived or set in the places where one is hosted (novels, legends, songs, films, historical episodes); points of interest specific to the user, filtered by category and with multimedia insights; experiences lived by other users, as authentic testimonials of their destination. Tourists visiting places of cultural interest could be involved in the creation of new digital resources (stories / comments, images and videos) that, stimulated, collected and framed in the best way, will contribute to enrich the development of new personal and engaging stories. In this way, each tourist, after completing their journey, will have the opportunity to bring with them and share on social media a memory of the lived experience, through a digital story that includes the main stages [22].

3.3. Text analysis and chatbots

The process that allows the machine to understand and relate to human beings is the Natural Language Processing (NLP) which is often joined by Machine Learning, the technology that deals with giving it a learning capacity. In particular, NLP has extended its study range beyond the single word to include entire sentences. This makes it possible to deal more effectively with the disambiguation problems that often arise. In fact, it is not uncommon to come across words that may have more meanings. The mapping of words and sentences has made it possible to avoid these pitfalls, allowing, for example, to assign to every single word the sense most consistent with the context in which it is inserted.

In recent years, we have moved from the purely conversational world to that of chatbots as a multimedia interface, in which text, images and command buttons coexist [23]. There are many recent literature studies on the implementation of chatbots related to the recommendations and support of the human being in various fields of application. Such systems are designed using Natural Language Processing techniques, such as sentence-classification, key-concept identification, Recurrent Neural Network, etc. [24–28]

4. The proposed architecture

The architecture of the CHAT-Bot is based on some main modules, as shown in Fig. 1. The storytelling module is closely related to the bot ability to guide the user through the whole experience, making the way of proceeding while leaving the user free to express himself and immerse himself in the personalized story of a place.

Each user acts differently from the others, becoming part of a creative process and creating a unique and unrepeatable visit. In planning an itinerary and in designing the narration, therefore, not all progress must be defined but a plurality of scenarios must be prepared that the user can explore freely up to crucial moments, common to all, or almost all, of the scenarios.

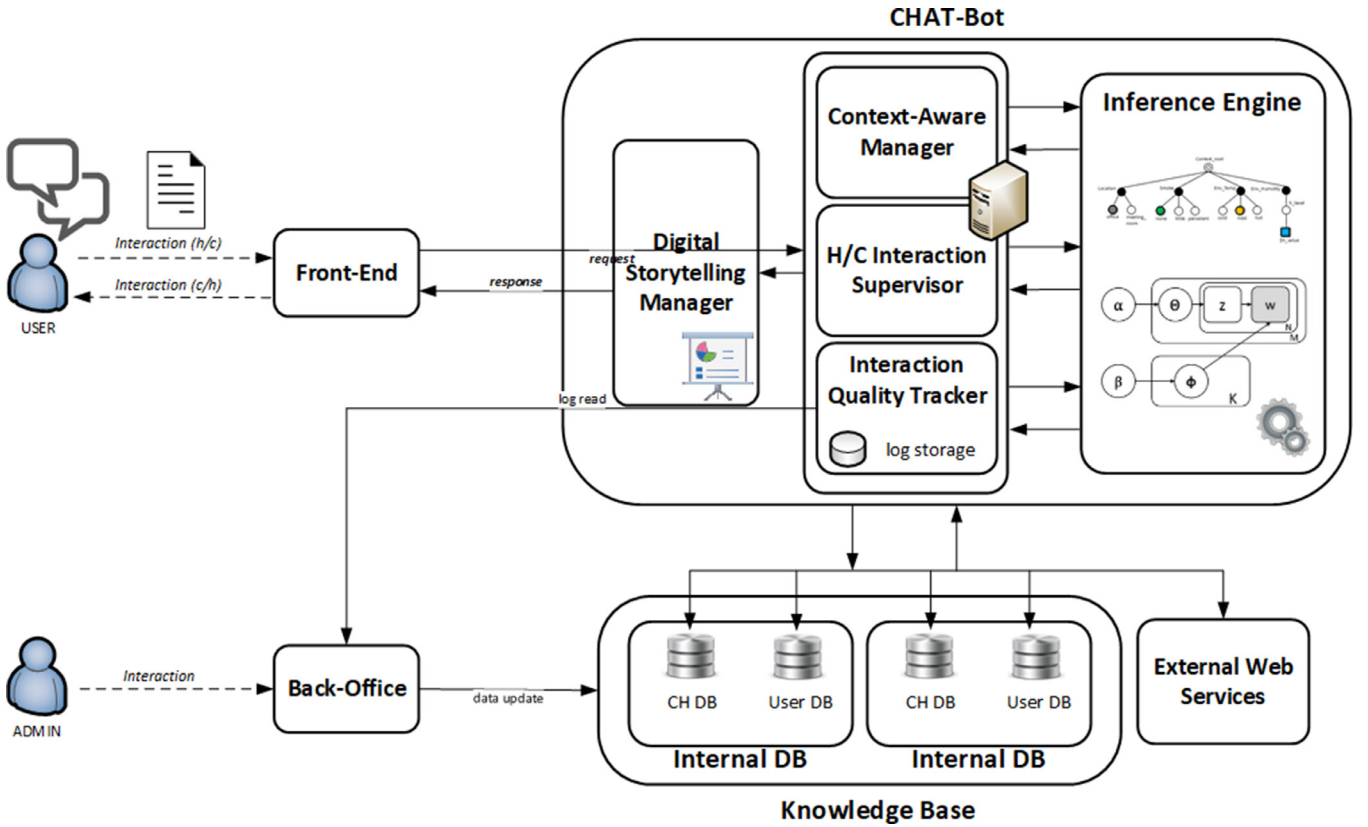


Fig. 1. Proposed architecture.

The Context-Aware Manager deals with representing all the possible contexts of use through the Context Dimension Tree and performing contextualized queries. In this way, it is possible to extract and provide personalized information by aggregating and custom-tailoring data and services extracted from different sources. Some resources are private (internal resources) or managed directly by the chatbot provider. These resources can be used, for example, to maintain the profiles of registered users, or the data of the museums reviewed, and the promotions offered to users. The chatbot can also interface with external services (external resources), for example for booking an art exhibition.

Other modules, such as the Human/Computer Interaction Supervisor and the Interaction Quality Tracker, have the following objectives:

- supervise the dialog, keeping track of timing of interaction, identifying ambiguous questions, or dialog sessions that are not convergent or too long, and so on;
- carry out monitoring interactions between the user and the chatbot, producing synthetic quality indicators and highlighting critical aspects useful for the improvement of the system.

The core of the architecture is the Inference Engine, which includes text analysis and context extraction. It is assumed that the text generated by a chat is a mixture of contextual information and that the use of some words helps to define the different context elements useful in the search for the same context that can be identified through the Context Dimension Tree (CDT).

Latent Dirichlet Allocation is a model suitable for this purpose as it can be used to explain the correlation between keywords and topics (in our case, context elements), as shown in the following Fig. 2. Through textual analysis, it is possible to know the user (citizen or tourist), where he is or where he would like to be

(museum, archeological park, etc.), the purpose of his visit (holiday, leisure or study) and what they need: services to book or buy tickets, information about timetables, multimedia contents, etc. For example, a possible context could be a tourist during holiday who wants to get services to access an archeological park: the chatbot, first through the analysis of the chat and then through the elaboration of the current context, is able to define the real intention of the user in order to better satisfy his needs, or to properly recommend specific services.

In practice, the interaction of the user with the chatbot is divided into shorter and simpler sentences (clusters), through appropriate Bayesian filters for keywords, assuming that each sentence is semantically related to the other. The proposed approach is therefore based on the following assumption: the probability that the word W belongs to the concept node N_C within the CDT is proportional to how much the argument (for example, the purpose of a tourist's visit to a city of art) has already been treated and the number of times that a word has been used for a specific topic. The application of this model provides a characterization of chats in an automatic way, without the needing of specify the semantic value of the words in the text.

Furthermore, using the LDA approach on a set of chats that belong to the same domain (in the case analyzed, tourism), it is possible to automatically extract a Mixed Graph of Terms (mGT) that can be used both for the design of the tree of context and the constraints associated with it is to detect the context extracted in real time from the user's chat with the bot [29].

In particular, LDA was mainly used to generate topics within chats (text documents). These topics were processed by the system as contextual elements suitable during the use of the Context Dimension Tree. According to the LDA model, a distribution of terms for each topic i is represented as a multinomial distribution φ_i drawn from a symmetric Dirichlet distribution with parameter

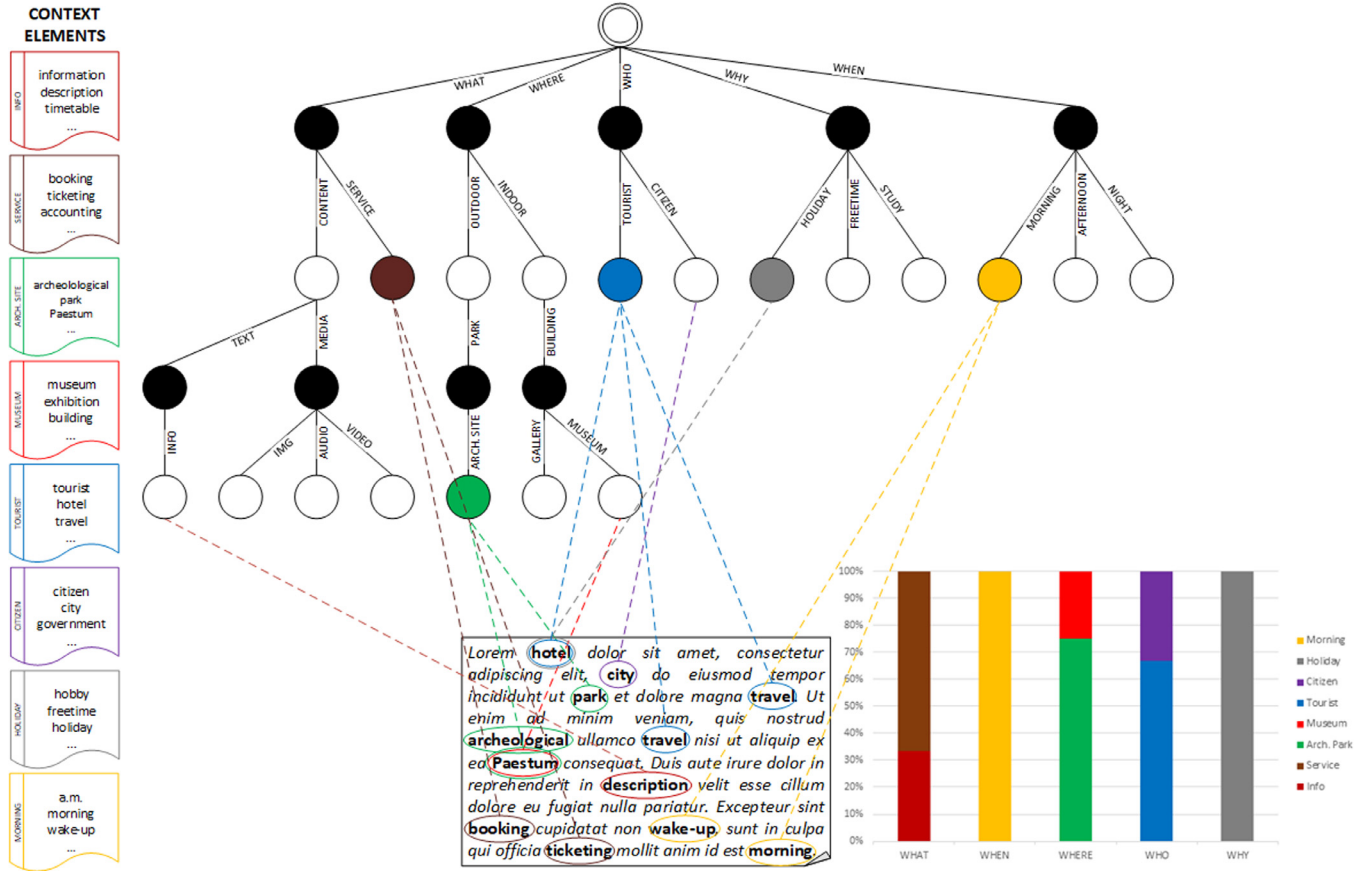


Fig. 2. Proposed approach for the definition of the context elements.

β :

$$p(\phi_i|\beta) = \frac{\Gamma(W\beta)}{[\Gamma\beta]^W} \prod_{v=1}^W \phi_{iv}^{\beta-1}$$

The topic distribution for a document d is also represented as a multinomial distribution Θ_d drawn by a Dirichlet distribution with parameter α :

$$p(\theta_d|\alpha) = \frac{\Gamma(\sum_{i=1}^K \alpha_i)}{\prod_{i=1}^K \Gamma(\alpha_i)} \prod_{i=1}^K \theta_{di}^{\alpha_i-1}$$

In this way, the topic z_{dn} for each index n token can be chosen from the distribution of the document topics as:

$$p(z_{dn} = i|\theta_d) = \theta_{di}$$

Each token w is chosen from a multinomial distribution associated with the selected topic:

$$p(w_{dn} = v|z_{dn} = i, \phi_i) = \phi_{iv}$$

LDA aims to find patterns of co-occurrence terms in order to identify consistent topics. If you use LDA to learn a topic i and $p(w = v | z = i)$ is high for a certain term v , then every document d that contains the term v has a high probability for the topic i .

It is possible to state that all the terms co-occurring with the term v are more likely to have been generated by the topic i .

4.1. Research and use of the context through mGT and CDT

A complex structure like the mGT can allow to capture and represent the contextual information contained in a set of chats that

belong to a specific domain (for example, tourism). This graph can be extracted automatically and used for the classification of the text, or to label the N_c concept nodes and know which of the nodes participate in the definition of the context at a given time. Formally, it can be defined as a graph $g = \langle N, E \rangle$ where:

- $N = \{R, W\}$ is a finite set of nodes, whose elements can be aggregates or aggregators.
- $E = \{E_{RR}, E_{RW}\}$ is a set of arcs that connect the aggregates and aggregators.

The proposed approach is essentially composed of two basic modules located within the Inference Engine: a module for the construction of the Mixed Graph of Terms and a module for extracting the context elements, as shown in Fig. 3(a).

- **Mixed Graph of Terms building module:** this module builds the mGT starting from a set of documents that belong to a specific domain (tourism) and that have been previously labeled in accordance with the contextual information contained. The mGT can also be used in the design phase of the Context Dimension Tree.
- **Context Mining Module:** this module involves the extraction of the context, or rather of the different context elements, thanks to the use of mGT as a context filter. The input of this module consists of a generic chat, the mGT extracted and the CDT in relation to the specific domain. The output is the context related to the chat.

Each context element is associated with a dedicated section of the database, which contains relevant and specific data. The contextual query is performed automatically by defining a global view given by the composition of the associated partial views. In addition to simple data, the same mechanism can be used for the

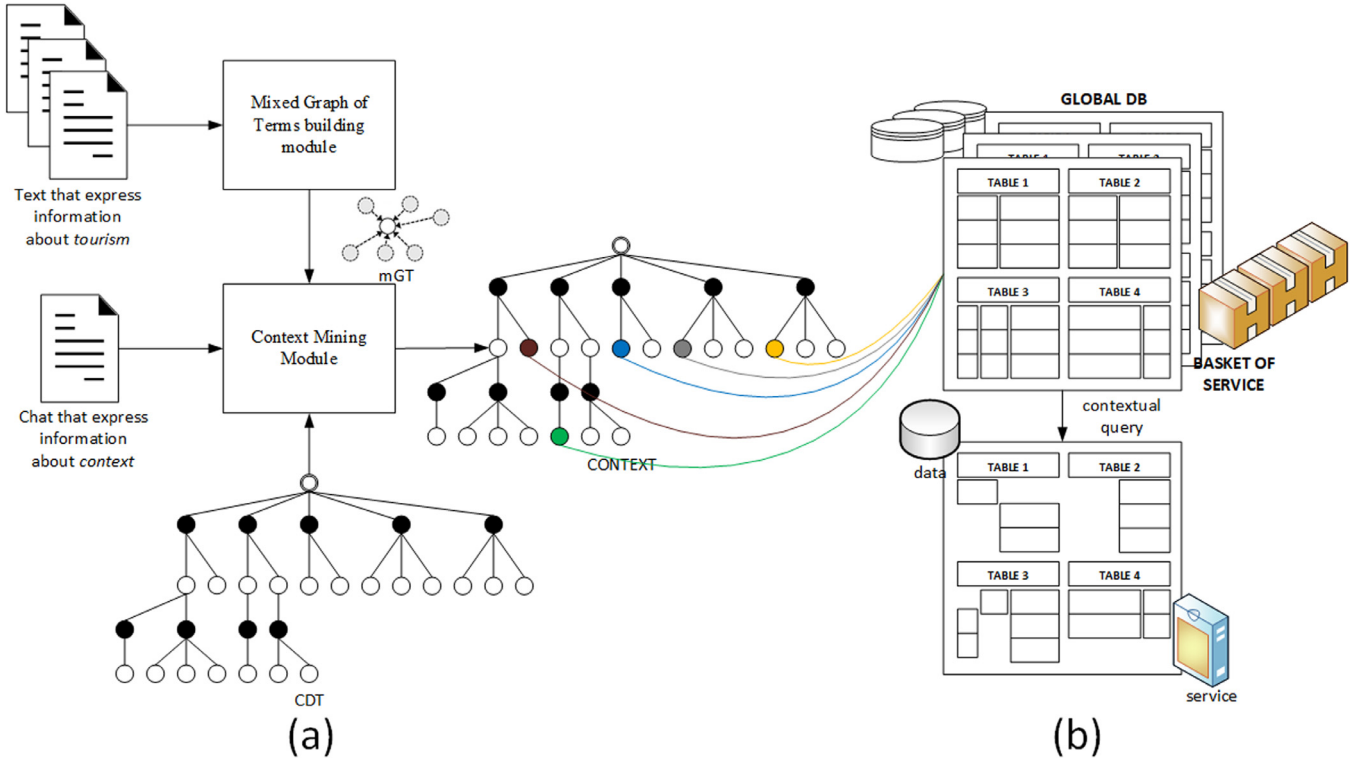


Fig. 3. Use of the context defined through mGT and CDT, an example.

selection of useful services related to the context identified, as shown in Fig. 3(b).

5. Experimental phase

Based on the proposed architecture, an application prototype was developed: a chatbot, designed and implemented, along with a server-side component, as described above (Fig. 4). The chatbot was initially designed to support tourists visiting some of the cultural sites of the Campania region of Italy (Paestum, Pompeii, Herculaneum). In this experimental phase, the main services and contents potentially useful for tourists have been identified.

After the interaction with the chatbot, 3150 users responded, according to the Likert scale, to a questionnaire comprising five sections. All participants owned a mobile device and they were between 18 and 62 years old. To each statement, present in a specific section, five possible answers were associated: “I totally disagree” - TD, “I disagree” - D, “Undecided” - U, “I agree” - A, “I totally agree” - TA.

Section A: 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.

Section B: conversation

1. The dialog with the chatbot took place smoothly and without unexpected jumps.
2. The system was able to correctly understand the intentions of the user.

Section C: presentation

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

Table 1

Experimental results.

Section	Answers				
	TD	D	U	A	TA
A	417	190	291	2857	2545
B	263	94	190	2916	2837
C	422	146	276	2845	2611
D	473	164	310	2573	2780
E	493	173	347	2737	2550

Table 2

Analysis of results.

Section	Percentage		
	Negative	Neutral	Positive
A	9,63%	4,62%	85,75%
B	5,66%	3,02%	91,32%
C	9,02%	4,38%	86,60%
D	10,11%	4,92%	84,97%
E	10,57%	5,51%	83,92%

Section D: usability

1. The chatbot interface is user-friendly.
2. Response times are adequate.

Section E: future developments

1. It would be useful to include in the chat other users (family and friends) with whom you share the trip.
2. It would be interesting to apply the same approach in other scenarios.

The Table 1 shows the aggregated results by section. Observing all the answers, the degree of user satisfaction is high.

In particular, according to Table 2, the positive responses (Agree and Totally Agree) reach a percentage always higher than 83%.

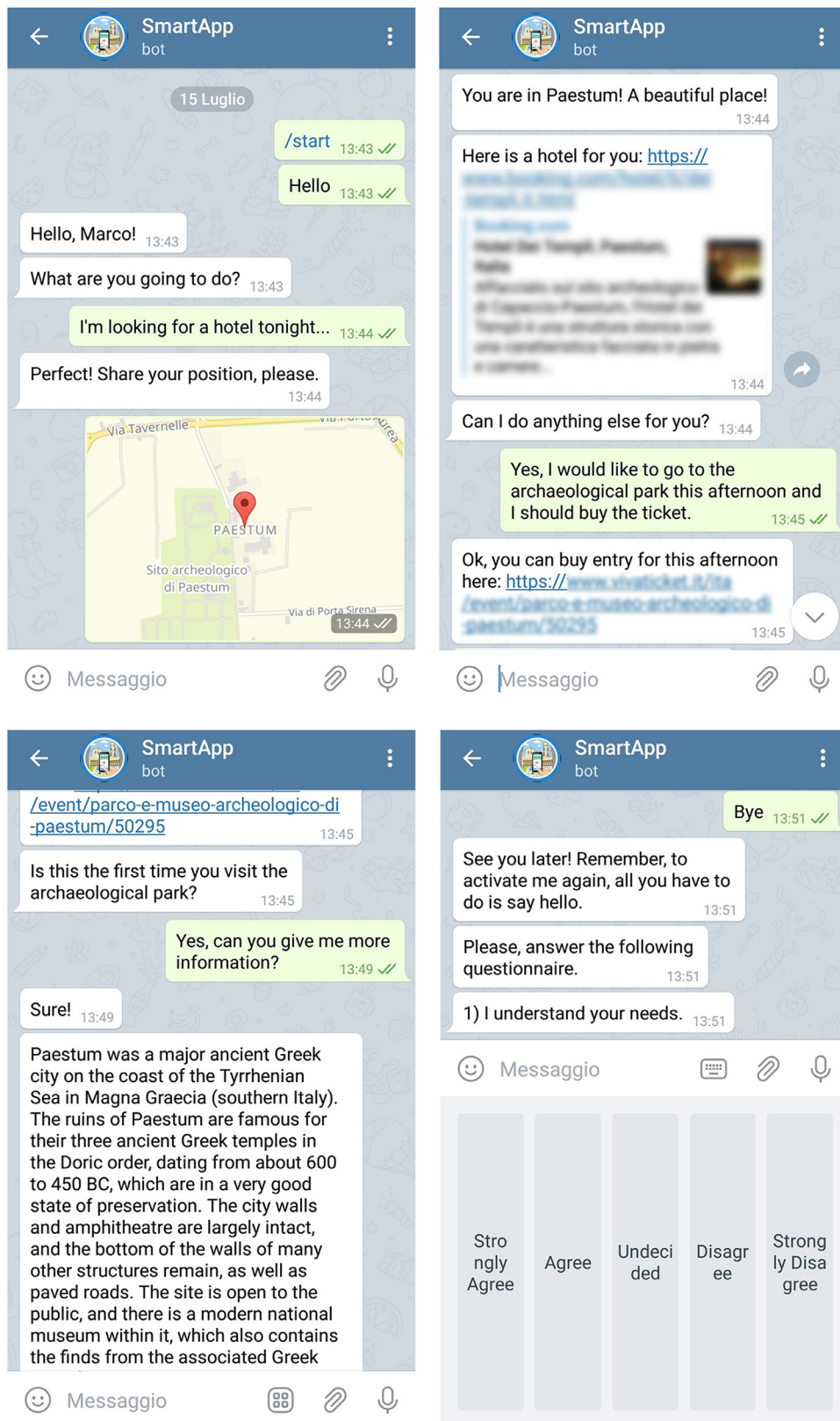


Fig. 4. Some screenshots of the CHAT-Bot.

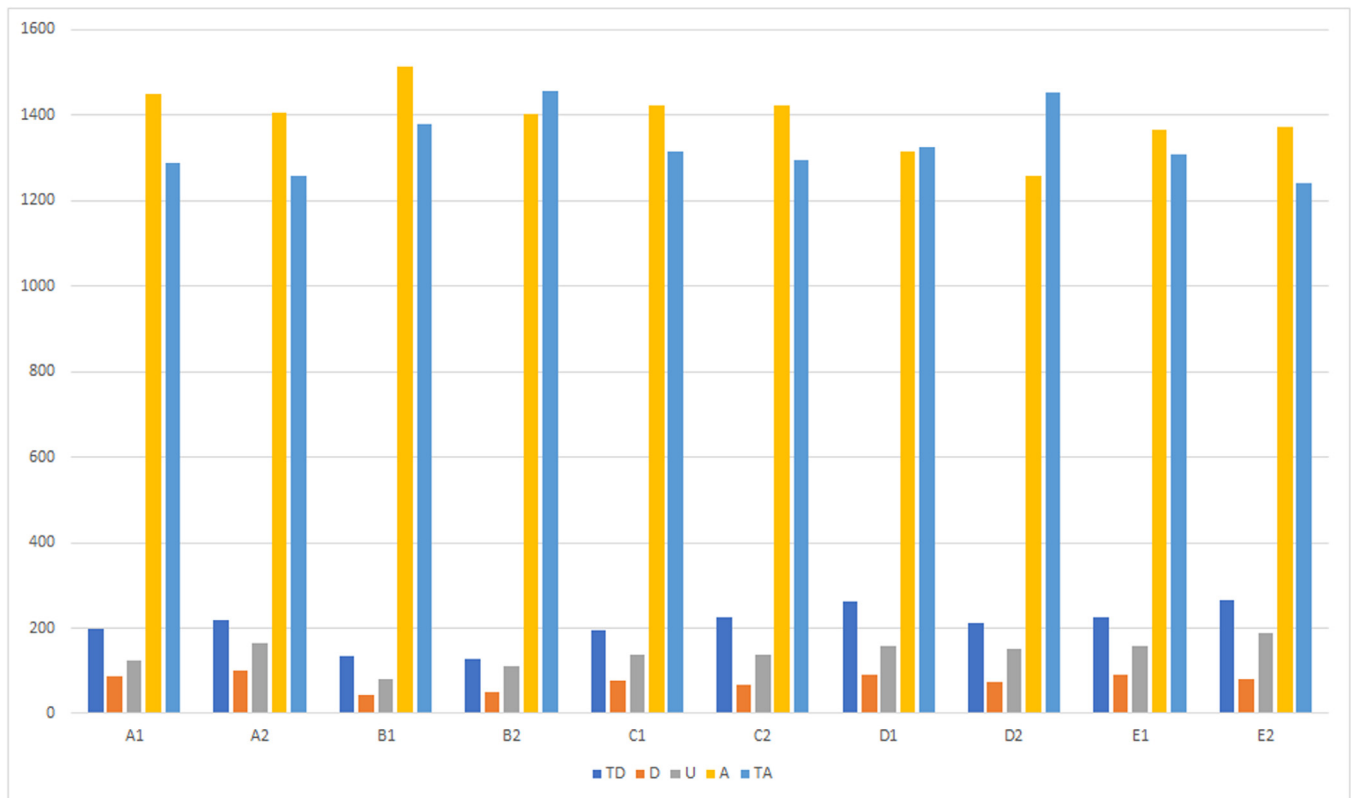


Fig. 5. Answers transd.

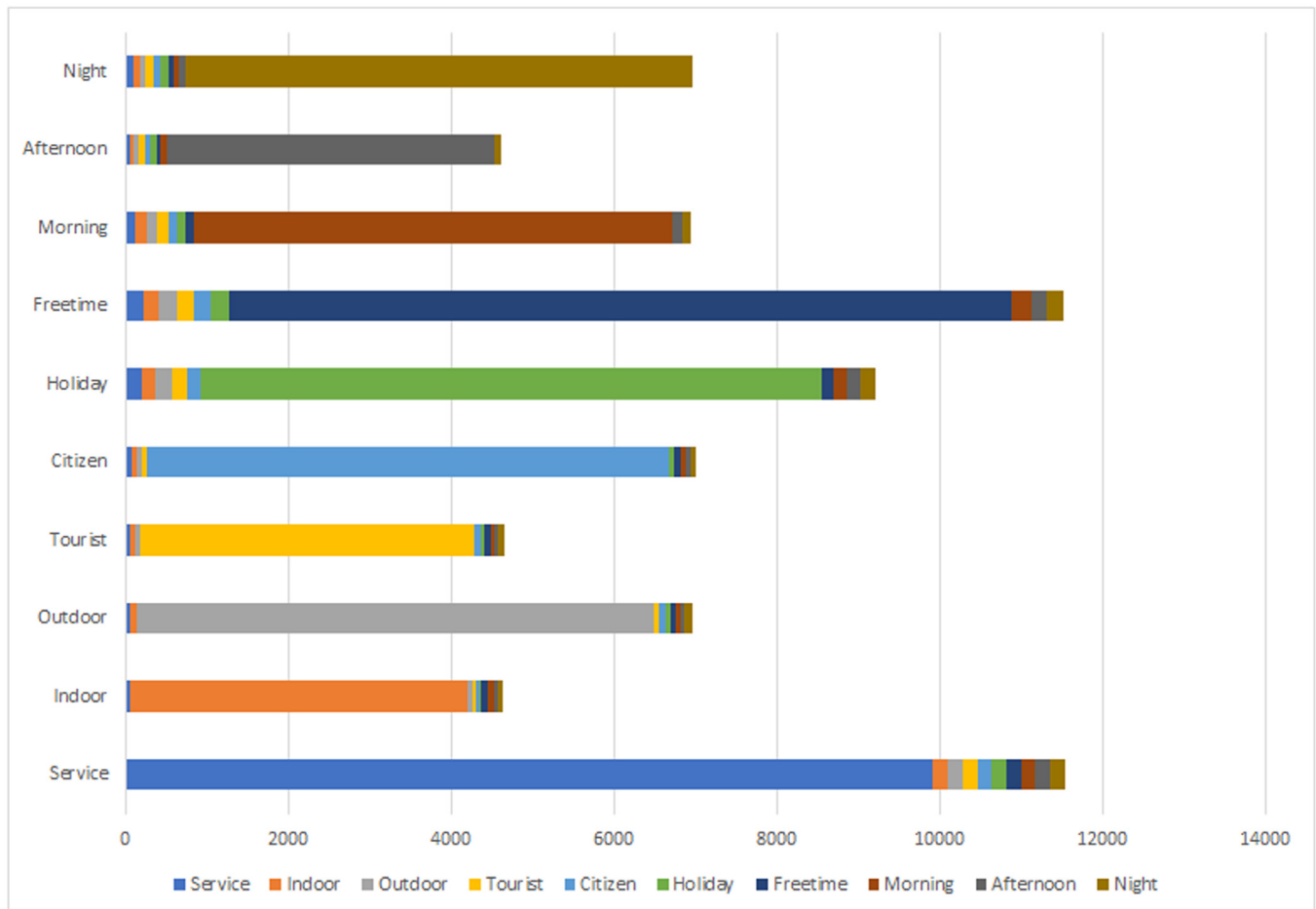


Fig. 6. Confusion Matrix representation.

Table 3
Precision and Recall.

	Precision	Recall
Service	86,32%	92,34%
Indoor	88,24%	80,51%
Outdoor	91,64%	86,08%
Tourist	88,41%	78,91%
Citizen	91,52%	87,03%
Holiday	83,39%	89,23%
Free time	84,15%	93,25%
Morning	83,90%	87,09%
Afternoon	89,89%	80,52%
Night	89,40%	87,80%

As can be seen from Fig. 5, the lowest number of positive feedbacks is found in the conversation section: some users have found it difficult to converse fluently with the chatbot, encountering some problems related to understanding the requests made.

This can be largely due to grammatical errors or dialect words not yet learned by the system in this initial state. On the other hand, section A, relating to the context-based recommendation form, shows very satisfactory results: the services and content proposed have satisfied the needs of the user, dynamically adapting to the current context. The results therefore suggest paying particular attention to machine learning in order to improve human-machine interaction.

A further analysis was carried out to verify the ability of the system to correctly identify the context elements starting from the interactions with the user. The results collected are related to the N_C concept nodes descending directly from the top-dimension of the CDT. The prototype created is in fact able to provide feedback relating to the assignment of a value to a N_D dimension node: correct assignment or incorrect assignment.

These results were collected in a confusion matrix, represented through a barchart (Fig. 6), which presents an overall accuracy of 87.31%.

In Fig. 6, it is possible to notice how the system is able to identify, in most cases, which nodes come into play in the definition of a context instance, these results in remarkable results in terms of precision and recall (table 3).

6. Conclusions

Today, the amount of data and services available require not only their mutual integration, but also their filtering in order to: provide the user in an appropriate way with a set of tailored data and services; operate on a manageable amount of data to improve processing efficiency; provide the user with only what is relevant based on contextual aspects, such as location and time.

In the world of tourism, for example, all this can be used to deepen the logic of integration and interoperability between platforms (existing or new), so as to allow automatic and adaptive construction to the context of products (tourist packages in terms of data and services) highly customizable and complete, going beyond the information phase. In this way, it is possible to facilitate the tourist at every moment of his travel experience: from the search for the destination, creating personalized and dynamic routes, up to the commentary of his own experience, orchestrating, according to the context, tourism promotion services, booking, e-ticketing, e-commerce, social networking, etc.

In this scenario, the interaction of the system with the user can take place not only via Web portal or mobile app but also through the now widespread chatbots. The proposed architecture allows the analysis of the text to perceive the context and recommend services and contents. In this way, the chatbot is able to correctly respond to the dynamic needs of tourists even if not di-

rectly questioned with a specific question at a time. Furthermore, the possibility of inserting a storytelling engine that is able to establish emotional ties with the user was investigated, making it part of a story that is both personalized and engaging, and increase engagement. The first experimental results are satisfactory and show the potential of the proposed approach. Future developments may include a greater interaction of the system with new heterogeneous sources of data and services, the application of the proposed methodology to more complex environments and an improvement thereof based on the feedback obtained.

Declaration of Competing Interest

None.

References

- [1] K. Ashton, That 'internet of things' thing, *RFID J.* 22 (7) (2009) 97–114.
- [2] D. Capriglione, M. Carratù, M. Ferro, A. Pietrosanto, P. Sommella, in: *Estimating the Outdoor PM10 Concentration Through Wireless Sensor Network for Smart Metering*, Springer, Cham, 2019, pp. 399–404.
- [3] F. Colace, D. Santaniello, M. Casillo, and F. Clarizia, "BeCAMS: A behaviour context aware monitoring system," in 2017 IEEE International Workshop on Measurement and Networking, M and N 2017 - Proceedings, 2017.
- [4] F. Clarizia, F. Colace, M. De Santo, M. Lombardi, F. Pascale, D. Santaniello, A. Toker, A multilevel graph approach for rainfall forecasting: A preliminary study case on London area, *Concurr. Comput. Pract. Exp.* (2019) e5289 May.
- [5] P. Albano, A. Bruno, B. Carpentieri, A. Castiglione, A. Castiglione, F. Palmieri, R. Pizzolante, K. Yim, I. You, Secure and distributed video surveillance via portable devices, *J. Ambient Intell. Humaniz. Comput.* 5 (2) (2014) 205–213 Apr..
- [6] F. Colace, M. Lombardi, F. Pascale, D. Santaniello, A. Tucker, and P. Villani, "MuG : A Multilevel Graph Representation for Big Data Interpretation," in IEEE 20th International Conference on High Performance Computing and Communications; IEEE 16th International Conference on Smart City; IEEE 4th International Conference on Data Science and Systems, 2018, pp. 1410–1415.
- [7] G. Annunziata, F. Colace, M. De Santo, S. Lemma, M. Lombardi, Appoggiomario: A context aware app for e-citizenship, in: *ICEIS 2016 - Proc. 18th Int. Conf. Enterp. Inf. Syst.*, 2, 2016, pp. 273–281.
- [8] F. Amato, A. Castiglione, A. De Santo, V. Moscato, A. Picariello, F. Persia, G. Sperli, Recognizing human behaviours in online social networks, *Comput. Secur.* 74 (2018) 355–370 May.
- [9] G. D'aniello, M. Gaeta, and M.Z. Reformat, "Collective perception in smart tourism destinations with rough sets," in 2017 3rd IEEE International Conference on Cybernetics, CYBCONF 2017 - Proceedings, 2017, pp. 1–6.
- [10] M. Casillo, F. Clarizia, F. Colace, M. Lombardi, F. Pascale, D. Santaniello, An approach for recommending contextualized services in e-tourism, *Information* 10 (5) (May 2019) 180.
- [11] F. Amato, V. Moscato, A. Picariello, F. Colace, M. De Santo, F.A. Schreiber, L. Tanca, Big data meets digital cultural heritage, *J. Comput. Cult. Herit.* 10 (1) (2017) 1–23 Apr..
- [12] B.N. Schilit, M.M. Theimer, Disseminating active map information to mobile hosts, *IEEE Netw.* 8 (5) (1994) 22–32 Sep..
- [13] J. Pascoe, N. Ryan, D. Morse, Issues in developing context-aware computing., *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 1999.
- [14] G. Chen, A Survey of Context-Aware Mobile Computing Research., Dartmouth Coll. Hanover, NH, 2000.
- [15] A.K. Dey, Understanding and using context, *Pers. Ubiquitous Comput.* (2001).
- [16] A. Rausero, D. Martinenghi, L. Tanca, Contextual data tailoring using ASP., *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (2013).
- [17] B. Schilit, N. Adams, and R. Want, "Context-aware computing applications," in 1994 First Workshop on Mobile Computing Systems and Applications, 1994, pp. 85–90.
- [18] G. D'Aniello, M. Gaeta, V. Loia, F. Orciuoli, and S. Tomasiello, "A dialogue-based approach enhanced with situation awareness and reinforcement learning for ubiquitous access to linked data," in 2014 International Conference on Intelligent Networking and Collaborative Systems, 2014, pp. 249–256.
- [19] A.S. Rao, A.V. Sharma, and C.S. Narayan, "A context aware system for an IoT-based smart museum," in 2017 2nd International Multidisciplinary Conference on Computer and Energy Science, SpliTech 2017.
- [20] G. D'Aniello, M. Gaeta, and M.Z. Reformat, "Collective perception in smart tourism destinations with rough sets," in 2017 3rd IEEE International Conference on Cybernetics (CYBCONF), 2017, pp. 1–6.
- [21] F. Colace, M. De Santo, S. Lemma, M. Lombardi, A. Rossi, A. Santoriello, A. Terribile, and M. Vigorito, "How to describe cultural heritage resources in the web 2.0 Era?," in Proceedings - 11th International Conference on Signal-Image Technology and Internet-Based Systems, SITIS 2015, 2016.
- [22] M. Garber-Barron and M. Si, "Towards interest and engagement: a framework for adaptive storytelling," in *Intelligent Narrative Technologies V (INT5)*, 2012.

- [23] F. Clarizia, F. Colace, M. Lombardi, F. Pascale, and D. Santaniello, "Chatbot: an education support system for student," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2018, vol. 11161 LNCS, pp. 291–302.
- [24] Y. Sun and Y. Zhang, "Conversational recommender system," in *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval - SIGIR '18*, 2018, pp. 235–244.
- [25] E. Haller and T. Rebedea, "Designing a chat-bot that simulates an historical figure," in *2013 19th International Conference on Control Systems and Computer Science*, 2013, pp. 582–589.
- [26] N. Zalake and G. Naik, "Generative chat bot implementation using deep recurrent neural networks and natural language understanding," *SSRN Electron. J.*, Mar. 2019.
- [27] J. Cerezo, J. Kubelka, R. Robbes, A. Bergel, *Building an expert recommender chatbot*, *Proc. 1st Int. Work. Bots Softw. Eng.* (2019) 59–63.
- [28] F. Colace, V. Loia, S. Tomasiello, *Revising recurrent neural networks from a granular perspective*, *Appl. Soft Comput.* 82 (2019) 105535 Sep..
- [29] F. Colace, M. De Santo, L. Greco, F. Amato, V. Moscato, and A. Picariello, "Terminological ontology learning and population using latent dirichlet allocation," *J. Vis. Lang. Comput.*, 2014.