Personalized and content adaptive cultural heritage path recommendation: an application to the Gournia and Çatalhöyük archaeological sites

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Abstract

Although abundant research work has been published in the area of path recommendation and its applications on travel and routing topics, scarce work has been reported on context-aware route recommendation systems aimed to stimulate optimal cultural heritage experiences. This paper tries to address this issue, by proposing a personalized and content adaptive cultural heritage path recommendation system, where location is modeled using mean-shift clustering trained with actual user movement patters. Additionally, topic modeling is incorporated to formalize the implicit cultural heritage content, while first order Markov models address the movement as a temporal transition aspect of the problem. The overall architecture is applied on data collected from actual visits to the archaeological sites of Gournia and Çatalhöyük and extensive analysis on visitor movement patterns follows, especially in comparison to the curated paths in the aforementioned sites. Finally, the offline evaluation results of the proposed recommendation scheme are encouraging, validating its efficiency and setting a positive paradigm for cultural heritage route recommendations.

Keywords Digital cultural heritage · Personalized Cultural User eXperience ·
Cultural heritage path recommendation · Route recommendation · Computer assisted
archaeology · User modeling

1 Introduction

Cultural heritage experiences are extremely complex to model and optimize since, apart from the standard complexity introduced to personalized content delivery, such as user preferences and spatial awareness, the content itself is multifaceted, enriched

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with aspects related to its origin and its correlation with the cultural user experience is far from trivial. Mining these underlying topics is rarely addressed, and expert curatorial approaches are instead incorporated. While travel recommendation, in terms of services and sights, is a well researched scientific domain, the cultural aspects of these recommendations are often ignored or at best manually introduced.

The current article addresses the aforementioned issues by investigating the way patterns, emerging from the interaction between visitor movement and the archaeological space, lead to new ways of understanding such spaces and thus provide insights to inform interpretive strategies at a conceptual and practical level. Additionally, the exploration and application of hybrid methodologies is critical in understanding how such complicated and fragmented spaces are experienced through movement. Towards this goal, current work explores the archaeological space by developing a novel mixed-method approach, which combines computation and ethnomethodology, as well as a qualitative and quantitative analysis on a range of visitor-generated data.

The research work presented here introduces a personalized, context and topic sensitive, cultural heritage path recommendation system. The proposed architecture incorporates *mean-shift clustering*, a non-parametric feature-space analysis technique for density function maximum values discovery, in order to model the archaeological space via user movement data training. The core contribution, in terms of cultural heritage content modeling, lies in the user and topic modeling approach. Although topic modeling is a theoretical abstraction attempting to conceptualize visitor and site aspects, the proposed system incorporates a hierarchical probabilistic model which introduces the notion of *topics* to quantify the relationship between visitors and landmarks. Route estimation is enhanced with location transition modeling based on a first-order Markov model, which makes the assumption that the next location to be visited is solely dependant on current location only (and not on the path as a whole). Finally, the recommendation is derived from the late fusion of the streams in an ensemble approach.

The system is validated via an application to the archaeological sites of Gournia and Çatalhöyük where recorded visitor locations and user preferences via questionnaires provide input to the personalized route recommendation system that suggests routes both offline and real time. Gournia, a Minoan archaeological site (1550–1450 BC) located in Eastern Crete, Greece was chosen because of the site's character, the dense layout and the preservation state of the remains as well as its minimum interventions and subtle interpretive programme.Çatalhöyük is a Neolithic site (7200–6400 BC) in Anatolia, central Turkey which presents a case of a World Heritage Listing, a thorough Heritage Management Plan and pioneering interventions for the preservation and protection of the site's fragile remains. While the above fact reflects a strong agenda for the presentation of the site to public audiences, at the same time it poses serious challenges as far as onsite intellectual and physical accessibility is concerned. The diversity in the current state of visitation, the level of accessibility and the different approaches in dealing with interpretation and visitor movement in the chosen sites provided a fertile ground for developing and validating our approach.

Lightweight GPS devices recorded the movement of visitors over a period spanning 4 years. An experimental procedure has been applied to the collected visitor data, that estimates the accuracy of the produced path re-commendations. The obtained results demonstrate a steady performance lead of the Topic Model fused with the first-order

Markov Model when compared to the simple Topic Model, for various examined hyper-parameter settings. This is a clear indication that, when it comes to cultural sites, the last landmark accessed by the visitor greatly affects her choice on what to see next.

The rest of the article is structured as follows; Sect. 2 discusses related work in terms of generic path recommendation, as well as computational applications in Cultural Heritage Sites. Section 3 presents the archaeological sites and the data collection process. Section 3.5 compares the first results of the analysis by comparing automatically extracted, via track clustering, points of user interest with respective points from curated routes. Section 4 outlines the proposed system's architecture and incorporates approaches for position clustering (Sect. 4.1) and user and topic modeling (Sect. 4.2). Finally, the experiments and the results are presented and discussed in Sects. 5 and 6, respectively, while the paper concludes in Sect. 7.

2 Related work

2.1 Path recommendation

Recommender Systems collect information on user preferences for a set or domain of items and are closely correlated to the user's online and social media behavior, as well as demographic and content-based information (Alexandridis et al. 2017). Since the users, themselves or via their behavior, are incorporated in these systems, so that the latter are by definition personalized. When context, such as location or content information is also taken into account, they can also be considered to be context-aware and based on implicit interaction rather than explicit user ratings or other evaluation/input. The recommendation itself is also inclined towards paths or routes in these location-sensitive systems and is expressed via related predictions and suggestions. While their goal is always influenced by the local aspects of the user's modeled behavior, it varies depending on the domain and overall scope of the application, as well as the input itself. Some research work focuses on user searches for local information about sights to visit and domain-specific recommendations (e.g., restaurants in Horozov et al. 2006). Other approaches concentrate on location-related aspects of the user in order to better model and predict spatiotemporal behavior such as Ashbrook and Starner (2003) and Zheng et al. (2009) for travelers and Krumm and Horvitz (2006) for drivers.

Mining approaches are also encountered in related bibliography where the contribution lies in discovering usable knowledge about movement behavior and trajectory patterns (Giannotti et al. 2007), big trajectory data approaches for personalized routes (Dai et al. 2015) or route optimization, in terms of fastest path finding, from user-specified multiple destinations (Lu et al. 2011). Multiple modalities fusion, such as images and related geotagging metadata, is also adopted, e.g. in Kurashima et al. (2013), where a travel route recommendation method is presented utilizing geotagged images in photo-sharing services and probabilistic user behavior modeling. Dynamic aspects of user's behavior, such as activities and established schedule, are also incorporated in Rodriguez et al. (2012), where interactive multi-criteria techniques are applied towards personalized tours based on the both the user's preferences and needs, along

with the area characteristics. Social and crowd-sourcing aspects are also integrated, such as the approach based on graph modeling for socio-spatial networks and presented in Doytsher et al. (2011), and *CrowdPlanner* (Su et al. 2014), the crowd-based system leveraging crowd knowledge to improve the recommendation quality.

An interesting classification of Recommender Systems, focusing on ubiquitous aspects and touristic application, is presented in Gavalas et al. (2014). It includes recommendations based on Points of Interests, such as attraction type and related informative content, touristic services, such as restaurants, hotels and transportation and routing services. More complex, challenging but also more personalized and adaptive classes are also identified; they include systems incorporating collaborative user-generated content, social media and networking activity, as well as long-term planning. Additionally, a wider scope classification is elaborated based on system architecture, user involvement and input criteria. Finally, the same survey discusses insights on the offered recommendation services and highlights challenges and promising research directions in the area.

2.2 Computer assisted heritage interpretation

Before providing a brief and focused background on computer-assisted onsite heritage interpretation that will frame our contribution to the field, it is deemed necessary to define the meaning and purpose of interpreting heritage broadly. Heritage interpretation today refers to a "constellation of communicative techniques" (Silberman 2013, p. 21) employed by stakeholders to raise public awareness about the significance, and meaning of tangible and intangible values of past societies (ICOMOS 2007) and to render them relevant to the present. In other words, it is the process of creating meaningful experiences and connections to the things we value from our shared past. The design of such experiences is a rather complicated endeavor when it comes to delivering interpretation at heritage sites.

Apart from the conceptual and contextual considerations in providing intellectual access and presenting aspects of the past to the public, onsite experiences and encounters with the physicality of such places which are vital to the interpretation process (Silberman 2013; Urry 1990; Uzzell 1998), add to the complexity of designing interpretation. The palimpsest of remains, the illegible remnants of once solid structures and settlements, the works of time and nature on monuments and the contemporary interventions (e.g., interpretive panels, walkways, roping) impact the way those places are accessed by individuals both on an intellectual and physical level.

Today, on-site heritage interpretation oscillates between visitor-centred approaches influenced by the museum studies and preservation-oriented approaches rooted in the conservation movement and the assumption that heritage values rely on the materiality of places (Araoz 2011; Silberman 2015; Uzzell 1998). However, in both cases, it has been established that public participation in heritage interpretation provides the desired two-way communication process for understanding heritage and creating more effective engagements (Silberman 2013).

In this frame and simply put, computer-assisted heritage interpretation is the field concerned with the development of systems and the design of new modalities for deliv-

ering digital content which complements onsite visitor experiences. The ever-growing interest in the field has been noted already by the ICOMOS Charters of Ename and London (Denard 2009; ICOMOS 2007) and illustrated by the European Commission reports and the more recent Horizon2020 funding scheme towards computational approaches to Cultural Heritage. The main contribution of computer-assisted onsite heritage interpretation is to augment visitors experience of the physical heritage sites by providing intellectual, contextual and location-based access to more heritage content, such as interactive, personalized or socially engaging stories (Katifori et al. 2016), graphical representations of artefacts stored at remote locations and reconstructed environments of the past.

Initially, collaborative projects showed interest in interpretive archaeology and information dissemination at cultural heritage sites and museums (Champion 2011; Noh et al. 2009; Kenderdine 2010). Among these, some stressed the importance of exploring the visitor–heritage site interaction through ethnomethodological practices for informing the design of such applications (Ciolfi and McLoughlin 2011; Chrysanthi 2015), while few have undertaken user evaluations for assessing the interpretive value along with the technological advancements (Economou and Pujol-Tost 2007; Kenderdine 2010). More recent work has focused on co-design approaches in authoring visitor experiences that empower cultural heritage professionals in their diverse roles to deliver engaging interpretation (Roussou et al. 2015; Not and Petrelli 2019). Particularly, Not and Petrelli (this volume) put co-design at the heart of developing an authoring environment for personalized interactive experiences that complement the interpretive value of physical settings and objects. Moreover, the notion and implementations of personalized (Vayanou et al. 2014; Katifori et al. 2014) guiding systems, mainly developed in the museum setting since the latter assumed a central role in heritage interpretation as a space created for this exact purpose (Bedford 2001; Johnsson 2006), started to influence onsite heritage interpretation. Naturally, different adaptability and interaction frameworks can effectively work in a museum space (Antoniou and Lepouras 2010; Pujol et al. 2013), a virtual space (Rajaonarivo et al. 2019) and a heritage site. For the latter, the type of heritage site, its interpretive and conservation scheme are critical parameters influencing the design. According to Ardissono et al. (2012), adaptation is an important component of personalized experiences in cultural heritage and refers to the different features taken into account during the visitor–heritage content and space interaction. Adaptation types which are important in the context of heritage sites are distinguished in location-aware, which consider the proximity to POIs of the site, and visitor-aware, which take into account individual or group modes and preferences for heritage interpretation.

From the first interactive context-aware mobile guides (Cheverst et al. 2000) up to more recent advances in recommenders for cultural heritage sites (Papagiannakis et al. 2008; Katifori et al. 2016), we have established that it is possible to create systems that will never let us get lost in contemporary urban or heritage settings (Jones 2011). Digital augmentations promise to provide an extended perception of the heritage space beyond its physical properties while purpose-built sensors and algorithms commit to delivering interpretations adapted to our needs and preferences (Ardissono et al. 2012; Damala et al. 2012; Pujol et al. 2013). Nowadays, personal mobile devices are perhaps the most sustainable solution for cultural heritage sites that cannot afford to spend their

funds on renewing outdated technologies and software. Systems utilizing GPS tracking and location-based interpretation to deliver digital content on personal mobile devices have been used at several heritage sites (Dupuy 2014; Liestøl and Rasmussen 2010). But perhaps the most obvious advantage of mobile technologies, coupled with the advantages on social media platforms, is the creation of content on the go. Based on the rich social media user data enriched with semantic knowledge through *Linked Open Data* (LOD), Sansonetti et al. (2019) have developed a system that personalizes information and itinerary recommendations.

Therefore, it is important to be able to conceptualize the visitors' behavior in a museum or a heritage site. In Lanir et al. (2017) a system for the automatic tracking of visitors' position, movement and interactions in a museum is outlined. However, it is primarily oriented towards the museum's curators, as a tool that would help them to understand visitor interest, rather than the visitors themselves. In a similar fashion, Zancanaro et al. (2007) presented a technique based on auto-associative Artificial Neural Networks (ANNs) that can cluster visitor behavior in the space of a heritage site; yet again, the aim of this procedure has not been the personalization for the visitor herself, but an analysis of her behavior from the viewpoint of the curator. Apart from conceptualizing behavior, Raptis et al. (2019) propose a framework that utilizes human cognition along with users' behavior in Cultural Heritage settings to tackle personalization in knowledge acquisition.

In Bohnert et al. (2008), two adaptive collaborative models are presented with the aim of personalizing user experience within a museum. Even though their methodology bears a resemblance to the work outlined in this submission (their *Transition Model* is analogous to the first-order Markov model that is described in more detail in the forthcoming sections), it is oriented towards the more "constrained" space of a museum, where, according to the authors, visitors rarely return to previously viewed exhibits. This is not the case, though, with open-space heritage sites, where visitors move freely in the environment and therefore they may return to the same point of interest more than once.

Nevertheless, Bohnert et al. (2008) conclusions are in accordance with previous work on visitor movement, which has already established that onsite experiences are primarily influenced and formulated by the way people move within a place influenced by the configurational properties, as well as the tangible and intangible affordances pertinent to the content of the site and the surrounding setting (Chrysanthi 2015). It is important then to turn the lenses to novel technologies and modalities of *human–computer interaction* that could be more effective in the frame of path recommendation at heritage sites.

3 Case study

3.1 Background

The chosen case study is Gournia, a Minoan archaeological site dated in 1550–1450 BC and located on a small hill, close to the Gulf of Mirabello of eastern Crete; an area particularly rich in Minoan Archaeology (Watrous et al. 2015). The reason for choosing

this particular site to develop, demonstrate and evaluate the proposed recommender system is twofold.

Firstly, the character, the dense layout and the preservation state of the site's remains make Gournia an intriguing example of heritage sites that can benefit from novel presentation strategies. More specifically, Gournia is the only Minoan town that is so extensively excavated. The most important features of the site, revealed in the early years of the twentieth century by Hawes et al. (2014), are the two-storeyed houses built on the slopes of the low hill, which still preserve the stone built ground-floor and underground rooms; two well-preserved peripheral paved streets that crossed at right angles with others and divide the town into *insulae*; the drainage system, which is still visible at various locations of the site; the central building, which is considered by archaeologists to be a small Palace and the seat of a local ruler, built on the top of the hill, to the west of the rectangular court (Preziosi 1983; Soles 1991); and finally the cemetery, where three tombs have been revealed and presented to the public (Vavouranakis 2006). Today, the site is open to the public, and of all sites in the Aegean, Gournia gives the visitor the clearest idea of what a town in Late Bronze Age Greece looked like. Scholars have also pointed out the resemblance of the settlement's layout with that of a typical Cretan village (Davaras 1989; Mantzourani 2002; McEnroe 2010). Nevertheless, the site is rather difficult to understand and thus wander around in a meaningful and comprehensible manner.

Secondly, in addition to its well preserved ancient path system, which is used for touring the site, the archaeological site presents a case with minimum interventions and a subtle interpretive programme, limited to a few information panels, a two-sided, folded brochure that comes with the entrance ticket and the optional official guidebook of the site, "Gournia" (Davaras 1989). Apart from the new excavation which took place between 2010 and 2014 and was led by the University of New York at Buffalo (Watrous et al. 2015), conservation works were implemented at the northern and central part of the site. Visitors enter from the NE of the fenced-off archaeological site, where a small ticket house is situated. Leaving aside the ticket house and a chemical toilet near the entrance of the archaeological site, there are no other visitor facilities or designated rest points, while only a few trees scattered around the site provide natural shading. Therefore, such rural prehistoric sites, with their sensitive fabric, their relatively poor preservation state and the applicable interventions for enhancing their presentation of the public—usually limited to conservation works—pose serious challenges in designing systems for on-site interpretation and presentation (Chrysanthi and Earl 2013; Hodder and Doughty 2007).

The Neolithic site of Çatalhöyük has attracted the international archaeological and other communities attention since its discovery in the late 50 s, due to its substantial size, occupying an area of 80×80 m at the Konya plain, the density of the tell settlement, the abundance of art with religious symbolisms and evidence of an advanced Neolithic culture (Birch 2014; Hodder 2007; Mellaart 1967; Matero 2000; Tringham 2012). Çatalhöyük is well known for the settlements character, comprised of eighteen levels of Neolithic occupation and the unique features of the houses. The streetless clusters of houses in the early levels, the entrances opened on the roofs and the inhabitants custom to bury their dead indoors and under plastered platforms revealed at a neighborhood scale constitute a unique architectural assemblage (Birch 2014; Rosenstock 2006). The

houses were also decorated with plastered bull skulls (bucrania), plaster reliefs, and wonderful paintings, both non-figurative and with complex narrative content (Hodder 2008, p. 196). Significant objects of the Neolithic everyday life were uncovered, some decorative (e.g. flint daggers with decorative bone handles, clay or stone figurines depicting human figures and animals) and other utilitarian objects (e.g. obsidian, flint, pottery, worked bone and clay balls) (Çatalhöyük Research Project 2005).

From 1993 until today, an international team of archaeologists, led by Professor Ian Hodder, has been researching and producing new knowledge about Çatalhöyük (Hodder 2007),[1] the social and cultural changes that occurred as humans adapted a sedentary mode of living, and how the Neolithic way of life spread from Anatolia to Europe (UNESCO 2012, pp. 2, 35).

Despite the rich interpretive resources that have been produced over the years and the dedicated spaces of interpretation, such as the Visitor Centre and Experimental House built for didactic purposes, the site is largely not accessible due to the fragile nature of the Neolithic structures which look incomprehensible to the untrained eye. The main archaeological site consists of exposed archaeological remains under the respective North and South Shelters which are connected through a single one-direction itinerary. The latter consists of consecutive dirty paths that link certain areas of interest and are constructed by the removal of existing vegetation while in certain areas are defined by roping. In contrast to Gournia, the visitor itinerary is rigidly defined, and visitors at the East Mound are always accompanied by either one of the appointed guards or by a trainee tourist guide by the Ege University of Turkey during the summer seasons. This way, visitors cannot walk freely around the archaeological site. Also, the increased demand for memorable onsite experiences particularly after the World Heritage listing is at odds with the visually poor Neolithic remains and the vast, archaeologically rich but under interpreted surrounding plain (Perry et al. 2014). In this case, where physical and intellectual barriers exist, context-aware route recommendation systems prevail as significant interpretive tools, providing onsite intellectual access and connection with the past.

In conclusion, both sites served as case studies of research that explored the visitor–archaeological space interaction in order to inform interpretive planning (Chrysanthi 2015). In this context, the documentation of visitor movement and behavior patterns offered unique datasets for developing our approach, while the results of this research were used to evaluate our findings. Hence, this was an ideal case study for the aims and purposes of our research.

3.2 Data gathering

The consent of visitors to participate in this study was critical, and it entailed a very brief introduction to the purpose and nature of the study, without providing information that might influence the subjects. The data used in this follow up study were created as part of a research project (Chrysanthi 2015) that underwent a thorough ethical review process since it involved human participants, and all data handling ever since

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[1] See also the Çatalhöyük Archive Reports 1993–2014 available at http://www.catalhoyuk.com/archive_reports/.

Table 1 The Gournia and Çatalhöyük GPS datasets

Year	Number of tracks	
	Gournia	Çatalhöyük
2011	24	–
2012	6	3
2013	32	24
2014	–	26
Total	62	53

is in compliance with the Southampton University's Ethics Policy. Participants of this study have read a participant information sheet which delineated their involvement in the study and signed the respective consent form.[2] Apart from securing visitors' consent, it was also crucial to approach visitors that represented different "profiles" (depending on their age, sex, country of origin, educational level, financial status, interest in cultural heritage etc.) to ensure the required polyphony in the dataset.

GPS tracking and camera recordings were employed for gathering visitor movement and interaction with the site data. Lightweight GPS devices, at the time of the survey, had proven to be the most suitable tool for tracking pedestrian movement in relatively small sized and entrance-exit controlled areas, such as archaeological sites (Shoval and Isaacson 2009). Each visitor was asked to carry a small lightweight wearable GPS device. Three GPS Garmin eTrex devices were employed, which usually visitors hung around their necks or placed in their pockets. Additionally, visitors were given the respective synchronized small digital camera and were instructed to take pictures during their visit, as they would normally do with their own camera. This method, called *Visitor Employed Photography* (VEP), has been commonly used in visitor studies for measuring visitor attention to exhibits or to the natural environment (Camp et al. 2000; Ham and Weiler 2006). This data collection method has proven to be unobtrusive to the visiting experience and often visitors reported that they were not always conscious of taking part in an "experiment" or having been "assigned a specific task". At Gournia, in total 62 GPS tracks were recorded and 1656 images were captured by visitors over a period spanning 3 years, while 53 GPS tracks were recorded in Çatalhöyük, again for a period of 3 years (Table 1). In terms of the GPS data quality, the open rural site, the good weather conditions and the lack of high vegetation provided an optimum accuracy reading of 3 m all around the sites. Additionally, the record interval was set to "time", and the GPS receiver which was set to retrieve its location once every 2 s, resulted in the collection of high resolution GPS data. The

[2] More specifically, participants agreed to the following; to be tracked by GPS devices during their visit to the archaeological sites, to take photos during this visit and hand them over to the survey conductor, and to fill in a questionnaire. They consented to the above knowing the following: (1) participation in this study is completely voluntary; (2) If they choose to be in this study, they may withdraw from it at any time without penalty or consequences of any kind, and they may request that any data collected be destroyed; (3) the survey results will be stored securely, remain confidential and will be disclosed only with their permission or as required by law; (4) all publications and other modes of data dissemination will anonymize participants; (5) in all cases, participants personal information will only be available to the research investigator who also conducted the survey.
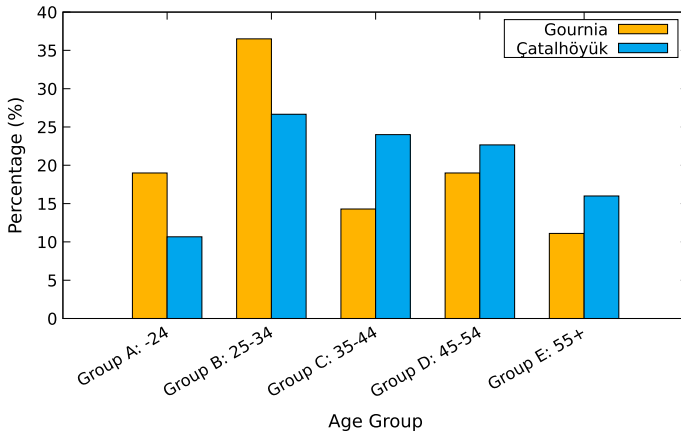
Fig. 1 Participants' age groups

recorded data adhere to the GPS Exchange Format (versions 1.0 and 1.1) and contain the track points of the path followed by every visitor. Each track point is described by its geographic coordinates (latitude, longitude), the elevation (w.r.t the sea level) and finally a timestamp.

Before presenting the main findings from visitor feedback, it is essential to provide some general demographic information about the profile of visitors who participated in this study (Fig. 1). Both women and men participated in the survey at Gournia, at equal percentages (50.8% and 49.2% respectively), of different age groups, while the majority demonstrated a high educational profile. Also, the place of origin varied but the most significant majorities originated from France, Italy, United Kingdom, Greece, Spain, Russia and the USA. The surveyed visitors at a percentage of 73% visited the site with friends and family and have had previous information about the archaeological site of Gournia before arriving at the site. The majority of visitors found relevant information mainly in books and magazines (69.8%), as well as on relevant websites (17%).

In the Çatalhöyük survey, the participating men were slightly more than women (61.43% vs. 38.57%). Nevertheless, the majority of them demonstrated a high educational profile and they mostly came from Turkey, USA, Italy, the Netherlands and UK. Most of the participants in the survey have read about the site in Books and Magazines (40%), on the Web (28%) or were informed from other means (other people, TV, etc).

3.3 User behavior

Cultural heritage sites visitors, considered as users, behavior and movement depends on a large number of factors of varying nature and form. The most prominent ones are related to the space itself, whether a closed or open space, the related scale as well as its structure in terms of user movement ability. Besides objective factors as the ones previously mentioned, users are also influenced by the wider context or by cognitive and social aspects of the overall User eXperience that could affect the user's behavior and movement patterns.

Data collected during a user's visit include the time spent to various Points of Interest, as well as different aspects of visitor behavior at specific points. Observations correspond to various parameters, such as visitor movement, role of labels, percentage of visitors who stop at a specific POI and visitor interaction with exhibits. Lanir et al. (2017) introduce two important factors in visitor behavior and the user's engagement with cultural sites:

– Attraction power indicates the relative amount of people who have stopped in front of an exhibit during their visit. It is calculated by dividing the number of people who stop, by the total number of people who have visited the museum. This measure provides us with an initial idea of the power of attraction of the exhibit.
– Holding power measures the average time spent in front of an exhibit. It is calculated by summing up the time a visitor spent in front of a specific exhibit. This measure provides us with an initial idea of the power of an exhibit to hold the interest of a visitor.

In order to fully understand and successfully interpret the cultural User eXperience information about the user, his preferences and the interaction context are required. Visitor behavior provides the necessary feedback about how visitors interact with the cultural heritage site. This would in turn provide links and correlation basis with the cultural thematic topic modeling, which can either be explicitly annotated by curators and experts or implicitly extracted by automatic systems. The current research addresses and compares both approaches.

3.4 Data processing

Initially, the aforementioned data were preprocessed in order to calculate the instant velocity of each visitor at any given point in her path. This measurement, when combined with the respective coordinates, allows for an initial estimation of the specific locations within the archaeological site that seemed to be of interest to this visitor along with the places she skipped. Subsequently, the amount of time each visitor spent at every point of interest has been calculated, which is the basis of the cultural profile building procedure. Figure 2 summarizes the path of sample visitor (drawn from the Gournia dataset). The colored circles designate the track points of the visit and the coloring is dependent on the instant velocity; blue circles designate a lower pace while red circles a higher pace.

It should be noted, at this point, that when the visitor is "standing" at a location in the site, her instant velocity is not necessarily equal to zero. This is due to the fact that, even when the visitor is not moving, she cannot stand totally still; therefore, the device at each time interval "reads" slightly different co-ordinates and as a result the instant velocity assumes small, non-negative values. When plotting instant velocity calculations for all visitors in both datasets in a histogram (Fig. 3), it becomes obvious that an instant velocity of less than 0.2 m/s (or 0.72 km/h) seems to be a good choice for considering a visitor to be standing still and consequently the instant velocity threshold was set to this value in the analysis that follows.
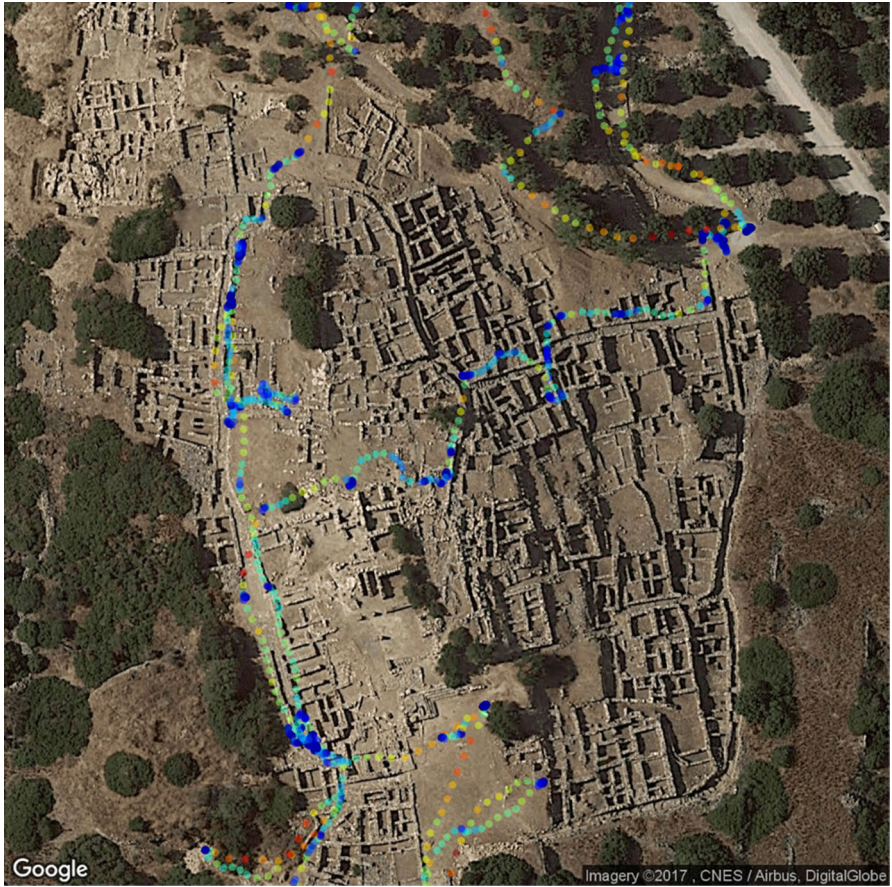
Fig. 2 Track points of a particular visit at Gournia (coloring based on instant velocity)
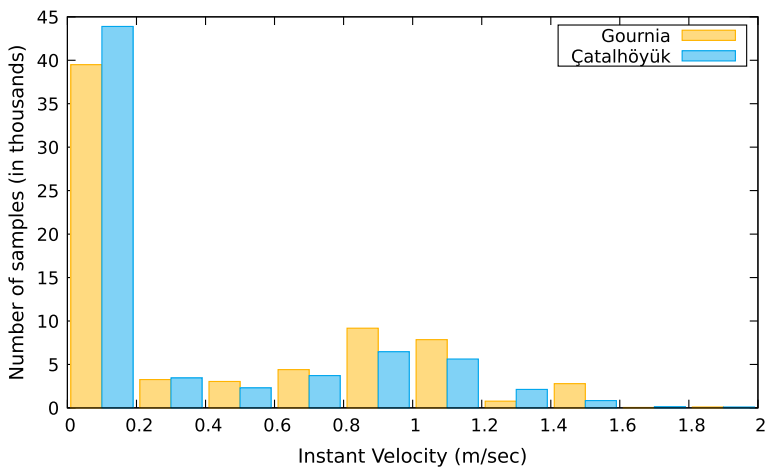

Fig. 3 Histogram of the instant velocity readings of all users in both datasets

3.5 Curated routes

3.5.1 Gournia site

For the purposes of the study, we proceeded in defining and curating two alternative paths based on the available interpretation of the site. The *first curated path* (CP1) is solely based on the eight information panels at the time of the study, which were designed and implemented by the local antiquities service (24th Ephorate of Prehistoric and Classical Antiquities of Greece) in collaboration with the Institute of Aegean Prehistory Study Centre for East Crete (INSTAP) and placed in areas of particular archaeological interest. CP1 is based on the following stops (Fig. 4):

1. The General Map is located at the beginning of the visitor tour at a location with a great panoramic view of the Minoan town's east slope. This is labeled as "The Minoan Town of Gournia" and it provides a brief history of the town's discovery and general contextual information regarding the character of the town and its features. This information panel also includes the town's layout plan with highlighted *Points of Interest* (POI), the preserved paths and the phases of the settlement.
2. A possible stone crucible, suggesting that the inhabitants may have worked with bronze metal was found in House Cf.
3. A clay wine press was found sitting on a stone bench in House Dd. A vessel placed under the spout on the floor would gather the juice from the crushed grapes. Similar structures for pressing grapes, called *patitiria*, can still be found in contemporary Greek villages.
4. The so-called Palace, possibly the seat of a local ruler, is built on the top of the hill, to the west of the rectangular court, which many of the private houses opened on to. The interior of the Palace is not as well preserved as other parts of the town, where some stone walls reach a height of 2–2.5 m. The information panel is located at the north-east of the Palace's court.
5. The Sacred Stone is an upright unworked stone which was deliberately set into the pavement of the street. Such objects and worshipers kneeling before them are depicted in Minoan seals.
6. The Shrine is located at the north-west of the palace where three steps are descending from the street. This is a rectangular room with a bench against the real wall dating to the Mycenaean period (1400–1200 BC). It is believed to be a small public shrine dedicated to the Minoan "Snake goddess", based on the cult objects found, including 3 statuettes of Goddesses with snakes wrapped around their bodies, an offering table, 3 lamp stands decorated with snakes and figurines of birds and snakes.
7. Three Tombs are located at the northern part of the settlement. One of them (Tomb III) dates from the Early Minoan to Middle Minoan Period (2600–1900 BC), while the two Middle Minoan (Tomb I and II) are graphically reconstructed by archaeologists (J. Soles) in the style of miniature houses. In front of Tomb II, a stone Kernos was found with a circle of small depressions cut into its upper surface into which offerings for the dead were placed.

Fig. 4 The 8 points of the first curated path (CP1) at Gournia

8. Finally, House Ac is the final stop to the visit of Gournia. The main entrance to the house from the road leads to a stone paved court. A mudbrick wall is still preserved and was probably used in the construction of the upper story. A portion of a window is also preserved at the back of room 7 and among the findings are storage pots, clay ritual vases as well as a potter's wheel.

The visitor is also given for free a two-sided, folded brochure that comes with the ticket of two euros and has the option to buy the official guidebook of the site (Davaras 1989). The main problem with both the brochure and the official guide is that they contain an overview map which does not provide the POIs of the archaeological site as the General Map does. Instead, the layout map annotates (with letters from A–G) the blocks of houses and includes a second plan of the palace with forty numbers that indicate the respective parts of the building. Similarly, the explanatory text of both paper-based media is focusing on the features of the palace rather than the whole town's features in a unified narrative. Evidently, the interpretive agenda of the paper-based media is not in alignment with the one provided on-site through the information panels. Based on the aforementioned reasoning, the *second curated path* (CP2) includes a combination of the most important and available to the visitors information about specific features of the site. The POIs used for CP2 are the following (Fig. 5):

1. The visitor begins from a great panoramic view of the Minoan town from the lower peripheral street where it meets the northern vertical path that climbs the slope of the hill.
2. See point 2 of CP1.
3. See point 3 of CP1.
4. The court of the Palace. The information panel is located at the north-east of the Palace's court.
5. The L shaped stairway which may have served as a theatral area leads from the court to the interior of the Palace.
6. See point 4 of CP1.
7. The store rooms of the Palace.
8. The Mycenaean period House He (1400–1200 BC).
9. See point 5 of CP1.
10. See point 6 of CP1.
11. See point 8 of CP1.
12. See point 7 of CP1.

3.5.2 Çatalhöyük site

As it has been previously mentioned, the visitor at Çatalhöyük is offered interpretation at three distinctive spaces of the "visitable" site: two interpretation spaces, the Visitor Centre and the Experimental House, and the actual archaeological site, the East Mound. For the purposes of this study, the curated path has focused on the main site, and apart from the onsite information panels, it has taken into account the guides tours as well as the visitor feedback (Fig. 6).

1. The suggested visit starts at the entrance of the archaeological site and follows the dirty path towards the North Shelter area. The visitor has a brief introduction to

Fig. 5 The 12 points of the second curated path (CP2) at Gournia

Fig. 6 The 8 points of the (single) curated path at Çatalhöyük

the site and is informed of the Mounds preservation strategies in place to ensure that both visitor experience and the protection of the sites natural environment are catered for.

2. At the time of data collection, the North Shelter area was accessible to visitors through a pathway system consisting of a raised board from metal and a wooden walkway placed on the contemporary ground level that runs across the western side of the Shelter and leading to the North Shelters exit. The latter path is made of interlocking wooden planking and further defined by low rope railings in order to prevent visitors from straying off the path. The raised path runs over the east side of Building 5, the first Neolithic house displayed at the site since 1998. This is the second POI of the curated path.

3. The third POI is Building 77 which can be approached from the south end of the raised path. This POI represents a Neolithic house that was destructed by fire where the visitor can still see the traces of the ladder, the oven and a platform with an installation of bulls horns.

4. The suggested path continuous to the South and South-East, passing through a refuse area between two building blocks and approaches Buildings 52 and 51. Building 52 is also a burnt building, but the question of what caused the fire is still under debate amongst specialists. The visitor is informed about the different interpretations offered by members of the excavation team concerning accidental and intentional destruction of buildings at Çatalhöyük by fire.

5. The itinerary continues to the South through a path that connects the two sheltered areas. Along this walk the visitor is offered interpretation about the environmental and topographical changes in the area since the Neolithic period, as well as contextual and comparative narratives including other Neolithic sites of Anatolia. This is an important addition to the existing interpretive programme which was requested by visitors of the site. Indeed, the path offers an ideal vista to the surrounding landscape from where visitors can be spatially oriented and receive interpretation about the distribution of other significant sites, as well as the environmental changes of the landscape as they overlook the current state of the plane from the top of the tell site.

6. The visit continues to the South Shelter area and the higher East vista from where the visitors are informed of the settlements eighteen levels of occupation and the intention of the sites director to expose and present this unique assemblage to the public.

7. The west lower vista area offers more detailed interpretation about the occupational phases of Çatalhöyük which are more visible from this part of the site.

8. From there the visitor follows the dirty path with direction to the North and back to the entrance of the archaeological site. A final stop is suggested at the spoil heaps remaining from the 1960s excavations which are now used for educational and training programmes. At this POI, visitors have the chance to get familiarized with the history of excavations.

4 Proposed path recommendation system

The proposed path recommendation system is outlined in Fig. 7. Initially, the GPS data (Table 1) are fed into the *Data Preprocessing* module. The objective of this step is to determine the points at which the visitors stand, according to the reasoning above. In the following, the data points of the previous steps are grouped around specific locations, a procedure to be discussed in the subsequent Sect. 4.1. Once the cluster centers
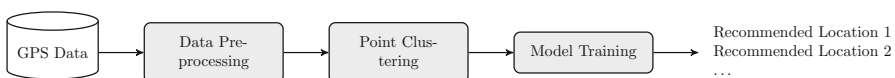

Fig. 7 Block diagram of the proposed recommendation system architecture

have been determined, two different recommendation models are trained, presented in Sects. 4.2 and 4.3, respectively, that finally recommend locations to visitors.

4.1 Location mean-shift clustering

Mean-shift clustering (Comaniciu and Meer 2002) is a non-parametric feature-space analysis technique that can discover the maximum values of a density function. It is a member of the broader family of *mode*-seeking algorithms and it has been extensively applied in various domains including image processing and computer vision.

The mean-shift procedure is able to estimate the modes of an unknown underlying distribution given some discrete data samples of that distribution (in our case, the locations the visitors accessed, as recorded by the GPS device they were carrying with them). It is an iterative procedure that starts with an initial estimate $\mathbf{c}^0$ for the cluster centers (please note that $\mathbf{c}^0$ is a vector). At iteration $t + 1$, the ith cluster center c_i is updated according to the formula below (Eq. 1)

$$c_i^{t+1} = c_i^t + m(c_i^t) \tag{1}$$

where $m(c_i)$ designates the weighted mean of the density and is defined as follows

$$m(c_i) = \frac{\sum_{x \in N(c_i)} K(x - c_i)x}{\sum_{x \in N(c_i)} K(x - c_i)} \tag{2}$$

In Eq. 2 above, $N(c_i)$ denotes the neighborhood of c_i and $K(x - c_i)$ is a kernel function. The most commonly used kernel is the Gaussian *Radial Basis Function* (RBF) Kernel which is equal to

$$K(x - c_i) = e^{\frac{||x - c_i||^2}{w^2}} \tag{3}$$

where w is the bandwidth parameter that tunes the density around each cluster center. The iterative procedure of Eq. 1 converges when the cluster centers do not "change" anymore.

The basic advantage of this technique is that, unlike other clustering methods (such as k-means), it is not necessary to determine the number of centers beforehand. Instead, their number and location is determined indirectly via the density parameter w. Setting it to a large value would result in more cluster centers that are "closer" in the underlying space while setting it to a small value would result to fewer cluster centers that would be located more distant in the underlying space.

4.2 User-topic modeling

A user model is a theoretical concept that tries to conceptualize and therefore explain the person's behavior in the archaeological site. Since many models exist in the literature (with some of them having been presented in Sect. 2), a necessary step is to choose

the most appropriate for each situation. In our case, where the space is constrained and the collected dataset is relatively small, we have opted for statistical models that are known to be more appropriate for similar situations.

The *Topic Model* is a hierarchical probabilistic model which introduces the notion of *topics* to quantify the relationship between *visitors* on one hand and the *landmarks* they have visited on the other. Topic models have been successfully used in a wide variety of applications in the area of *information retrieval* (Blei et al. 2003; Hofmann 2003), as well as user interest and preference modeling and personalization (Iwata et al. 2009; Abel et al. 2011). In this setting, a visitor is considered to have an interest in a set of topics, where each topic is expressed as a probability distribution over the landmarks. Those topics are not known in advance and are in fact estimated by the topic modeling algorithm. For this reason, topics are also referred to as the *latent features* of the model.

The contribution of this approach on designing cultural heritage path recommenders, regardless of the accessibility level, is twofold. Firstly, topic modelling prevails as the most suitable and compatible method with the visitor–space interaction approach for understanding the requirements of physical spaces such as heritage sites before designing interpretation. Besides, the visitor-centred approach lies at the heart of this research and presents a solid theoretical and empirical background in a large body of work concerning both museum settings (Bitgood and Patterson 1986a, b; Bitgood et al. 1988; Klein 1993; Serrell 1998) and heritage sites (Chrysanthi 2015; Lekakis 2008; Massung 2010; Silberman 2013; Solomon 2008; Urry 1990; Uzzell 1998; Witmore 2004). Secondly, it adds new questions to the debates concerning the formation and perception of heritage spaces. On the one hand, the approach seems to bridge the existing tensions between authoritative approaches to interpretation and the demand for participatory heritage (Roued-Cunliffe and Copeland 2017, p. 213) by offering the so-called two-way communication. This communication is enabled between heritage interpreters and visitors since the modelled visitor feedback informs interpreters about their preferences; as well as between visitors and heritage sites since the system is constantly trained by visitor onsite behavior to offer updated and more personalized recommendations.

Several topic modeling techniques exist in the literature, the most popular of which are *Latent Dirichlet Allocation* (LDA) (Blei et al. 2003), *Latent Semantic Analysis* (LSA) and *Probabilistic* LSA (PLSA) (Hofmann 1999). The latter has been the technique of choice in this contribution.

More formally, let $u \in U$ be the set of visitors (users) and $l \in L$ be the set of the landmarks they visit. Let $h^u \equiv (l_0, l_1, \ldots, l_{t-1})$ be the sequence of landmarks visited by u from the beginning of her visit and up until time $t - 1$. The objective of the model is to predict the landmark she is going to visit next.

The basic assumption made by the topic model is that future landmarks are conditionally independent from the history h^u of visitor u. Therefore, the probability of u visiting landmark l_t next, given the landmarks she has visited so far, is given in the following Eq. 4

$$P(l_t|h^u) = \sum_{z \in Z} P(z|h^u) P(l_t|z) \tag{4}$$

where $P(z|h^u)$ is the probability that the "hidden" topic z is of interest to u and $P(l_t|z)$ is the probability that landmark l_t is part of topic z. In simpler words, the first term of the product of Eq. 4 represents visitor interest in the specific topic while the second term quantifies the coverage (or the "trend") of the topic.

Since both probabilities of the right-hand side of Eq. 4 cannot be determined analytically, an *Expectation–Maximization* (EM) algorithm is used to approximate them. The EM algorithm is particularly useful in determining the maximum likelihood in statistical models that are dependent upon "latent" parameters, like in our case. It is an iterative procedure that consists of two steps; the *Expectation Step* that computes the posterior probability of the latent topics z given the parameters l_t, h^u of the model (Eq. 5)

$$P(z|l, h^u) = \frac{P(z|h^u)P(l|z)}{\sum_{z' \in Z} P(z'|h^u)P(l|z')}$$ (5)

and the *Maximization Step* which updates the model parameters in order to maximize their likelihood (Eqs. 6, 7)

$$P(z|h^u) \propto \sum_{l \in L} N(l, h^u)P(z|l, h^u)$$ (6)

$$P(l|z) \propto \sum_{u \in U} N(l, h^u)P(z|l, h^u)$$ (7)

where $N(l, h^u)$ is the number of times landmark l occurs in the history of u. Initially, $P(z|h^u)$ and $P(l|z)$ assume some random values and subsequently the steps described in Eqs. 5–7 are repeated until convergence (that is, when $P(z|h^u)$ and $P(l|z)$ reach an equilibrium).

4.3 Markov-Topic fusion model

The *Markov-Topic Model* is an extension to the *Topic Model* presented in Sect. 4.2 above, that incorporates a *first-order Markov model*. The latter model dictates that the next landmark l_t to be visited by the user is dependent only on her current location l_{t-1}. Let $h'^u \equiv (l_0, l_1, \ldots l_{t-2})$ be the landmarks visited by u before she reaches current location l_{t-1}. Then $h^u \equiv (h'^u, l_{t-1})$ and the Markov Property sets that the probability of visiting l_t next is

$$P(l_t|h_u) = P(l_t|l_t - 1, h'^u) \equiv P(l_t|l_{t-1})$$ (8)

The probability $P(l_t|l_{t-1})$ is again approximated using *Maximum Likelihood Estimation* (Eq. 9)

$$P(l_t|l_{t-1}) = \frac{N(l_{t-1}, l_t)}{N(l_{t-1})}$$ (9)

where $N(l_{t-1}, l_t)$ is the number of times landmark l_t is visited after l_{t-1} in the dataset and $N(l_{t-1})$ is the number of times l_{t-1} is visited in the dataset.

Therefore, in the combined Markov-Topic Model, the probability of landmark l_t appearing in the history of user u is

$$P(l_t|h_u) = P(l_t|l_{t-1}, h'^u) = \frac{P(l_t|l_{t-1})}{C(h^u)} \frac{P(l_t|h^u)}{P(l_t)} \tag{10}$$

where $P(l_t|l_{t-1})$ is the contribution of the Markov Property (Eq. 9) in the model, $P(l_t|h^u)$ is the contribution of the Topic Model (Eq. 4), $C(h^u)$ is a normalization factor that turns Eq. 10 into a probability distribution and finally $P(l_t)$ is the probability of landmark l_t appearing in the path. The latter may be set to the following ratio

$$P(l_t) = \frac{N(l_t)}{N} \tag{11}$$

where $N(l_t)$ is the number of times landmark l_t appears in all paths and N is the total number of all landmarks appearing on all paths.

4.4 Evaluation plan

User experience is a complex concept and this also affects its evaluation when it is related to interaction with a system, product or service. UX's complexity and ambiguity is expressed in the numerous definitions found in related literature. Morville (2004) introduced the UX hive with cells corresponding to different aspects of the system, product or service:

Useful: fulfill a need
Usable: easy to use
Desirable: evoke positive emotional reactions
Findable: locatable and navigable
Accessible: accessible to all user groups
Credible: believe and trust

Adding the Cultural aspect to the interaction context and the overall User eXperience makes the modeling, design, implementation and evaluation processes further increases their complexity and ambiguity. Although numerous, and ever increasing, systems aim to enhance the Cultural UX their effectiveness is evaluated using much different methods with accordingly varying goals (Koutsabasis 2017). Empirical evaluation is dominating the field of CUX evaluation but its parameters vary significantly in terms of UX modeling, overall approach, data collection and participants. CUX evaluation typically employs users interacting with the system in different cultural heritage context and its results are derived by observation or experiment. Evaluation methods includes observation, interviews and focus groups, user testing, field studies, questionnaires, surveys, diary studies and probes.

As Konstan and Riedl (2012) argue, evaluating the user experience of a recommender system requires a broader set of measures than have been commonly used,

and suggest additional measures that have proven effective. While existing datasets and quantitative metrics provide an estimation of the system's efficiency, measuring user experience requires both algorithms and user interactions evaluated in field studies measuring behavior in natural context.

5 Experiments

5.1 Clustering analysis

5.1.1 Qualitative analysis

In an effort to evaluate the results of the track clustering approach (Sect. 4.1), the generated locations have been plotted alongside the locations deriving from the curated paths. The first observation from the comparative study is that the clustered points are generated in proximity or coincide with the curated points. In the case of Gournia, five out of eight onsite information panels appear in the cluster approach results (Fig. 8) and at Çatalhöyük, one out of four respectively.

While the overlapping points is an expected result and show that the approach is successful in considering the cultural content parameter, a closer look is required to interpret the results where the curated points were ignored by the system. In the case of Gournia, and as it has been established from previous work, the remaining three information panels were not very popular (Chrysanthi and Caridakis 2015; Chrysanthi 2015). Also, there was only a single overlap between clustered points and curated points deriving from the paper-based interpretive media (Fig. 11). This point is located at the southern part of the archaeological site where the rare Mycenaean period remains are located (House He). In the case of Çatalhöyük, apart from the coinciding information panel (Building 5), the rest of the panels as well as the wooden path in the North Shelter where constantly relocated throughout the years of data collection, according to the excavation requirements each time. In essence, the visitor inconsistent movement/linger data regarding the highlighted locations of archaeological interest may have influenced the results.

However, the most interesting observation concerns the clustered points that do not coincide with the curated points. Based on the analysis at Gournia, apart from the entrance-ticket house stop, the first clustered point in the NE part of the site is related to a vantage point where visitors have the first impressive panoramic view of the Minoan town remains (Fig. 9).

The next popular linger location is to the north edge of the palace, near the identified remains of a bathroom. This is a feature of the site that is not highlighted in the interpretive media. Hence, it was not included in the curated paths. To decode why this particular location attracted visitors' attention, we consulted the results from previous work on the image analysis (Chrysanthi 2015). Based on the latter, 42% of the images of this area's hotspot concern views offered from this location towards the sea with direction to the North and the surrounding mountainous landscape with direction to the South and East of the site. The second (21%) and the third (19%) most popular themes recorded in this location are the remains of a drainage pipe and other wall

Fig. 8 Curated (red) versus Clustering-derived POIs (green) for the first curated path (CP1) at Gournia. (Color figure online)

Fig. 9 A panoramic view of the Gournia town from NE

remains from the northern part of the palace. Finally, a stone basin (10%) and the steps leading to the west paved street (8%) were the themes represented the least. The above analysis indicates that certain locations of the site attract visitor attention because they combine some interesting features rather than a single distinctive one. Consequently, our approach favors an exploration of the archaeological site that takes into account the things that visitors appreciate the most and reveals its non-contrived qualities both of archaeological and natural interest.

Characteristic examples of the above offer clustered points at the northern part of the Gournia site (Fig. 11), and the TP and TPC areas of Çatalhöyük (near the South Shelter) at locations with new archaeological discoveries and ongoing conservation work. Visitors' interest in the archaeological process, as well as the conservation techniques, were also addressed in the questionnaire feedback both at Gournia and Çatalhöyük.

This approach then, also raises the awareness that certain favored features of archaeological sites appear to be neglected in official interpretations, such as their surrounding landscape. Scholars, influenced by the research field of landscape archaeology (Thomas 2001), study rural archaeological sites with close reference to their broader setting; the surrounding landscape. In the context of heritage, the landscape plays a significant role in the hierarchy of spatial scales as one of the attributes of places (Graham et al. 2016). Including landscapes in heritage interpretation, can be valuable for the public understanding of and engagement with archaeological sites (Mosler 2006). As it became evident in the visitor study at Gournia, the natural setting of the site, the surrounding landscapes and the sea view, constitute very important aspects of

Fig. 10 View of the visitor itinerary and the surrounding landscape from the top of the East Mound at Çatalhöyük

the visitor experience. It provides a visual backdrop, whose properties such as form, color and light affect the attractiveness of a particular location as well as the whole place (Mosler 2006, p. 33). The visual attractiveness of landscapes is manifested in the plurality of images captured from existing vantage points and from different angles. This fact is also validated by the results in the case of Çatalhöyük, where visitors both showed interest (linger behavior) and requested more information (questionnaire data) along the path that connects the two sheltered areas and offers views to the surrounding landscape and nearby settlements (Fig. 10). The system took into account both the visitor behavior as well as the cultural curation to recommend the respective point of interest.

On the other hand, and in cases where the system deals with multiple parameters that influence visitor movement and interaction with the site, such as dense cultural and natural content, in addition to multi-directional configurations of space, the resulted points tend to incorporate this kind of "tensions" and complexities by generating mid-distance points. Such locations are observed at Gournia, North of the court in the palace area (Fig. 11) and at Çatalhöyük, in the South Shelter (Fig. 12).

Finally, our approach ignores existing paths which are not included in the curation scheme since they are not intended for visitors. A characteristic example of this is an alternative pathway bypassing the South Shelter at Çatalhöyük site and joining the path leading to the exit. This path was created mainly for facilitating fieldwork practicalities and is also used by fast track tourist groups who only visit the east vista of the South Shelter area (Perry et al. 2014). Evidently, although the system had input data indicating movement along this path, it chose to ignore it, as cultural and other patterns of movement behavior in the area, weighted more.

Fig. 11 Curated (red) versus Clustering-derived POIs (green) for the second curated path (CP2) at Gournia. (Color figure online)
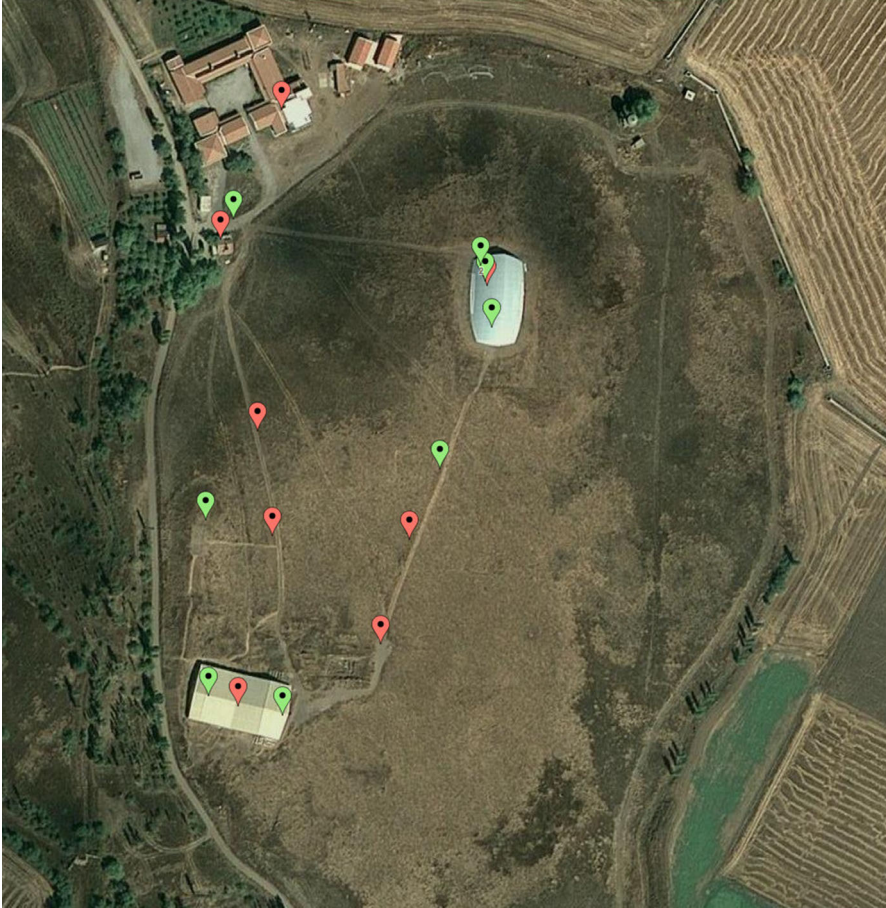
Fig. 12 Curated (red) versus Clustering-derived POIs (green) at Çatalhöyük. (Color figure online)

5.1.2 Quantitative analysis

In order to better estimate the proximity of the cluster centers to the curated points discussed above, we have performed the quantitative analysis presented in Table 2. More specifically, the average minimum distance between each point in the three curated paths and the most proximate cluster center is displayed. This is a way of evaluating the degree to which the cluster centers deviate from the points in the curated paths. As it is evident, the average deviation is between 12 and 20 m for all three paths. If the bandwidth parameter w of the mean-shift clustering algorithm is taken into account (3rd column of Table 2), it becomes clear that in all three cases, even though there exists a deviation between the exact location of cluster center and the curated point, they nevertheless fall within the same cluster, thereby further bolstering the choice of the specific clustering technique.

Table 2 Average minimum distance between the points of the curated paths and the cluster centers

Paths	Average minimum distance (m)	Bandwidth parameter w (m)
Gournia: 8 points (CP1)	15.99 ± 5.91	20
Gournia: 12 points (CP2)	12.59 ± 7.57	25
Çatalhöyük: 8 points	19.94 ± 11.55	30

Table 3 Influence of bandwidth in the number of clusters for the mean-shift clustering algorithm

Bandwidth parameter w (m)	Number of cluster centers		Silhouette coefficient	
	Gournia	Çatalhöyük	Gournia	Çatalhöyük
5	166	91	0.4477	0.4580
10	47	30	0.4920	0.6222
15	27	20	0.4994	0.6202
20	12	13	0.4244	0.5774
25	8	9	0.4232	0.7254
30	5	8	0.4398	0.7272

5.2 Path recommendation

In order to assess the performance of the proposed path recommendation system, a number of experiments have been conducted on the collected GPS datasets (Table 1). After the data preprocessing stage (Sect. 3.4), the points are clustered using the mean-shift clustering algorithm (Sect. 4.1). Since this procedure is dependent on the bandwidth parameter w, a number of clusterings have been produced for different values of w so as to determine its optimal level. Table 3 summarizes the influence of w to the number of produced cluster centers. In the Gournia dataset, the optimum value lies in the range of [20, 25] and for this reason both the upper and lower limit values have been included in the experiments, since the number of the obtained cluster centers ideally corresponds to the number of POIs in the two curated paths presented in Sect. 3.5.1. Similarly, for the Çatalhöyük dataset, the respective optimal value is 30 (Sect. 3.5.2).

Table 3 also includes the *Silhouette coefficient* (Rousseeuw 1987), a *validity index* (metric) for evaluating the quality of clustering algorithms. Domain values of the said coefficient fall in the range $[-1, +1]$, with higher values (closer to 1) indicating that samples are well matched to their assigned cluster and poorly matched to all other clusters. Consequently, the presented values are yet another indication of the suitability of the clustering algorithm (Sect. 4.1), in addition to the reasoning of Sect. 5.1.

The user models of Sects. 4.2 and 4.3 are also dependent on the length of the latent feature space (hyper-parameter z). Since the number of the cluster centers is relatively small (8 and 12 respectively), the number of the latent feature space also assumes small positive values (up to 12) in all cases. Finally, a *leave-one-out* cross-validation experimentation protocol has been employed in order to estimate the performance of each system. At each iteration of the protocol, the last 75% of the locations visited

by a particular user were extracted from the dataset and formed the test set. The remaining first 25% of the locations visited by the said user, along with the locations visited by all other users formed the training set, which was used to train the models. Then both models produced recommendations for the n subsequent locations to visit, where n is equal to the size of the test set. Those n recommendations were in turn compared to the actually visited locations by the (single) user in the test set, in order to calculate the accuracy of the recommended path. Of course, this requirement (of having accumulated the first 25% of the path prior to producing recommendations) is only part of this specific experimental procedure and not a hard threshold on the approach itself.

It should be noted that it wouldn't be sufficient to just recommend all other POIs not visited yet by the user, as visitors move freely in the sites and therefore they may visit the same POI more than once. Consequently, in the experiments that follow, the objective of the recommendation system is to not only predict the POIs to be visited but the number of times this is going to happen, as well. Additionally, the proposed algorithm requires the visitor to have visited only a few points (i.e. at the entrance of the site) prior to starting producing recommendations. Since the number of landmarks (l) and topics (z) remain constant (and of small magnitude) only $N(l, h^u)$, the number of times landmark l appears in the history of user u, will be incremented at each step (Sect. 4.2). Therefore, as the right-hand side of Eqs. 6 and 7 is modified slightly, the Expectation–Maximization algorithm will rapidly converge to a new optimal point, rendering the overall procedure computationally feasible, even for the handheld devices visitors carry. A similar analysis is also valid for the case of the Markov-Topic fusion model (Sect. 4.3).

6 Results

Figure 13 summarizes the accuracy of both models for the Gournia dataset, when the data points are clustered to 8 and 12 centers, respectively. The results presented are averaged for all 62 runs of the experimentation protocol and their statistical significance is asserted by the Wilcoxon signed rank test (p value < 0.01). A first observation is that the Topic Model fused with the first-order Markov Model (Markov-Topic) outperforms the simple Topic Model for all sizes of the latent feature space. The margin is around 5% for small values of z and is increasing as z grows to more than 10% in both cases. This observation is yet another indication that the current location of the visitor influences, to a certain extent, the location she is going to visit next.

Another interesting remark is that the performance of both models remains stable, as long as the latent feature space is smaller, or at least equal, to the number of the clusters. This is especially evident in the eight cluster case. On the other hand, in the twelve cluster case, the models seem to become less stable in terms of the prediction accuracy when the latent feature space becomes bigger than the cluster centers. Again, this behavior is justified by the fact that in topic modeling, by design, the latent feature space is supposed to be smaller in dimension than the variable it tries to model (the visited landmarks in this case).
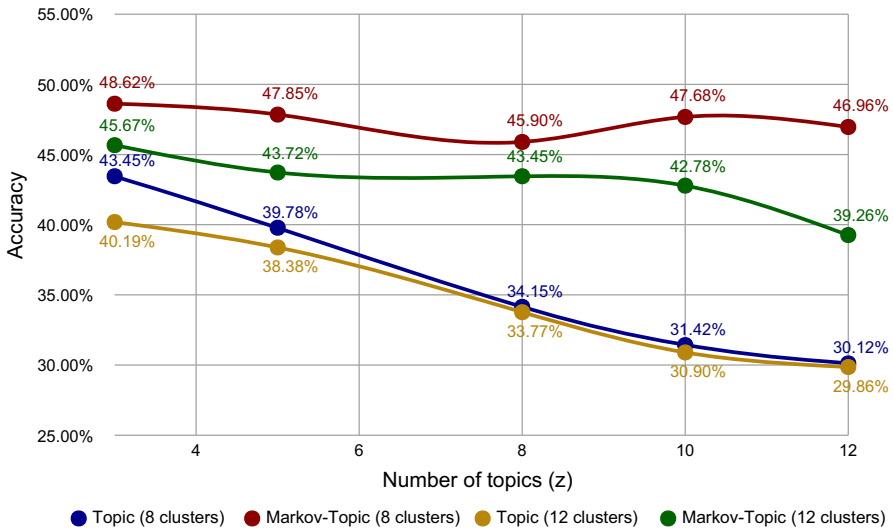
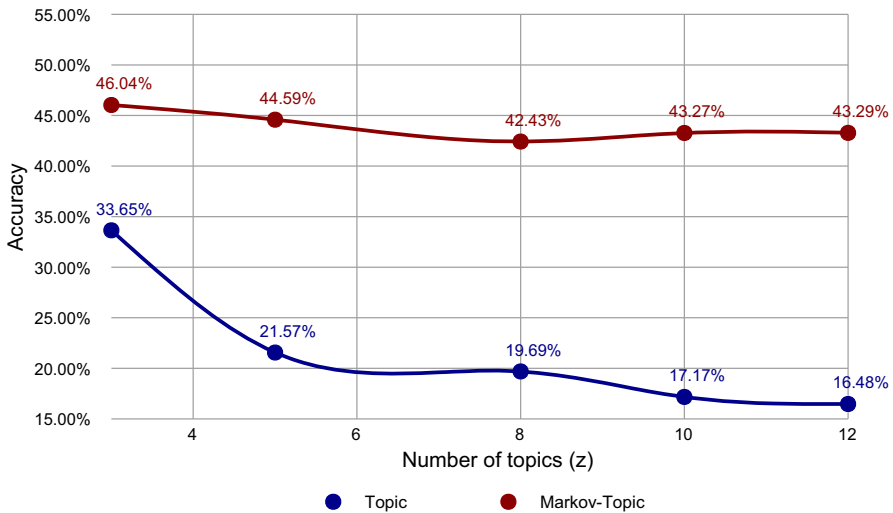**Fig. 13** Comparison of Topic and Markov-Topic Models in the Gournia dataset

Fig. 14 Comparison of Topic and Markov-Topic Models in the Çatalhöyük dataset

Figure 14 displays the accuracy of both models for the Çatalhöyük dataset when the data points are clustered to 8 centers. Similar to the previous case, the results are averaged for all 53 runs of the experimentation protocol and their statistical significance is again asserted by the Wilcoxon signed rank test (p value < 0.01). The performance of the Markov-Topic Model is superior to the Topic model in this case as well; a further indication of the suitability of the approach. The performance lead is also getting bigger along the increase of the latent feature space, at a bigger pace when compared to the Gournia dataset.

Once again, the performance of both models is better for small values of the feature space (smaller than the number of clusters). However, the stability of the Markov-Topic model is apparent for larger values of z, while the efficiency of the Topic model clearly deteriorates. Finally, an interesting side-observation is that the first-order Markov model is able to mitigate the negative effect of the increased latent feature space when the number of centers is smaller (8 centers in Figs. 13 and 14 compared to 12 centers in Fig. 13).

7 Conclusion and future work

The research work presented in the current article addressed the topic of personalized and context-aware cultural heritage path analysis and recommendation, experimentally validated on the archaeological sites of Gournia and Çatalhöyük. More specifically, the locations of archaeological and natural significance, vantage points and other points of interest are modeled using topic modeling, thus enhancing the typical route recommender system with cultural content, besides user and context, awareness. This aspect of route recommendation has been largely ignored by the abundance of generic or domain specific (e.g., tourism) work published in the wider research area of path recommendation and constitutes the presented work's core scientific contribution. Additionally, curated paths, as point sequences, were compared to automatically extracted points, via clustering, derived from actual user tracks, further validating the cultural content consideration as a parameter of the system.

Overall, the proposed architecture includes a preprocessing module of the raw GPS data and location is modeled using mean-shift clustering, trained with actual user movement patterns. Once the cluster centers have been determined, two different recommendation models are trained, one based on user and topic modeling and an ensemble structure incorporating first-order Markov models, thereby addressing the temporal aspect of the problem. The obtained results demonstrate a significant performance lead of the Topic Model fused with the first-order Markov Model when compared to the simple Topic Model. The results validate the efficiency in modeling and incorporating the cultural content of the route into the recommended path.

The curation of the three alternative paths, based on the available interpretation of the site and the comparison of the curated points of the paths to the points derived from the clustering process, provided useful insights on both the curation itself as well as the actual user movement patterns, as depicted in the clustering results. For example, contextual information regarding the site's location such as the impressive panoramic view of the Minoan town remains in the NE part of Gournia, is overseen from the route's curators but arises from the automatic analysis. On the other hand, the system generates some mid-distance points instead of curation-defined clearer ones, influenced by the dense cultural and natural content originated tendencies, as depicted in the visitors' movement patterns.

Since the system proposed in the current article is a cultural route recommender system, an empirical evaluation method will be adopted to measure its efficiency regarding Cultural User eXperience, apart from the purely quantitative performance (accuracy). This will allow the evaluation to depict aspects beyond system performance, as a rec-

ommender approach. UX aspects within the Cultural Heritage context will be defined in order to model CUX and field study evaluation (visitor behavior monitoring) will be fused with questionnaires, interviews and focus groups to assess the influence of the recommendation module to the user's visit. Participants will, although not finalized, include visitors of the Gournia and Çatalhöyük archaeological sites and more sites will be considered so as to additionally validate the approach's generalization to other sites. Test and control groups will be defined and implicit (empirical methods) and explicit (field observation and system usage logs) data collection methodologies will be applied.

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