Review

Intelligent tourism recommender systems: A survey

Joan Borràs [a,b,*], Antonio Moreno [b], Aida Valls [b]

[a] Science & Technology Park for Tourism and Leisure, C/Joanot Martorell, 15, 43480 Vila-Seca, Catalonia, Spain
[b] Intelligent Technologies for Advanced Knowledge Acquisition (ITAKA), Departament d'Enginyeria Informàtica i Matemàtiques, Universitat Rovira i Virgili, Av. Països Catalans, 26, 43007 Tarragona, Catalonia, Spain

A R T I C L E   I N F O

A B S T R A C T

Recommender systems are currently being applied in many different domains. This paper focuses on their application in tourism. A comprehensive and thorough search of the smart e-Tourism recommenders reported in the Artificial Intelligence journals and conferences since 2008 has been made. The paper provides a detailed and up-to-date survey of the field, considering the different kinds of interfaces, the diversity of recommendation algorithms, the functionalities offered by these systems and their use of Artificial Intelligence techniques. The survey also provides some guidelines for the construction of tourism recommenders and outlines the most promising areas of work in the field for the next years.

© 2014 Elsevier Ltd. All rights reserved.

1. Introduction

The amount of information available in the World Wide Web and its number of users have experienced an enormous increase in the last decade. All this information may be particularly useful for those users who plan to visit an unknown destination. Information about travel destinations and their associated resources, such as accommodations, restaurants, museums or events, among others, is commonly searched for tourists in order to plan a trip. However, the list of possibilities offered by Web search engines (or even specialised tourism sites) may be overwhelming. The evaluation of this long list of options is very complex and time consuming for tourists in order to select the one that fits better with their needs.

Personalization techniques (Gao, Liu, & Wu, 2010) aim to provide customised information to users based on their preferences, restrictions or tastes. They are particularly relevant in recommender systems (Adomavicius & Tuzhilin, 2005), whose objective is to filter irrelevant options and to provide personalised and relevant information to each particular user. In the tourism field, travel recommender systems (Ricci, 2002) aim to match the characteristics of tourism and leisure resources or attractions with the user needs. These systems are especially useful if they can automatically learn the user's preferences through the analysis of her explicit or implicit feedback (Sieg, Mobasher, & Burke, 2007). Explicit

data may be given by the user in different ways, for instance whenever she specifies her cultural interests by filling in a form. Implicit interests can be inferred by the system through the analysis of the behaviour of the user.

In many cases recommender systems not only take into account the preferences of the tourist but they also analyze the dynamic *context* (Dey & Abowd, 1999) of the trip. This is especially useful when tourists are already at the destination and they are willing to use their mobile devices to customise their trips in real time. The context can include aspects like the tourist's location, the time of the visit or the current weather (Lamsfus, Alzua-Sorzabal, Martin, Salvador, & Usandizaga, 2009). Approaches that take context into account can send suggestions proactively, depending on the current state of the tourist. For example, a museum that was planned to be visited today may be too far from the visitor and she may not have enough time to reach it, so the plan scheduled for tomorrow may be changed to include the visit to the museum.

The last ten years have witnessed an explosive increase in the use of mobile technology among tourists. Therefore, e-Tourism systems (Buhalis, 2003) provide a good opportunity for mobile services that help visitors by offering recommendations based on their preferences and their current context.

This paper focuses on tourism recommender systems that employ Artificial Intelligence (AI) techniques at some point. Some examples can be the following:

- *Intelligent autonomous agents* may analyse the behaviour of a user, learn automatically the user profile and provide proactive recommendations depending on the current context (Batet, Moreno, Sánchez, Isern, & Valls, 2012).

- Some systems go beyond offering a list of recommended tourist attractions and use automated *planners* to schedule these recommendations within a route that can span several days (Vansteenwegen, Souffriau, Vanden Berghe, & Van Oudheusden, 2010).
- Other approaches take into account the opening and closing times of the attractions, or the time needed to go from one point of interest to another, hence offering a detailed timetable of the visit. However, this is a very complex planning and scheduling problem for which it is difficult to guarantee an optimal solution. Some systems solve this complexity with the use of AI *optimization* techniques, such as *ant colony* or *meta-heuristic iterative* methods (Lee, Chang, & Wang, 2009).
- Automatic *clustering* algorithms may be applied to classify tourists with similar tastes or similar features (Gavalas & Kenteris, 2011).
- *Approximate reasoning* methodologies, like *fuzzy logic* or *Bayesian networks*, may be used to manage the imprecision related to the inference of the preferences of the user (Huang & Bian, 2009).
- *Reasoning* procedures, like rule-based systems, are also employed to deduce the user's preferences (Lamsfus, Alzua-Sorzabal, Martin, & Smithers, 2011).
- Formalisms developed in the knowledge representation field of AI, like *ontologies*, are commonly used to represent (and reason about) the tourism domain knowledge (Moreno, Valls, Isern, Marin, & Borràs, 2013).

The contributions of this article are twofold. On the one hand, it provides a comprehensive review of the tourism recommender systems published in scientific journals and conferences since 2008, with an especial focus on the ones that employ AI techniques. Commercial products are not considered in this review, as it is usually not possible to know how they have been designed and implemented. Several aspects of these systems are analysed, such as their interface, their functionalities, the recommendation mechanisms and the AI methods and techniques employed. This review provides an up-to-date state of the art of the field of intelligent tourism recommenders, which may be useful not only to the scientists working in this field but to designers and developers of intelligent recommender systems in other domains. On the other hand, the paper also provides guidelines to be followed in the design of this kind of intelligent systems and an outline of some of the most promising research lines that may be pursued in the near future.

The reminder of this review is structured as follows. In the next section we analyze which interfaces are commonly used by tourism recommender systems to interact with users, discussing especially the differences between mobile and Web-based approaches. After that we survey the main functionalities offered by these systems, ranging from the recommendation of a tourist destination to the automatic construction of a detailed complex schedule of a visit of several days to a certain area. Section 4 comments the recommendation methods employed by e-Tourism recommenders, focusing on content-based and collaborative approaches. The next section exposes the use of AI techniques from different fields like multi-agent systems, approximate reasoning, knowledge representation, etc. A comparison with previous surveys on tourism recommenders is given in Section 6. The paper concludes with a global analysis of the surveyed systems and some suggestions of lines of future work in the field.

2. Interface

This section analyses the user interfaces of recent tourism recommender systems. Most of them offer a Web-based interface and/or an interface specifically designed to be used in mobile devices. Table 1 classifies the most relevant e-Tourism recommenders in these two broad categories, and Fig. 1 shows the percentage of surveyed systems in each of them. A Web-based interface is the option chosen by most of the systems, since it permits an easy access from any computer connected to the Web without any kind of downloading, installation and configuration. However, due to the enormous increase in the use of smart phones connected to the Web in the last years, more than half of the reviewed systems have specific interfaces for mobile devices.

There are some recommender systems that have been designed as desktop applications and do not offer any of the two usual kinds of interfaces (e.g., Kurata, 2011). This kind of applications can usually be implemented more quickly than the mobile or Web-based ones; however, they require downloading and installing the program, which is not comfortable to most of the tourists that want to get recommendations as simply as possible without being bothered by technical details.
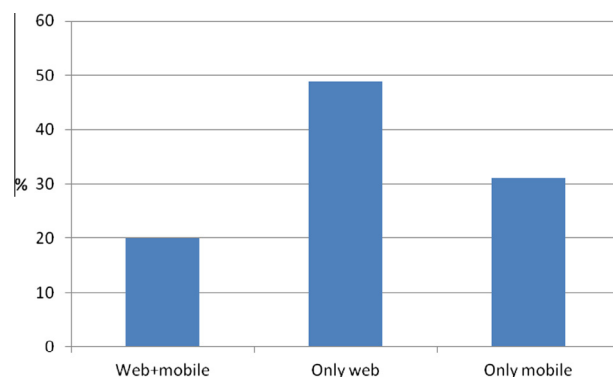

Fig. 1. Interfaces used in the reviewed works (in%).

Table 1
Review of user interfaces.

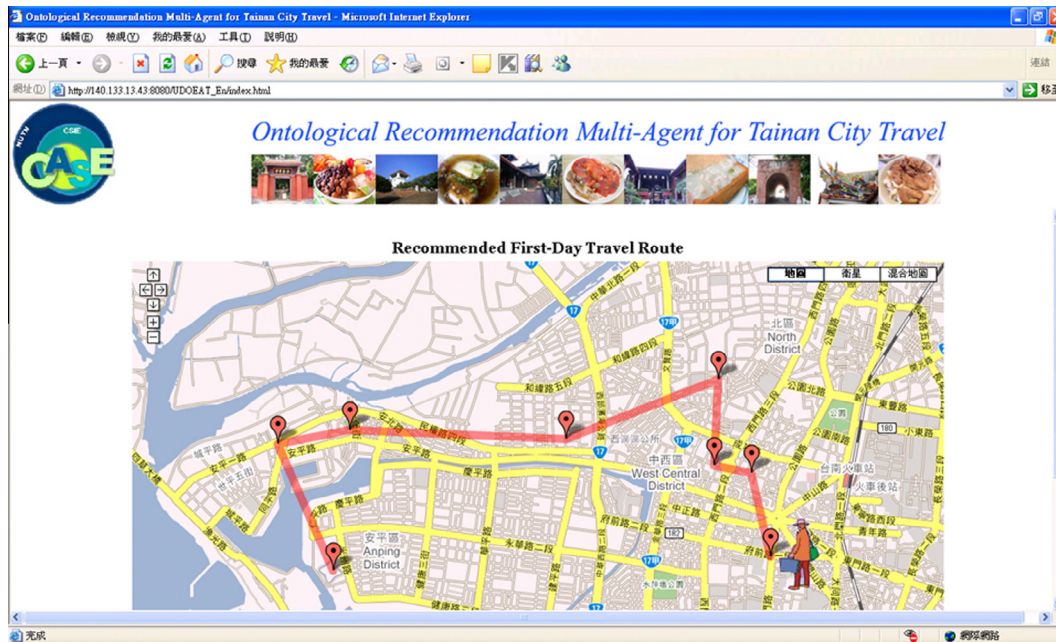| Interface	References
Web + mobile	Venkataiaha et al. (2008),(Lamsfus et al. (2009), Niaraki and Kim (2009), Vansteenwegen et al. (2010), Gavalas and Kenteris (2011), Rey-López et al. (2011), Borràs et al. (2012a), Ruotsalo et al. (2013) and Umanets et al. (2013)
Only web	Coelho, Martins, and Almeida (2009), Huang and Bian (2009), Lucas, Laurent, Moreno, and Teisseire (2009), Lee et al. (2009), Ruiz-Montiel and Aldana-Montes (2009), Jannach et al. (2010), Mínguez et al. (2010), Sebastià et al. (2010), Yang (2010), Borràs et al. (2011), García-Crespo, López-Cuadrado, Colomo-Palacios, González-Carrasco, and Ruiz-Mezcua (2011), Linaza, Aguirregoikoa, García, Torres, and Aranburu (2011), Lorenzi et al. (2011), Luberg et al. (2011), Montejo-Ráez et al. (2011), Sebastià et al. (2009), Garcia et al. (2011), Wang et al. (2011), Koceski and Petrevska (2012), Gyorodi et al. (2013), Kurata and Hara, (2013), Lucas et al. (2013) and Savir et al. (2013)
Only mobile	Castillo et al. (2008), Ceccaroni et al. (2009), García-Crespo et al. (2009), Yu and Chang (2009), Ricci et al. (2010), Martin et al. (2011), Batet et al. (2012), Martínez-Santiago et al. (2012), Noguera et al. (2012), Braunhofer et al. (2013), Garcia et al. (2013), Meehan et al. (2013), Rojas and Uribe (2013) and Yang and Hwang (2013)

Fig. 2. Personalized route through Tainan City (from Lee et al., 2009).

The following subsections review some approaches based on Web or mobile interfaces.

2.1. Web-based recommenders

The use of a Web-based interface is the most common option adopted by e-Tourism recommenders. This kind of interfaces allows tourists to look for information in a user-friendly manner. Users normally have a rich interaction with the system using a wide screen which allows displaying a large amount of data extended with maps, images or even high quality videos. Moreover, the mouse permits to interact easily with the computer and move through maps, perform zoom actions, select items or even drag and drop them. This is very useful for tourists when they are still in the planning stage of their trips. Nevertheless, Web-based applications are usually not designed to be used during the stay since most of the tourists will not have easy access to computers with Internet connection. Although an increasing number of tourists have mobile handsets or tablets with Internet connection, the information-ridden Web pages usually shown by recommenders cannot be easily read or manipulated on such small screens. In the remainder of this section we comment some interesting features exploited in Web-based interfaces to improve the interaction with the users.

Venkataiaha, Shardaa, and Ponnadaa (2008) report the design of two visualisation systems (called *discrete* and *continuous*) for a tourism recommender and compare the interaction of the users in both cases. The former provides a high quantity of information in the screen at the same time, and it was determined that users needed too much time and effort to understand it. The latter aggregates all the information into a single video clip that combines the most relevant media content, including text, photographs and videos.

The approach shown in Lee et al. (2009) is one of the firsts that embeds Google Maps Services[1] in their Web pages (Fig. 2) in order to plot the travel route on a map, so that tourists can follow the per-

sonalised itinerary to enjoy cultural heritage and local gourmet food during their stay at Tainan City.

Other Web-based recommender systems that display in a map the places scheduled to be visited in a single day are *e-Tourism* (Sebastià, Garcia, Onaindia, & Guzman, 2009), *City Trip Planner* (Vansteenwegen et al., 2010), *Otium* (Montejo-Ráez, Perea-Ortega, García-Cumbreras, & Martínez-Santiago, 2011) and *EnoSig-Tur* (Borràs et al., 2012a). In this last system the user introduces her socio-demographic information and general preferences (left image of Fig. 3), and then she will receive recommendations of attractions spread out over the province of Tarragona, a wide region of Spain (right image of Fig. 3). The last Web page shows a high quantity of information, such as geo-localised attractions classified by categories, a route indicating driving times between the suggested activities, their approximate visiting times, etc.

The *VIBE virtual spa advisor* (Jannach, Zanker, & Jessenitschnig, 2010) keeps an avatar-based conversation with the tourist in order to acquire the user's visit requirements through personalised forms. The main point of this approach is its dynamicity. If a new attribute has to be added to the product catalogue, it is automatically taken into account not only in the recommendation and preference elicitation processes, but also in the Web interface which is changed accordingly. The Web site has a section for domain experts, in which they can add or modify logical conditions that govern the conversational and recommendation procedures.

Wang, Zeng, and Tang (2011) show how Semantic Web technologies may be integrated with Web 2.0 services to leverage each other's strengths. To do so they proposed an ontology-based tourism recommender that allows the automatic and dynamic integration of heterogeneous on-line travel information. The platform is built in Ruby on Rails with view extensions to create rich Ajax Web-based applications. They also use third party services to provide additional features, such as Google Map, Yahoo Weather, and WikiTravel.

2.2. Mobile recommendations

Systems that offer mobile interfaces have increased considerably in the last few years, due to the large number of users acquir-

---

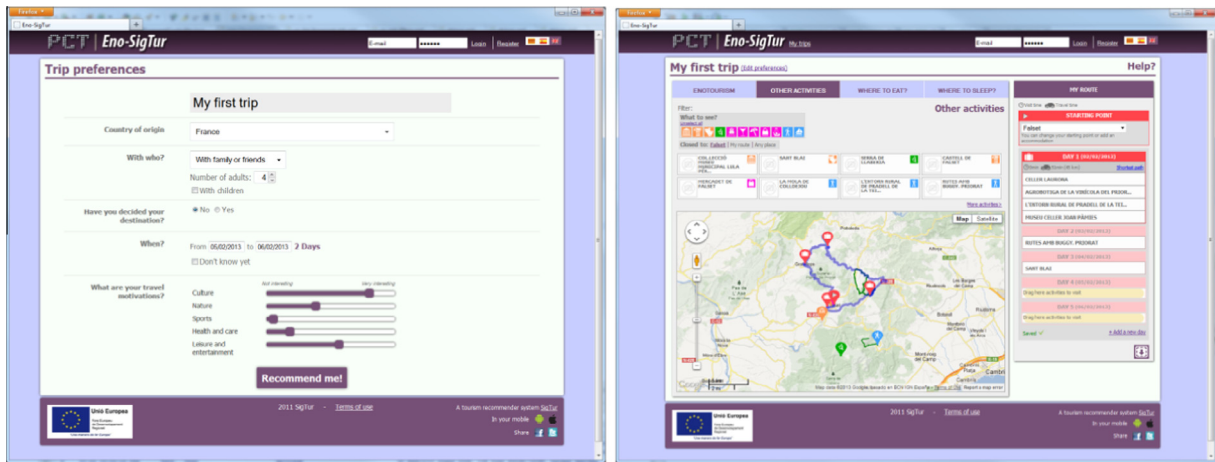[1] https://developers.google.com/maps/ (last access March 2014).

Fig. 3. Web version of EnoSigTur: introduction of initial user profile and route planner (from Borràs et al., 2012a).

ing mobile devices with Internet connection or, more recently, the well-known smartphones. Mobile devices are small and their Internet connection is usually slow; thus, the quantity of information that can be shown in these devices cannot be compared with a standard Web page. Therefore, mobile tourism recommender systems have to make an effort to provide only the information that is essential for the user, and it must be well structured in order to be displayed correctly in small screens. Moreover, the user's interaction with the system is limited, since even the basic actions made in Web-based interfaces (scrolling, introducing text) are not that easy. However, it is fair to say that the latest smartphones with bigger touchscreens provide a better user interaction. Furthermore, the main advantage of mobile devices is that they allow the use of the system in any place with an Internet connection, so that tourists may access information, discover places or modify their trips during the stay. Besides, most mobile systems are equipped with GPS and the recommender may know the present location of the user and it may offer geo-referenced information, advice or recommendations based on this knowledge.

One of the first approaches in the field that used mobile systems was reported in Yu and Chang (2009). This system, designed for PDAs, offers location-based recommendation services to support personalised tour planning. Recommendations are based on tourists' preferences, location and time. Fig. 4 shows the mobile user interface in four separated screenshots. The first one shows the different mobile tourism services (restaurant, hotel, sightseeing spot, user profile, and tour plan recommendation). The second image illustrates the interface for setting user preferences. The third screenshot shows the recommended tour plan with information about the places to visit, such as names, descriptions, photos or visiting time frames. Finally, the last image displays the tour plan on Google Maps.

Another approach compatible with PDAs is *MTRS* (Gavalas & Kenteris, 2011). The authors argue that tourists may have problems to connect with the Internet, either because they are in a rural area or because they are foreigners and cannot afford the roaming costs abroad. They propose to solve this problem by installing an infrastructure to support proximity detection and a cost-effective means for remote content update. In fact, they propose to use small- to medium-scale wireless sensor networks. Through this infrastructure, they introduce the concept of 'context-aware rating', in which user ratings uploaded through fixed Internet connection infrastructures (located at the rated places) are weighted higher to differentiate them from users that provide an evaluation using the Internet away from the visited place.

Fig. 4. Prototype system for Windows mobile devices (from Yu & Chang, 2009).

Another product using mobile devices is *MapMobyRek* (Ricci, Nguyen, & Averjanova, 2010) that exploits quite well its interface by showing recommendations in lists and on maps. This system permits to compare two items with their characteristics displayed side-by-side in order to decide the one that is preferred.

GeOasis (Martínez-Santiago, Ariza-López, Montejo-Ráez, & Ureña-López, 2012) acts as a tourist guide that describes the places to visit while the tourist approaches the recommended locations. The system uses the mobile GPS device to know the tourist location and speed in order to estimate the available time to give the explanations. Users can interact with the system in two ways: using a tactile interface or using a voice-based interface (voice recognition and text-to-speech software).

Despite the existence of several mobile tourism recommenders, not many of them use the newest technologies in mobile devices, such as the Android or iPhone platforms. Some examples that use these popular and rising platforms are reviewed below.

The *moreTourism* (Rey-López, Barragáns-Martínez, Peleteiro, Mikic-Fonte, & Burguillo, 2011) Android-based platform provides information about tourist resources through the use of mashups, integrating images, videos, augmented reality services, geo-location, guide services, access to urban networks, etc. Another approach that uses Android platforms is *EnoSigTur* (Borràs et al., 2012a). Fig. 5 shows some screenshots of the mobile version of *EnoSigTur*: a list of recommended places, the route of the trip and detailed information of an attraction.

LiveCities (Martin, Alzua, & Lamsfus, 2011) uses the notification service of Android systems to provide push information according to the user context. This information can be plain text, audio, video or HTML. The *STS* system (Braunhofer, Elahi, Ricci, & Schievenin 2013) is a powerful Android application with a good design interface that permits the user to enter accurate information about her interests and opinions on the trip and the visited attractions (see Fig. 6).

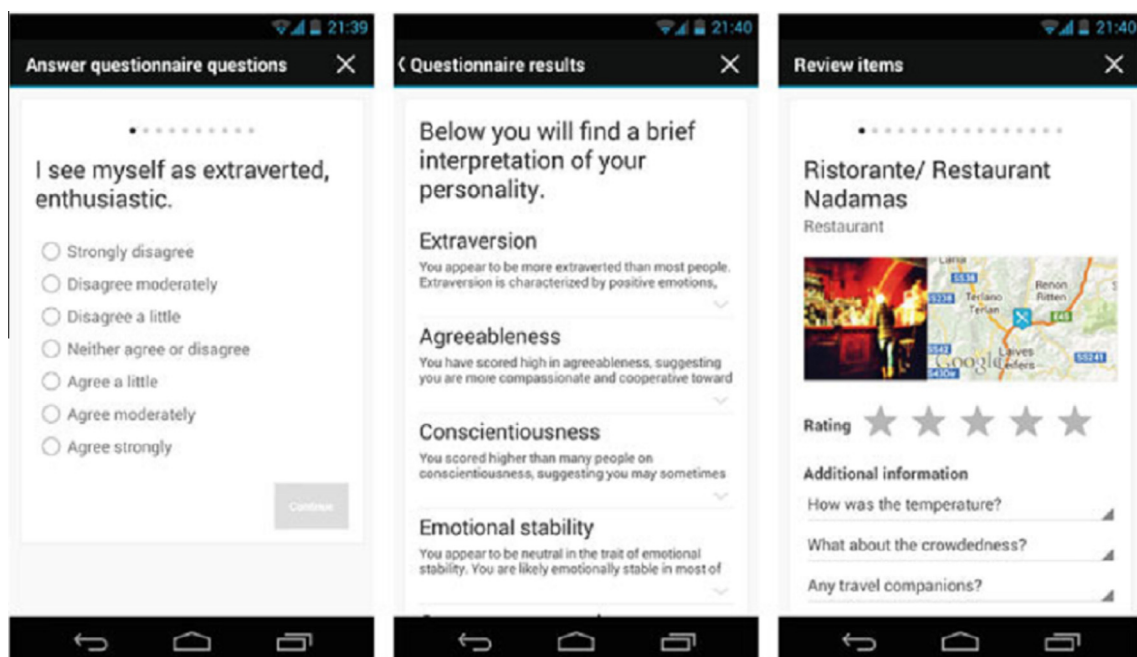**Fig. 5.** Mobile version of EnoSigTur (from Borràs et al., 2012a).

Fig. 6. Preference elicitation from the mobile interface of the *STS* system (Braunhofer et al. 2013).
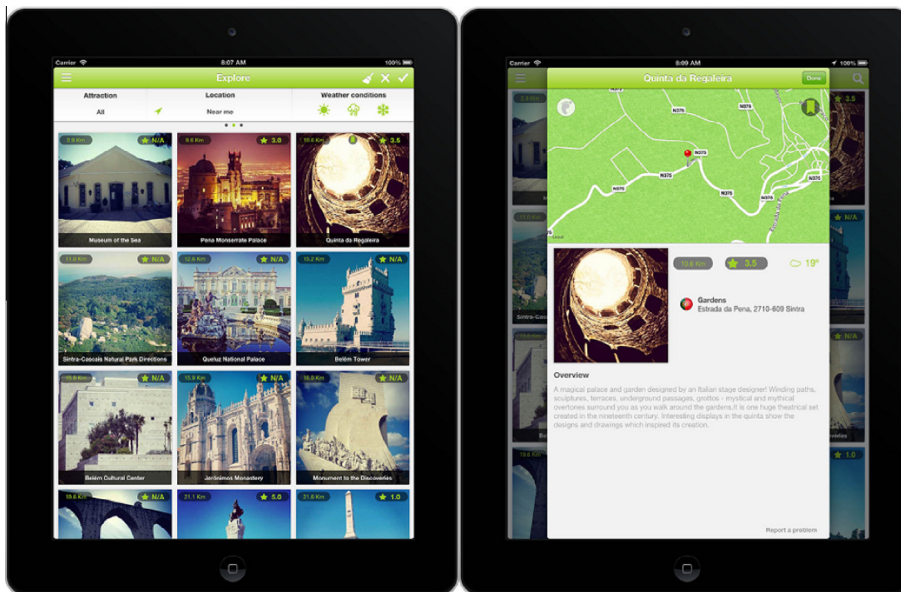
Fig. 7. iPad version of the *GUIDEME* system (Umanets et al. 2013).

The recent *GUIDEME* system (Umanets, Ferreira, & Leite 2013) features a good implementation for mobile devices since its designers have not only developed an app for phones but also for tablet devices. In particular, the app is built for the iOS platform and it is adaptive to the screen sizes with specific adjustments for both iPhone and iPad devices. Fig. 7 shows screenshots of its iPad version. *REJA* (Noguera, Barranco, Segura, & Martínez, 2012) also works for iOS platforms.

3. Functionalities

In this section we describe the general functionalities provided by the reviewed tourism recommender systems. Table 2 catalogues the approaches in four broad groups, depending on the services they offer: suggestion of a destination and construction of a whole tourist pack, recommendation of suitable attractions in one specific destination, design of a detailed multi-day trip schedule, and social capabilities. Fig. 8 gives a visual estimation of the percentage of systems that offer each of them. These aspects are commented in more detail in the following subsections, with examples of the most prominent proposals.
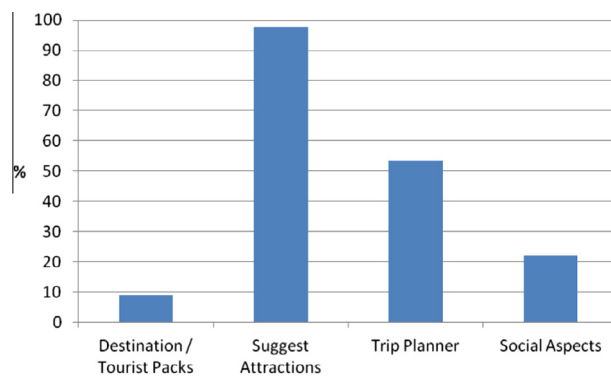

Fig. 8. Functionalities applied in the reviewed approaches (in%).

3.1. Travel destination and tourist packs

Some of the reviewed systems focus on the recommendation of a destination that suits the user's preferences. This is the case of systems like *PersonalTour* (Lorenzi, Loh, & Abel, 2011), *Itchy Feet*

Table 2
Review of user functionalities.

Functionalities	References
Destination/tourist packs	Seidel et al. (2009), Yu and Chang (2009), Lorenzi et al. (2011) and Koceski and Petrevska (2012)
Suggest attractions	Castillo et al. (2008), Coelho et al. (2009), Ceccaroni et al. (2009), García-Crespo et al. (2009), Huang and Bian (2009), Lamsfus et al. (2009), Lucas et al. (2009), Lee et al. (2009), Niaraki and Kim (2009), Ruiz-Montiel and Aldana-Montes (2009), Yu and Chang (2009), Jannach et al. (2010), Mínguez et al. (2010), Ricci et al. (2010), Sebastià et al. (2010), Vansteenwegen et al. (2010), Yang (2010), Borràs et al. (2011), Fenza et al. (2011), Gavalas and Kenteris (2011), Kurata (2011), Linaza et al. (2011), Lorenzi et al. (2011), Luberg et al. (2011), Martin et al. (2011), Montejo-Ráez et al. (2011), Rey-López et al. (2011), Sebastià et al. (2009), Garcia et al. (2011), Wang et al. (2011), Batet et al. (2012), Borràs et al. (2012a), Koceski and Petrevska (2012), Martínez-Santiago et al. (2012), Braunhofer et al. 2013, Garcia et al. (2013), Gyorodi et al. 2013, Kurata & Hara 2013, Lucas et al. (2013), Meehan et al. (2013), Rojas and Uribe (2013), Ruotsalo et al. (2013), Savir et al. (2013), Umanets et al. (2013) and Yang and Hwang (2013)
Trip planner	Castillo et al. (2008), Coelho et al. (2009), Ceccaroni et al. (2009), García-Crespo et al. (2009), Huang and Bian (2009), Lucas et al. (2009), Lee et al. (2009), Niaraki and Kim (2009), Yu and Chang (2009), Mínguez et al. (2010), Sebastià et al. (2010), Vansteenwegen et al. (2010), Kurata (2011), Linaza et al. (2011), Luberg et al. (2011), Montejo-Ráez et al. (2011), Rey-López et al. (2011), Sebastià et al. (2009), Garcia et al. (2011), Wang et al. (2011), Batet et al. (2012), Borràs et al. (2012a), Kurata & Hara 2013, Lucas et al. (2013) and Savir et al. (2013)
Social aspects	Coelho et al. (2009), Ceccaroni et al. (2009), García-Crespo et al. (2009), Vansteenwegen et al. (2010), Rey-López et al. (2011), Sebastià et al. (2009), Garcia et al. (2011), Garcia et al. (2013), Meehan et al. (2013), Umanets et al. (2013) and Yang and Hwang (2013)

(Seidel, Gärtner, Pöttler, Berger, & Dittenbach, 2009) and *MyTravelPal* (Koceski & Petrevska, 2012). *PersonalTour* is used for travel agencies to help their costumers to find the best travel packages according to their preferences. Once the recommendation process is finished, a rated list of options is presented to the costumer. Table 3 shows an example of the hotel recommendation service. After that, the customer can rate each item of each travel service.

Itchy Feet not only recommends tourism destinations but also provides purchasing services for booking a trip and assistance from professional travel agents. Users make search requests, which are handled by autonomous agents that search for information in the internal database as well as in external data sources. The results are shown to the user through the interface, where recommended items (flights and hotels) can be selected and purchased.

MyTravelPal (Koceski & Petrevska, 2012) first recommends areas of interest over a region graphically (see Fig. 9), where the size of the circle indicates the level of affinity with the user. Once the user focuses on a particular area, their tourist resources are also shown and sized depending on the affinity to the user profile.

3.2. Ranked list of suggested attractions

Most Tourist recommender systems tend to suggest places once the user has decided the destination of the trip or she is already there. These systems are more complex, since they can suggest a large number of attractions, accommodations, restaurants or even temporal events. In this con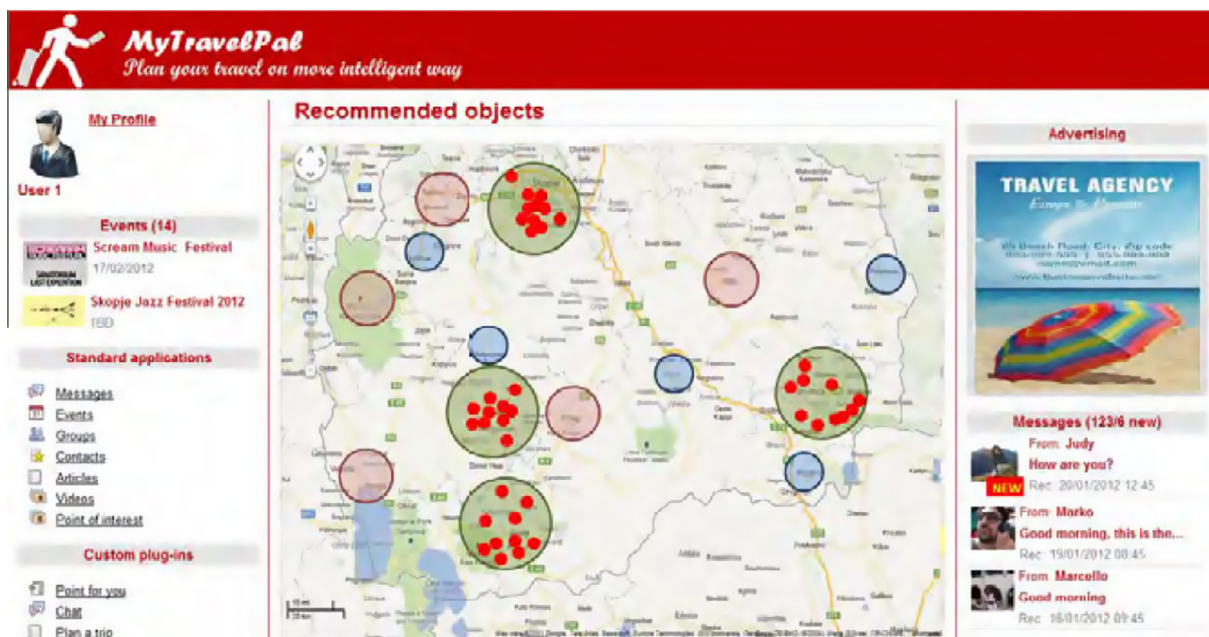text the capability of recommenders to classify and rank only those elements considered important for a particular user among the huge quantity of available information is very useful. With the support of these systems the users can find interesting places in an efficient way and even discover unexpected ones that may be of their interest. The activities to be recommended are normally stored in a static database, although some systems (e.g. *Otium*, Montejo-Ráez et al., 2011) extract automatically information about events from the Web to ensure that they always provide updated information.

This kind of recommender systems (e.g. Borràs et al., 2011; Fenza, Fischetti, Furno, & Loia, 2011; Ruiz-Montiel & Aldana-Montes, 2009; Sebastià et al., 2009) usually provide a list of activities that match the user profile, have been visited and/or positively evaluated by similar users in the past, or are similar to activities previously enjoyed by the user. Thus, they include mechanisms to compare the user preferences with the features of an object, or to compare the similarities between two users or two objects (more details on the recommendation techniques are given in Section 4). The selection of the recommended items may also take into account contextual factors, like the present location of the user (Noguera et al., 2012). Some systems are also capable of justifying the provided recommendations (e.g. Jannach et al., 2010).

SMARTMUSEUM (Ruotsalo et al., 2013) is an example of a more complex recommendation system, which detects automatically if the user is outdoors or indoors, based on her location. For the first case, it can display the recommendations on a map. For indoor scenarios, it gives a list of the most relevant objects according to the

Table 3
Example of hotel recommendation in PersonalTour (adapted from (Lorenzi et al. (2011)).).

Id	Hotel name	City	Hotel category	Room category	Room type	Swimming Pool	WiFi
1	Libertel	Paris	Economic	Standard	Double	No	Yes
2	Palladium	Punta Cana	Resort	Luxe	Double	Yes	Yes
3	Amadeus	Milan	Economic	Standard	Single	No	Yes
4	Riu Palace	Cancun	First	Luxe	Double	Yes	Yes
5	WestIn	Aruba	Economic	Luxe	Double	Yes	Yes

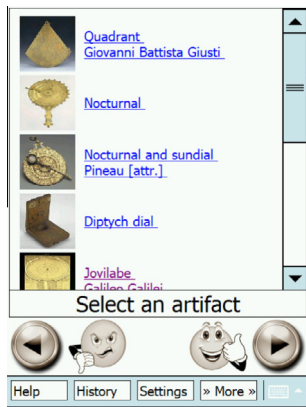**Fig. 9.** *MyTravelPal* – recommendation of regions of interest.

Fig. 10. List of recommendations of specific objects for indoor scenarios.

user's preferences. This is useful, for instance, in museums, where the number of objects to see may be relatively high (Fig. 10).

3.3. Planning a route

There are several projects that not only provide a list of the places that fit better with the user's preferences but also help tourists to create a route through several attractions.

CT-Planner (Kurata, 2011; Kurata & Hara, 2013) offers tour plans, as shown in Fig. 11, that are refined gradually as the user's expresses her preferences and requests (duration, walking speed, reluctance to walk, etc.). It displays a radar chart that represents the user's preferences and a cartoon character as a navigator, in order to enrich the sense of user-friendliness and interactivity.

There are several systems that provide an initial set of recommended activities (or an initial plan), with which the user can directly interact to add more activities, remove activities, select an activity to be visited, change the order of visit, etc. The planning component of the recommender system takes into account important factors like the expected duration of the visit, the opening and closing times of the attractions and the distance between them. Some relevant examples include *EnoSigTur* (Borràs et al., 2012a), *City Trip Planner* (Vansteenwegen et al., 2010), *CRUZAR* (Mínguez, Berrueta, & Polo, 2010), *Smart City* (Luberg, Tammet, & Järv, 2011), *Otium* (Montejo-Ráez et al., 2011) and *e-Tourism* (Sebastià et al., 2009). A more detailed review of trip planning functionalities is available in (Vansteenwegen & Souffriau, 2011). Some advanced recommenders, like *SAMAP* (Castillo et al., 2008) and *PaTac* (Ceccaroni, Codina, Palau, & Pous, 2009), are capable of analysing the connection possibilities between the activities using different means of transport (walking, by bike, by car, or by public transport).

Some of these systems incorporate more complex *Geographical Information Systems* (GIS) to manage the geographical data associated to the touristic points and events. (Huang & Bian, 2009) argued that it is computationally unfeasible to maintain large amounts of spatial data and use them in planning procedures. Hence, they used existing geospatial Web service technologies, in concrete the ESRI ArcWeb Service,[2] to obtain the location of the attractions, the distance between them given their street address, and driving directions between two attractions. *GeOasis* (Martínez-Santiago et al., 2012) continually calculates the position and the speed of the user. The estimated time to reach a place is considered in order to create the plan in real time. The key aspect is the prediction of where the user will be in the immediate future: in a city, near a city or on the road. If the user is already in a city, the planning algorithm checks the nearest places to the user without taking into

account the route or the speed, since it is considered that the user is close to them. If the user is near a city, the planning algorithm checks the most relevant attractions in it. If the user is on the road, but not near a city, then the planning algorithm is more complex because it considers temporal constraints. The plan is not computed by the server but by the client application, since it is constantly checking the location by GPS. Routes are computed using Google Maps as an external resource.

Once the visit plan has been completely defined, the user may wish to retrieve the full schedule to follow the route. This retrieval can take different forms. Systems like *SAMAP* (Castillo et al., 2008) or *EnoSigTur* (Borràs et al., 2012a) allow downloading a PDF file that contains a geo-referenced map with a detailed explanation of the plan. In others, like *City Trip Planner* (Vansteenwegen et al., 2010) and Otium (Montejo-Ráez et al., 2011), the user can download the route to a mobile phone.

3.4. Social aspects

Several projects (e.g. Ceccaroni et al., 2009; Garcia, Torre, & Linaza, 2013; Umanets et al., 2013; Vansteenwegen et al., 2010) have paid special attention to the inclusion of *social* functionalities that allow users to share material (pictures, comments, evaluations) and interact with other tourists. These aspects may be very interesting to help to promote the use of a recommender among the visitors of a particular city. Recommenders like *moreTourism* (Rey-López et al., 2011) and *Itchy Feet* (Seidel et al., 2009) allow users not only to interact over popular social networks but also to create location-based activity groups that can be employed to post comments, join groups for doing common activities or interact with other users. The system *e-Tourism* (Garcia, Sebastià, & Onaindia, 2011) allows to create plans that accommodate the preferences of a whole group of visitors.

In *iTravel* (Yang & Hwang, 2013) users communicate among them with mobile peer-to-peer communications to send ratings of attractions. Their navigation map not only displays the location of attractions but also the position of near-by users with which it is possible to communicate. Fig. 12 shows a map with recommended attractions (green pins) and nearby users (blue pins).

The *VISIT* system (Meehan, Lunney, Curran, & McCaughey, 2013) applies sentiment analysis techniques (using the Alchemy API[3]) to analyse the updates about a given attraction in Twitter and Facebook and identify if users are expressing positive or negative comments about it. This information is shown with green and red colours by the system in its interface, so that the user may easily identify those places visitors are loving most today and which not.

4. Recommendation techniques in e-Tourism

Recommender systems have been classically classified, according to the way in which they analyze the information of the user and filter the list of items, into content-based, collaborative and demographic systems (Burke, 2002; Manouselis & Costopoulou, 2007; Montaner, López, & de la Rosa, 2003). In this section we introduce these three paradigms, analyzing its use in current tourism recommender systems. In addition, we present the different user models that have been employed in those systems.

4.1. Approaches to recommendation

Content-based (CB) systems calculate a degree of similarity between the users and the items to be recommended. The process

---

[2] http://www.esri.com/news/arcuser/0403/arcweb.html (last access March 2014).

[3] AlchemyAPI (2014). Alchemy API: Transforming text into knowledge. [Online] http://www.alchemyapi.com/.

Fig. 11. CT-Planner2 user interface (from (Kurata, 2011)).

Fig. 12. Navigation map of *iTravel* (from Yang & Hwang, 2013).

is carried out by comparing the features of the item with respect to the user's preferences. So, it is assumed that both users and alternatives share a common representation (e.g., they are composed of the same set of attributes or keywords). The output of the comparison process is usually an overall performance score, which indicates the degree of matching between the user's profile and each alternative. The higher the score is, the higher the performance of the alternative for a given user. Sometimes these methods also take into account the rating history of the user. In this approach, the recommendation system relies on having an accurate knowledge of the user's preferences to be able to select the appropriate

items. This kind of approaches may suffer from the "*cold start*" problem when a new user enters in the system, because we can elicit poor knowledge about the user in an initial stage. Some solutions to this problem are explained later in this section.

In CB systems the recommendation process is mainly focused on defining an appropriate measure to compare a user and an item. The two most common approaches are the aggregation of ratings and distance calculation.

- When the user profile is represented as a rating vector with the degree of interest of the user in each attribute, each rating can be interpreted as a performance score that can be used to evaluate an alternative. The goal is then to calculate an overall interest score for a certain alternative. The simplest approach consists of using an aggregation operator to combine the user ratings on the concepts that define a certain alternative (Batet et al., 2012). More sophisticated aggregation methods have also been applied, like AHP (*Analytic Hierarchy Process*) (Huang & Bian, 2009; Niaraki & Kim, 2009).
- When the items and the users are described by a list of keywords, some similarity measures can be applied. For example in Lamsfus et al. (2009) items and users are described using concepts from an ontology, which defines archetypes of tourists (e.g. cultural, sportive or adventurous), and the cosine similarity between the two vectors (user and item) is calculated. A similar approach is proposed in Gyorodi, Gyorodi, and Dersidan (2013) with ad-hoc hierarchies of tags for locations that are rated by users. The locations ratings are then compared to the user's tags. In García-Crespo et al. (2009) a feature-based similarity algorithm is applied, using several ontologies as reference. In Fenza et al. (2011) classification rules are automatically generated and later used to define the matching degree between the user and the item.

Other methods of recommendation exploiting AI techniques are explained in Section 5, such as the ones using rules or probabilistic information.

Collaborative (CL) systems make recommendations based on groups of users with similar preferences. The similarity between users is normally computed by comparing the ratings that they give to some of the items. When the system identifies who are the people that share similar interests with the current user, then the items that those people liked are recommended to this user. In this approach, some feedback about the provided recommendations is necessary, in order to know which items the user has liked or disliked (e.g. which places she has enjoyed visiting). Two types of CL methods are distinguished: *user-based* and *item-based*. The former finds neighbours of a target user by matching her opinions with the ones of the other users in the system. The latter builds groups by finding similarities on the items that the users liked (or disliked) in the past.

Two weak points are recognised in CL systems: "*data sparsity*" and "*grey sheep*". The former occurs when the number of ratings from users is small in comparison with the total number of items, so that the probability of finding users that rate the same items is too low to make good estimations. The latter, "grey sheep", refers to a user with a profile different from the rest of users of the system. In this case, it is difficult to find appropriate items to recommend because we do not have information about similar users. Finally, this approach also suffers from the *scalability* problem if the community of users is large.

Demographic-based (DM) systems rely on the demographic data of the user (e.g. age, country of origin, level of studies, etc.). In this case, the recommendation is not based on the user's interests and preferences but on her personal characteristics. In this approach, users are usually assigned to a certain stereotypical class depending on their demographic data, so that the members of the same group share a common demographic profile. The system has internal knowledge about the standard preferences of each stereotype, which is used to provide the recommendations to the users. The definition of stereotypes of tourists is not new in this field. Many studies have defined segments of tourists according to their behaviour in different cities or territories (Brewer, 1984; Marques, 2009; Tsung-Chiung, Chyong-Ru, & Wan-Chen, 2012). Specific stereotypes provide precise descriptions of what tourists want and how they act in different situations. This information is normally used as a guide to conduct business with tourists, but it can also be exploited in recommender systems.

Since each of the approaches has some drawbacks, the combination of different techniques is also a widespread practice.

Fig. 13 shows the distribution of the types of recommendation techniques used in the field of tourism recommenders, in percentages. Half of the works use a mixture of techniques (53%), combining mainly CB methods with CL filtering or with DM techniques. The rest of the systems apply a single approach, having a clear predominance for the techniques based exclusively on the description of the content of the alternatives (38% of the reviewed papers).

Hybrid systems can integrate these techniques in different ways. Three approaches can be distinguished:

1. Selection of the method: the system incorporates DM, CB and CL methods, but only one of them is applied depending on the particular situation of each user. For example, the first time the user arrives, a method based on demographic data is used. Later on, if similar users can be found, a CL recommendation is made. Otherwise, a CB procedure is applied. This is the case of Martínez, Rodríguez, and Espinilla (2009), Huang and Bian (2009) or Noguera et al. (2012).
2. Sequential use: each recommendation technique is used in different stages of the process. For example, *SPETA* (García-Crespo et al., 2009) has four steps: first, contextual information such as the location or time are used to make the first selection of appropriate options; second, a more fine grained set of results is obtained using knowledge-based filtering techniques, by calculating the semantic similarity between the user preferences and the touristic services; third, preferences and CL techniques are used to refine the set of options; finally, in the fourth step, a vector of preferences is used to make the final selection. In Braunhofer et al. (2013) CL filtering with DM and personal information is applied in a training phase to build a prediction model in different contexts. Once the model has been trained, CB techniques generate the list of recommendations by computing ratings for each item based on the current and predicted values.
3. Integrated use: both CB and CL techniques are combined during the execution. For example, in *SigTur* (Borràs et al., 2011) different ratings are calculated to estimate the interest of an activity for a target user. Ratings are obtained using DM-clustering, CL-clustering and CB similarity; afterwards, these ratings are merged to find an overall quality rating for each item and make the filtering of the best tourist attractions. In Lucas et al. (2013) the users are classified into groups using simultaneously personal demographic data (DM), information about the content of the items previously selected by the user (CB) and the information of other users (CL). Then a set of fuzzy rules is automatically generated so that new users can be automatically classified into several groups (with different membership degrees). The list or recommended items is finally derived from a prediction based on the groups the user belongs to.

In the survey we have observed an increasing trend in the exploitation of CL filtering techniques since 2012, mainly in hybrid systems. More precisely, from 2008 to 2011 only 25% of systems used such method, whereas since 2012 the percentage has increased to 75% (see Table 4).

4.2. Representation of the user profile

A key component in recommender systems is the user profile, which stores the information related to the user preferences and permits to make personalised recommendations. Different user profile models have been developed. The simplest model associates to each user a list of preferred keywords or categories in which items are pre-classified. However, this information is usually too general to provide accurate recommendations. A more widespread approach consists of storing a vector with numerical ratings corresponding to the attributes of the items. This rating indicates the degree of interest of the user with respect to each attribute. This vector approach facilitates the inclusion of other types of features
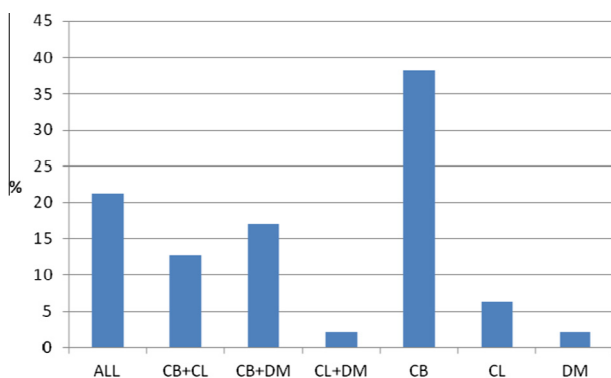

Fig. 13. Recommendation techniques used in the reviewed works (in%).

Table 4
Review of recommendation methods used.

Recommendation method	Reference
ALL	Lucas et al. (2009), Ruiz-Montiel and Aldana-Montes (2009), Borràs et al. (2011, 2012a), Batet et al. (2012), Koceski and Petrevska (2012), Braunhofer et al. 2013, Garcia et al. (2013), Lucas et al. (2013) and Meehan et al. (2013)
CB + CL	Castillo et al. (2008), García-Crespo et al. (2009), Fenza et al. (2011), Rey-López et al. (2011), Noguera et al. (2012) and Rojas & Uribe 2013
CB + DM	Coelho et al. (2009), Ceccaroni et al. (2009), Lamsfus et al. (2009), Niaraki and Kim (2009), Mínguez et al. (2010), Yang (2010), Martin et al. (2011), Sebastià et al. (2009) and Garcia et al. (2011)
CL + DM	Gavalas and Kenteris (2011)
CB	Huang and Bian (2009), Lee et al. (2009), Seidel et al. (2009), Yu and Chang (2009), Jannach et al.,(2010), Ricci et al. (2010), Sebastià et al. (2010), Vansteenwegen et al. (2010), García-Crespo et al. (2011), Kurata (2011), Linaza et al. (2011), Lorenzi et al. (2011), Luberg et al. (2011), Montejo-Ráez et al. (2011), Martínez-Santiago et al. (2012), Gyorodi et al. (2013), Kurata and Hara (2013) and Ruotsalo et al. (2013)
CL	Savir et al. (2013), Umanets et al. (2013) and Yang and Hwang (2013)
DM	Wang et al. (2011)

in the profile, such as demographic information, as can be seen in Codina and Ceccaroni (2010), Garcia et al. (2011), Mínguez et al. (2010) and Kurata and Hara (2013).

These basic models can be extended by means of some AI knowledge representation techniques. One possibility is to use *semantic models*, in which the domain knowledge usually takes the form of an ontology. For example, the keyword list may contain names of classes in the ontology (i.e. concepts) and the ratings vector can also be defined in the space of the concepts in the ontology. *Uncertainty models* have also been incorporated into some recommender systems to be able to handle the credibility associated to the information stored in the profile. The rating values are uncertain in many situations, especially when they are not given explicitly but have to be inferred from the user interaction with the domain items. A confidence degree can be associated to each rating in the profile and can be used as a weighting factor in the exploitation stage. More details about these techniques are given in Sections 5.5 and 5.4, respectively.

In order to produce up-to-date personalised recommendations to the same user along time, the user model has to be updated. Feedback information is used to modify the profile when any change on the user's preferences is detected. This information can be collected explicitly or implicitly. Explicit feedback is obtained by means of the direct interaction with the user. The decision maker is requested to fill in some form (giving her opinion on different values of the criteria or indicating her location) or to rate a set of alternatives. This approach provides precise knowledge because the data is given directly by the user. However, it is usually considered quite an intrusive way of elicitation, and many users are not keen on spending time in answering this kind of questions. Techniques based on implicit feedback aim at collecting the user information by analysing her behaviour in the system, such as

the alternatives that are selected, purchased or viewed. More sophisticated tools study the sequence of actions done by the user on a certain alternative, or even the amount of time spent with each one. The main advantage of these methods is that an additional effort from the user is not required. For example, in Savir, Brafman, and Shani (2013), the travellers modify a trip plan and the system observes the modifications to adjust the budget, daily time, maximum travel distance, transportation constraints, etc. Other works (Albanese, Chianese, d'Acierno, Moscato, & Picariello, 2010; Albanese, d'Acierno, Moscato, Persia, & Picariello, 2013; Moscato, Picariello, & Rinaldi, 2013) analyze the sequence of accesses to information, to deduce which is the most accessed object after viewing a specific one. They use both low level (colour, texture) and high level (author, type) features of objects to compare the usage behavioural patterns. Despite the advantages of implicit feedback, this kind of data is more uncertain than explicit information, so less confidence must be given to it when the profile is modified. In this review we observed that around 60% of the works use only explicit feedback, whereas the rest combine explicit and implicit feedback. The most common approach in explicit feedback collection consists of requiring the user to vote the different options proposed by the system. The most sophisticated approach is presented in the *VIBE* system (Jannach et al., 2010), which builds personalised dialogues to gather new knowledge about the user preferences.

5. Use of AI techniques in tourism recommender systems

This section makes a brief review of the main AI techniques and tools employed in tourism recommender systems in the last years, which are summarised in Table 5.

Table 5
Review of the AI techniques used.

AI techniques	References
Multi-agent systems	Castillo et al. (2008), Ceccaroni et al. (2009), Lee et al. (2009), Seidel et al. (2009), Sebastià et al. (2010) and Lorenzi et al. (2011)
Optimization techniques	Castillo et al. (2008), Lee et al. (2009), Garcia et al. (2010), Vansteenwegen et al. (2010), Garcia, Vansteenwegen, et al. (2013) and Meehan et al. (2013)
Automatic clustering	Castillo et al. (2008), García-Crespo et al. (2009), Martínez et al. (2009), Fenza et al. (2011), Gavalas and Kenteris (2011), Batet et al. (2012), Noguera et al. (2012), Lucas et al. (2013), Kurata & Hara 2013, Ruotsalo et al. (2013) and Moreno et al. (2013)
Management of uncertainty	García-Crespo et al. (2009), Huang and Bian (2009), Lamsfus et al. (2009), Lamsfus et al. (2011), Pinho et al. (2011), Wang et al. (2011), Hsu et al. (2012), Lucas et al. (2013), Meehan et al. (2013) and Ruotsalo et al. (2013)
Knowledge representation	Castillo et al. (2008), Ceccaroni et al. (2009), Lamsfus et al. (2009), Lee et al. (2009), Sebastià et al. (2009), Sebastià et al. (2010), Garcia et al. (2011), García-Crespo et al. (2011), Wang et al. (2011), Alonso et al. (2012), Batet et al. (2012), Martínez-Santiago et al. (2012), Lucas et al. (2013), Ruotsalo et al. (2013) and Moreno et al. (2013)

5.1. Multi-agent systems

Agents are autonomous and proactive software entities capable of obtaining information from their environment and acting in an intelligent way upon it in order to try to accomplish a set of goals or objectives. *Multi-agent systems* are groups of agents that communicate between themselves to share information and resources, coordinate their activities and cooperate in the joint efficient solution of a distributed problem (Wooldridge, 2009).

Turist@ (Batet et al., 2012) is an agent-based system that provides personalised recommendations on cultural activities. The architecture of the system is shown in Fig. 14. There is one agent for each kind of cultural activity, which maintains a small database with the events of that type available in the city (museums are the exception, as there is one specific agent for each museum in the city). The user interacts with the system through a graphical interface provided by a *User Agent*. A *Broker Agent* mediates the communication between the *User Agents* and the cultural activities agents. The user can make specific queries, can evaluate an activity that she has attended, or can ask for a personalised recommendation. The core of Turist@ is the *Recommender Agent*, which maintains a user profile for each tourist. This profile is initialised with some basic information on high-level cultural interests provided by the user when she uses the system for the first time. The *Recommender Agent* dynamically and automatically refines this initial knowledge about the user preferences by analysing the user's queries and evaluations. The *User Agent* can also provide proactive recommendations, because it knows the position of the user in the city and can suggest cultural activities that fit the user's preferences and are located in the vicinity. The system uses both CB and CL recommendation techniques.

The idea of having an initial profile and refining it by analysing the explicit (evaluations) and implicit (actions) activities of the tourist is also given in Ceccaroni et al. (2009). That work proposes to have a *Profile Management Agent*, which not only initializes the profile (by fitting the user into stereotyped classes) but also modifies it depending on the feedback provided by the tourist. In this agent-based proposal there are *Information Service Agents* that retrieve touristic information from databases and ontologies, and a *Personalization Agent* that, given the user profile and the available touristic data, applies CB recommendation techniques to select the items that should be suggested.

In *PersonalTour* (Lorenzi et al., 2011) there is a set of *Travel Agents*, and each of them is specialised in the recommendation of flights, hotels or attractions. When a new costumer arrives and expresses her preferences, these agents collaborate among themselves in order to propose a travel package to the tourist. The user can later evaluate each of the components of the package, providing a feedback to the system so that the degree of expertise of each *Travel Agent* can be conveniently updated.

Some recommenders (e.g. Castillo et al., 2008; Lee et al., 2009; Sebastià, Giret, & Garcia, 2010) "agentify" the different components of the system (the interface with the user, the capture of her requirements and preferences, the analysis of the suitability of each attraction, the creation of a route among the selected points of interest), although there is not any kind of complex communication or coordination between them. In all these systems the agents seem to work in a sequential fashion, without any kind of coordinated effort. Therefore, the full potential of distributed, concurrent and coordinated behaviour of agents is not employed.

5.2. Optimization techniques

Many tourism recommender systems have to solve complex planning and scheduling problems, which are well known to be NP complete and, therefore, cannot be optimally solved in an efficient way. In some cases, researchers have opted for the use of different kinds of optimization techniques which, although in many cases they do not guarantee the optimal solution, offer an affordable computational cost.

One example is the agent-based travel route recommender for Tainan (Lee et al., 2009), that uses *ant colony* optimization techniques. In these methods a set of autonomous entities (which represent the *ants*) cooperate through pheromone-mediated indirect and global communication to find a good solution to the travelling salesman problem (in this case, to plan a route that goes through different points of interest around the city). *CT-Planner4* (Kurata & Hara, 2013) uses a *genetic algorithm* to construct the plan to visit a city. In each iteration of a cyclic process it considers a population of different possible plans, which are evaluated according to their utility for the user; the best ones are mutated and recombined via crossover to generate another population for the next iteration. After a certain number of iterations, the best plan is finally selected. The authors of the *VISIT* system (Meehan et al., 2013) propose to make recommendations adapted to the context of the user, that is composed of different factors (location, time, weather, social media sentiment and user preferences). In that work, they suggest the idea of using an *artificial neural network* to assess the relevance of each context component for each user.
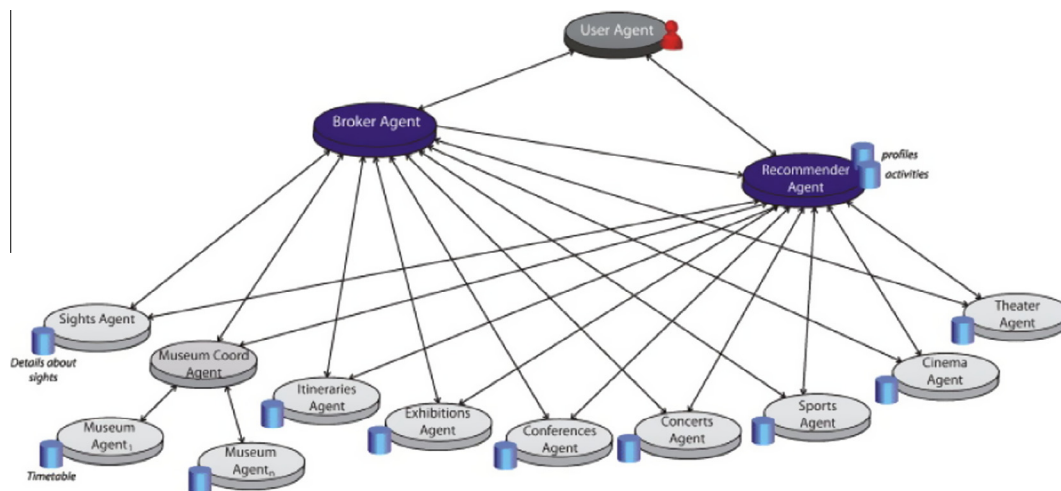

Fig. 14. Multi-agent based architecture of Turist@ (from Batet et al., 2012).

Some heuristic procedures to build travel itineraries were explored in the *City Trip Planner* system and related works (Garcia, Arbelaitz, Linaza, Vansteenwegen, & Souffriau, 2010; Garcia, Vansteenwegen, Arbelaitz, Souffriau, & Linaza, 2013; Vansteenwegen et al., 2010). One possibility is the use of *Iterated Local Search*, a meta-heuristic iterative method that builds sequences of solutions generated by a local search. The heuristic perturbs the solution found by the local search (a route to visit some city attractions) to create a new solution. Then, it takes the best solution as the new starting solution for the local search. The process is repeated until a termination criterion is met. Another option that was studied is the use of meta-heuristic iterative *Greedy Randomised Adaptive Search* methods (Souffriau, Vansteenwegen, Vanden Berghe, & Van Oudheusden, 2011). In each iteration a list of possible visits is generated from an initial solution which contains only the start and end of each tour. Those visits that have a heuristic value below a certain threshold are eliminated. A random visit from the remaining list is selected and applied to the current solution.

Most of the tourism recommender systems that build personalised routes or itineraries implement an ad-hoc planning mechanism, but some of them apply more classical domain-independent AI planning techniques. For instance, in the *SAMAP* system (Castillo et al., 2008) the use of heuristic, A* and hierarchical temporal planners was explored.

5.3. Automatic clustering

Many tourism recommenders employ techniques based on CL filtering, in which the users of the system are partitioned into groups that share some common characteristics. The basic idea of these methods is that it can be appropriate to recommend to the user those items that have been positively valued by similar tourists. The concept of similarity employed to group users may be based on demographic information, on the general preferences of the users over diverse types of touristic activities, or on the explicit ratings of individual activities. In any case, the automatic clustering tools developed in AI may be successfully used to classify the tourists. This section comments different alternatives that have been used in touristic recommender systems.

A very simple way of associating a new user with similar past users of the system is to employ the *k-nearest neighbours* approach (Dasarathy, 1991), calculating which are the k past users of the system who were more similar to the current one (e.g. Martínez et al., 2009; Noguera et al., 2012). Having done that, the information on those users may be employed to provide recommendations (e.g., the activities that were more highly valued for them). In *SAMAP* (Castillo et al., 2008) the similarity between users is based on the preferences expressed over the concepts of a domain ontology (a portion of it may be seen in Fig. 15). For instance, the system could easily infer that a user that likes *Cinema* is more similar to a user that enjoys *Theatre* than to another that prefers *Sport* activities. Scalability is one of the main problems to be addressed when using this method.

A common option to group the users into different classes is to use the *k-means* algorithm (e.g. Gavalas & Kenteris, 2011; Pinho, da silva, Moreno, de Almeida, & Lopes, 2011). The initial seeds of the k desired clusters are established in some application-dependent way. Then there is an iterative process in which, in every step, the objects are sorted into the nearest cluster and the cluster prototypes are recalculated. The method converges to a solution when the objects belong to the same clusters in two consecutive iterations. In Moreno et al. (2013) the *k-means* algorithm is applied with three different purposes: to obtain a set of initial tourist segments,
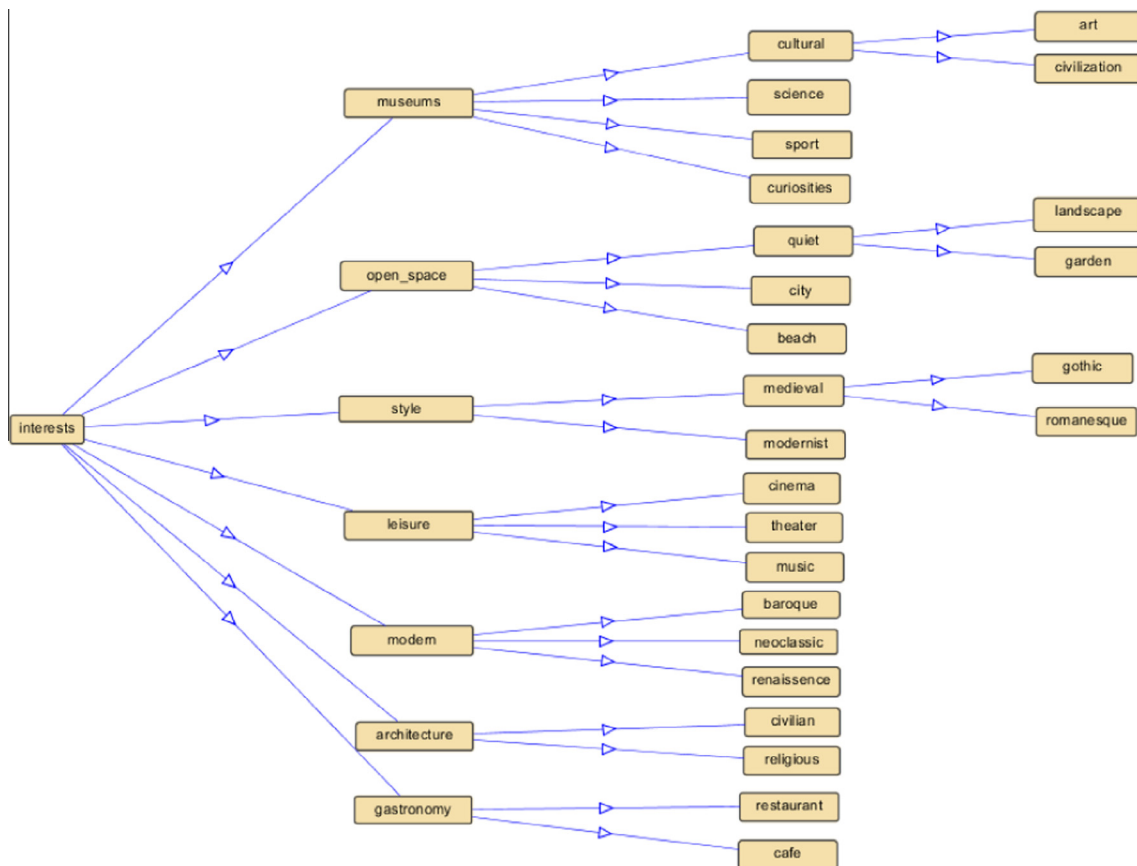

Fig. 15. Portion of the *SAMAP* domain ontology (adapted from Castillo et al., 2008).

to obtain classes of users with similar demographic characteristics, and to classify users according to the explicit ratings they have provided. In the first case, the historical data of 30,000 questionnaires was used to compute a set of 100 generic tourist types (segments). Each of them had an associated prototype and a preference level for each kind of activity. New users fill a small form with some basic personal and preference data and it is possible to compute the segment to which they belong, guiding the initial recommendations. The demographic classification is mainly based on the country of origin, the travel group composition, the travel budget and the accommodation type. Aggregation operators like *OWA* (Yager, 1988) and *LSP* (Dujmovic & Nagashima, 2006) are used to join the similarities on these different kinds of data. The classification of the users according to their ratings uses the well-known *Pearson correlation* as similarity measure.

The recommender system described in Fenza et al. (2011) proposes the use of the uncertain version of k-means, *fuzzy c-means*. The result of this algorithm is a fuzzy partition of a set of objects into clusters, so that each object has a degree of membership between 0 and 1 to each cluster, and the addition of the degrees of membership to all the clusters is 1. This algorithm is both applied to users and to touristic points of interest (POIs). After the definition of clusters of users and POIs, the system is able to derive rules that characterise them, that are used to integrate new users and new POIs to the clusters in which they fit better. This work also proposes to build *association rules*, which explain the relationship between clusters of users (plus contextual information) and clusters of POIs. These rules permit to determine the kind of touristic activities that should be recommended to a certain type of users. Very similar techniques are employed in the *PSIS (Personalised Sightseeing Information System)* recommender (Lucas et al., 2013).

Turist@ (Batet et al., 2012) also employs CL filtering recommendation techniques that require the definition of classes of similar users. The clustering is applied every time that 10 new users join the system, so classes are periodically recomputed. The employed clustering system is *ClusDM* (Valls, 2003), which builds a hierarchy of classes taking into account the interests of the users in general kinds of activities and their demographic data. The tree generated by the algorithm can be cut at different levels to generate partitions with the desired number of classes.

The use of Support Vector Machines (SVMs) as a classification technique in tourism recommender system is suggested in the *SPETA* system (García-Crespo et al., 2009). Tourist preferences on several kinds of tourist activities are stored in a vector, and the characteristics of each activity are also stored in the same way. Thus, SVMs may be used to compute the distance between the user's preferences and the recommendable items, so that the most appropriate ones can be efficiently found.

5.4. Management of uncertainty

The task of recommending activities to a tourist is not simple, as there is not any clear and precise relationship between the characteristics and preferences of a visitor and the POIs available at a given destination. Some of the techniques developed in the AI field of *approximate reasoning* have been proposed to represent and reason about this uncertain relationship.

One possibility is to use *Bayesian networks* (Pearl, 1988). A Bayesian network is an acyclic graph in which edges represent relationships of causality or influence between nodes. Nodes that do not have any parent have an associated probability table, indicating how likely they are to occur. Nodes that have n parents have a conditional probability table of 2^n nodes, indicating how likely they are to occur depending on the presence (or absence) of their parents. A very simple use of Bayesian networks is presented in Hsu, Lin, and Ho (2012), where a number of attributes (age, nationality, occupation, income, travel motivation, etc.) influence directly on the probability that a certain touristic point is interesting for the user. The initial Bayesian network was built after the analysis of more than 2400 questionnaires. A more complex application of this kind of networks is given in Huang and Bian (2009) and Wang et al. (2011). They propose a network (see Fig. 16) in which the age, occupation and personality influence the type of user which, along with the travel motivation, influences the probability of the user liking a certain kind of touristic destinations. Specific touristic events are not included in the network.

Another common option to manage uncertainty is the use of *fuzzy logic*. A fuzzy variable make take as values a series of linguistic labels. Each linguistic label has an associated fuzzy set, in which every value in the domain of reference is assigned a membership value to the set between 0 and 1. In that way, fuzzy logic provides a generalisation of standard logic. Fuzzy sets and fuzzy reasoning may be used to represent the preferences of the user and to calculate how they fit with the characteristics of a tourist attraction (García-Crespo et al., 2009; Lee et al., 2009), to obtain the degree of membership of each user to different groups of users (Pinho et al., 2011) or to represent contextual aspects of the journey (Meehan et al., 2013). For instance, if the weather conditions are represented with a value between 0 and 1, instead of using a simple Boolean value for good/bad weather, it is possible to make a more fine grained analysis of the weather conditions and reason about its influence on the recommendation of each cultural activity.
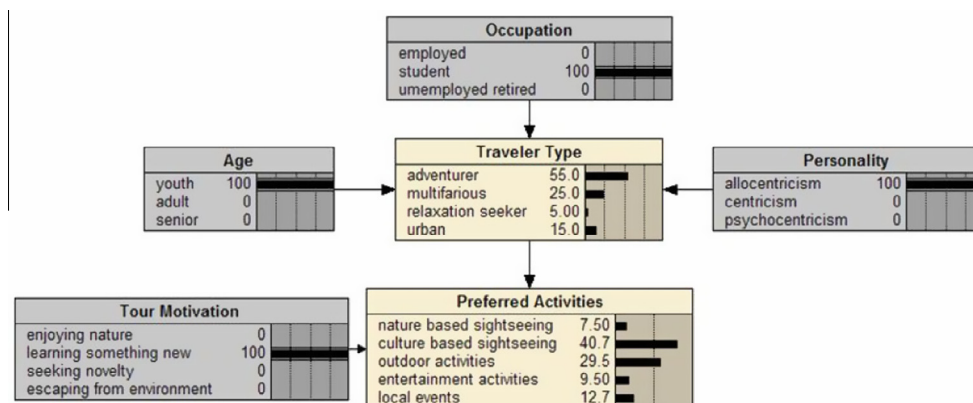

Fig. 16. Use of a Bayesian network to detect the preferred kind of tourist activities (from Huang & Bian, 2009).

Some touristic recommender systems also employ a rule-based approach, but without the addition of a fuzzy component. For instance, in the *CONCERT* system (Lamsfus et al., 2009; Lamsfus et al., 2011) there are rules that detect the events to be recommended depending on the user preferences and the context, such as this one:

hasFoodPreferencesRule: (v? red:type dcl:Visitor), (?v dcl:hasPreferences ?p), (?p red:type dcl:FoodPreferencesDemographics), (?v dcl:usesDevice ?d), (?d dcl:isConnectedToNetwork ?n), (?n dcl:hasLocation ?l), (?l dcl:hasEnvironment ?e), (?e dcl:offersKindOfTourismConcepts ?s), (?s dcl:isRestaurantOfTypeVegetarian ?r) => print (?r dcl:isTourismServiceOfferedToVisitor ?v)

5.5. Knowledge representation

Recommender systems in e-Tourism need, as any knowledge-based intelligent system, a way to represent in an efficient way the domain knowledge, so that it can be used in their reasoning processes. The knowledge representation and reasoning techniques developed in AI are adequate tools for this purpose. In particular, nowadays the most common way of representing domain knowledge is the use of ontologies. An *ontology* describes a shared and explicit formal conceptualization of a given domain. Its main components are classes (representing concepts, usually organised in some kind of hierarchical structure), taxonomical and non-taxonomical relationships (Sánchez & Moreno, 2008a, 2008b), axioms (Sánchez, Moreno, & Del Vasto-Terrientes, 2012) and instances (representing specific objects).

There are several tourism recommenders that employ ontologies to formalize the domain knowledge. Most systems have generic ontologies that store information about different aspects that have to be taken into account in the recommendation of cultural activities. For example, the system described in Wang et al. (2011) includes a generic travel ontology (with information about accommodation, restaurants, transport, shopping, culture, etc.) and a user ontology in which the demographic characteristics of the tourists and their preferences are modelled. Other systems like *GeOasis* (Martínez-Santiago et al., 2012), *SAMAP* (Castillo et al., 2008) (see Fig. 15), SMARTMUSEUM (Ruotsalo et al., 2013) and the one proposed in Alonso et al. (2012) also include ontologies to model the different kinds of touristic activities and to be able

to reason on them in a semantic fashion. These systems use ontology-based similarity measures to deduce if two kinds of activities are similar, and this knowledge may also be used to compute the similarity between users and provide recommendations based on CL filtering techniques.

Two systems that make a heavy use of ontologies are *SigTur* (Borràs et al., 2011; Moreno et al., 2013) and *e-Tourism* (Garcia et al., 2011; Sebastià et al., 2009; Sebastià et al., 2010). They use domain ontologies that detail the different kinds of leisure activities available in the city. For instance, Fig. 17 shows a portion of the *SigTur* ontology, which has more than 200 concepts organised in a hierarchy of 5 levels.

SigTur stores in each node of the ontology the preference of the user (and the confidence of the system on that preference). These values are initialised with a small questionnaire filled by the user when entering the system (preferences on the most generic concepts are transmitted through their children to all the hierarchy). When the user performs actions on the recommended activities (e.g. adds an activity to the current travel plan) the system updates the preferences on the concepts associated to that activity and spreads this information through their parents in the ontology. Thus, there is an ontology-based dynamic management of the user preferences (Borràs, Valls, Moreno, & Isern, 2012b). The *e-Tourism* system follows a similar approach, in which the user preferences are updated after analysing the explicit ratings she has provided.

There are systems that propose the use of a set of ontologies, instead of having a single integrated ontology. *PaTac* (Ceccaroni et al., 2009) includes separate ontologies about cultural activities, restaurants, entertainment, hotels, etc. The authors propose to link those ontologies with standard temporal and geo-location ontologies provided by the W3C consortium and with a User Model ontology that contains different kinds of touristic stereotypes. *CONCERT* (Lamsfus et al., 2009) models all the context associated to a travel in a network of ontologies called *ContOlogy*, which includes 11 separate ontologies that deal with aspects like tourism services, preferences, activities or travel motivations.

Normally the ontologies used by recommender systems are designed ad-hoc for a specific application and built manually. A way to reduce the cost of the construction of the ontology (Ruíz-Martínez, Miñarro, Castellanos, García, & Valencia, 2011) is to populate it in automatic fashion, by analysing electronic resources (e.g.
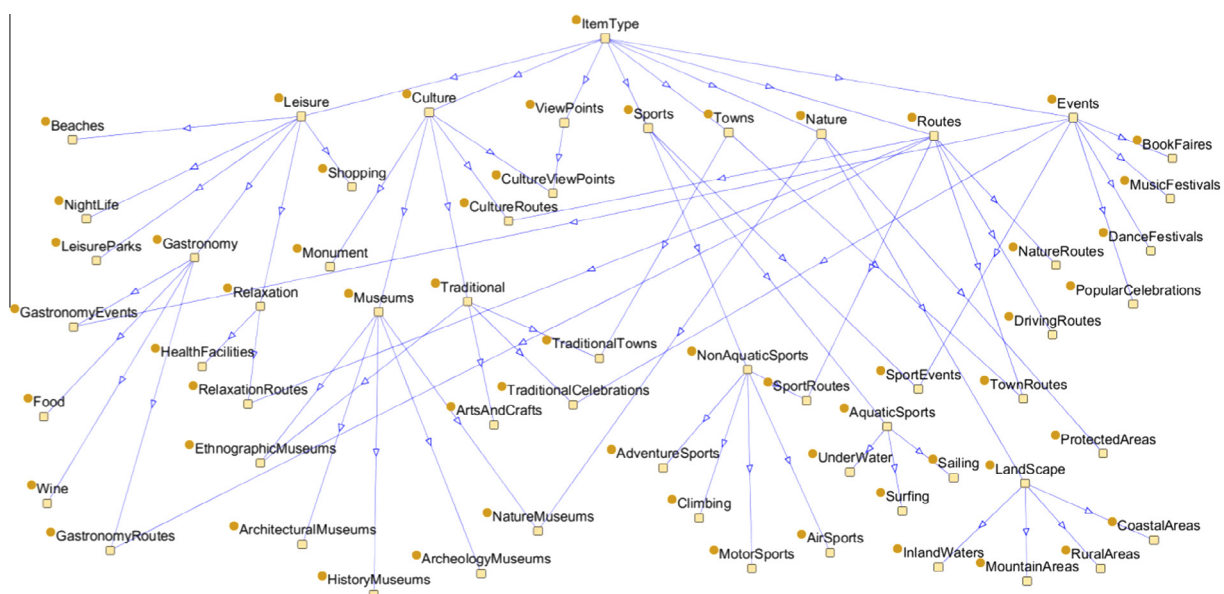

Fig. 17. Portion of the tourism ontology developed in *SigTur* (from Moreno et al., 2013).

Web pages), extracting the appropriate information about tourist activities and creating the associated instances. A similar proposal was made in Vicient, Sánchez, and Moreno (2013).

6. Related reviews

There have been some previous papers explaining the application of recommender systems in the tourism area, which are chronologically mentioned in this section. Ricci (2002) and Staab and Werthner (2002) explain in a very generic way the characteristics of travel recommender systems with some examples, without making an exhaustive review or comparing different approaches. Werthner (2003) gives also a very generic description of technological approaches applied to tourism, where some examples related to Artificial Intelligence are mentioned. However, it does not provide any review or comparative analysis of different systems. Berka and Plößnig (2004) provides a brief guide on how to design recommmender systems for tourism, but it does not attempt to make a survey of the area either. The survey that is more similar to this work is Kabassi (2010). It is mainly a classification of tourism recommender systems (until early 2009) under different criteria: kind of objects they recommend (hotels, flights, restaurants, etc.), hardware support (computer or handheld device), individual/group recommendations, explicit/implicit acquisition of information from the user, recommendation technique (content-based, collaborative or hybrid) and personalization techniques (mainly decision-making tools and Bayesian networks). The authors of that paper basically group the systems in these categories, without making a deep analysis or explanation of all these possibilities. It does not provide any guideline on how to build this kind of systems and it does not consider the latest advances in the last five years, which are the basis of our study (advanced geolocalisation capabilities of mobile phones and tablets, context-aware recommendations, semantic management of preferences, use of social networks, etc.). Gretzel (2011) makes an analysis of tourism recommenders from the point of view of social sciences, not from the technological perspective. The author of this paper argues that intelligent systems are necessary in the tourism domain because there are many complex aspects to be managed: the mobility of tourists, the increased risk and uncertainty experienced in unfamiliar environments, the distributed nature of information sources, the idiosyncratic quality of tourism decision-making, the multifaceted nature of tourism experiences, and the interdependency of suddecisions. A description of some systems that tackle those issues is done. The author also comments the main issues on the design and the evaluation of those systems, focusing on the user interaction, the context, the social perspective and the decision making process to maximise tourists utility; however, this work does not cover the use of intelligent techniques.

The main recommendation methods applied in tourism are reviewed in Felfernig et al. (2007). This paper presents some examples of the use of these techniques, but they are not deeply described nor compared. This paper emphasises some interesting topics like group recommendation and context-aware recommendations in mobile devices. Finally, it is worth mentioning the paper (Vansteenwegen & Souffriau, 2011), that makes a deep overview of systems built between 2001 and 2011 that compose trip plans, although they only comment this single functionality. The authors compare each of the reviewed references in terms of these planning functionalities: personal interest estimation, selection and routing, mandatory points of interest, dynamic recalculation (update plan in real time when unexpected events occur), multiple day decision support (enable plans for multiple days), opening hours, budget limitations, max-n Type (limitation of activity types per day), mandatory types, weather dependency, scenic routes (build paths with beautiful views rather than the shortest ones), hotel selection, public transportation and group profiles. This paper describes how the orienteering problem and its extensions can be used to model trip planning functionalities.

In summary, as far as we know, there is not any recent survey of tourism recommenders with the technological focus, novelty and breadth of coverage of this paper.

7. Conclusions

This final section contains a brief summary of the work presented in this paper, describing some points that should be taken into account by scientists aiming to design and develop tourism recommender systems, and an outline of several lines of future work.

7.1. Summary and guidelines to develop tourism recommenders

Tourism recommender systems give personalised and relevant suggestions to tourists whenever they visit unknown places. They provide support tools to make the process of deciding what to do more manageable. In this article we have reviewed tourism recommender systems published mainly in AI-related scientific journals and conferences since 2008.

We first analysed the interfaces used by these systems and we pointed out the predominance of Web-based approaches, which are especially useful for tourists when they are planning a visit before the stay. However, lately the usage of mobile platforms has widely increased, since they allow a direct access to the information about attractions during the stay. Moreover, they also permit to personalise and contextualise the gathered information, for instance taking the current location of the user into account. However, we have noticed that new mobile platforms such as Android or iPhone have been weakly exploited. Since these platforms are currently being widely used for tourists when visiting places, it is necessary to address the development of applications for those systems and to create responsive Web designs that permit to adapt the content to any viewing device. Tourism recommender systems, as we have seen, not only manage textual information, but most of them use images, pictures and interactive maps.

We have also analysed the main functionalities of the reviewed tourism recommender systems. Most of the approaches suggest points of interest in a destination according to the user preferences. These suggestions may be shown in a ranked list ordered by importance or they may be integrated in a scheduled plan. Usually the system provides only a list and a planner that the user can employ to build manually the detailed plan. However, some approaches can make this process automatically, hence providing an almost complete route taking the context of the user into account, such as location, time and opening hours, among others. This is a novel issue and it may be extended in the future with more functionalities and contextual elements. Another aspect added in the last years is the use of social features that allow tourists to share information among friends.

The recommendation process is a crucial aspect in tourism advisory systems, hence we have analysed the main mechanisms used in the reviewed articles. The most popular approaches use content-based, collaborative and demographic-based techniques. These techniques suffer from several problems when applied individually. Hence, a good practice is the combination of several techniques together to overcome the mentioned drawbacks. We observed that the most recent approaches follow this trend and propose hybrid recommendation methods, including also contextual information. However, there are still a large number of approaches that apply only content-based methods. In tourism

recommender systems it is also a good practice to include a diversification mechanism to avoid content-based problems and to offer unexpected and off-the-beaten-track alternatives to tourists. Recommenders need to learn and manage the user profile to make accurate personalised suggestions. This user profile can be represented by a vector of words or be extended with semantic and uncertainty models which offer a richer representation of the user's preferences. These preferences can be acquired explicitly or implicitly. The most common method is the acquisition of explicit information. However, we consider interesting to apply a combination of both methods. Even though implicit information is inherently more uncertain, it is also less intrusive for users and it is easy to collect it directly by monitoring the interaction of the users with the system.

We have also shown how a wide range of Artificial Intelligence techniques are already being employed in e-Tourism recommenders. Knowledge representation and reasoning techniques are commonly used to represent and reason about the tourism domain. In this field it is especially promising the introduction of semantic measures of similarity between users and items (or between users), taking advantage of detailed ontological representations of the domain. Intelligent autonomous agents may be used to provide proactive recommendations depending on the context; therefore, their use may be especially relevant in the case of mobile-based recommenders. Approximate reasoning techniques are applied to manage the uncertainty on the user's preferences, making them an ideal option when the user feedback is only implicit. Reasoning procedures of different kinds may be employed to infer the user's preferences. Automatic clustering algorithms may be successfully used to classify tourists with similar tastes or similar features. Finally, optimization techniques offer cost-effective solutions to complex planning and scheduling problems when the system wants to build automatically a multi-day route.

As a result of this analytic review, some basic guidelines that can be followed in the design and development of Tourism recommender systems may be given:

- The use of both a Web and a mobile version of a recommender system can be suggested as a good practice, since the Web version can be comfortably used at the home of the tourist to select the destination, the activities to be carried out and a global planning of the routes, whereas the mobile version (that should run on the latest and most widely spread platforms) may permit to follow the route *in situ*, receive more detailed information about the visited places, receive proactive recommendations depending on the user preferences, or even share the travel experience through social networks. The mobile version should provide a rich graphical interaction with the user, to enhance the tourist experience (e.g. augmented reality approaches) and also exploit heavily contextual information (e.g. the current time, the location of the user, etc.) to improve the accuracy of the recommendations and adapt it to the dynamically changing circumstances of the trip. It is sensible to design dedicated Web interfaces for mobile devices, or even better to create responsive Web designs that provide an optimal viewing experience for any device (from personal computers to mobile phones or tablets). A very interesting topic is to extend the current formats with videos, 3-dimensional objects or augmented reality, as some approaches already start to do.
- Another way of getting more information from the user and to improve the information that the recommender has on her interests is the exploitation of all the data provided by social networks and other Web 2.0 applications, including the relationships between users and the different kinds of content they provide (comments, pictures, ratings). This aspect is certainly very relevant in the tourism field, due to its highly social nature.

Thus, it is important to include in tourism recommenders as many possibilities of sharing information (pictures, videos, comments, ratings, localisation, etc.) as possible. The analysis of the social relationships of the users is a recent area of work that can surely lead towards the discovery of more accurate recommendations that fit better with the user's tastes, by taking into account the opinions of her closest friends, weighting the opinions depending on the strength of the relationship with the acquaintance, etc.

- In any kind of recommender systems it is essential to have the precise information about the user's interests stored in her profile. The particular characteristics of the tourism field offer the possibility to define new mechanisms to analyse the interaction of the user not only with the recommender system but also with the related environment, in order to learn automatically (and dynamically adapt) the user's preferences. In particular, contextual recommendations are key in the success of any recommender of tourist activities.
- It is also becoming increasingly clear that, in order to provide precise recommendations, it is necessary to move away from purely textual information and represent in a semantic way (e.g. through the use of ontologies) both the preferences of the user and the features of the different kinds of cultural and leisure activities. Having this structured information, it is possible to define and use complex semantic similarity techniques to compare users, compare objects or compare the preferences of the user with the characteristics of the objects.

7.2. Lines of future work

This section briefly comments three relevant issues that are currently being studied in the development of e-Tourism recommenders: the diversification of the suggestions provided to the user, the use of social data available in current Web 2.0 applications, and the improvement of the recommendations by leveraging the extra capabilities of mobile devices.

- Content-based systems focus on recommending items similar to the user's profile, which may cause overspecialized results, leaving aside other items that might be interesting for the user. This is an important issue in some applications in the field of tourism. Some recommender systems aim at making publicity of "different" or new sorts of activities which may be ignored by most visitors (e.g. a new restaurant or a new guided tour). It has also been argued that a smart recommender should provide a diversified list of recommendations (e.g., even if the system knows that the user is interested in going to the beach, it is not very exciting to show a list of ten different beaches and not to suggest other kinds of related activities). In Savir et al. (2013) a measure of balance between the number of attractions of a certain type and the minimum rating threshold is proposed in order to keep a fixed diversity level in the activities proposed in a trip. The *SigTur* recommender system Borràs et al. (2011) also includes a diversification mechanism that aims to widen the range of suggested activities. In Ruotsalo et al. (2013) the objects of a museum are gathered in clusters sharing the same features so that the recommendation procedure picks a representative number of objects from each cluster to increase the diversity of the proposal made to the visitor.
- Recent recommender systems exploit the power of new Web-based applications, like social networks. In addition to offering social functionalities, these tools facilitate the use of collaborative filtering techniques, since this kind of technologies permit new forms of rating items or collecting user information at an individual level or at a social level. They are known as social recommender systems (Noel et al., 2012). These tools can be used

both to identify groups of items and to build groups of users. For example, in *moreTourism* (Rey-López et al., 2011) the users have an associated tag cloud with terms relevant to their profile, and a new tag is created for each attraction based on the tags of the users who liked it. This information is used to compare the tag clouds of users and items and find coincidences. *TasTicWiki* obtains information about the user interactions with the items by analyzing the searches, readings and editions in a wiki (Ruiz-Montiel, Molina-Castro, & Aldana-Montes, 2010). This information is used to calculate the satisfaction degree that an article in the wiki has for a certain user. Another example is found in *SPETA* (García-Crespo et al., 2009), which maintains a social network profile of the user, so that the user's contact data is taken into account in order to analyze the interactions between the users. Trust is another component that appears when dealing with social recommenders. It has been argued that ratings of credible users should be treated with higher weights than others (Gavalas & Kenteris, 2011).

- A special characteristic in tourism, which distinguishes it from other domains in which recommenders have been applied, is the mobility of the users, which may need recommendations in different moments and in different places. For this reason, this particular type of recommender systems has started to incorporate *context-aware* techniques. The success of this approach is due to the widespread use of mobile devices, as introduced in Section 2.2. Many tourism recommenders run on phones, so the user's location can be used to guide the filtering of the items to be shown (Kurata, 2011; Lamsfus et al., 2009; Yang, 2010). Not only the current location of the user is important, but also the places that have already been visited (Gavalas & Kenteris, 2011; Umanets et al. 2013). Other features that are considered as contextual information in tourism recommender systems are, for instance, the current weather to decide if it is more appropriate to recommend indoor or outdoor activities (Braunhofer et al. 2013; García-Crespo et al., 2009; Gavalas & Kenteris, 2011) or the motion speed and time to generate plans (Noguera et al., 2012). In the system described in Niaraki and Kim (2009) a complex model of the context is considered for constructing personalised route plans. The context information is organised on a hierarchy, including aspects related to the traffic, weather, safety (like telephone booth, side road parking, medical centre, etc.), facilities (gas station, etc.) and tourist attractions (fishing zone, recreation place, seaside, etc.). In Amato, Mazzeo, Moscato, and Picariello (2013b) four main parameters for the context are set: (i) time (time needed by the user to reach the place, the opening/closing times, etc.); (ii) location of the user and the place; (iii) weather and environmental conditions (e.g. temperature, humidity, rainfall degree, wind, season, moment of the day, etc.); (iv) social factors (number of users close to the place and number of positive/negative feedbacks). Moreover, the same authors extended the work (Amato, Mazzeo, Moscato, & Picariello, 2013a) to indoor scenarios to analyze room crowd, room fitness, network performances, location and time interval. They use a pre-filtering strategy to select those alternatives that satisfy the user's needs and a post-filtering strategy to arrange the recommended items based on their contextual values. This dimension is devised as a crucial point in the success of recommender systems in tourism, due to the inherent mobile behaviour of the users in this specific application domain.

Acknowledgements

References

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering, 17*, 734–749.

Albanese, M., Chianese, A., d'Acierno, A., Moscato, V., & Picariello, A. (2010). A multimedia recommender integrating object features and user behavior. *Multimedia Tools and Applications, 50*(3), 563–585.

Albanese, M., d'Acierno, A., Moscato, V., Persia, F., & Picariello, A. (2013). A multimedia recommender system. *ACM Transactions on Internet Technology (TOIT), 13*(1), 3.

Alonso, K., Zorrilla, M., Confalonieri, R., Vázquez-Salceda, J., Iñana, H., Palau, M., Calle, J., & Castro, E. (2012). Ontology-based tourism for all: Recommender and information retrieval system for interactive community displays. In *Proceedings of eighth international conference on information science and digital content technology* (pp. 650–655).

Amato, F., Mazzeo, A., Moscato, V., & Picariello, A. (2013b). Exploiting cloud technologies and context information for recommending touristic paths. In *Intelligent distributed computing VII – proceedings of the seventh international symposium on intelligent distributed computing, IDC 2013, Prague, Czech Republic* (pp. 281–287).

Amato, F., Mazzeo, A., Moscato, V., & Picariello, A. (2013a). A recommendation system for browsing of multimedia collections in the internet of things. In *Internet of things and inter-cooperative computational technologies for collective intelligence* (pp. 391–411). Berlin, Heidelberg: Springer.

Batet, M., Moreno, A., Sánchez, D., Isern, D., & Valls, A. (2012). Turist@: Agent-based personalised recommendation of touristic activities. *Expert Systems with Applications, 39*, 7319–7329.

Berka, T., & Plößnig, M. (2004). Designing recommender systems for tourism. In *Proceedings of the 11th international conference on information technology in travel & tourism (ENTER'2004)*.

Borràs, J., de la Flor, J., Pérez, Y., Moreno, A., Valls, A., Isern, D., et al. (2011). SigTur/E-destination: A system for the management of complex tourist regions. In R. Law, M. Fuchs, & F. Ricci (Eds.), *Information and communication technologies in tourism 2011* (pp. 39–50). Springer.

Borràs, J., Moreno, A., Valls, A., Ferré, M., Ciurana, E., Salvat, J., Russo, A., & Anton-Clavé, S. (2012a). Uso de técnicas de inteligencia artificial para hacer recomendaciones enoturísticas personalizadas en la Provincia de Tarragona. In *IX Congreso turismo y tecnologías de la información y las comunicaciones, Málaga, Spain* (pp. 217–230). ISBN: 978-84-615-9946-2.

Borràs, J., Valls, A., Moreno, A., & Isern, D. (2012b). Ontology-based management of uncertain preferences in user profiles. In S. Greco, B. Bouchon-Menier, B. Bouchon-Menier, G. Colletti, M. Fedrizzi, B. Matarazzo, & R. Yager (Eds.), *Information processing and management of uncertainty in knowledge-based systems part II. Communications in computer and information science (CCIS)* (Vol. 298, pp. 127–136). Springer-Verlag.

Braunhofer, M., Elahi, M., Ricci, F., & Schievenin, T. (2013). Context-aware points of interest suggestion with dynamic weather data management. In *Information and communication technologies in tourism 2014* (pp. 87–100). Springer International Publishing.

Brewer, J. D. (1984). Tourism and ethnic stereotypes: Variations in a Mexican town. *Annals of Tourism Research, 11*(3), 487–510.

Buhalis, D. (2003). *ETourism: Information technology for strategic tourism management*. Englewood Cliffs: Prentice Hall.

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User Modeling and User-Adapted Interaction, 12*(4), 331–370.

Castillo, L., Armengol, E., Onaindía, E., Sebastiá, L., González-Boticario, J., Rodríguez, A., et al. (2008). Samap: An user-oriented adaptive system for planning tourist visits. *Expert Systems with Applications, 34*, 1318–1332.

Ceccaroni, L., Codina, V., Palau, M., & Pous, M. (2009). PaTac: Urban, ubiquitous, personalized services for citizens and tourists. In *Third international conference on the digital society (ICDS 2009), February 1–7, 2009, Cancun, México* (pp. 7–12).

Codina, V., & Ceccaroni, L. (2010). Taking advantage of semantics in recommendation systems. In R. Alquézar, A. Moreno, & J. Aguilar (Eds.) (pp. 163–172). Amsterdam, The Netherlands, The Netherlands: IOS Press.

Coelho, B., Martins, C., & Almeida, A. (2009). Adaptive tourism modeling and socialization system. In *CSE '09 proceedings of the 2009 international conference on computational science and engineering* (Vol. 4, pp. 645–652).

Dasarathy, B. (1991). *Nearest neighbour (NN) norms: NN pattern classification techniques*. IEEE Computer Society Press.

Dey, A., & Abowd, G. (1999). Towards a better understanding of context and context-awareness. In *HUC '99: Proceedings of the first international symposium on handheld and ubiquitous computing*.

Dujmovic, J., & Nagashima, H. (2006). LSP method and its use for evaluation of java IDEs. *International Journal of Approximate Reasoning, 41*, 3–22.

Felfernig, A., Gordea, S., Jannach, D., Teppan, E., & Zanker, M. (2007). A short survey of recommendation technologies in travel and tourism. *OEGAI Journal, 25*(7), 17–22.

Fenza, G., Fischetti, E., Furno, D., & Loia, V. (2011). A hybrid context aware system for tourist guidance based on collaborative filtering. In *Proceedings of IEEE int. conference on fuzzy systems* (pp. 131–138).

Gao, M., Liu, K., & Wu, Z. (2010). Personalisation in web computing and informatics: Theories, techniques, applications, and future research. *Information Systems Frontiers, 12*, 607–629.

Garcia, A., Arbelaitz, O., Linaza, M. T., Vansteenwegen, P., & Souffriau, W. (2010). Personalized tourist route generation. In F. Daniel, F. M. Facca (Eds.), *10th International conference on web engineering 2010, ICWE2010: Vol. 6385. LNCS* (pp. 486–497).

Garcia, I., Sebastià, L., & Onaindia, E. (2011). On the design of individual and group recommender systems for tourism. *Expert Systems with Applications, 38*, 7683–7692.

Garcia, A., Torre, I., & Linaza, M. T. (2013). Mobile social travel recommender system. In *Information and communication technologies in tourism 2014* (pp. 3–16). Springer International Publishing.

Garcia, A., Vansteenwegen, P., Arbelaitz, O., Souffriau, W., & Linaza, M. T. (2013). Integrating public transportation in personalised electronic tourist guides. *Computers & Operations Research, Special issue: Transport Scheduling, 3*, 758–774.

García-Crespo, A., Chamizo, J., Rivera, I., Mencke, M., Colomo-Palacios, R., & Gómez-Berbís, J. M. (2009). SPETA: Social pervasive e-tourism advisor. *Telematics and Informatics, 26*, 306–315.

García-Crespo, A., López-Cuadrado, J. L., Colomo-Palacios, R., González-Carrasco, I., & Ruiz-Mezcua, B. (2011). Sem-fit: A semantic based expert system to provide recommendations in the tourism domain. *Expert Systems with Applications, 38*(10), 13310–13319.

Gavalas, D., & Kenteris, M. (2011). A web-based pervasive recommendation system for mobile tourist guides. *Personal and Ubiquitous Computing, 15*, 759–770.

Gretzel, U. (2011). Intelligent systems in tourism: A social science perspective. *Annals of Tourism Research, 38*(3), 757–779.

Gyorodi, R., Gyorodi, C., & Dersidan, M. (2013). An extended recommendation system using data mining implemented for smart phones. *International Journal of Computers and Technology, 11*(3), 2360–2372.

Hsu, F. M., Lin, Y. T., & Ho, T. K. (2012). Design and implementation of an intelligent recommendation system for tourist attractions: The integration of EBM model, Bayesian networks and google maps. *Expert Systems with Applications, 39*, 3257–3264.

Huang, Y., & Bian, L. (2009). A Bayesian network and analytic hierarchy process based personalized recommendations for tourist attractions over the internet. *Expert Systems with Applications, 36*(1), 933–943.

Jannach, D., Zanker, M., & Jessenitschnig, M. (2010). Developing knowledge-based travel advisor systems: A case study. In N. Sharda (Ed.), *Tourism informatics: Visual travel recommender systems, social communities, and user interface design* (pp. 38–53). Hershey, PA: Information Science Reference.

Kabassi, K. (2010). Personalizing recommendations for tourists. *Telematics and Informatics, 27*(1), 51–66.

Koceski, S., & Petrevska, B. (2012). Empirical evidence of contribution to e-tourism by application of personalized tourism recommendation system. *Annals of the Alexandru Ioan Cuza University – Economics, 59*(1), 363–374.

Kurata, Y., & Hara, T. (2013). CT-planner4: Toward a more user-friendly interactive day-tour planner. In *Information and communication technologies in tourism 2014* (pp. 73–86). Springer International Publishing.

Kurata, Y. (2011). CT-planner2: More flexible and interactive assistance for day tour planning. ENTER 2011. In *Information and communication technologies in tourism* (pp. 25–37). Innsbruck, Austria.

Lamsfus, C., Alzua-Sorzabal, A., Martin, D., & Smithers, T. (2011). An evaluation of a contextual approach to visitor information system. In R. Law, M. Fuchs, & F. Ricci (Eds.), *Proceeding of the ENTER conference* (pp. 191–202). Innsbruck, Austria: Springer-Verlag (pp.179–189).

Lamsfus, C., Alzua-Sorzabal, A., Martin, D., Salvador, Z., & Usandizaga, A. (2009). Human-centric ontology-based context modelling in tourism. In *Proceedings of the international conference on knowledge engineering and ontology development, Funchal, Madeira, Portugal, October 6–8, 2009* (pp. 424–434).

Lee, C. S., Chang, Y. C., & Wang, M. H. (2009). Ontological recommendation multi-agent for Tainan city travel. *Expert Systems with Applications, 36*, 6740–6753.

Linaza, M. T., Aguirregoikoa, A., García, A., Torres, J. I., & Aranburu, K. (2011). Image-based travel recommender system for small tourist destinations. In *Information and communication technologies in tourism 2011* (pp. 1–12). Innsbruck, Austria.

Lorenzi, F., Loh, S., & Abel, M. (2011). PersonalTour: A recommender system for travel packages. In *Proceedings of the 2011 IEEE/WIC/ACM international conference on intelligent agent technology, IAT 2011, Lyon, France, August 22–27. IEEE/WIC/ACM international conferences on web intelligence and intelligent agent technology.*

Luberg, A., Tammet, T., & Järv, P. (2011). Smart city: A rule-based tourist recommendation system. In R. Law, M. Fuchs, & F. Ricci (Eds.), *Information and communication technologies in tourism 2011. ENTER 11, January 26th–28th 2011, Innsbruck, Austria.* Springer-Verlag.

Lucas, J., Laurent, A., Moreno, M., & Teisseire, M. (2009). Fuzz-CBA: Classification à base de règles d'association floues et systèmes de recommandation. *Rencontres Francophones sur la Logique Floue et ses Applications*, 283–290.

Lucas, J., Luz, N., Moreno, M., Anacleto, R., Figueiredo, A., & Martins, C. (2013). A hybrid recommendation approach for a tourism system. *Expert Systems with Applications, 40*(9), 3532–3550.

Manouselis, N., & Costopoulou, C. (2007). Analysis and classification of multi-criteria recommender systems. *World Wide Web, 10*(4), 415–441.

Marques, S. S. (2009). Fabrication of image-destination: The impact of stereotypes at the level of tourism. *Revista Turismo & Desenvolvimento*, 12.

Martin, D., Alzua, A., & Lamsfus, C. (2011). A contextual geofencing mobile tourism service. In R. Law, M. Fuchs, & F. Ricci (Eds.), *Proceeding of the ENTER conference* (pp. 191–202). Innsbruck, Austria: Springer-Verlag.

Martínez, L., Rodríguez, R. M., & Espinilla, M. (2009). REJA: A georeferenced hybrid recommender system for restaurants. In *Proceedings of IEEE/WIC/ACM international conference on web intelligence and intelligent agent technology* (pp. 187–190).

Martínez-Santiago, F., Ariza-López, F., Montejo-Ráez, A., & Ureña-López, A. (2012). GeOasis: A knowledge-based geo-referenced tourist assistant. *Expert Systems with Applications, 39*(14), 11737–11745.

Meehan, K., Lunney, T., Curran, K., & McCaughey, A. (2013). Context-aware intelligent recommendation system for tourism. In *Proceedings of the 11th IEEE international conference on pervasive computing and communications* (pp. 328–331).

Mínguez, I., Berrueta, D., & Polo, L. (2010). CRUZAR: An application of semantic matchmaking to e-tourism. In Y. Kalfoglou (Ed.), *Cases on semantic interoperability for information systems integration: Practices and applications* (pp. 255–271). Hershey, PA: Information Science Reference.

Montaner, M., López, B., & de la Rosa, J. L. (2003). A taxonomy of recommender agents on the internet. *Artificial Intelligence Review, 19*(3), 285–330.

Montejo-Ráez, A., Perea-Ortega, J. M., García-Cumbreras, M. A., & Martínez-Santiago, F. (2011). Otium: A web based planner for tourism and leisure. *Expert Systems with Applications, 38*, 10085–10093.

Moreno, A., Valls, A., Isern, D., Marin, L., & Borràs, J. (2013). SigTur/e-destination: Ontology-based personalized recommendation of tourism and leisure activities. *Engineering Applications of Artificial Intelligence, 26*, 633–651.

Moscato, V., Picariello, A., & Rinaldi, A. M. (2013). Towards a user based recommendation strategy for digital ecosystems. *Knowledge-Based Systems, 37*, 165–175.

Niaraki, A. S., & Kim, K. (2009). Ontology based personalized route planning system using a multi-criteria decision making approach. *Expert Systems with Applications, 36*, 2250–2259.

Noel, J., Sanner, S., Tan, K. -N., Christen, P., Xie, L., Bonilla, E. V., Abbasnejad, E., & Della Penna, N. (2012). New objective functions for social collaborative filtering. In *Proceedings of the 21st int. conf. on world wide web* (pp. 859–868).

Noguera, J. M., Barranco, M. J., Segura, R. J., & Martínez, L. (2012). A mobile 3D-GIS hybrid recommender system for tourism. *Information Sciences, 215*, 37–52.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems. Networks of plausible inference.* Morgan Kaufmann.

Pinho, J., da silva, B., Moreno, M., de Almeida, A. M., & Lopes, C. (2011). Applying recommender methodologies in Tourism sector. Highlights in practical applications of agents and multiagent systems. In *Advances in Intelligent and Soft Computing* (pp. 101–108). Springer.

Rey-López, M., Barragáns-Martínez, A. B., Peleteiro, A., Mikic-Fonte, F. A., & Burguillo, J. C. (2011). moreTourism: Mobile recommendations for tourism. In *IEEE int. conf. on consumer electronics* (pp. 347–348).

Ricci, F. (2002). Travel recommender systems. *IEEE Intelligent Systems, 17*(6), 55–57.

Ricci, F., Nguyen, Q. N., & Averjanova, O. (2010). Exploiting a map-based interface in conversational recommender systems for mobile travelers. In N. Sharda (Ed.), *Tourism informatics: Visual travel recommender systems, social communities, and user interface design* (pp. 73–93). Hershey, PA: Information Science Reference.

Rojas, G., & Uribe, C. (2013). A conceptual framework to develop mobile recommender systems of points of interest. In *International workshop on advanced software engineering. Proceedings jornadas chilenas de computación, Chile, November 2013.*

Ruíz-Martínez, J. M., Miñarro, J. A., Castellanos, D., García, F., & Valencia, R. (2011). Ontology population: An application for the e-tourism domain. *International Journal of Innovative Computing, Information and Control, 7*(119), 1–19.

Ruiz-Montiel, M., & Aldana-Montes, J. (2009). Semantically enhanced recommender systems. *On the move to meaningful internet systems: OTM 2009 workshops* (Vol. 5872, pp. 604–609). Springer.

Ruiz-Montiel, M., Molina-Castro, J. J., & Aldana-Montes, J. F. (2010). TasTicWiki: A semantic Wiki with content recommendation. In *Proceedings of the fifth workshop on semantic wikis-linking data and people. Seventh extended semantic web conference* (pp. 31–40).

Ruotsalo, T., Haav, K., Stoyanov, A., Rochee, S., Fanid, E., Deliaic, R., et al. (2013). SMARTMUSEUM: A mobile recommender system for the web of data. *Web semantics: Science, services and agents on the world wide web, 20*, 50–67.

Sánchez, D., & Moreno, A. (2008a). Pattern-based automatic taxonomy learning from the web. *AI Communications, 21*(1), 27–48.

Sánchez, D., & Moreno, A. (2008b). Learning non-taxonomic relationships from web documents for domain ontology construction. *Data and Knowledge Engineering Journal, 64*, 600–623.

Sánchez, D., Moreno, A., & Del Vasto-Terrientes, L. (2012). Learning relation axioms from text: An automatic web-based approach. *Expert Systems with Applications, 39*, 5792–5805.

Savir, A., Brafman, R., & Shani, G. (2013). Recommending improved configurations for complex objects with an application in travel planning. In *Proceedings of the seventh ACM conference on recommender systems* (pp. 391–394). ACM.

Sebastià, L., Garcia, I., Onaindia, E., & Guzman, C. (2009). E-tourism: A tourist recommendation and planning application. *International Journal on Artificial Intelligence Tools, 18*(5), 717–738.

Sebastià, L., Giret, A., & Garcia, I. (2010). A multi agent architecture for Tourism recommendation. Trends in practical applications of agents and multiagent systems. *Advances in Intelligent and Soft Computing, 71*, 547–554.

Seidel, I., Gärtner, M., Pöttler, M., Berger, H., & Dittenbach, M. (2009). Itchy feet: A 3D e-tourism environment. In N. Sharda (Ed.), *Tourism informatics: Visual travel recommender systems, social communities, and user interface design*. Hershey, PA: IGI Global.

Sieg, A., Mobasher, B., & Burke, R. (2007). Learning ontology-based user profiles: A semantic approach to personalized web search. *IEEE Intelligent Informatics Bulletin, 8*(1), 7–18.

Souffriau, W., Vansteenwegen, P., Vanden Berghe, G., & Van Oudheusden, D. (2011). The planning of cycle trips in the province of East Flanders. *Omega, 39*, 209–213.

Staab, S., & Werthner, H. (2002). Intelligent systems for tourism. *IEEE Intelligent Systems, 17*(6), 53–64.

Tsung-Chiung, W., Chyong-Ru, L., & Wan-Chen, Y. (2012). Segmenting indigenous tourists from a serious leisure perspective. *Journal of Vacation Marketing, 18*(1), 17–29.

Umanets, A., Ferreira, A., & Leite, N. (2013). GUIDEME – A tourist guide with a recommender system and social interaction. In *Conference on electronics, telecommunications and computer (CETC), Lisboa, December 2013*.

Valls, A. (2003).*ClusDM: A multiple criteria decision method for heterogeneous data sets* (Ph.D. thesis). AI Communications 16 (pp. 129–130).

Vansteenwegen, P., & Souffriau, W. (2011). Trip planning functionalities: State-of-the-art and future. *Information Technology and Tourism, 12*(4), 305–315.

Vansteenwegen, P., Souffriau, W., Vanden Berghe, G., & Van Oudheusden, D. (2010). The city trip planner: An expert system for tourists. *Expert Systems with Applications, 38*(6), 6540–6546.

Venkataiaha, S., Shardaa, N., & Ponnadaa, M. (2008). A comparative study of continuous and discrete visualisation of tourism information. *ENTER 2008 conference, international federation for information technology and travel & tourism (IFITT), Innsbruck, Austria, 23–25 January 2008*.

Vicient, C., Sánchez, D., & Moreno, A. (2013). An automatic approach for ontology-based feature extraction from heterogeneous textual resources. *Engineering Applications of Artificial Intelligence, 26*(3), 1093–1106.

Wang, W., Zeng, G., & Tang, D. (2011). Bayesian intelligent semantic mashup for tourism. *Concurrency and Computation: Practice and Experience, 23*, 850–862.

Werthner, H. (2003). Intelligent systems in travel and tourism. In *IJCAI* (Vol. 3, pp. 1620–1625).

Wooldridge, M. (2009). *An introduction to multiagent systems*. John Wiley and Sons.

Yager, R. (1988). On ordered weighted averaging operators. Operators in multi-criteria decision making. *IEEE Transactions on Systems, Man and Cybernetics, 18*, 183–190.

Yang, W. S., & Hwang, S. Y. (2013). ITravel: A recommender system in mobile peer-to-peer environment. *The Journal of Systems and Software, 86*(1), 12–20.

Yang, Y. (2010). Semantic user model inferences for travel recommender systems. In N. Sharda (Ed.), *Tourism informatics: Visual travel recommender systems, social communities, and user interface design* (pp. 23–37). Hershey, PA: Information Science Reference.

Yu, C. & Chang, H. (2009). Personalized location-based recommendation services for tour planning in mobile tourism applications. In *Proceedings of the 10th international conference on e-commerce and web technologies, Linz, Austria, September 1–4: Vol. 5692. Lecture notes in computer science* (pp. 1–49).