Interactive and Context-Aware Systems in Tourism

Dietmar Jannach and Markus Zanker

Abstract Travelers and tourists nowadays rely on a variety of online services or mobile apps for planning their trips, for making travel arrangements and making the choice between touristic offers during the trip. Prominent types of applications are hotel search and booking sites, travel planning applications, and in particular recommender systems. Academic research is often concerned with algorithmic aspects of such systems, e.g., by proposing techniques that find optimal routes or make recommendations based on long-term preference models. In the tourism domain, however, such systems must often be highly interactive, e.g., to let users state and revise their preferences in an incremental way. In many cases, the system also has to take the user's context (e.g., their location) into account to make meaningful recommendations. In this chapter we first briefly review typical interactive e-Tourism applications and then focus on the class of interactive and context-aware recommender systems. In that context, we will survey previous approaches to interactive recommendation in the tourism domain and then highlight open questions and outline future directions in the area.

Key words: Recommender Systems; Context Awareness; User Interaction

1 Introduction

Travelers and tourists nowadays use various online applications and mobile apps during the different phases of their trips. Before their travel, they, for example, use tourism information portals for destination search, hotel booking sites to find and

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reserve an accommodation, and they plan their routes and make transactions on transportation provider (e.g., airline) websites. During their trips, they furthermore might use various sorts of systems that help them find points of interests (POIs), like local attractions or museums, or that help them find events to attend or restaurants to visit. Finally, after their trips, travellers can use rating and review sites to share their experiences with others and to give feedback to the service providers. An overview of a selected set of such applications is shown in Table 1.

Table 1 Overview of Selected Interactive Tourism Applications

Type of applications	**Phase**	**Examples**
Information search	Pre-trip	Tourism portals, destination finding websites, review sites
	On trip	Point of Interest search, event or restaurant search
Planning	Pre-trip	Route/itinerary planning
	On trip	Tour planning
Transactions	Pre-trip	Hotel booking sites, airline; transportation provider websites
	On trip	Event ticket booking, transportation booking
Feedback	Post-trip	Rating and review sites
		Complaint forms

In the context of such travel- and tourism-related applications, the literature in particular in the field of computer science often focuses on algorithmic aspects. Examples include techniques for improved personalized or collaborative search (Sah and Wade, 2016; Arif et al., 2012), algorithms for itinerary planning (Roy et al., 2011; Dunstall et al., 2003; Niknafs et al., 2003; Refanidis et al., 2014), next-POI recommendation algorithms (Liu et al., 2013; Sang et al., 2012), and techniques for proactive and mobile systems (Braunhofer et al., 2015; Gavalas et al., 2014; Höpken et al., 2010).

Within these application areas, *recommender systems* play an important role. These systems are designed to help users deal with information overload and make item suggestions to users, often in a personalized way (Jannach et al., 2010). The earliest application fields of recommender systems include news filtering. Not long after, they were applied for music recommendation and on e-commerce shops. Today, automated recommendations are omnipresent in our online world, and have also been applied in various forms in the tourism context. Prominent examples include the recommendation of destinations, hotels, events, restaurants, or points of interest in general (Jannach et al., 2012a; Liu and Xiong, 2013; Lian et al., 2014; Macedo et al., 2015). With respect to our overview of selected applications in Table 1, recommender systems support information search and decision making tasks, both before and during the trip.

Like for the other mentioned tourism-related applications, the research landscape in the field of recommender systems is dominated by algorithmic works and offline experimentation (Jannach et al., 2012b).[1] Usually, the research goal of such algorith-

[1] An overview of the corresponding technology can be found in Chapter **X** of this book on Recommender Systems.

mic works is to learn statistical or machine learning models on historical datasets, and the evaluation of these models is based on abstract computational measures, e.g., like the Root Mean Square Error when the goal is to predict, for example, which rating a user will give to a hotel.

In the context of various tourism applications, however, such traditional approaches, cannot be applied for two reasons. First, typical recommendation algorithms, e.g., based on collaborative filtering, are often designed to operate based on long-term preference information of the individual user. Such information, however, cannot be assumed to be generally available when a user visits a hotel booking or destination search platform. Therefore, means are required to *interactively* acquire the user's needs and preferences. Second, in several application domains in tourism, the suitability of a recommendation depends on the given *context* of the user. A typical example is the current location of the user in a restaurant recommendation scenario or the current weather when the goal is to select a suitable point-of-interest to visit.

In this chapter, we will review challenges and approaches to build interactive and context-aware systems in the tourism domain. Recommender systems will serve as our guiding application scenario, but we will also provide pointers to related types of information systems where appropriate. Next, in Section 2, we give a survey of the design space when building interactive applications for information search and recommendation and provide corresponding examples. After that, in Section 3, we will first discuss the concept of context awareness and then briefly review in which form context awareness has been integrated in certain classes of tourism information systems.

Generally, this chapter continues existing lines of research which emphasize that in real-world applications, many other factors beyond prediction accuracy determine the success of recommender systems and related applications for information search (Xiao and Benbasat, 2007; Konstan and Riedl, 2012; Jannach et al., 2016b). Among these aspects, in particular the design of the user experience or the capability of the system to establish trust in the recommendations, e.g., through the provision of explanations, play an important role.

2 Interactive and Conversational Systems in Tourism

In many publications on the topic of recommender systems, questions of the user interface design are not specifically discussed. The implicit assumption of these typically algorithmic works is that the recommender system automatically learns a model of the user's preferences, either from explicitly provided ratings or by monitoring the user's behavior over time. The recommendations are then presented—without the user explicitly requesting them—in the form of an ordered list.

In various applications in the tourism domain, these assumptions do not hold. Even for the comparably simple class of hotel booking portals, it is required to interactively collect some information from the user about their short-term needs.

The minimum amount of information usually collected on such platforms is the destination (city), arrival and departure dates, and the number of travellers. But even in such comparably simple and non-personalized applications, a number of design choices exist. Should we, for example, ask the user for information about the type of the trip, e.g., business or private; should we ask for demographics? Also when the search results are presented, various design alternatives can be considered. How many filtering and ranking criteria should we present to the users to help them navigate the result set? Should we present an explanation in case the hotels are not ranked on obvious criteria like the price or the distance to the city centre? Which features of the individual hotel should we display in the result list? Furthermore, if the booking platform also allows users to rate the hotels after the trip—what kind of rating scale should we use (e.g., 1-to-5, 1-to-7). Or, should we allow the user to provide ratings in multiple dimensions like value for money or cleanliness?

For more complex applications, including recommender systems, even more design choices exist when building an interactive application. In the following, we will discuss possible design alternatives and existing insights from the literature in this respect. We will organize our discussions using the conceptual structure proposed in (Jugovac and Jannach, 2017), as summarized in Figure 1. First, we will review the various ways in which we can elicit the (short-term) preferences from the user in Section 2.1. Afterwards, in Section 2.2, we present alternative interaction designs for the phase when the search results or recommendations are proposed to the user. In general, our review in these sections will follow the structure from (Jugovac and Jannach, 2017), with a particular emphasis on the tourism domain.

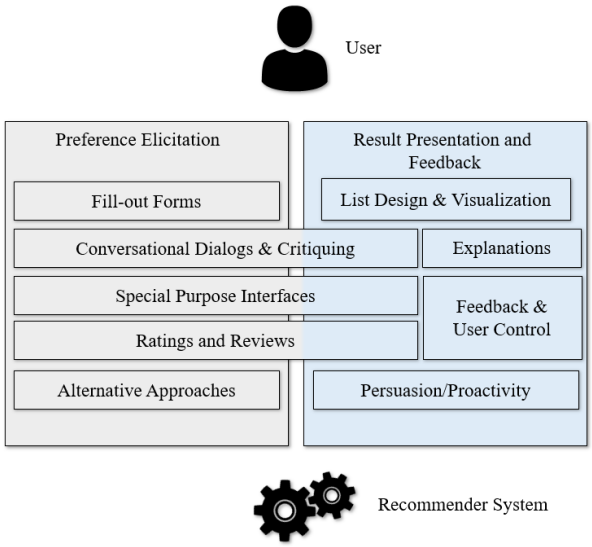

Fig. 1 Overview of Interaction Design Space, Adapted from (Jugovac and Jannach, 2017).

2.1 Preference and Needs Elicitation Phase

In many e-Tourism applications, as mentioned above, it is necessary to interactively acquire the user's short-term needs, preferences, and constraints. Long-term preferences obtained from a series of past interactions are often not available, because consumers might travel only one or a few times a year. At the same time, preferences might also change significantly between these interactions. Various design choices exist in terms of how the preferences can be acquired.

2.1.1 Fill-out Forms

Today, the most common form of eliciting user information is to provide fill-out forms for users. Such forms are common both for transactional applications (e.g., airline booking sites) as well as for search applications (e.g., on TripAdvisor). In particular on hotel booking sites, users are initially only asked for the minimum amount of information including arrival and departure date. More detailed preferences can often only be stated when the initial results are presented. In these cases, users can then sort the results in different dimensions or apply additional constraints regarding prizes, etc.

Fill-out forms have a number of advantages, most notably that online consumers are used to them. Today, the user interfaces of most major booking sites are almost identical and almost no alternative elicitation methods, e.g., based on free text input or search interfaces, can be found. Nonetheless, also simple form-based interaction mechanisms have to be designed with care. Small changes can make a big difference as discussed in (Kohavi et al., 2012), where a number of surprising outcomes of A/B tests of user interface variants at Microsoft Bing are reported. Furthermore, one has to keep in mind that complex preference forms have their limitations when it comes to mobile devices, and not all user interface controls can be used on touch devices.

2.1.2 Conversational Approaches

In some e-Tourism application domains, it is important to acquire the preferences of the users on a fine-grained level, e.g., in order to make personalized travel recommendations. Static fill-out forms have their limitations in such settings, as all users would be asked the same set of very detailed questions.

Conversational recommender systems approach the preference acquisition problem from a different angle and are often designed to mimic the behavior of an advisor at a travel agency. Typically, such systems guide the user through a series of questions, sometimes in a personalized and adaptive way (Jannach and Kreutler, 2005; Mahmood and Ricci, 2009; Göker and Thompson, 2000). Figure 2 shows screens from a knowledge-based and interactive virtual spa advisor.

Such adaptive and conversational dialogs have different advantages over static fill-out forms. They can, for example, reduce the cognitive complexity for the user

(a) Interactive form-based preference acquisition

(b) Presentation of personalized results.

Fig. 2 Dialog Pages of an Interactive Advisory System (Jannach et al., 2007).

by supporting an incremental and user-adaptive preference elicitation process. Depending on the domain, such interfaces can also help to educate the user about the domain and about the possible choices, e.g., by providing additional information during the dialog or explanations at the end of the process.

Critiquing is an alternative, and more restricted form of conversation (Burke, 2002; Ricci and Nguyen, 2007). In these approaches, the idea is to present the user with an item recommendation very early in the process and to let them apply *critiques* regarding the presented item. Typical critiques for a restaurant recommendation could be "less expensive" or "closer by". Differently from the previously described adaptive approaches, critiquing has the advantage that there is basically only one type of feedback pattern involved, which is intuitive to understand. On the other hand, when users are only allowed to apply one critique at a time, the entire process of finding a suitable item can be tedious. Compound critiques, where multiple characteristics can be changed at a time are helpful in this context, but the interaction can still become difficult to understand by the user when, after a certain interaction, no item recommendation remains.

For conversational approaches, mechanisms to deal with such situations were proposed, e.g., in (Felfernig et al., 2015). However, one main challenge of conversational systems that encode domain knowledge is that their creation and maintenance can be labor-intensive despite the existence of special-purpose development environments as proposed in (Jannach and Kreutler, 2007).

In recent years, and in particular with the emergence of voice assistants, we can observe that the interest in conversational approaches increased again. Differently from past knowledge-based approaches, the goal of more recently proposed approaches is to *learn* how to conduct dialogs using machine learning techniques, in particular using neural approaches (Christakopoulou et al., 2016; Gao et al., 2018). Today, such approaches still suffer from a number of limitations, but significant progress can be expected in the future, in particular when hybrid approaches are applied that also incorporate explicit domain expertise as well as linguistic knowledge.

2.1.3 Special Purpose Interfaces

For certain classes of applications, in particular for problems like tour or itinerary planning, special-purpose user interfaces are required. In (Kurata and Hara, 2014), a tour planning system is proposed, where the users first select a destination and then make a choice between various travel styles such as "city walking" or "walk with children". After this initial specification, a more complex interface is shown which visualizes the proposed tour on a map and provides a number of ways for users to fine-tune the tour characteristics. A similar map-based visualization approach for tour planning was chosen also in (Yahi et al., 2015). In this system, users can either provide start and end points when initiating the tour planning process or develop the itinerary step-by-step in an incremental approach.

Both proposed interaction approaches (Kurata and Hara, 2014; Yahi et al., 2015) were validated through user studies. In general, whenever special purpose user

interfaces are proposed, also for other domains like travel package configuration (Xie et al., 2013), extensive validation steps are required to ensure that the chosen user interface is suitable for a potentially very diverse population of end users.

2.1.4 Rating Interfaces

In the traditional literature on recommender systems, algorithms were often designed to work based on explicit item ratings taken, e.g., from movie review sites or e-commerce shops. Such approaches have also been applied in the tourism domain, for example for hotel recommendation. However, since the user's short-term intents and specific constraints are usually dominant, rating-based recommendation systems only play a minor role in the tourism domain.

Ratings are nonetheless very important in tourism applications, in particular in the context of rating and review sites like TripAdvisor or Yelp. While providing a rating interface might appear trivial at first glance, there are numerous ways how these interfaces can be designed. The options, for example, include the choice of the rating scale, which can range from very coarse-grained, i.e., unary (e.g., only "thumbs up" or "like"), over binary feedback systems, to multi-level feedback scales. Furthermore, it is common for certain applications that consumers can provide feedback on several dimensions of a touristic offering, e.g., the cleanliness of a hotel or the friendliness of the staff. In particular when such multi-dimensional feedback mechanisms are provided, it has to be taken care that the user interface does not become too complex and overloaded, as with the increase of the number of feedback options the reliability of the responses can decrease.

2.2 Result Presentation Phase

Especially in applications for information search and interactive recommendation, the systems at some stage enters a phase in which search results or a set of (initial) recommendations presented.[2] Again, a variety of options exist of how to design the user interface.

2.2.1 Result List Presentation and Visualization

A first set of question relates to what is actually displayed on the screen, e.g.:

- How many items should be displayed?
- What is the default ranking order?
- Should there be an explanatory label for the recommendations?

[2] Such a discrimination of phases does not exist in all types of applications. In interactive tour planners, for example, the solutions are incrementally constructed only after very limited input.

- Should the list be oriented horizontally or vertically?
- Which item details should be provided?
- Should items be grouped or presented side by side?
- Should items be only ranked by their assumed relevance or should list diversity also be considered?

All of these questions can have an impact on the user experience. Too long lists of choices might overwhelm the user; too little item detail in the overview lists might require users to inspect each item before deciding; too short lists might raise the user's impression of not having the full picture of the space of options. In particular with respect to the size of the choice set, a number of research works exist, e.g., (Iyengar and Lepper, 2000), which found that having too many options can be frustrating.

Besides the presentation of a flat list of items, alternative visualizations were proposed in the research literature. One can, for example, highlight certain elements in the list which are of assumed particular importance for the user (Waldner and Vassileva, 2014). This way, users can still see the full range of options while at the same time being pointed to a subset of objects of higher relevance. Other approaches use various forms of 2D or 3D representations to show the relationships between the items, e.g., similarities to each other or relation to objects that the user has seen or purchased before (Parra et al., 2014; Kunkel et al., 2017). In general, in the context of these advanced approaches, more research is required to understand to what extent these academic approaches are applicable in practical settings. The most established and "natural" form of visualization often is the use of maps, e.g., in the context of next-POI recommendation or interactive itinerary planning.

2.2.2 Explanation

The acceptance and success of decision support and recommender systems, not only in tourism, can depend on whether or not users *trust* the system and its suggestions. Many factors can contribute to user trust in an information system, like the reputation of the provider or repeated past positive experiences with the system. In that context, *Explanations* can also be a valuable means to increase the user's trust. Explanations for decision support systems have been explored for decades, in particular in the context of early knowledge-based systems in the medical domain. Later on, explanations have been a subject of research in the area of recommender systems, see (Nunes and Jannach, 2017; Tintarev and Masthoff, 2011; Friedrich and Zanker, 2011) for recent overviews.

Explanations are implemented in the context of decision support and recommender systems in different ways. One basic form of explaining is to use a corresponding label on top of the item list, e.g., "Similar objects," "Trending," etc. A more elaborate way of explaining is to generate textual explanations based on the inferences that were made by the underlying reasoning engine, e.g., a recommendation algorithm. Early approaches were based on inference traces of rule-based systems from the 1980s, but such explanations are generally too difficult to understand for end users. In the above-described spa advisory system, the explanations

were therefore based on automatically combining pre-defined text fragments based on the requirements of the user and the constraints that were applied to filter the results. A main advantage of such knowledge-based explanations is that the quality of what is presented to the user can be guaranteed. On the other hand, writing, maintaining, and testing the templates requires some knowledge-engineering effort.

When machine learning approaches are used for recommendations, explaining can become more difficult. For early recommendation approaches that were based on nearest-neighbor techniques, a number of possible explanation techniques were discussed in (Herlocker et al., 2000). With today's complex machine learning techniques and in particular with deep learning approaches, the situation has become worse, because the resulting "models" that are learned by these techniques cannot be interpreted anymore. Therefore, alternative explanation approaches are required, e.g., ones that artificially construct plausible explanations for a given set of recommendations and inputs without considering how the recommendations were actually determined. Alternatively, approaches exist that try to generate recommendations by combining textual information about the items (in the form of latent-topic models) with latent-factor models that are obtained from rating information (Rossetti et al., 2013).

2.2.3 Feedback and User Control

Explanations, as briefly discussed above, are often an entry point for users to give feedback to the system and to influence the system's suggestions (termed *user control*). Figure 3 shows a screen capture of the explanation and feedback system implemented at Amazon.com. The figure shows that Amazon uses previous user actions to justify the recommendation (e.g., "because you purchased," "because your wish list includes"), and also lets the user state that these previous interactions should not be considered in the future for recommendations.

Fig. 3 Screen Capture of Amazon's Explanation and Feedback Mechanism.

YouTube.com over the years also implemented similar feedback mechanisms, where users can state for each recommended track if they do not like a given video recommendation, a certain channel, etc. According to a survey among students in (Jannach et al., 2016a), these feedback and control mechanisms, despite being conceptually very simple, are not used to a large extent by the participants. Among the reasons for not relying on these features are privacy concerns and also the fear of being unable to *undo* some of the settings afterwards.

Academic approaches are often much more complex than those that can be found in practice. They, for example, provide 3D visualizations (Kunkel et al., 2017) for users to interact with or even let them choose the recommendation strategy (Ekstrand et al., 2015). To what extent such approaches can be used in practice, is open to some question and needs further validation. Generally, because of the cognitive complexity for users to give detailed and structured feedback to an interactive system, today's information systems in tourism usually do not provide such mechanisms. The only ways users can give feedback often is to provide positive or negative ratings on the recommendations themselves.

2.2.4 Proactive Approaches

A final consideration in the context of presenting suggestions or informing tourists before and during their travel is related to the *proactivity* level of the systems. Newsletters are among the simplest forms of proactive notifications that are used by tourism portals, and they inform users, sometimes in a personalized way, of current offers. During or immediately before the trip, other basic forms of proactive notifications are often sent out by airlines to announce flight-schedule changes.

With the spread of almost constant internet connectivity on mobile devices, push notifications of that type have become more *intrusive*, i.e., there is a risk that such notifications interrupt the user too often, leading to a *reactant* behavior on the user's side in the worst case (Fitzsimons and Lehmann, 2004). A small number of studies on proactive recommendations can be found in the literature, e.g., (Lacerda et al., 2013; Sabic and Zanker, 2015). In (Lacerda et al., 2013), for example, the authors developed and tested an explore-exploit mechanism, where they sent out notifications to a subset of the users. Based on their reactions, the notifications were then sent out to a larger user group or not.

Generally, the literature on proactive notifications—in particular on the optimal selection of the point in time of sending out the messages—is comparably sparse. One factor that adds to the complexity of this problem is that it can depend on the users' current context if they feel interrupted by an incoming notification at a certain point in time.

3 Context Awareness of Systems in Tourism

Context awareness is not only important for proactive notifications, as discussed in the previous section, but also for a number of further information systems in tourism. Generally, building context-aware applications has become more attractive in recent years with the fast development of smartphones, which nowadays have a multitude of sensors, and the almost constant connectivity to the internet. A number of potentially relevant context factors were identified in the literature in e-Tourism and beyond, including, for example: *(i)* time (time of the day, week, season), *(ii)* geographic location (current and past), *(iii)* social context (group situation or not), *(iv)* weather (current and predicted), *(v)* user activity (in-car, doing sports, etc.).

3.1 Background

Generally, we can distinguish between the *representational* and the *interactional* context (Dourish, 2004) in information systems. In the former case, the contextual situation of a user is captured by a set of predefined context variables and this set of variables is considered to be stable (e.g., the weather is assumed to be always relevant). The interactional context, in contrast, is a different concept, where a context variable might only be relevant for a given object and activity.

Context awareness has been studied in different areas and from different perspective, e.g., in the field of ubiquitous systems and to some extent also in the field of recommender systems, see (Adomavicius and Tuzhilin, 2011) for an overview. From a technical viewpoint, a number of general strategies for incorporating context awareness where identified in the past. Roughly speaking, there are approaches that filter out objects that are not relevant for a given context *before* or *after* the recommendations are computed in a context-agnostic way. The alternative idea is to directly embed context-aware mechanism within the core recommendation algorithms.

But, not only the content, e.g., the recommendations, can be adapted in an application based on the current usage context. In (Höpken et al., 2010) the authors propose a conceptual and technical framework that considers both user interface adaptation, content adaptation, and interaction modality adaptation[3]. In the following sections, we will discuss a few examples of context-aware applications in the tourism domain. These application examples usually limit themselves to the level of content adaptation, i.e., the content is contextualized, but the user interface remains unchanged.

[3] See also (Kobsa et al., 2001) for a discussion of different forms of adaptation.

3.2 Application Examples

3.2.1 Tour and Journey Planning

The work by Cheverst et al. (2000) is one of the earlier examples of a context-aware tourism application—a tour guide—that was designed for a mobile device connected to a network. In these pre-smartphone times, the system was designed to run on a Personal Digital Assistant (PDA) and received its location information through messages sent by base stations that were part of the system. Contextualization was based on the user's explicitly stated preferences and other factors. In the main application, users could create a tour consisting of a set of attractions, and the system would then help them by navigating them through the tour. The system would dynamically update the recommendations, e.g., based on time constraints or attraction opening times.

Generally, this work illustrates how much technology has evolved in the past twenty years. Smartphones of today usually do not require WiFi access and can operate over the mobile network almost without connection loss. Today's smartphones also have built-in GPS sensors, higher screen resolutions, intuitive touch interfaces, as well as substantially longer battery lives. Nonetheless, some of the key challenges mentioned in (Cheverst et al., 2000) remain the same, including the complexity of the user interface. Another interesting observation in (Cheverst et al., 2000) was that some users were frustrated when the system preempted some information from them, because it was not considered relevant for the given context.

Tour planning support is also the focus of more recent works, e.g., (Yahi et al., 2015; Kurata and Hara, 2014), where a tour usually consists of a sequence of POIs to visit within a defined area. Interestingly, even though these newer approaches rely on publicly available services like Google Maps and GPS positioning, they do not consider the user's current context. Instead, they support a planning scenario where the user fully defines the tour before starting it. Being able to update the tour based on the user's current location, like in (Cheverst et al., 2000), could therefore be an interesting extension of these newer works.

In *journey planning*, the task is usually not to create a list of POIs to visit, but rather to compute detailed directions of how to travel between two locations using different transportation modes, e.g., by public transport, taxi, etc. A study on the role of contextual factors in this problem setting was made in (Codina et al., 2015). In this work, ten contextual factors were considered, including two user-related ones (*companionship* and *purpose* of the journey) and eight environmental-based ones (time of day, weather, temperature, crowdedness, illumination, moisture, pollution, and pollen concentration). Both offline experimentation as well as a user study indicated that considering context information is valuable. However, it remained unclear from the study which of the factors were the most relevant ones. More research is therefore required to understand which context factors one should consider for a given application scenario and which factors might even introduce noise.

3.2.2 POI Recommendation

POI recommendation is related to the tour planning problem, with the focus being often on recommending an immediate next point of interest or a set of next POIs without particular order. Such recommendations can be based simply on the user's past preferences, e.g., extracted from past movement trajectories (POI visits) (Huang and Gartner, 2014; Liu and Seah, 2015), but also based on the current context of the user.

An early personalized sightseeing recommender that also implements an itinerary planning functionality was proposed in (Ardissono et al., 2003). Users of the system could specify factors like time and location explicitly as an input, i.e., there was no automatic contextualization. A particular feature of the system, however, was that it took preferences of a group of tourists into account and made proposals for the different types of group members (e.g., children), which were also supported by explanations.

Today, contextualization can be automated much better, and many different types of context information beyond the user's current location, which is the most commonly used factor (del Carmen Rodríguez-Hernández et al., 2015), are often available. In (Meehan et al., 2013), for example, the authors propose a hybrid recommendation system which considers a multitude of factors, including user location, time of the day, weather conditions, the user's current preferences, and also the current "sentiment" of a point of interest, which is obtained from social media data. Unfortunately, the value of considering this unusual type of context information was not evaluated in detail in this work.

This work therefore shares certain limitations with other approaches, where it is not clear how important certain context factors actually are for users. In (Baltrunas et al., 2011), therefore, the authors systematically investigate the relevance for various factors for selecting points of interests in a user study. The considered factors include, for example, the budget of the traveler, the time of the day, the distance to the POI, the crowdedness, weather, mood, the purpose of the trip, the available time, etc. The main findings of the study were that there are context factors that are generally important, i.e., do not depend on the type of the POI (like the distance to the POI and the available time), and factors that are more important only for certain POI types.

3.2.3 Next-in-Sequence Recommendation

In the previous application examples, the representational context is considered, i.e., the relevant context factors are pre-defined and explicit. There are, however, also application scenarios where the contextual situation can be implicitly taken into account by considering a user's recently observed behavior and comparing it to sequences observed for other tourists. A prominent example is the problem of *successive* POI recommendation as done, e.g., in (Cheng et al., 2013). In this particular work, the authors not only consider sequential check-in patterns obtained from location-based social networks, but also take the user's movement constraints into

account when determining the recommendations. A similar approach was later taken in (Feng et al., 2015), where embeddings were used instead of matrix factorization to achieve higher personalization performance.

Generally, in recent years an increasing interest in *sequence-aware* recommender systems can be observed, see (Quadrana et al., 2018) for an overview. These types of recommender systems are designed to detect patterns within sequential or time-ordered logs of user interactions and do not rely on traditional user-item rating matrices anymore. Given the sequential log data, sequence-aware algorithms can in particular also take certain types of contextual factors into account, such as short-term user intents, seasonal patterns, or recent popularity trends in the community.

4 Expected Future Developments

Interactive and context-aware applications in tourism will continue to increase in importance in the future, e.g., due to constantly improved mobile devices, the lowered costs of internet connectivity, and the availability of various types of data. Here, we focus on three main areas. The first one is directly related to the mentioned technological advances and to societal phenomena. The second focuses on improved user modeling and personalization, and a third one concerns the capability of interactive applications to influence the behaviour of users.

4.1 Increased Context Awareness Based on Various Types of Data

Nowadays, the set of contextual features that are used in tourism applications seem to be mostly limited to the user's geographic location. Sometimes, temporal aspects like the time of the year (season) or the current time are considered, for example to check opening hours of points of interest. Already today, however, much more information about the user's context is theoretically available.

On the one hand, there are increasingly more sensors that are carried by the user that can be considered, e.g., smart watches that collect information about the user's physiological condition. Furthermore, our daily environment is starting to fill with all sorts of devices and appliances which not only take measurements about their own state and the surroundings but which are also connected to the network in the Internet-of-Things. In the tourism domain, such devices can be used for different purposes. An intelligent camera could, for example, be used to determine the crowdedness of a point of interest. Other sensors could measure and report microclimatic conditions at a certain geographic location. Finally, there is also the societal phenomenon that many users share information about their current whereabouts on various social media channels such as Instagram, Facebook, or Twitter. Leveraging user-generated information, e.g., for recommendations based on hotel reviews, is nothing new in the tourism domain. However, there still is a huge potential of leveraging up-to-date

information about the user's context, e.g., about their social environment and other people who currently accompany the current user.

4.2 Alternative Forms of Preference Elicitation

Explicitly-stated user preferences, as mentioned above, play an important role in many tourism applications, where we do not have long-term user profiles at our disposal and where the user preferences can change each time the application is used. The predominant way of acquiring user preferences, e.g., on hotel search and booking platforms, is to ask them about certain features of the objects-of-interest. Users can, for example, first specify a location, then enter price ranges or distance constraints until the system comes up with a list of matching results or recommendations.

In future applications, we might also see less "feature-oriented" and static approaches to acquire user preferences. On the one hand, certain types of contextual information can be leveraged to make inferences about the user's preferences, as described previously. On the other hand, we might also see alternative forms of preference elicitation in the future.

Already today, there are several applications that are voice-controlled, in particular on smart phones or personal assistants like Amazon Alexa or Google Home. Initial approaches exist in the academic literature to build, e.g., voice-controlled recommender systems, but these systems are often at an early stage and can have difficulties to understand the user's intent and the state of the conversation.

But also in traditional settings, where users interact with a web application, innovation is possible. One particular aspect to consider here is that tourism as a leisure activity—can have a strong emotional component. While some decisions by users can be mostly rational in some tourism context, e.g., finding a suitable hotel for a business trip, there might be non-rational or subconscious aspects that influence the users' decisions. One recent approach that tries to capture the user's preferences and probably latent wishes was proposed in (Neidhardt et al., 2015). Here, the authors moved away from asking users about their touristic preferences, but rather showed them various types of pictures with relations to touristic activities. The selection of pictures was then taken to make inferences about the user's assumed travel preferences. A number of related research works can be found in the area of *personality-based* recommender systems, where the goal is to consider a user's personality traits when making item suggestions (Nunes and Hu, 2012).

4.3 Persuasive User Interfaces

A final perspective regarding future research in interactive tourism application is the increased consideration of *persuasive* approaches. The concept of persuasion, in general, can have a negative connotation. Persuasion can be seen as a means to nudge

customers to behave in a way desired by the service provider. While this might be beneficial for the provider, at least in the short term, it might lead, for example, to user choices that are based on an overestimation of the value of a touristic offering. Such overestimates can, for example, be induced by explanations that are provided by recommender systems (Herlocker et al., 2000).

However, we are considering more positive forms of persuasion here, e.g., where explanations are used in a recommender system (Yoo et al., 2013) not only to help users make better decisions but also increase their confidence in their choices. This increased choice confidence can then also have a positive effect on the provider, i.e., when customers continue to use the provided service in the future after repeated positive experiences. In the context of persuasion, there is also a lot of potential in the area of *proactive* systems, as briefly discussed above. There are several application areas in the tourism domain, where the system might proactively, e.g., based on knowledge about the users location and environment, make suggestions. Such suggestions could, for example, include the recommendation of nearby alternative points of interests during a city trip in case the original plans do not work out, e.g., because of weather conditions or a closed attraction. Another form of positive persuasion could be based on *reminders*, e.g., when a system reminds the user of a past positive experience, for example with a certain restaurant.

4.4 Privacy and Ethical Issues

Already many of today's technical interactive and context-aware solutions in the tourism domain collect lots of data about the users, their preferences, location, or activity patterns. With the constantly increasing number of sensors on mobile devices and constant network connectivity, even more data can be made available to service providers in the future. At the same time, the techniques for (real-time) data analytics constantly improve as well. These developments can easily lead to privacy issues, in particular when the organizations that collect the data also share them with other businesses or when there are data breaches.

More research is therefore required to ensure the privacy of customers as much as possible in the future. In the field of recommender systems, different proposals were made for privacy protection, e.g., by using obfuscation or encryption techniques (Badsha et al., 2016; Zhan et al., 2010) or by distributing the data, see also (Jeckmans et al., 2013) for an overview. However, at the moment it is unclear if such ideas have made their way out of academic environments and are applied in practical applications. Generally, in terms of privacy the EU General Data Protection Regulation is a step in the right direction, but it might be insufficient to protect customers in case of data breaches.

Besides privacy issues, the recent boom of machine learning, and more generally, artificial intelligence based applications led to increased concerns regarding ethical issues. The use of persuasive technology, as mentioned above, can for example be easily misused to manipulate consumers to make certain choices or decisions. Such

malicious behavior is probably difficult to avoid. However, there is the other danger that an AI-based system makes or recommends decisions that can be considered biased or unfair, e.g., because they simply reinforce patterns they observe in the historical data. In recent years, the awareness of the problem has increased in different research communities, leading to academic conference series, e.g., on fairness, accountability, and transparency in machine learning.

Similar initiatives exist in the context of recommender system, where the overarching goal is that of "responsible" search and recommendation (Ekstrand et al., 2019). Different technical approaches were put forward in this context which, for example, aim to provide better explanations for users, or which try to account for potential biases in the data. The underlying problem, however, is much more than a technical one, and it is, for example, not clear for many practical applications what fairness means. Therefore, much more interdisciplinary research is needed to address these issues which can have huge societal impacts, see (Ledford, 2019) for an example where algorithmic bias affected millions of people in the health-care domain.

5 Summary

This chapter has discussed the role of interactive and context-aware approaches in the tourism domain. Specifically, we have provided an overview of the design space of building interactive applications, with a specific focus on recommender systems and advice-giving systems. Furthermore, we have discussed context awareness in e-Tourism settings and have reviewed a number of application examples. In the final section of the paper, we have outlined a number of expected developments and areas of future research.

6 Cross-References

Related chapters in this book:

- Recommender systems
- User modeling
- HCI methods
- Web technologies & web applications
- Mobile applications, adaptation, location-based services and social networks
- Artificial intelligence & machine learning
- Travel decision making

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