12

Recommendations in ubiquitous environments

In previous sections we restricted our discussion of the application and use of recommender systems to the context of traditional websites. When information systems extend their reach to offer access and interaction opportunities virtually anywhere, however, the so-called ubiquitous environments become application domains for recommender systems.

In this chapter, we therefore discuss the idiosyncrasies of recommending in ubiquitous environments compared with traditional web applications. First we reflect on the evolution of mobile systems and the associated technological issues in a short introductory statement. Second, we focus on the challenges and proposed algorithms for introducing additional context data, such as location. Finally, we provide an overview of selected application domains and related work.

12.1 Introduction

Mobile applications have always been a domain for recommendation because small display sizes and space limitations naturally require access to personalized information, on one hand, and location provides an additional exploitable source of user feedback, on the other hand. Since the end of the 1990s, research into mobile applications has focused heavily on adaptivity with regards to heterogenous hardware and software standards (see Miller et al. 2003). Therefore, most proposed mobile applications have remained in a prototypical state and have been evaluated only in small field trials with a limited scope for usage. One exception in this respect is the ClixSmart system (Smyth and Cotter 2002), which personalizes users' navigation on mobile portals and has been evaluated and fielded in real-world scenarios. For most scientific prototypes, however,

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wider productive use has been hindered for reasons such as restrictive hardware requirements or client-side software installations.

Nevertheless, some of these limitative circumstances are now starting to disappear. For instance, the latest generation of smart phones (and also netbooks) not only has more powerful CPUs and better displays than previous generations, but many of these devices also come with built-in GPS modules that can be used to determine geographical position, which can, in turn, be used as contextual knowledge. In addition, modern wireless broadband data transfer standards and low network access prices make this technology affordable for a broader user community. Therefore, location-aware mobile applications, such as Google Maps, have already become common among early technology adopters. Subsequently, research is beginning to focus on user experience and interaction design. In a current study conducted by Jannach and Hegelich (2009), the impact of different algorithms recommending games were compared. However, only 2 percent of all mobile users participating in this field experiment actually rated at least one of the proposed items explicitly. Thus, sparsity of user feedback in particular must be addressed when building recommender systems in the mobile context. Further research questions that come up in ubiquitous application domains are, for instance

- What are the specific goals of recommender systems in a mobile context? Do users expect serendipitous recommendations, or is it more important to be pointed to things that are close to one's current position?
- What are the implications of contextual parameters such as localization for the design of recommendation algorithms? Is location just another preference, a requirement that is always strictly enforced, or something in between?
- Is there something such as a mobile application domain, or are there plenty of different scenarios that only partially share common characteristics, such as city and museum guides, recommender systems for tourists and visitors, or ad-hoc work networks, to name a few?
- What role does the modality of interaction play when addressing users "on the go"? Pushing information can be useful to draw recipients' attention to "windows of opportunity" close to them, but the users' permission is surely needed. Comparable to permission-based marketing, how should permission protocols for "push" recommendations function?

Although these questions remain essentially unanswered because of the lack of results from case studies and surveys, we discuss current research into the context awareness of recommendation algorithms, present selected examples of pilot systems in different application domains (in Subsection 12.3), and conclude with a short summary.

12.2 Context-aware recommendation

Context awareness is a requirement for recommender systems that is particularly relevant in ubiquitous domains. Whereas some researchers denote virtually any domain aspect as context, we will denote as context only situation parameters that can be known by the system and may have an impact on the selection and ranking of recommendation results. Shilit et al. (1994) name the most important aspects of context as where you are, who you are with, and what resources are nearby. Exploiting the current location of the user, his or her companions, and the availability of resources in his or her surroundings can considerably increase the perceived usefulness of a mobile application. Dix et al. (2000) discuss awareness of space and location with respect to interactive mobile systems from a design perspective that also includes virtual worlds, although we will focus only on physical worlds in our discussion. Ranganathan and Campbell (2003) see context as "any information about the circumstances, objects or conditions surrounding a user that is considered relevant to the interaction between the user and the ubiquitous computing environment". Thus, context denotes additional information to what is traditionally represented in a user model, such as demographics or interests, and refers to "physical contexts (e.g., location, time), environmental contexts (weather, light and sound levels), informational contexts (stock quotes, sports scores), personal contexts (health, mood, schedule, activity), social contexts (group activity, social activity, whom one is in a room with), application contexts (emails, websites visited) and system contexts (network traffic, status of printers)" (Ranganathan and Campbell 2003). As becomes obvious from this enumeration, the border between user model and context is not well defined. In particular, differentiating between ephemeral and short-term user interests, with the latter constituting largely what is also considered as personal or application context, has always been the focus of user modeling and personalization research.

A context-aware user model for personalization is also sketched by Anand and Mobasher (2007). A person buying and rating books might do this in different situations. Sometimes the person buys fiction books for himself or herself, but sometimes books are work related or for children. Thus, Anand and Mobasher (2007) argue that aggregating all the information in a simple, not context-aware, user profile is suboptimal, and they propose a recommendation method that can take this contextual information better into account. Their approach relies on a more complex user model that has both long-term and short-term memories, supporting the automated generation of "contextual cues" from the short-term memory.

Thus, even early recommendation systems such as Fab (Balabanović and Shoham 1997) that differentiated between short- and long-term interest profiles can be seen as implementing some form of context awareness. However, here we denote only approaches that focus on impersonal context parameters, such as location, as context-aware.

Schwinger et al. (2005) give an overview of the different levels of context awareness implemented by mobile tourism guides, and Höpken et al. (2008) present a two-dimensional framework that matches contextual dimensions with the adaptation space of a mobile tourist guide. They argue that a mobile guide possesses several dimensions according to which its functionality and appearance can be adapted, such as content elements (e.g., topic, textual content, images); interface design issues such as modality, layout and structure, or navigation options, and behavioral and interactivity aspects. Therefore, they propose that a change in a specific context dimension such as the client technology of the device can have implications for several of the adaptation dimensions. Whereas Höpken et al. (2008) address adaptation aspects in general of ubiquitous applications with web interfaces, in this section we focus only on the implications of context-awareness for the function of recommendation systems themselves.

At a minimum, most systems filter the presented information content according to users' current location and consider additional preferences (e.g., "display only objects from category A"). However, such approaches are quite static and do not include machine learning aspects such as content-based or collaborative filtering. Lee et al. (2006), for instance, first mine relevant personal factors from historic data that seem to influence users' choice for restaurants and produce a recommendation list based on the user's personal preferences. Second, restaurant recommendations considering only their proximity to the user's current location are computed, and finally a weighted list of both is presented to the requestor.

Adomavicius et al. (2005) consider the notion of context in recommendation by proposing a multidimensional approach. They formalize contextual information in a general way by encompassing additional data dimensions. Adomavicius and Tuzhilin (2005) traditionally understand recommendation as a two-dimensional function $rec : U \times I \mapsto R$ that maps a user (U) and an item dimension (I) onto a utility score R, as already discussed in Chapter 5. Consequently, the multidimensional approach defines the rating function rec_{md} over an arbitrary n-dimensional space $D_1 \times \cdots \times D_n$:

$$rec_{md} : D_1 \times \cdots \times D_n \mapsto R \tag{12.1}$$

The domain space D_i can, for instance, be *location, time*, or *companion*. To derive predictions from such multidimensional ratings data, a reduction-based approach can be employed that restricts the ratings matrix to entries that conform to the context criteria. For instance, when one wants to compute whether a user will like a specific restaurant that is situated in a city, only ratings of restaurants in the city and none located in the countryside will be considered. Such an approach makes sense only if the quality of recommendations is improved when the ratings input is reduced by a specific situational context such as location. In addition, exploiting only a limited segment of ratings data based on some contextual parameters sharply aggravates the cold-start problems mentioned in Chapter 2. In particular, reduction-based approaches that consider several contextual dimensions in parallel become rather impractical for applications with a relatively small-scale user base. Adomavicius et al. (2005) therefore propose additional enhancements such as aggregating several contextual segments and combining the approach with traditional two-dimensional recommendation as a fallback scenario. An obvious example is the aggregation of ratings from Monday to Friday as weekday ratings, in which an aggregation function such as *average* is employed to resolve potential conflicts when the same item is rated by the same user at different time points.

Adomavicius et al. (2005) experimentally evaluated their approach in the movie domain, in which for instance they employed the place where the movie was watched (home or theatre), the time (weekday or weekend), the type of friends who were present, as well as release information about the movie indicating its novelty as contextual data dimensions. Their approach was able to outperform a traditional two-dimensional collaborative filtering recommender system in terms of accuracy on an historical dataset. However, they observed that not all contextual segments positively contribute to recommendation results, and therefore they employed a preselection mechanism that identifies segments that reach significant improvements.

Another approach, presented by Bohnert et al. (2008), studied the sequence patterns of visitor locations in museums and developed interest and transition models to predict a visitor's next locations. They collected a dataset from tracking real visitors in a museum that contains the sequences of exhibitions they observed, as well as their interest profiles. The latter were derived from content descriptions of exhibits and by interpreting relative viewing times of exhibits as implicit ratings. The *interest model* considers only the visitor's relative interest and does not take the order of visits into account. In contrast, the *transition model* reflects the probabilities of transitions between two exhibitions (i.e., locations) that allows the algorithm to predict the next locations by finding a maximum probability sequence of k unvisited exhibitions. Although their findings need to be considered preliminary because of the small size of the dataset, they observed that the transition model significantly outperformed the interest model and that a hybrid exploiting both models could provide only minor additional improvements. In any case, this is an additional argument in favor of considering the location context in ubiquitous recommendation applications.

Ranganathan and Campbell (2003) applied first-order predicate calculus to ensure a transparent line of reasoning on context models. Contexts are thus first-order predicates, and logical rules allow higher-level concepts to be derived from low-level sensor information. Thus the proposed system represents a deductive user model for context management that can be queried by recommendation algorithms in order to receive input for personalization.

Having discussed the different viewpoints of context-awareness and hinted at a few computation schemes that can reason on context, we now examine the variety of different systems and prototypes that have been constructed.

12.3 Application domains

Mobile recommendation applications have been shown to be a very active area, and applications have been fielded in domains such as tourism, cultural heritage, or commerce in general.

M-Commerce. M-commerce refers to monetary transactions that are conducted via wireless networks. The adoption of context awareness for m-commerce applications is crucial for their success. Tarasewich (2003) distinguished between the context of the participant, the environment he or she is in, and the activities currently being carried out. Ngai and Gunasekaran (2007) provide meta-research classifying published work on m-commerce. Both motivate the necessity of information reduction and context sensitivity for this application domain, although recommendation is not explicitly mentioned. However, recommender system research is particularly active in the following subfield of m-commerce.

Tourism and visitor guides. The tourism industry as one of the biggest economic sectors worldwide, together with the fact that travelers have specific information needs, makes this domain a natural choice for mobile information systems. Kabassi (2010) provides a coherent overview of recommendation applications that also includes a comparative analysis with respect to contextual aspects such as weather, season, or distance. Cyberguide, an experimental tour guide that provides location-aware services (Abowd et al. 1997), was one of the pioneers in this field. It requires, however, a specific personal digital assistant

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(PDA) hardware platform. In comparison, the GUIDE system (Cheverst et al. 2002b) is a context-aware mobile guide for visitors to the city of Lancaster, requiring an end system with a touch screen and the ability to run Java applications. The system offers its users adaptive pull-based access to information that builds on existing wireless networking infrastructure. In addition, Cheverst et al. (2002a) explored the appropriateness of information push for this application domain in a small field trial. One of the findings was that people showed enthusiasm for push-based guidance information, but context-aware support requires very fine-grained location information. For instance, users want to be notified when they take a wrong turn, or an attraction should be announced when it first comes into the visitor's field of vision. However, such detailed context information requires specific hardware that cannot be assumed to be available in a usage scenario with a wider scope.

Ardissono et al. (2005) presented the interactive tourist information guide INTRIGUE, which was developed on the basis of a multiagent infrastructure for the personalization of web-based systems. It not only personalizes the content presented by ranking items according to assumed user interest but also customizes the information according to the display capabilities of the user device (Ardissono et al. 2003). INTRIGUE incorporates a fuzzy utility-based personalization approach for ranking results, and it also supports group recommendation.

The Dynamic Tour Guide (DTG) is a mobile agent that supports visitors in locating attractions of interest and proposes personalized tour plans for the German city of Goerlitz-Zittau (Kramer et al. 2006). It implements a semantic match algorithm to determine the user's assumed interest for city attractions and computes a personalized tour plan. Comparable to INTRIGUE, the DTG system also needs initial acquisition of personalization knowledge. The system is aware of the location and time context, for instance, and the description of an attraction depends on the user's position. The tour plan is rearranged based on the progress made and the remaining time. However, the system is not specifically a tour guide with detailed background knowledge about sights and attractions; rather, the system focuses on offering a wide range of useful information during a visit to the historic city.

The COMPASS application (van Setten et al. 2004) is a context-aware mobile personal assistant based on 3G network services. It uses a recommendation service to offer its users interactive maps with a set of nearby points of interest. The system integrates different types of context awareness, such as location, time, or weather, with recommendation functionality. Interestingly, one of the findings of van Setten et al. (2004) is that a large share of users want to decide for themselves which contextual factors should be taken into account and

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which should not. Nguyen and Ricci (2007a) developed a critique-based mobile recommender system that recommends restaurants and enables its users not only to specify their initial preferences but also to critique recommended items. Thus users can not only reject a proposal but can also give reasons why. Their user study showed that the additional constraints acquired from users during the interactive process lead to more satisfied users.

Adaptation to technical restrictions such as display size and personalization of presented content, as addressed by some of the aforementioned systems, are provided by the innsbruck.mobile system (Höpken et al. 2006). Its focus lies on widespread and actual use among tourists, and therefore avoids client-side installation requirements. One of its novelties is the support of two different types of communication paradigms. First, information seekers have personalized browsing access to categories such as events, sights, restaurants, or accommodations. However, in addition to its web-based information pull service, the system also supports context-aware information push (Beer et al. 2007) that regularly provides, for instance, weather and news messages as well as security warnings. It is configured by event-condition-action rules, in which events trigger the evaluation of the subsequent conditions. Examples of possible events are rapid weather changes, time points, or intervals, as well as users entering specific location areas. An outstanding pecularity of innsbruck.mobile is that prior to its development, substantial empirical research was performed into the usage intentions of Tyrolean tourists. Rasinger et al. (2007) asked tourists if they would use, for instance, a sightseeing or event guide, and what type of features, such as search and browse functionality, recommendation, or push services, would be most useful. Interestingly, users identified weather and news, transport and navigation, and security to be the most important mobile information services for tourists.

SPETA (Garcia-Crespo et al. 2009) is a recently proposed social pervasive e-tourism advisor that combines Semantic Web techniques, geographic information system (GIS) functionality, social networks features, and context awareness. Its recommendation functionality consists of of a hybridization component that combines several filters that reduce the set of potential recommendations based on context, domain knowledge, and collaborative filtering in parallel.

Cultural heritage and museum guides. Mobile guides for archeological sites or museums providing multimedia services, such as Archeoguide (Vlahakis et al. 2002) or MobiDENK (Kroesche et al. 2004), typically impose specific hardware requirements on their potential users. MobiDENK runs on a PDA and is a location-aware information system for historic sites. It displays multimedia background information on monuments of historic significance. Archeoguide goes a step further and reconstructs ruined sites and simulates ancient life in an augmented reality tour with a head-mounted display. As already outlined in Section 12.2, Bohnert et al. (2008) analyzed the sequence patterns of museum visitors' locations to predict their next locations. The museum guide LISTEN, presented by Zimmermann et al. (2005), generates a personalized three-dimensional audio experience based on the assumed interests of users because of their walking patterns and their specific location. For determining the latter, sensors of the ubiquitous environment provide input to the system, and actuators display visual and acoustic objects. Pilot applications for such ubiquitous technologies are also popular for the domain of home computing and consumer electronics in general, as the reader will see next.

Home computing and entertainment. Nakajima and Satoh (2006) present, for instance, software infrastructure that supports spontaneous and personalized interaction in home computing. Their notion of "personalized" basically means that users are able to personally configure and adapt smart devices in their environment based on their preferences and on specific situations. In this respect, "portable personalities" denotes the existence of distributed user models for the same user, each of which holds only partial information. Thus merging, harmonization, and reuse of these models becomes necessary when personalization and recommendation are applied in scenarios such as those discussed by Uhlmann and Lugmayr (2008).

12.4 Summary

Rapid technical advancements toward ever more powerful mobile devices and their fast market penetration are reality. Therefore, mobile applications – and ubiquitous applications in general – constitute a promising application domain for different types of personalization and recommendation. The context awareness of applications is thereby a necessity, as they have to coexist with activities such as walking, driving, or communicating. This is the main difference from traditional web applications that may assume the undivided attentiveness of their users.

When analyzing the distribution of research work on recommendation in mobile and ubiquitous environments, it is obvious that the tourism application domain is by far the most active field. Despite this, not many applications have been evaluated in broad field studies and involving not only students, perhaps with the exceptions of Rasinger et al. (2007) and Jannach and Hegelich

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(2009), for instance. One of the challenges for wide-scale application of tourism recommenders is the availability of extensive and accurate resource data. For instance, a mobile restaurant recommender requires not only the positioning coordinates of all restaurants within a specific region but also some additional qualitative data, such as the type of food served, the atmosphere perceived by guests, or the business hours. As acquisition and maintenance of product data are quite cost-intensive, only widespread use and acceptance of mobile recommendation applications by end users will justify the development effort. An approach that partially addresses this problem by automated generation of additional semantic knowledge from geocoded information objects is presented by Zanker et al. (2009). It derives qualitative evidence for a given object, such as proximity to beaches or aptness for specific sports activities, from the fact that other geocoded objects that are known to be beach resorts or sports facilities are nearby. They apply this approach to the tourism domain to help users identify regions that match their holiday preferences and interests.

One even more fundamental bottleneck will have to be resolved before recommendation applications can become successful in ubiquitous environments: technical interoperability between ubiquitous devices themselves (Shacham et al. 2007) and the privacy concerns of users.

When seen only from the viewpoint of recommendation technology, in most practical applications support of context basically denotes the filtering out of inappropriate items based on context parameters such as location. Consequently, more research with respect to context awareness in recommender systems in the sense of Adomavicius et al. (2005) will be needed.