A Short Survey of Recommendation Technologies in Travel and Tourism

A. Felfernig, S. Gordea, D. Jannach, E. Teppan, M. Zanker

University Klagenfurt
Institut für Wirtschaftsinformatik und Anwendungssysteme
{felfernig, gordea, jannach, teppan, zanker}@uni-klu.ac.at

Abstract

Recommendation has a long history as a successful application area of Artificial Intelligence. The demand of e-commerce platforms (e.g., amazon.com) to improve the accessibility of large product- and service assortments contributed to an increased popularity of recommendation technologies. Three basic technologies supporting the personalized recommendation of products and services are presented in this paper. In order to take into account the focus of this special issue, we provide a discussion of the application of those technologies in the tourism domain (e.g., recommendation of travel destinations) with a special focus on mobile environments.

Recommendation Technologies

The increasing size and complexity of product assortments offered by e-commerce platforms requires appropriate technologies which alleviate the retrieval of products by online customers. Different recommendation technologies have been developed to help customers to easily find the best matching product. Those technologies have been successfully applied in different domains such as financial services, electronic goods, or movies. An overview of applications exploiting recommender technologies can be found in [16].

The most widespread technology is *collaborative filtering* (CF), which exploits user ratings of products in order to identify additional products that the active user may like as well [6]. *User-based* and *item-based* collaborative filtering are two basic variants of this technology. As shown in Figure 1, both variants are predicting to which extend the active user (in this case *User3*) would like currently unrated items. User-based approaches to collaborative filtering try to identify the *k nearest neighbours* of the active user (users having similar tastes), and calculate a prediction of the active user's rating for a specific item. This rating can be defined, for example, as the weighted average of the k nearest neighbours' ratings [6]. In the simplified example of Figure 1, *User1* is found to be the nearest neighbour (k=1) of *User3* (the active user) and his/her rating for the 4^{th} product ('Conspiracy Theory') will be taken as prediction for the rating of *User3* (rate=2). In contrast, item-based collaborative filtering is searching for items which received similar ratings from other users and were also (positively) rated by the active user. In the example given, ‘Pretty Women' has been rated by all users. This is the most similar item to ‘Conspiracy Theory’ and it is assumed that *User3* will have the same preference for ‘Conspiracy Theory’ (rate=1).

Product	Content-based			Collaborative		
	Genre	Starring	Price	User1	User2	User3 (active)
Pretty Woman	Romance	gere, roberts	13	1	3	1
Runaway Bride	Romance	gere, roberts	10	4	2	3
Under Suspicion	Thriller	hackman, freeman	13	3	2	3
Conspiracy Theory	Thriller	gibson, roberts	10	2	3	?

Figure 1: Content-based and Collaborative Filtering Recommendation (k=1, 1=very good; 4=bad).

Content-Based Filtering (CBF) provides recommendations for preferred product categories [5]. Let us assume, the active user has rented the ‘Pretty Women’ movie - using descriptions of genre, starring and price, CBF recommends, for example, ‘Runaway Bride'. If no product categorization is available, and the items are represented only as free text descriptions (e.g., Netnews, books, emails etc.), alternative CBF solutions based on, for example, information retrieval techniques are available [14], [15]. They extract a set of keywords from textual product descriptions, compute the users preferences expressed in terms of keywords which are contained in products bought by the user, and build the list of recommendations by searching for products that match the user’s preferences.

CF and CBF technologies exploit user preferences and allow acceptable recommendation accuracy for frequently bought products such as music or video DVDs, books, Netnews, Internet radio etc. *Amazon.com* is probably the most popular online shop that implements these approaches. When accessing product descriptions, a list of CF recommendations is available for users in the *section* '*Customers who bought this item also bought*', while the content-based suggestions can be accessed via '*Look for related items by keyword*' and '*Look for similar items by category*' links.

There are other types of products (in many cases high-involvement products) which are less frequently bought and their purchase is related to higher risks (e.g., financial services, cars, electronic goods, services in the tourism domain). When recommending such products, recommender applications must support a more detailed elicitation of user requirements. Deep domain knowledge has to be exploited in order to be able to make more precise and more trusted recommendations. Knowledge-based (KB) recommender technologies [4], [8] support sales processes of high involvement products. KB recommenders are based on a detailed description of the product domain in the form of structured product descriptions and constraints. The identification/construction of user preferences usually takes place in the context of an explicit sales dialog. The major advantage of this type of recommendation technology is the explicit representation of product, marketing and sales knowledge. Such a representation allows the calculation of explanations which provide, for example, a detailed argumentation as to why a certain product fits to the wishes and needs of a given customer.

Each of the presented recommendation paradigms has its own advantages and disadvantages. Hybrid recommenders combine two or more of these paradigms in order to mutually eliminate disadvantages and to improve recommendation accuracy, robustness and trust in calculated recommendations (see, e.g., [6]).

Recommender Systems in Travel and Tourism

The travel and tourism industry is one of the most important and dynamic sectors in Business-to-consumer (B2C) e-Commerce. According to [25], already in 2003 this single sector made up more than fifty percent of the global B2C turnover. A variety of recent studies (e.g., by the European Travel Commission – ETC) revealed that at least in developed countries, the Web is nowadays already the primary source of information for people when searching or booking suitable travel destinations [12]. Consequently, the domain has always been at the forefront of Information Technology [25] and still is a highly attractive research area as lots of potentials are not yet fully exploited. In this context, recommender applications can be valuable tools supporting, for example, information search, decision making, and package assembly.

When looking at today's e-Tourism web sites we can observe that only some of the existing systems provide services that go beyond a pure booking system's functionality. Popular online 'travel agencies' like Expedia (www.expedia.com) at least aim at exploiting the potential of Web communities by letting their customers rate individual hotels or destinations. Still, in these applications the average ratings of other customers merely serve as another piece of information for a certain hotel or destination but there is typically no recommendation service available.

The reasons why established recommendation techniques like amazon.com cannot be directly applied to the tourism domain are manifold. Collaborative filtering techniques work best when there exists a broad user community and each user has already rated a significant number of items. As individual travel planning activities are typically much less frequent like, for example, book purchases, and in addition the items themselves may have a far more complex structure, it is hard to establish reasonable user profiles. Therefore, many approaches aim at eliciting the preferences and requirements in a conversational dialog (e.g., [12], [19], [21]) using, for example, knowledge-based approaches [4], [8] for generating recommendations. Online users may be different with respect to their background knowledge, their mental models ([17], [27]), or their capabilities of expressing their needs and requirements. Dialog design, usability aspects, and adaptivity are thus central in application and user interface design [20]. In [21] for instance, a critique-based dialog style is proposed which has already been successfully employed in other domains; [12] describes a tourism advisory application based on knowledge-based personalization and multi-step, adaptive dialogs.

The problem of 'group recommendation' is another typical aspect in tourism-related recommender systems, i.e., the problem of generating proposals that 'maximize' the overall acceptance of members of a travel group that have different interests. Although this problem is not new in recommender systems (think of TV program or movie recommenders), there is only little research in the specific context of recommender systems in tourism (see, e.g., [3]).

Finally, another important facet which makes recommendation in the tourism domain more complex is the fact that a single trip arrangement may consist of several, independently configurable services [20]. Typically, only pre-defined packages like 'flight and hotel' or 'all-inclusive' arrangements are available online. As the segment of individualized travel arrangements is constantly growing, it will be increasingly important that future systems support such packaging services. Nevertheless, only first attempts in that direction can be found in literature today (see [3], [9], or [19]).

Mobile Systems and Recommendation

With respect to mobile recommender applications the tourism domain is a very active area. The idea of providing context-aware information services to tourists has already a considerable tradition. For instance [1] present their mobile tour guide that displays points of interest (POIs) on an interactive map dated back in 1997. Since then much more examples of mobile tour guides und context-aware applications have been reported, such as an electronic guide for the city of Lancaster [7], the COMPASS project in the Netherlands [24], MobiDenk - a location-aware information system for historic sites [13] or Berlintainment - an entertainment guide for the city of Berlin [26].

Although a variety of mobile and context-aware applications already exists, there are still major shortcomings. Most systems are research prototype applications that are only evaluated in small field trials with a limited scope for usage. Many times a wider productive use is impossible for the two following reasons. First, mobile guides might have restrictive hardware requirements like a specific type of PDA (Portable Digital Assistant), the availability of GPS (Global Positioning System) functionality or client-side software installations. However, new generations of mobile phones having larger display sizes, more standardized browsing capabilities and broadband data transfer will ease these hardware requirements. Second, the availability of extensive and accurate resource data is another bottleneck. 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 opening hours. As acquisition and maintenance of product data are quite cost-intensive, only widespread use and acceptance of mobile recommendation application by end-users will make the data effort worth.

Context-awareness is a common characteristic for all these systems [10], [18]. Shilit et al. [23] name the most important aspects: '*where you are*', '*who you are with*' and '*what resources are nearby*'. Exploiting the current location of the user, her/his companions as well as the availability of resources in her/his surrounding can increase considerably the perceived usefulness of a mobile application. While [22] give a coherent overview of different levels of context-awareness implemented by mobile tourism guides, we want to focus on the implications of context-awareness for recommendation technology.

Currently, most reported systems filter the presented information content according to users' current location and their additional preferences (e.g., 'display only objects from a specific category'). This constitutes already a considerable degree of personalization and reduces information overload. However, such approaches do not employ traditional recommendation techniques such as content-based or collaborative filtering. Adomavicius et al. [2] therefore developed a multidimensional approach that allows them to incorporate contextual information with filtering applications. They understand the term contextual information in a general way such that it encompasses any additional data dimension. They extend the traditional two-dimensional (user x product) representation of rating data to a n-dimensional data cube. In their experimental evaluation in the movie domain they for instance employed the place where the movie was watched (home vs. theatre), the time (weekday or weekend), the type of friends who were with as well as release information on the movie indicating its novelty as contextual data dimensions.

Considering this contextual information aggravates the cold-start problems mentioned in the introduction due to the high degree of data sparsity. Adomavicius et al. [2] therefore introduce reduction-based estimations that outperform traditional two-dimensional recommender systems in their experimental setup. Another more advanced recommendation technique that has also been fielded for some experimental evaluation was presented by [21]. They developed a location-aware critiquing system that allowed its users to determine nearby restaurants that conformed to their interactively entered criteria and critiques on previous proposals. It is implemented by a rich-client application that has to be installed on the PDA and communicates with the central server.

The etPlanner system [11] is currently under development by the Austrian network for e-tourism. It focuses on widespread and actual use among tourists and therefore avoids client-side installation requirements. One of its novelties are the support of two types of communication paradigms with its users. First, information seekers have personalized browsing access to categories like events, sights, restaurants or accommodations. In a second step, users may also receive personalized push messages that inform them about changing weather conditions if they are out hiking or make them propositions on leisure activities based on their preferences. A first version has already been deployed for public use. Additional recommendation features will be added for future versions when more information-rich user profiles will be available.

Conclusion

This paper provides an overview of recommendation technologies applied in existing commercial environments. Application examples are mainly given from the tourism domain where recommendation technologies hold an extremely important role. Recommendation technologies in this application domain will be even more important in the future. A special research focus has to be set on the development of recommendation formalisms taking into account the current context (dimensions such as time, space, mood or social environment) of the user/customer.

References

[1] G. Abowd, C. Atkeson, J. Hong, S. Long, R. Kooper and M. Pinkerton: Cyberguide: a mobile context-aware tour guide, ACM Wireless Networks, 5(3):421-433, 1997.

[2] G. Adomavicius, R. Sankaranarayanan, S. Sen and A. Tuzhilin: Incorporating Contextual Information in Recommender Systems Using a Multidimensional Approach, ACM Transactions on Information Systems, 23(1):103-145, 2005.

[3] L. Ardissono, A. Goy, G. Petrone, M. Segnan and P. Torasso: INTRIGUE: personalized recommendation of tourist attractions for desktop and handset devices, Applied AI, Special Issue on Artificial Intelligence for Cultural Heritage and Digital Libraries. 17(8-9):687-714. Taylor and Francis, 2003.

[4] Robin Burke. Knowledge-based recommender systems. Encyclopedia of Library and Information Systems, 69, 2000.

[5] D. Billsus and M. J. Pazzani. User modeling for adaptive news access. User Modeling and User-Adapted Interaction, 10(2-3):147–180, 2000.

[6] Robin Burke. Hybrid recommender systems: Survey and experiments. User Modeling and User-Adapted Interaction, 12(4):331–370, 2002.

[7] K. Cheverst, N. Davies, K. Michell, A. Friday, C. Efstratiou: Developing a Context-aware Electronic Tourist Guide: Some Issues and Experiences. CHI Letters, 2(1):17-24, 2000.

[8] A. Felfernig, G. Friedrich, D. Jannach, and M. Zanker, An Environment for the Development of Knowledge-based Recommender Applications, to appear in International Journal of Electronic Commerce (IJEC), 2007.

[9] D. R. Fesenmaier, F. Ricci, E. Schaumlechner, K. Wöber, and C. Zanellai, DIETORECS: Travel Advisory for Multiple Decision Styles, Enter 2003, 2003.

[10] P. Hertzog, M. Torrens: Context-aware Mobile Assistants for Optimal Interaction: a Prototype for Supporting the Business Traveller, 9th International Conference on Intelligent User Interfaces, pp.256-258, 2004.

[11] W. Höpken, M. Fuchs and M. Zanker: etPlanner: A hybrid recommender system for mobile travel planning, OEGAI Journal, 24(4), pp. 26-31, 2005.

[12] D. Jannach, M. Zanker, M. Jessenitschnig, O. Seidler: Developing a conversational travel advisor with Advisor Suite. To appear in ENTER 2007, 2007.

[13] J. Krösche, J. Baldzer, S. Boll: MobiDENK-Mobile Multimedia in Monument Conservation. In: IEEE MultiMedia, 11(2):72–77, 2004.

[14] D. Mladenic. Text-learning and related intelligent agents. IEEE Intelligent Systems, 14:44–54, 1999.

[15] R. J. Mooney, L. Roy, Content-based book recommending using learning for text categorization, Proceedings of the fifth ACM conference on Digital libraries Publisher, ACM Press, pp. 195-204, 2000.

[16] M. Montaner, B. Lopez, and J. De la Rose, A Taxonomy of Recommender Agents on the Internet, Artificial IntelligenceReview, 19:285–330, (2003).

[17] B. Pan, and D. R. Fesenmaier, Exploring the structure of travel planning on the Internet, to appear in Annals of Tourism Research.

[18] A. Pashtan, R. Blattler, A. Heuser and P. Scheuermann: CATIS: A Context-Aware Tourist Information System. 4th International Workshop of Mobile Computing, 2003.

[19] F. Ricci, and F. Del Missier: Supporting Travel Decision Making through Personalized Recommendation. In C-M Karat, J. Blom, and J. Karat (eds.), Designing Personalized User Experiences for eCommerce, Kluwer Academic Publisher, 221-251, 2004.

[20] F. Ricci, Travel recommender Systems, IEEE Intelligent Systems, November/December 2002, pp. 55-57.

[21] F. Ricci and Q. N. Nguyen, Critique-Based Mobile Recommender Systems, OEGAI Journal, 24(4):2005.

[22] W. Schwinger, C. Grün, B. Pröll, W. Retschitzegger, A. Schauerhuber: Context-awareness in Mobile Tourism Guides, Technical report – Institute of Bioinformatics JKU Linz, [ftp://ftp.ifs.uni-linz.ac.at/pub/publications/2005/0405.pdf], 2005.

[23] B. Shilit, N. Adams and R. Want: Context-Aware Computing Applications. In: IEEE Workshop on Mobile Computing Systems and Applications. Santa Cruz, CA, 1994.

[24] M. van Setten, S. Pokraev and J. Koolwaaij: Context-Aware Recommendations in the Mobile Tourist Application COMPASS. International Adaptive Hypermedia Conf., LNCS 3137, pp. 235–244, 2004.

[25] H. Werthner, Intelligent Systems in Travel and Tourism, Proceedings of the 18th International Joint Conference on AI (IJCAI), Acapulco, Mexico, August 9-15, 2003.

[26] J. Wohltorf, R. Cissée and A. Rieger: BerlinTainment: An Agent-Based Context-Aware Entertainment Planning System. IEEE Communications, 43(6):102-109, 2005.

[27] Z., Xiang and D. Fesenmaier, An analysis of two search engine interface metaphors for trip planning, Information Technology & Tourism, 7(2):103-117, 2005.