13

Summary and outlook

13.1 Summary

Recommender systems have their roots in various research areas, such as information retrieval, information filtering, and text classification, and apply methods from different fields, such as machine learning, data mining, and knowledge-based systems. With this book, we aimed to give the reader a broad overview and introduction to the area and to address the following main topics:

- *Basic recommendation algorithms*: We discussed collaborative and content-based filtering as the most popular recommendation technologies. In addition, the basic recommendation schemes, as well as different optimizations, limitations, and recent approaches, were presented.
- *Knowledge-based and hybrid approaches*: As the value of exploiting additional domain knowledge (in addition to user ratings or item "content") for improving a recommender system's accuracy is undisputed, two chapters were devoted to knowledge-based and hybrid recommender systems. We discussed both knowledge-based recommendation schemes, such as constraint and utility-based recommendation, as well as possible hybridization strategies.
- *Evaluation of recommender systems and their business value*: In most cases, recommender systems are e-commerce applications. As such, their business value and their impact on the user's decision-making and purchasing behavior must be analyzed. Therefore, this book summarized the standard approaches and metrics for determining the predictive accuracy of such systems in the chapter on recommender systems evaluation. A further chapter was devoted to the question of how recommender systems can influence the decision-making processes of online users. Finally, a comprehensive

https://doi.org/10.1017/CBO9780511763113.015 Published online by Cambridge University Press

case study demonstrated that recommender systems can help to measurably increase sales.

- *Recent research topics*: Further chapters of the book were devoted to research areas at the forefront of the field. Topics included the opportunities for employing recommendation technology in Web 2.0, ubiquity aspects for recommendations, and the question of how to prevent attacks on recommender systems.

Even though this book covered a broad range of topics, it cannot cover every possible technique or algorithm optimization in detail owing to its introductory nature and the speed of development within the field. Therefore, selections and compromises had to be made, for instance, with respect to the presented application domains. Examples were given for both classical domains, such as books or movies, and less obvious application fields, such as financial products. A discussion of further application domains, such as music recommendation or recommenders for the tourism domain (see, e.g., Staab et al. 2002 or Jannach et al. 2007), which also have their own peculiarities and may require specific recommendation techniques, is beyond the scope of this book.

13.2 Outlook

We conclude the book with a subjective selection of current developments, as well as emerging future problem settings in recommender systems research, many of which were not or were only partially covered in this work.

Improved collaborative filtering techniques. Although a massive number of algorithms and optimizations for the basic CF schemes have been developed over the past fifteen years, new techniques or combinations of CF methods are continually being proposed. A recent example for a rather simple approach is described by Zhang and Pu (2007), whose basic idea is to recursively make predictions for neighbors of the active user u who are very similar to u but have not rated the target item, to improve recommendation accuracy. In addition to such improvements, the Netflix Prize (Bell et al. 2009) competition[1] gave CF research an additional boost recently: in 2006, the online DVD rental company Netflix announced a US $1 million prize for the team whose recommendation system could improve the accuracy of their existing recommendation algorithm (measured in terms of the root mean square error [RMSE]) by 10 percent. The competition was won in 2009 in a joint effort by

[1] http://www.netflixprize.com.

https://doi.org/10.1017/CBO9780511763113.015 Published online by Cambridge University Press

four different competitors. The accuracy improvements were reached by using a combination of various techniques (Töscher et al. 2008). The main aspects were the inclusion of the time aspect as a third aspect beside movies and users, the calculation and combination of various predictors, new techniques such as "neighborhood-aware matrix factorization", and the automatic fine-tuning of parameters.

Context awareness. Time aspects – as mentioned above – are only one of many additional pieces of information that could be taken into account in recommendation tasks. Recent works, for instance, have also tried to take additional context aspects of the user into account. Under the term *context*, various aspects of the user's situation can be subsumed:

- A rather simple form of contextual information, which was discussed in Chapter 12, is the user's current geographical location, which might be exploited not only for ubiquitous or mobile recommendation scenarios but also in the context of the geospatial web in general.
- Time, in the sense of weekday or current time of the day, can also be seen as contextual information. Users might, for instance, be interested in different news topics at different times of the week.
- The emotional context of the user is another interesting dimension that will surely have an impact in some domains. For instance, in the classic movie domain, the user's mood will obviously affect how much users like movies of specific genres. González et al. (2007) present an approach that captures this emotional context of users.
- Accompanying persons represent another context dimension that is surely relevant for making recommendations. The term *group recommendations* has become popular in this regard and is used, for instance, by McCarthy et al. (2006).

When the context of the user's decision process is captured explicitly, recommender systems may exploit *multicriteria ratings* containing this contextual information as an additional source of knowledge for improving the accuracy of recommendations. In contrast with classical settings, which allow each user issues exactly one rating per item, multicriteria ratings would, for example, permit the user to evaluate a movie along different dimensions, such as plot, actors, and so forth. Initial promising methods for exploiting this additional information are reported by Adomavicius and Kwon (2007) and Lee and Teng (2007). One practical example for the use of multicriteria ratings is the e-tourism platform tripadvisor.com. There, users can rate hotels along dimensions such as value, price, or location. Unfortunately, however, no standard datasets for

multicriteria ratings are freely available yet, which makes the development and comparison of different methods extremely difficult.

Recommendation on algorithms and techniques. Since the first algorithms and systems that have now become known as recommender systems were developed, myriad new techniques and improvements have been proposed. Thus, from the perspective of design science (Hevner et al. 2004) the research community was very productive in coming up with more scalable and more accurate algorithms. From the viewpoint of behavioral science, however, more research efforts are needed before we can develop an explanatory theory as to why and how recommender systems affect users' decision processes. In addition, prescriptive theory is required to guide practitioners in terms of which domains and situations are suitable for which recommendation algorithms. Some initial thoughts toward *recommending recommenders* were made by Ramezani et al. (2008), but clearly more research in this direction will take place.

User interaction issues/virtual advisors. More elaborate user interaction models are relevant not only in mobile recommender systems but also in classical web-based systems, in particular where additional knowledge sources, such as explicit user preferences, can be leveraged to improve the recommendation process. The provision of better explanations or the use of "persuasive" technologies are examples of current research in the area. In addition, we believe that more research is required in the area of conversational user interaction – for example, into the development of dialog-based systems for interactive preference elicitation. Also, the use of natural language processing techniques, as well as multimodal, multimedia-enhanced rich interfaces, is, in our opinion, largely unexplored, although it is an important step in the transition between classical recommender systems and "virtual advisors" (Jannach 2004).

Such next-generation recommenders might someday be able to simulate the behavior of an experienced salesperson. Instead of only filtering and ranking items from a given catalog, future advisory systems could, for instance, help the user interactively explore the item space, conduct a dialog that takes the customer's skill level into account, help the user make compromises if no item satisfies all of his or her requirements, give intuitive explanations why certain items are recommended, or provide personalized arguments in favor of one particular product.

Recommendation techniques will merge into other research fields. Over the past few years, the research field has experienced considerable growth; the annual ACM conference series on recommender systems attracted more than

200 submissions in 2010. We expect that additional interest in the basic building blocks of recommendation systems, such as user modeling and personalized reasoning, will come from neighboring and related fields such as information retrieval. The personalization of search results might transform search engines into context-aware recommender systems in the future. Moreover, the enormous growth of freely available user-generated multimedia content, thanks to Web 2.0, will lead to emphasis on personalized retrieval results (Sebe and Tian 2007). Analogously, recommending appropriate items could also be of interest in other fast growing areas such as the "Internet of Things" or the "Web of Services". Thus the authors are convinced that knowledge of recommendation techniques will be helpful for many application areas.