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PREFACE

Preface to the special issue on user interfaces for recommender systems

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1 User interfaces for recommender systems

Recommender systems provide a valuable support for users who are searching for products and services that match their preferences and needs. There are three basic approaches to the recommendation of products and services. *Collaborative techniques* (Konstan et al. 1997) calculate recommendations by determining nearest neighbors whose rating behaviors are similar to the one of the active user. In this context, items are recommended which are not known by the current user but have been rated positively by the nearest neighbors. *Content-based* recommendations (Pazzani and Billsus 1997) are determined on the basis of the similarity between the preferences of a user (stored in a user profile) and the corresponding item descriptions. A typical example for the application of content-based approaches is the recommendation of interesting web sites (Pazzani and Billsus 1997). Finally, *knowledge-based recommendation* determines items of relevance for the user either by interpreting an explicitly defined set of filtering rules (constraints) (Felfernig and Burke 2008) or by taking into account the similarity between a set of explicitly defined user requirements and the elements of the underlying item set (Burke 2000).

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The practical relevance of recommender systems is shown by a variety of commercial applications such as Amazon, Netflix, Trip Advisor, and Yahoo. Recommender systems research has long focused on optimizing the predictive accuracy of recommendation and filtering algorithms, a trend epitomized by the recent Netflix prize. An extremely important dimension very often not captured in this attention on predictive accuracy is the nature and perceived qualities of recommender systems from the user's point of view. The user interface (UI) of a recommender system can have a critical and decisive effect on factors such as the overall system usability, system acceptance, item rating behavior, selection behavior, trust, willingness to buy, willingness to reuse the recommender system, and willingness to promote the system to others. Exactly such aspects are the focus of this special issue on *UIs for Recommender Systems*.

Although not in the primary focus of existing research, impacts of recommender UIs on user behavior have already been analyzed. Cosley et al. (2003) showed that the presentation of item ratings in collaborative recommenders has a significant impact on the own rating behavior. For example, ratings were higher in conditions were the UI presented inflated predictions to the user. In the same line of research, Adomavicius et al. (2011) analyze the existence of anchoring effects in collaborative filtering scenarios. The results of their experiments clearly confirm the results of Cosley et al. (2003) and show in more detail the impacts of different types of rating drifts on a user's rating behavior. Beenen et al. (2004) examined explanations that users provide for their ratings, and found that users whose explanations were cited as useful were much more likely to rate additional items. The outcome of this study was that positive reinforcement significantly increases the average number of item ratings per user. Pu and Chen (2011) provide an in-depth analysis of common design pitfalls when developing UIs for preference elicitation, preference revision, and explanation. Felfernig et al. (2006) analyze the impact of different recommender UI functionalities such as explanations, product comparison pages, and repair actions on factors such as perceived increase of domain knowledge, increase of usability and trust. An in-depth discussion on the impact of explanation interfaces on the perceived level of trust can be found in Pu and Chen (2006). An overview of different possible impacts of decision-psychological phenomena on decisions taken in recommendation scenarios can be found in Mandl et al. (2010).

2 About this special issue

Research on *recommender UI* is becoming increasingly popular in this highly interdisciplinary research field. The goal of this special issue is to show novel and innovative related research results. The following contributions have been accepted for publication in this special issue.

In their paper on *Evaluating Recommender Systems from the Users Perspective: Survey of the State of the Art*, Pearl Pu, Li Chen, and Rong Hu examine the state of the art relative to user experience research in recommender systems. The authors focus on three basic types of user interaction and UI issues: preference elicitation, preference refinement, and recommendation result display. Their analysis of existing research is the basis for a comprehensive set of *usability design guidelines* intended, for example, to enhance a users' trust in the recommender system, to engage users to provide ratings and other feedback, to increase the perceived system usefulness, and to decrease the perceived cognitive efforts.

Alina Pommeranz, Joost Brokens, Pascal Wiggers, Willem-Paul Brinkman, and Catholijn Jonker present their work on *Designing Interfaces for Explicit Preference Elicitation*. The authors present three user studies in which they analysed different preference elicitation interfaces. The results of these studies are documented in terms of *four design guidelines* for preference elicitation interfaces which are: (1) users willing to spend more effort in preference elicitation should be able to do so, (2) affective feedback interfaces (e.g., in terms of so-called *affect buttons*) should be considered as a means of detailed preference feedback, (3) design interfaces should be organized in an explorative fashion where the consequences of preference shifts are easily visible, and (4) preference elicitation processes should not start from scratch but rather rely on initial system preference suggestions.

In their paper on *Evaluating the effectiveness of explanations for recommender systems*, Nava Tintarev and Judith Masthoff analyze the impact of explanations in terms of effectiveness and user satisfaction. In their studies, an explanation is deemed effective if the users preference for an item does not change after consumption, in other words, the explanation was sufficiently good that the user could accurately assess the desirability of the item in advance. User satisfaction is a different measure based on user ratings for explanations. The major learnings from the studies are that the personalization of explanations can be detrimental to effectiveness and that users are more satisfied with feature-based explanations (item features are described, e.g., *this movie belongs to the genre* '*drama*') compared to baseline explanations (no item features described, e.g., *this movie is one of the top 50 movies in our database*).

With their paper on *Explaining the user experience of recommender systems*, Bart P. Knijnenburg, Martijn C. Willemsen, Zeno Gantner, Hakan Soncu, and Chris Newell are proposing a framework to support user-centric evaluations of recommender systems. The framework includes *objective system aspects* (what the system does, e.g., the used algorithms), *subjective system aspects* (how the system is perceived, e.g., in terms of usability), *experience* (e.g., evaluation of the decision process), *interaction* (objective effect of using the system, e.g., purchasing an item), and *personal and situational characteristics* (e.g., demographics and choice goals). It provides a basis for explaining *why users like a recommender application and how this user experience comes about*. The presented framework has been evaluated in empirical studies. It can serve as a basis for industry researchers to conduct more in-depth evaluations of their solutions and for researchers to better estimate the real-world impact of their recommender systems.

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