Human Decision Making and Recommender Systems

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Recommender Systems have already proved to be valuable for coping with the information overload problem in several application domains. They provide people with suggestions for items which are likely to be of interest for them; hence, a primary function of recommender systems is to help people make good choices and decisions. However, most previous research has focused on recommendation techniques and algorithms, and less attention has been devoted to the decision making processes adopted by the users and possibly supported by the system. There is still a gap between the importance that the community gives to the assessment of recommendation algorithms and the current range of ongoing research activities concerning human decision making. Different decision-psychological phenomena can influence the decision making of users of recommender systems, and research along these lines is becoming increasingly important and popular. This special issue highlights how the coupling of recommendation algorithms with the understanding of human choice and decision making theory has the potential to benefit research and practice on recommender systems and to enable users to achieve a good balance between decision accuracy and decision effort.

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1. INTRODUCTION

A primary function of recommender systems is to help people make good choices and decisions. But research on recommender systems has focused mainly on (a) ways of eliciting and modeling users' preferences and (b) algorithms for identifying items that a user is likely to evaluate positively [Ricci et al. 2011]. Surprisingly less attention has been devoted to the decision making processes of users that are triggered or supported by the system. Even systems that do explicitly aim to support the decision making

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process could benefit from greater use of knowledge about human decision making. And the growing amount of research on users' interaction with recommender systems, which aims to enhance their usability and acceptance and improve the experience of users of these systems, can be expanded to consider support for specific aspects of decision making.

This special issue highlights research that explicitly considers ways in which an understanding of human choice and decision making can benefit research and practice on recommender systems.

2. MODELS OF HUMAN-DECISION MAKING

Customers of bricks-and-mortar stores can benefit from the support of human sales experts. In online sales environments, recommender systems take over the role of sales experts supporting online users in finding products and services (items) that fit their wishes and needs [Bo and Benbasat 2007]. Both user groups are regarded as important market segments that make the understanding of human decision behavior a crucial issue [Jarvenpaa et al. 2000; Thompson and Yeong 2003]. Human decision behavior is explained by different models of human decision making (see, e.g., [Simon 1955; Payne et al. 1993; Gigerenzer 2007; Kahneman 2011]); here, we briefly introduce selected models.

Traditional economic models. Traditional microeconomic models of human decision making are based on the assumption that consumers are making optimal decisions [Grether and Plott 1979; McFadden 1999]. In these models, human decisions are assumed to be the result of a formal evaluation process which relies on the assumption that preferences are known from the beginning of the decision process and that they remain stable. However, this is an idealized assumption which may not hold in real-world scenarios. For instance, customers who have a price limit in mind often purchase a car which is more expensive simply because finding out about previously unknown features made them change their mind. Evidence against the assumption of a complete set of stable preferences led to alternative models of human decision making [Simon 1955; Payne et al. 1993; Gigerenzer 2007].

Preference construction. The fact that humans often do not have a clear picture of their preferences from the very beginning but rather develop their preferences within the context of a decision process is part of the more general phenomenon of *preference construction* [Bettman et al. 1998; Lichtenstein and Slovic 2006]. Within the scope of a decision process, preferences are strongly influenced by the goals of the customer, existing cognitive constraints, and the personal experience of the customer [Warren et al. 2010]. Given that users may not have stable preferences, the interaction mechanisms provided by a recommender system and the information shown to a user can have a large impact on the outcome of a decision process.

Effort-accuracy framework. A decision process can be interpreted as involving a tradeoff between the decision making effort and the accuracy of the decision outcome. The effort-accuracy framework is based on the idea that human decision behavior is adaptive and consumers apply different decision strategies depending on the decision context [Payne et al. 1993]. This interpretation of human decision behavior clearly contradicts economic models [Grether and Plott 1979; McFadden 1999] in which optimality plays a predominant role and aspects such as cognitive effort are neglected. The complexity of decision tasks, limited cognitive resources and knowledge of users, and the tendency to reduce the overall decision effort together lead to a limited rationality of individuals which Simon named *bounded rationality* [Simon 1955]. Preference construction processes based on bounded rationality are susceptible to different kinds of decision effects (or biases) which potentially lead to suboptimal outcomes (see, for example, [Mandl et al. 2011]). The impact of such effects on decision making in recommender systems will be discussed in the following.

3. IMPACT OF HUMAN DECISION MAKING ON RECOMMENDER SYSTEMS

Interacting with a recommender system involves making various types of decision, such as selecting a song or movie from a recommendation list, selecting specific feature values (e.g., a camera's size or zoom factor) as criteria, selecting feedback features to be critiqued in a critiquing-based recommendation session, or selecting a repair proposal for inconsistent user preferences when interacting with a knowledge-based recommender. As was mentioned in the previous section, users often do not know or reflect on their preferences beforehand, so they may need to construct them within a specific recommendation scenario. Moreover, there exist various well-established decision-psychological phenomena, such as context effects, primacy/recency effects, and framing effects, which presumably influence users' decision making when they are using recommender systems [Mandl et al. 2011]. For instance, Cosley et al. showed that a user's rating behavior can be affected by a display of the system's predicted ratings; that is, users tend to shift their rating toward the prediction that the system shows [Cosley et al. 2003]. In the same line of research, Zhang and Adomavicius et al. analyzed anchoring effects in recommender systems [Zhang 2011; Adomavicius et al. 2011a]. The results of their experiments clearly confirm the results of Cosley et al. and show in more detail the impact of different types of user interfaces on a user's rating behavior.

Thus, research on human decision making in recommender systems has become increasingly important and popular in this highly interdisciplinary research field. In a typical contribution, Haubl and Trifts studied the effect of recommendation agents on the quality and efficiency of users' purchase decisions [Häubl and Trifts 2000]. They demonstrated that the use of recommendation agents can reduce consumers' search effort for product information, decrease the size of their consideration sets while increasing their quality, and improve the quality of their purchase decisions. In addition, considering that accurate decisions are normally thought to be made via compensatory strategies, such as ones that require a decision maker diligently to examine all relevant alternatives and compare their prospective pros and cons attribute by attribute [Einhorn and Hogarth 1981; Payne et al. 1993], Pu and Chen investigated how to support such strategies in the context of recommenders [Pu and Chen 2005; Chen and Pu 2009]. Their studies showed that providing effective tradeoff support (like example critiquing technology) can generate significantly positive effects on various factors, including system acceptance, users' perceived decision quality, willingness to buy, and willingness to reuse the recommender system in the future. From the perspective of interface design, Felfernig et al. analyzed the impact of different recommender UI functionalities, such as explanations, product comparison pages, and repair actions, on facilitating users' decision processes and enhancing their perceived domain knowledge and trust [Felfernig et al. 2007]. The role of recommendation explanation in aiding users' decision making was further discussed in depth by Pu and Chen [Pu and Chen 2006].

In this special issue, we aim to present, in journal-length articles, further research that takes theories from decision psychology and cognitive psychology into account in explaining users' preference construction and decision making process in the context of recommender systems. We aim to encourage the development of more effective decision and interface technologies for recommender systems so as to allow users to achieve the ideal balance between the decision accuracy that they can attain and the decision effort that they need to invest.

4. ARTICLES IN THE SPECIAL ISSUE

Three articles were accepted for publication in this special issue; all three are based on the *preference construction* model of human decision making.

Interesting and novel decision making and recommendation scenarios include those where the user is required to make a sequence of choices rather than just selecting one good item. “An English-Language Argumentation Interface for Explanation Generation with Markov Decision Processes in the Domain of Academic Advising” by Dodson, Mattei, Guerin and Goldsmith focuses on such a scenario. Their system interactively generates conversational English-language explanations of the actions suggested by an optimal policy of a specific Markov Decision Process. The system advises undergraduate students at a large university on what courses to select in the coming semester(s). The explanations, which are based on a novel argument-based approach with conversational English text, are generated from domain-specific and domain-independent information, and are aimed at persuading end users to implement the recommended actions by convincing the user of the “goodness” of such actions. The proposed approach is largely domain-independent; it can therefore be applied in other sequential decision making application scenarios.

A practical example on how to exploit user decision making patterns to improve the accuracy of a recommender system is presented in the article “Rating Bias and Preference Acquisition” by Freyne, Berkovsky and Smith. The authors propose to explore a novel dimension of information to enhance the recommender system’s accuracy: besides the user preference for an item and the features of the item, they leverage the additional value hidden in user ratings to ascertain the importance of certain domain features. This knowledge is effectively exploited to design an active learning algorithm that analyses the input of users, determines how they are reasoning, and responds by requesting ratings of items that contribute high-value information to the system. Experiments on users’ ratings on a corpus of recipes show that there are stable user biases towards certain features (cuisine type, key ingredient, and complexity). Leveraging those user biases to obtain specific ratings has a positive impact on the recommender’s accuracy.

An analysis of the cognitive processes adopted by users involved in a decision about whether or not disclose their personal information to a recommender system is presented in “Making Decisions about Privacy: Information Disclosure in Context-Aware Recommender Systems” by Knijnenburg and Kobsa. This complex process, called “privacy calculus”, was studied in an online experiment with 493 participants using a mock-up of a context-aware recommender system which recommends apps for Android phones on the basis of users’ context and demographics. The aim of the experiment was to evaluate how users perceive and balance the benefits of information disclosure with privacy concerns. The experiment introduces two strategies to influence information disclosure based on the type of justification message and the order in which disclosure requests are made, and it shows that these aspects affect the perception of and experience with a system, which in turn drive information disclosure decisions. More specifically, the results show that disclosure justification messages are perceived to be valuable, even though they do not increase disclosure and they decrease users’ trust and satisfaction. As regards the order in which disclosure requests are made, results show that manipulating the order of the requests increases the disclosure of items requested early but decreases the disclosure of items requested later.

5. DISCUSSION AND OPEN ISSUES

Research on human decision making in recommender systems is still in its infancy. There are numerous challenges to be tackled; some of these are discussed in the following.

Recommender systems research has mainly viewed the decision making process as a "black box". Indeed, in the canonical recommendation scenario, the only information stored and analyzed is that concerning the end points of the transaction: the user, the item shown to the user and, at the opposite end, the (buying/rating) decision taken by the user about that item. The richness and complexity of the tens of decision points that brought the user to the final decision are largely ignored, even though they may reflect the real motivations for the user decision. In other words, recommender systems research could benefit from storing and analyzing user decision processes at a finer-grained subtransactional level, which takes into account both observable and unobservable events and is able to organize and correlate them with the help of scientific findings from psychology.

With a few exceptions, research related to human decision making with recommender systems focuses on single-user scenarios. One major issue for future research is to take into account the specifics of group decisions. For example, knowledge-based recommender systems for travel destinations have to support group decision making since travel destinations are selected by groups (family and/or friends) [Jameson 2004]. In a similar fashion, recommender systems supporting requirements negotiation have to take into account group decision processes [Felfernig et al. 2012]. In these scenarios, the awareness of the specifics of group decision processes is a major precondition for the successful implementation of recommender systems. For an in-depth analysis of the commonalities and differences between decision biases of individuals and groups, we refer to [Kerr et al. 1996].

Another interesting topic that deserves more research work is modeling the impact of contextual factors in decision making processes that are supported by recommender systems [Adomavicius et al. 2011b]. In recommender systems research, context is defined as any information or conditions that can influence the *perception* of the usefulness of an item for a user. But how context influences the users' decision making processes is still not completely clear. For instance, in [Kahneman 2011], the author discusses how context influences the interpretation of ambiguous information and how it is used to suppress doubts. It is shown that context does play a more fundamental role in decision making and it is therefore necessary to elaborate more sophisticated theories. In fact, recommender systems have only tried so far to understand how context influences the rating behavior of the users and how this influence can be quantitatively modeled in the core recommendation algorithms [Adomavicius et al. 2011b].

Personal factors such as personality, mood, and emotions can also influence users' decision making process [Gonzalez et al. 2002]. For instance, Hu and Pu found that recommender systems that consider the user's personality are more effective in terms of increasing users' loyalty towards the system and decreasing their cognitive effort, compared to the non-personality-based systems [Hu and Pu 2009]. In [Chen et al. 2013], the authors discuss whether and how personality influences users' needs for recommendation diversity. Emotion was also embedded in recommender system with the aim of enhancing the system's performance (see e.g., [Gonzalez et al. 2007]). However, few have taken these factors into account in modeling users' decision processes and the construction of their preferences in the context of recommenders.

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