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Interactive recommender systems: A survey of the state of the art and future research challenges and opportunities

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ABSTRACT

Recommender systems have been researched extensively over the past decades. Whereas several algorithms have been developed and deployed in various application domains, recent research efforts are increasingly oriented towards the user experience of recommender systems. This research goes beyond accuracy of recommendation algorithms and focuses on various human factors that affect acceptance of recommendations, such as user satisfaction, trust, transparency and sense of control. In this paper, we present an interactive visualization framework that combines recommendation with visualization techniques to support human-recommender interaction. Then, we analyze existing interactive recommender systems along the dimensions of our framework, including our work. Based on our survey results, we present future research challenges and opportunities.

1. Introduction

No matter whether we notice it or not, we encounter recommender systems almost everyday, such as Ad recommendations in any possible corner of a web page or product recommendations in online shops. Due to their ability to solve the increasingly severe problem of information overload, recommender systems have gained massive attention over the past decades. The Netflix Prize (Bennett & Lanning, 2007) between 2006 and 2009 and several other challenges organized at the Recommender Systems (RecSys) conference attracted numerous researchers from machine learning and data mining research fields.

Whereas several algorithms have been developed and deployed to suggest relevant items to a user (Adomavicius & Tuzhilin, 2005), there are still several challenges that need to be resolved before recommender systems can realize their full potential. Several recommendation algorithms suffer from *cold start* issues, i.e. they cannot make effective recommendations for new users or for new items that have no explicit or implicit relevance indicators yet (Burke, 2010). In addition, recommender systems often appear as a *"black box"*, i.e. they do not offer the user any insight into the system logic or justification for the recommendations (Sinha & Swearingen, 2002). This black box nature of recommender systems prevents users from comprehending recommended results and can lead to *trust* issues when recommendations fail (Herlocker, Konstan, & Riedl, 2000). In addition, the approach does not enable users to provide feedback. As the predication of the current interest of the user is often a challenging task, there is a need to develop mixed-initiative approaches that enable users to help steer this process. Such mixed-initiative approaches are also promising to address other issues of recommender systems, such as increasing *diversity* (Hu & Pu, 2011) and *novelty* (Herlocker, Konstan, Terveen, & Riedl, 2004) of recommended results, and their deployment in *high-risk application domains* such as health-care and financing (McSherry, 2005).

In recent years, researchers have become more aware of the fact that effectiveness of recommender systems goes beyond recommendation accuracy (Swearingen & Sinha, 2001). Thus, research on these human factors has gained increased interest, for instance by combining interactive visualization techniques with recommendation techniques to support transparency and controllability of the recommendation process. Visualization leverages visual representations to facilitate human perception, while interaction stresses user involvement through dialogue with the system.

We have presented an interactive visualization to support exploration, transparency and controllability of recommendations at the ACM Conference on Intelligent User Interfaces (IUI) in 2013 (Verbert, Parra, Brusilovsky, & Duval, 2013). Several other researchers have proposed interactive visualizations as a means to support interaction with recommender systems. In this article, we analyze these interactive recommender systems and their support

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to address the following challenges: (1) transparency and justification, (2) user control over the recommender system, (3) lack of diversity, (4) cold start issues and (5) contextual information acquisition and representation. The research contributions are threefold:

1. We present an interactive visualization framework for recommender systems. The framework integrates visualization and recommendation techniques to address several issues of recommender systems, including cold start, user control and transparency.
2. Then we present an analysis of existing interactive recommender systems along the dimensions of our framework.
3. Based on the analysis, we identify future research challenges and opportunities to advance the research field.

The article is organized as follows: we present recommendation algorithms and visualization techniques in Section 2. Section 3 presents our interactive visualization framework for recommender systems and elaborates the research objectives of our work. Section 4 presents a comprehensive overview of existing interactive recommender systems. An analysis of these systems along the dimensions of our framework is elaborated in Section 5. Finally, we present future research directions and challenges based on our analysis.

2. Background

2.1. Recommendation algorithms and their limitations

Recommender algorithms are often broadly categorized in three areas: *collaborative filtering* recognizes commonalities between users or between items on the basis of explicit (ratings, tags, etc.) or implicit (actions like reading, downloading.) relevance indications (Burke, 2010). A standard user-based collaborative filtering algorithm first identifies similar users based on their overlapping interactions or similar ratings of common items. It then makes recommendations based on preferences of these similar users. A standard item-based recommendation algorithm analyzes similarities between items and then uses these similar items to identify the set of items to be recommended. Collaborative filtering is the most widely implemented and most mature technology (Burke, 2002). *Content-based filtering* matches descriptions of items to descriptions of users (Pazzani & Billsus, 2007). They base their predictions on information about individual users and items, and ignore contributions from other users. This approach relates most closely to our work on metadata (Ternier et al., 2009). *Hybrid recommender systems* combine recommendation techniques, to gain better performance with fewer drawbacks (Burke, 2002).

Recent research on recommender systems is increasingly oriented towards incorporation of contextual information into the recommendation process (Adomavicius & Tuzhilin, 2005). While traditional recommender systems represent the users with simple user models, context-aware recommender systems consider additional information to improve quality of recommendations. For instance, a movie recommender based on collaborative filtering represents the user as a vector of ratings over a set of films, but a context-aware recommender can consider who is accompanying the user – a child or another adult – to make a more appropriate suggestion. Although “user company” is a typical example of context, there is no clear consensus about its definition and several disciplines understand context differently (Adomavicius & Tuzhilin, 2012). Despite this, a well cited definition of Dey (2001) states that context is *“any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves.”*

Dourish (2004) expands this definition by considering context from social and technological perspectives (Adomavicius & Tuzhilin, 2012). The social perspective understands context as something describing interactions rather than a setting or situation. The technical perspective represents context as a predefined set of observable attributes. We have analyzed several technical definitions of context in Verbert et al. (2012). In summary, most definitions include attributes to represent location, time, computing context, user context, activity of the user, physical conditions such as weather and noise level, or social relations. Context-aware recommender systems try to adapt recommendations to one or more of these contextual attributes and have been proven to provide better predictive performance in a number of domains. Emotion is one of the most popular contextual attributes (Zheng, Mobasher, & Burke, 2013). Examples of other attributes that have been considered in context-aware recommender systems include weather (Hong, Suh, Kim, & Kim, 2009) and noise level (Yau & Joy, 2007).

Contextual information can be obtained in a number of ways, including *explicitly* from the user or *implicitly* from the environment, for instance by obtaining the current location or device type. Contextual information can also be *inferred* by analyzing user interactions with tools and resources, for instance to estimate the current interest of the user.

Although these algorithms have been implemented and validated on a large scale in several application areas (Nageswara & Talwar, 2008), there are important challenges that need to be addressed before recommender systems can realize their full potential:

1. Collaborative recommendation techniques often suffer from *cold start* issues, i.e. they cannot make effective recommendations for new users or for new items that have no explicit or implicit relevance indicators yet (Burke, 2010).
2. It is *difficult to explain* the rationale behind recommendations to end users (Herlocker et al., 2000): the complexity of recommendation algorithms often prevents users from comprehending recommended results and can lead to *trust issues* when recommendations fail. This complexity is often aggravated by contextual recommendation algorithms that use various types of contextual information in the recommendation process.
3. *Contextual information* can be substantially enriched in non-obtrusive way by exploiting new sensors, particularly in mobile devices like smart phones or tablet computers. In addition, there is a need for developing *richer interaction capabilities* for contextual recommender systems (Adomavicius & Tuzhilin, 2012). The current black box nature of recommender systems prevents users to provide input into the recommendation process in an interactive and iterative manner. As the predication of the current task or interest of the user is a challenging task, there is a need to develop mixed approaches that enable users to help steer this process.

2.2. Visualization techniques

Data visualization is a well established research field. The distinction is often made between *information visualization* and *scientific visualization*. Information visualization focuses on representing abstract data. A typical example is a graph visualization that shows relationships between people or a time line visualization that represents the evolution of concepts over time. Scientific visualization is specifically concerned with data that has a well-defined representation in 2D or 3D space. Emphasis is on realistic renderings of volumes, surfaces, illumination sources, etc.

In this article, we are most interested in *information visualization*: the use of interactive visual representations of abstract data