Understanding user preferences and goals in recommender systems

Martijn C. Willemsen

Eindhoven University of Technology,
Eindhoven, the Netherlands
M.C.Willemsen@tue.nl
www.martijnwillemsen.nl

Abstract

Recommender systems typically use collaborative filtering: information from your preferences (i.e. your ratings) is combined with that of other users to predict what other items you might also like. Much of the research in the field has focused on building algorithms that provide recommendations based purely on predicted accuracy [5]. However, these models make strong assumptions about how preferences come about, how stable they are, and how they can be measured [4]. Having a background in decision psychology I have studied how the preference elicitation methods of recommender systems can be better understood and improved based on psychological insights. I will illustrate this with an example of new choice-based preference interfaces we have developed. Users are more satisfied with a method that measures their preferences through a series of choices than with a rating-based preference elicitation, because the rating-based is more effortful and provides more obscure movies [2]. However, a drawback is that recommendation lists of choice-based preference elicitation contain mostly popular movies, and further research has investigated that showing trailers can help to reduce this popularity effect a bit as users are able to use the trailer to inspect less well-known items [3].

Moreover, recommender systems should also align with user goals. Many real-life recommender systems are evaluated mostly on (implicit) behavioral data such as clicks streams and viewing times. However, such an approach has limitations and I will show how a user-centric approach can help better understand why users are satisfied or not, for example why users prefer diversify over prediction accuracy as it reduces choice difficulty [8]. The behaviorist approach to evaluation also misses that users' short term goals (i.e. their current behavior) might not be representative of the goals they want to attain (i.e. their desired behavior) [1]. This is especially relevant in health and life style domains [6] where people are in need of support while changing their current behavior. I will elaborate on an example in the energy recommendation domain, and show how a different type of recommender approach and interface might help users to save more energy [7].

Speaker

Dr. Martijn Willemsen is an expert on human decision making in interactive systems. He is working as an associate professor in the Human-Technology Interaction group of Eindhoven University of Technology (The Netherlands). His primary interests lie in the understanding of cognitive processes of decision making by means of process tracing and in the application of decision making theory in interactive systems such as recommender systems. He is also an expert on user-centric evaluation of adaptive systems. He is part of the core team of the Customer Journey Research Program in the Data Science Center Eindhoven (DSC/e) and is teaching in the joint BSc and MSc data science programs of the Jheronimus Academy of Data Science (jads.nl).

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