

Explaining Social Recommendations to Casual Users: Design Principles and Opportunities

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ABSTRACT

Recommender systems have become popular in recent years, and ordinary users are more likely to rely on such service when completing various daily tasks. The need to design and build explainable recommender interfaces is increasing rapidly. Most of the designs of such explanations are intended to reflect the underlying algorithms by which the recommendations are computed. These approaches have been shown to be useful for obtaining system transparency and trust. However, little is known about how to design explanation interfaces for casual (non-expert) users to achieve different explanatory goals. As a first step toward understanding the user interface design factors, we conducted an international (across 13 countries) online survey of 14 active users of a social recommender system. This study captures user feedback in the field and frames it in terms of design principles and opportunities.

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; See <http://acm.org/about/class/1998/> for the full list of ACM classifiers. This section is required.

Author Keywords

Explainable Intelligent User Interface; Social Recommender

INTRODUCTION

It is not a new idea to provide an explanation of a decision support system (DSS). The kinds of explanation provided are usually associated with the inference methods: for example, in a Bayesian network-based system, the purpose of such an explanation is to help the user understand the model or reasoning process [2]. The target users of these explanation designs are somehow domain experts or skilled workers. With the rapid growth of data causing information overload, more and more applications rely on recommender systems (RS), such as e-commerce, social media, news agencies, and even government services. It is not surprising that an RS is serving a more extensive range of users, from domain experts to an ordinary end user with no relevant technical background.

However, similar to DSSs, most of the RS explanation designs are intended to reveal the state of the system. For example, providing an explanation to reflect the underlying algorithm by which the recommendations are computed has proved to be useful for gaining system transparency [2] and trust [1]. There is limited understanding of how to design the explanation interfaces in different explanatory goals for casual (non-expert) users. In this paper, we plan to collect the feedback from end users and discuss the implications of design principles and opportunities in explaining social recommendations.

METHODOLOGY: INTERNATIONAL ONLINE SURVEY

As a first step towards understanding the design factors of explanatory interfaces, we deployed a survey through a social recommender system, Conference Navigator [3], and analyzed data from the respondents. We targeted the users who had created an account and casually (not frequently) interacted with the system in their previous conference attendance. The survey was made by sending the invitation to the qualified users. We sent out 89 letters, and a total of 14 participants (7 female) replied to create the pool of participants for the user study. The participants were from 13 different countries; their ages ranged from 20 to 40 ($M=31.36$, $SE=5.04$). We did an online survey to collect necessary demographic information and self-reflection about how to design an explanation function in seven explanatory goals [2]. The proposed questions are: *How can an explanation function help you to perceive system* 1) **Transparency** - explain how the system works? 2) **Scrutability** - allow you to tell the system it is wrong? 3) **Trust** - increase your confidence in the system? 4) **Persuasiveness** - convince you to explore or to follow new friends? 5) **Effectiveness** - help you make good decisions? 6) **Efficiency** - help you to make decisions faster? 7) **Satisfaction** - make using the system fun and useful? We asked the participants to answer each question in 50-100 words, in particular reflecting the explanatory goals of the social recommendation.

INITIAL ANALYSIS AND DISCUSSION

1) **Transparency**: 71% of respondents pointed out the *reasons* of generated social recommendation that help them to perceive higher system transparency. For instance, the personalized explanation (*what is [the] similarity between my interest and the recommended person?*), the linkage and data sources (*providing me a reason for the "linkage"*), reasoning method (*... providing deeper information on how the score amount up ...*) and understandability (*allow users to see the connection between people and understand how they are connected.*)

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2) Scrutability: Half of the respondents mentioned they needed an “inspectable detail” to figure out the wrong recommendation: for example, the details of similarities or differences (... *by checking the similarity description, I could understand if the recommendation is good or not.*), the reason for the recommendation (*Showing from where the data used to make recommendations ... allow me to check the system*) or comparing the expected item (*I can compare an explanation [with what] I was expected to see and decide whether the system is wrong.*). 35% of respondents reported the mechanism of accepting user feedback on improving wrong recommendations, such as a space to submit user ratings or yes/no options. 14% of respondents preferred a dynamic exploration process to determine the recommendation quality, such as (*In my case, it was difficult to find the “correct” results, and I think I was telling the system that the results were wrong by keep trying to change the weight of each component.*).

3) Trust: 28% of respondents mentioned that they trusted the system more when they perceived the benefits of using the system, such as when an explanation on success stories was provided (... *those who have followed recommendations ... they collaborated later together.*) or periodical performance updates (*report monthly for instance the performance of the system.*). 35% of respondents preferred to trust a system with reliable and informative explanations: a wrong explanation hurt the reliability (... *it can be also dangerous [to lose trust] if you are wrong.*), more detailed information (... *exposing main components influenced the recommendation.*) or understandable (*Trust comes from understanding, especially if the output is not correct.*). 35% of respondents mentioned they trust a system with transparency (*I think my answer for this question will be very similar to that regarding transparency.*) or passed their verification (*Once I verify that the first data is reliable, I would increase my confidence.*).

4) Persuasiveness: Half of the respondents mentioned the explanation of social familiarity would persuade them to explore novel social connections; namely, when shown social context details (*if I can understand the social relations between people, I'm more confident to follow new friends.*) or shared interests (*I would follow new friends if the system shows me that my interesting is aligned with new friends.*). 21% of respondents indicated that an informative interface can boost the exploration of new friendship; for example, a friendly interface (*if the system looks pretty and friendly enough to use, I will be convinced more to explore*) or one that is proactive & up-to-date information (*If the system is more active, providing updated information ... , I will follow.*). 28% of respondents preferred a design that inspired curiosity (*People are curious... an explanation can be perceived as a “trail” of interactions*), implicit relationships (... *shows people implicitly in your network*). One respondent proposed an interesting idea to have a “mutual explanation” among users, say (*we both see the explanation and reason why we should connect*).

5) Effectiveness: 64% of respondents mentioned that the aspects of social recommendation relevance helped them to make a good decision. The aspect included explaining the recommendation process (*if the process of recommendation is clear ... it can help me to make good decisions.*), understandable (*The clearer the explanation and the similarity between me*

and the recommended person is, the more effective the system will be.) or more informative (*I think having more information always help us make better decisions.*). 28% of respondents suggested a reminder that a historical or successful decision could help them to make a good decision, i.e., a previously-made user decision (*remind me of recent decisions I made and allow me to change my ideas easily*) and success stories (*looking at successful historical interactions would help me to have a sense of effectiveness.*).

6) Efficiency: 28% of respondents mentioned that a proper highlighting of the recommendation helped to make the decision faster. For example, emphasizing the relatedness (*Highlighting some recommended items that are strongly related to the user.*), identifying the top recommendations or providing success stories (*I would like to see how ... effective such interactions ended up*). 28% of respondents preferred a tunable or visualizable interface to accelerate the decision process, such as tuning the recommendation features (*I think the sliders for different dimensions are very important in making quick decisions ...*), visualizing the recommendations (*Having visual representations of complex aggregated non-obvious relations can help to make decisions faster*). However, the explanations may not always be useful. 21% of respondents argued that the explanation would prolong the decision process instead of speeding it up: the user may need to take extra time to realize the explanations (*I don't think ... they can help me to make decisions faster. Actually, it will take longer to me.*).

7) Satisfaction: The feedback on how an explanation can help the user satisfy the system was varied. Three aspects were received an equal 7% of respondents' preference. That is, users preferred to view the feedback from the community (*if I can see how others rated the recommended person, this data is very interesting.*), shown the historical interaction record and provided a personalized explanation. Two aspects received an equal 14% of respondents' preference; i.e., a focus on a friendly user interface (*I wish the system could look prettier.*) and saved decision time (*Recommend good items, save user time*). 21% of respondents reported a higher satisfaction on using the explanation as a “small talk topic”, i.e., as an initial conversation in a conference (... *initiate a conversation by highlighting how this system recommendation me to you.*). 28% of respondents preferred an interactive interface for perceiving the system to be fun, e.g., a controllable interface (*Interacting with the UI and watching the results change accordingly can be interesting.*).

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