Explaining Recommendations in an Interactive Hybrid Social Recommender

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ABSTRACT

Hybrid social recommender systems use social relevance from multiple sources to recommend relevant items or people to users. To make hybrid recommendations more transparent and controllable, several researchers have explored interactive hybrid recommender interfaces, which allow for a user-driven fusion of recommendation sources. In this field of work, the intelligent user interface has been investigated as an approach to increase transparency and improve the user experience. In this paper, we attempt to further promote the transparency of recommendations by augmenting an interactive hybrid recommender interface with several types of explanations. We evaluate user behavior patterns and subjective feedback by a within-subject study (N=33). Results from the evaluation show the effectiveness of the proposed explanation models. The result of post-treatment survey indicates a significant improvement in the perception of explainability, but such improvement comes with a lower degree of perceived controllability.

CCS CONCEPTS

• **Information systems → Recommender systems**; • **Human-centered computing → HCI design and evaluation methods**.

KEYWORDS

Hybrid Recommendation, Explanation, User-Driven Fusion

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1 INTRODUCTION

The goal of social recommender systems is to reduce information overload by eliciting user preferences and proactively recommending relevant items or people [8]. A number of practical social recommenders use multiple sources of information to generate recommendation and fuse recommendations from different sources using a hybridization strategy, which assigning static weights to all sources [3]. Usually, the optimal weights are picked or learned using ground truth data (i.e., known ratings or user interests). However, user needs may vary in different social contexts. For example, users can turn to a social recommender system to find a domain expert for a Ph.D. committee or to find a collaborator for a course project. While an "optimal" static fusion could provide the best ranking across the cases, it might be sub-optimal in each specific case.

It is a challenge to recognize changing user needs and preferences and to seamlessly adjust social recommendations. One possible solution that has been explored over the last few years is to increase the system's overall *controllability*, so that the user can adjust recommendations based on their current social information needs [9, 11, 23, 24]. Several studies have demonstrated that users appreciate controllability in their interactions with the recommender system [5, 9, 11, 18, 24]. In these studies, users were allowed to "influence" the presented recommendations by interacting with different kinds of visual interfaces. It has also been shown that the visualization has helped users to understand how their actions can impact the system [10], which contributes to the overall *inspectability* [11] or *transparency* of the recommendation process [21].

A visual interface for the user-controlled hybrid fusion of recommender sources cannot assure that the users will understand the underlying rationale of each contributing recommender; namely, the recommendation algorithm [10]. We believe that to increase the transparency of social recommender systems, interactive user interfaces should be augmented with multiple kinds of explanations for each recommendation source or engine [7, 14]. For example, [17] proposed a three-dimensional explanation model using human, feature, and item information for explaining social recommendations. A useful explanation model would help users to understand the recommendation reasoning process, which allows the users to make a better decision or persuade them to accept the suggestions from a system [20]. Nonetheless, little is known about how the user will interact with the system when both the fusion process and reasoning process are transparent.

In this paper, we investigated the effects of adding *explanations* to an interactive hybrid social recommender system. We conducted an online user study (N=33) at three research conferences to evaluate user behavior and obtained subjective feedback of the six proposed explainable interfaces. This study intends to answer two research questions: 1) Which visualization is better for explaining an interactive hybrid social recommender system? 2) How do the explanations affect user perception and interaction with an interactive hybrid social recommender system? Our contributions can be summarized in three-fold: First, we confirm the user-driven fusion principle using a state-of-the-art user-controllable interface.

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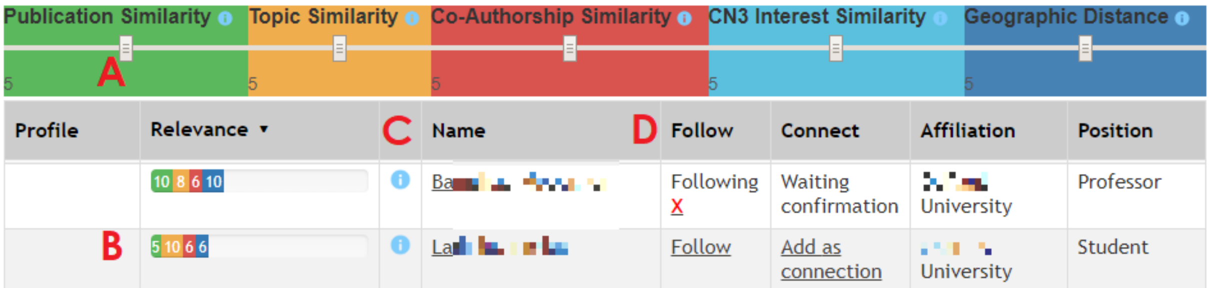

Figure 1: The design of Relevance Tuner+: (A) relevance sliders; (B) stackable score bar; (C) explanation icon; (D) user profiles.

Explain: 'Publication'	Explain: 'Topic'	Explain: 'Co-Authorship'	Explain: 'CN3 Interest'	Explain: 'Geographic'
Why Relevance = 10?	Why Relevance = 8?	Why Relevance = 6?	Why Relevance = 0?	Why Relevance = 10?

Figure 2: The pop-up window of clicking the *explanation icon* (shown in Figure 1 Section C).

Second, we provide a new exploratory model (with six explainable interfaces) for explaining an interactive hybrid social recommender system. Third, we show evidence to support the interaction effect between the factors of controllability and explainability.

2 RELATED WORK

Recommender systems explored two principal ways to offer users some form of control over the recommendation process. The first method is through preference elicitation: let the user tell the system what they like, e.g., through forming a user profile [10] or through an adaptive dialog [13]. The second method is through controlling the results: let the user adjust the recommendation profile [9] to fuse recommendations from different sources of relevance [5, 23] or to influence the presented layout [1, 18, 24]. While focused on control, all these approaches contributed to increased transparency of the recommendation process.

An alternative approach to increase the process transparency and user satisfaction explored in the literature is providing explanations for recommendations [4]. Explanations that expose the reasoning behind a recommendation could especially increase system transparency [21]. In an attempt to combine these independent streams of research, we focus on adding explanations to a controllable interactive social recommender interface and study users' subjective feedback and behavior across all design components.

3 EXPLAINING IN INTERACTIVE SOCIAL RECOMMENDER

3.1 Recommender Engines and Interface

In this work, we propose *Relevance Tuner+*, an extension of our earlier system [23], which provides a controllable interface for the user to fuse social recommendations from multiple sources. A total of five recommender engines were introduced in this study: *1) Publication Similarity:* cosine similarity of users' publication text. *2) Topic Similarity:* topic modeling similarity of research interests (topics). *3) Co-Authorship Similarity:* the degree of network distance, based on a shared co-authorship network. *4) CN3 Interest Similarity:* the number of papers co-bookmarked, as well as the authors co-followed. *5) Geographic Distance:* a measurement of the geographic distance between affiliations.

The users can "tune" (re-rank) the social recommendations using five sliders (see Figure 1, Section A). The user can *explore* the relevance scores (sum of personalized relevance score of five recommendation engines) through the colored stackable bars in Section B and *access* more information about recommended people using links in Section D. In this study, we introduced a new *explanation icon* in Section C. The user can *inspect* the relevance by clicking the icon. A window will pop up (Figure 2) to show a clickable explanation table. A click on the first-row cell will open a visual explanation of calculated relevance for the selected recommendation engine (as shown in Figure 3 (a) to (e)). A click on the second-row cell will show the calculation process of the relevance scores (Figure 3f). In this design, we attempted to separate the explanation for the fusion process, which the user can influence by tuning the sliders from the explanation of each relevance obtained by clicking the explanation icon. To be more specific, we intend to help the user to get explanations for two kinds of questions: fused relevance questions (i.e., *"Why this recommendation is ranked at the top?"*) and engine relevance questions (i.e., *"Why topic relevance is equal to 8?"*).

3.2 Presentation of Explanations

Instead of using a context-specific visualized recommendations [11, 24], we added an *explanation icon* next to each social recommendation, leaving the choice of requesting the details behind the reasoning to the users. The information was provided by a hybrid explanation approach [14, 17], which mixed multiple visualization components for explaining the details of the recommendation engine. A total of five visual explanations and five equations (one for each relevance) were proposed. We referred *the user* to present the current log-in user who is using the interface. We used *attendee* to represent the recommended conference attendee being inspected.

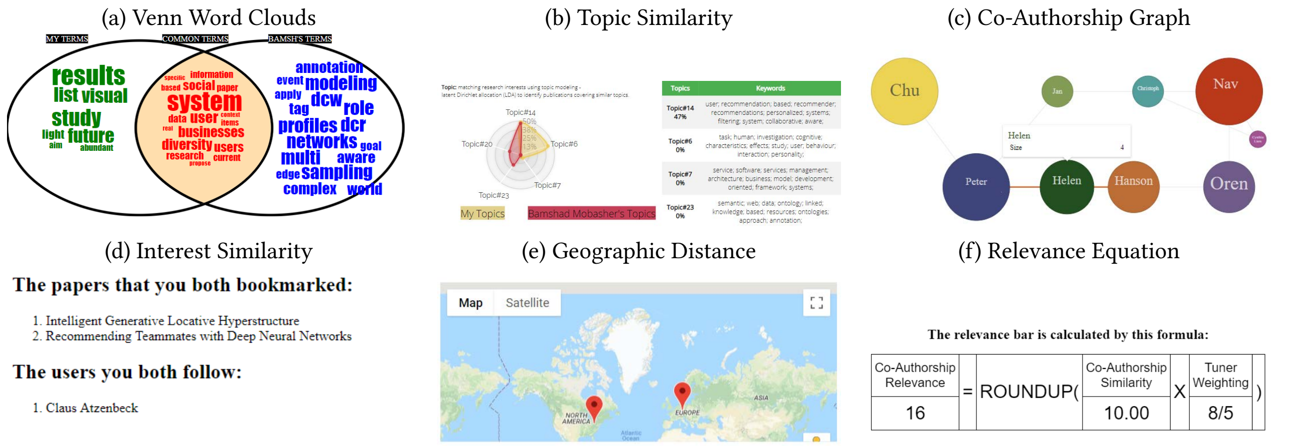

Figure 3: We presented six interfaces for explaining the social recommendations. a) Venn Word Clouds; b) Topic Similarity; c) Co-Authorship Graph; d) Interest Similarity; e) Geographic Distance; f) Relevance Equation. The visualization (a) to (e) is matched with the corresponding recommendation engine (first row of Figure 2), but (f) was adopted across five recommendation engines (second row of Figure 2).

Publication Similarity: we adopted a *Venn word cloud* visualization inspired by *tag cloud* [7, 18] as an approach to explaining the text-level similarity between the publication of the user and the attendee (Figure 3a). This visualization presented the *terms* of the paper title and abstract. The font size indicates the term frequency in the documents. The user's terms and the attendee's terms will be presented on the left and right, respectively. The terms in the middle presented the *words-in-common*, which means the terms were appearing in the publications of both scholars.

Topic Similarity: we presented research topics in a radar chart and the topical words of each research topic in a table [25]. The visualization design can be found in Figure 3b. The radar chart was presented in the left side. We selected top 5 (ranked by *beta* value from a total of 30 topics) topics of the user and compared them with the attendee. A table with topical words was presented in the right so that the user can inspect the context of each research topic.

Co-Authorship Similarity: we presented co-authorship network in a path graph [22]. The visualization design can be found in Figure 3c. For connecting the user (yellow circle in the left) to the attendee (red color in the right), we tried to find six possible paths (one shortest and five alternatives) by direct and in-direct co-authorship. The circle size represented the connectivity, i.e., *Peter* is the only node that scholar *Chu* can reach scholar *Nav*, so the circle size was the largest one (size = 6).

Interest Similarity: we presented co-bookmarking (conference paper) / co-following (conference attendees) information in an itemized list, inspired by the user-based approach [17]. The visualization design can be found in Figure 3d. We used two itemized lists to show this information. The design helps the user to inspect the overlapped items that the recommendation engine used to calculate the similarity.

Geographic Distance: we plotted cities of affiliations on a world map, inspired by location-based explanation [17]. The visualization design can be found in Figure 3e. We bundled the *Google Map API* for presenting the geo-location of the two affiliations on the map. The two *pins* were the affiliated institution of the user and the target user so that the user can inspect the geo-distance, regions or countries information.

Relevance Equation: we used *relevance equation* (Figure 3f) to explain the calculation process of each of the five relevance scores shown in the stackable bars (Figure 1 Section B). The relevance score equals the recommendation engine similarity multiply by tuner weighting with a roundup function. For example, if the user tunes the *Co-Authorship Similarity* to 8 (Figure 1, Section A), then the normalized tuner weight is $\frac{8}{5} = 1.6$. As explained in Figure 3f, to obtain the resulting source relevance score 16, the tuner weight is multiplied by the source similarity score 10.

4 EVALUATION

4.1 Setup

The recommendations produced by all five engines are based on data collected by the Conference Navigator 3 system [2, 23]. To recruit the user study participants, we sent out invitation emails to attendees of three conferences. A total of 345 emails were sent. We received 43 responses (response rate=12.46%). After sending the personalized study link to all respondents, there were 33 participants (12 female) who eventually accepted and completed the online user study. The participation is voluntary. The participants attended Hypertext 2018 (10 participants); UMAP 2018 (12 participants) or EC-TEL 2018 (11 participants). Their ages ranged from 20 to 59 (M=31.00, SE=7.74). All of them could be considered as knowledgeable in their research area and had at least one academic publication at the corresponding conference.

To assess the value of the proposed interface, we compared the explainable and controllable Relevance Tuner+ interface (*Tuner+*) with a controllable-only interface (Section C in Figure 1 removed) (*Baseline*). The online study adopted a within-subjects design. A two-minute tutorial video was provided for participants to familiarize themselves with the interface before each treatment. All

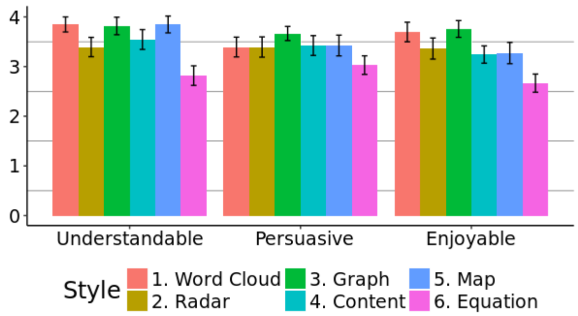

Figure 4: The user feedback of six explanation styles.

participants were asked to use each interface for three information seeking tasks and to fill out a post-stage questionnaire. The order of question was the same to all participants with a 5-point scale (1=Strongly Disagree and 5=Strongly Agree). The order of treatment was randomized to control for the effect of ordering (half of the participants started the study with the baseline interface). To minimize the learning effect (becoming familiar with the conference data), we used data from different years of the same conference (EC-TEL 2017 & 2018) or alternative conferences (HT/UMAP 2018) in the two treatments.

Participants were given the same three tasks for each treatment. The tasks were explicitly designed to be diverse but realistic tasks that could be naturally pursued by attendees of research conferences. **Task 1:** "Please use the system to follow four conference attendees you would like to talk during the coffee break." **Task 2:** "Your advisor asks you to follow four conference attendees with close connection with your research group. He/she would also appreciate that the scholars be from different regions of the world." **Task 3:** "Please use the system to find four committee member candidates for your dissertation defense. The candidates should be senior scholars with expertise close to your research field". The participants were asked to pick suitable candidates among conference attendees, based on their best judgment in each task.

4.2 Data and Measurements

We collected action logs for slider manipulations, explanation clicks, and the time to complete the tasks. The post-stage survey comprised of 16 questions that covered different user experience (UX) dimensions. In the *Tuner+* treatment, three extra questions were presented for collecting the user feedback on each explanation design. We then built a structural equation model (SEM) for analyzing the UX concepts and directionality of causal effects. We followed the framework introduced in [12]. We planned three latent constructs: two subjective system aspects (SSA) (perceived control & perceived transparency) and one user experience (EXP) (satisfaction). The model fit the statistics of $\chi^2(66) = 411.65$, $p < 0.001$, $RMSEA = 0.18$, $90\%CI : [0.13, 0.17]$, $CFI = 0.88$, $TLI = 0.89$. The three factors listed below showed good convergent validity (AVE) and internal consistency (Cronbach's α).

- *Perceived Control* (SSA) ($AVE = .60, \alpha = .77$): 3 items, e.g., "I feel in control of modifying my preferences","I became familiar with the recommender system very quickly".
- *Perceived Transparency* (SSA) ($AVE = .55, \alpha = .81$): 5 items, e.g., "The recommender explains why the conference attendees are recommended to me","I understood why the contacts were recommended to me".
- *Satisfaction* (EXP) ($AVE = .64, \alpha = .91$): 8 items, e.g., "The recommender helped me find the ideal contacts at conference", "Overall, I am satisfied with the recommender".

4.3 Results

In the *baseline* group, we found that the participants extensively used the relevance sliders to complete the three assigned tasks ($M = 56.78$, $SD = 42.21$, $User\ Count = 30$). There were only three users who didn't interact with the sliders. In the *Tuner+* group, we found a similar pattern in using the sliders ($M = 64.63$, $SD = 43.84$, $User\ Count = 32$) that almost all participants did interact with the sliders. However, only around 50% of the participants clicked on the explanations icon ($M = 5.90$, $SD = 8.36$, $User\ Count = 17$), i.e., the relevance sliders were used by the participants more extensively than the explanation icon. The participants spent more time to complete the three assigned tasks in *Tuner+* group i.e., when the explanations were provided ($M = 733.69$, $SD = 766.10$, in seconds), than *baseline* group ($M = 573.21$, $SD = 567.48$).

Figure 4 shows user feedback on the six explanation styles. For a more *understandable* visualization, the explanation style of *word cloud*, *graph*, and *map* received higher scores. For better *persuasive*, i.e., convincing the user to accept the recommendation, the explanation style of *graph* outperformed the other visualizations. One participant specifically commented that the social network visualization is *"really interesting and useful"*. For better satisfying the user (*enjoyable*), the explanation styles of *word cloud* and *graph* were preferred by the participants after experiencing the system.

We performed a Wilcoxon signed-rank test for analyzing the subjective feedback (shown in Figure 5). We found that many user-ratings are comparable between treatments, which means that adding an explanation icon to the system does not impact the UX dimensions. However, we found that the participants agreed that the *Tuner+* interface was significantly better in providing *explainability (Q5)*, which indicated the attached explanations were useful in gaining system transparency and providing the reasoning process of social recommendations. Interestingly, we also found that if the explanations were presented, the participants' perception of the *easy-to-use interface (Q7)* and *perceived control (Q8)* were significantly decreased, which implied the users might experience difficulties with a possibly overwhelming amount of information.

We confirmed the finding in SEM analysis (shown in Figure 6), we found that adding extra explanations (OSA) decreases the user perception of controllability (SSA). In *Tuner+* condition the participants to click the explanation icons more (INT) to inspect the social recommendations, which increases the average time spent (INT) in completing the tasks. If more time spent on each task, the subjective system aspect (SSA) on *perceived control* decreases. However, we also found the participants who perceived more *transparency* will positively associate this with *perceived control* and *satisfaction*. The pattern implied the extra amount of information would not impair those who perceived higher system explainability and understanding.

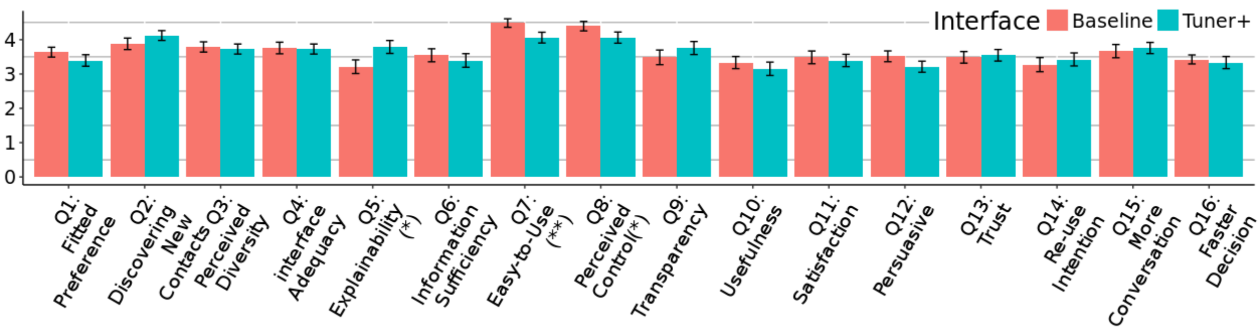

Figure 5: User feedback analysis: the result shows that the *Tuner+* interface received a significantly higher rating in the aspect of explainability (Q5). (Statistical significance level: (**) $p < 0.01$; (*) $p < 0.05$)

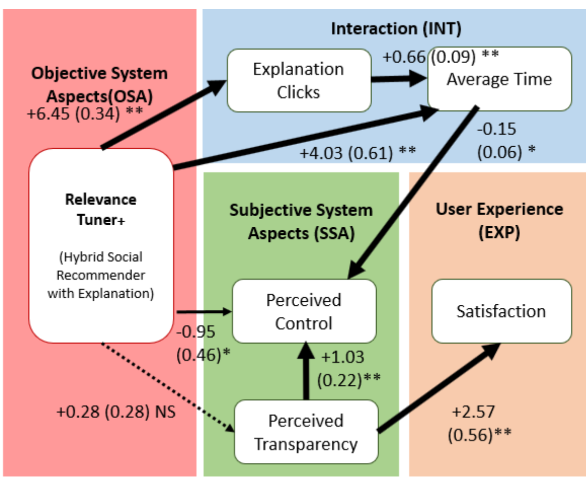

Figure 6: The structural equation model (SEM) of the experiment. The number (thickness) on the arrows represents the β coefficients and standard error of the effect. (Statistical significance level: (**) $p < 0.01$, (*) $p < 0.5$, (NS) no significance)

5 DISCUSSION AND CONCLUSIONS

This paper presents an evaluation of explainable recommendations in an interactive hybrid social recommender, *Relevance Tuner+*. Our works extended the earlier version of the controllable interface *Relevance Tuner* with explanations in the form of five visualizations and five equations. We found that the user extensively uses sliders to adjust source weights while completing the conference-attendee exploration tasks. The result supports prior findings [23] that an interactive interface helps to improve the user experience and initiate user-driven exploration. At the same time, the explanations were not used as heavily. Among visual explanations *word cloud* and *graph* were rated with a higher score in the aspects of understandable, persuasive and enjoyable (shown in Figure 4).

We also found an interesting perception trade-off between controllability and explainability. More specifically, the experiment result indicates that when users can inspect the social recommendation with an on-demand explanation, it increases their perception of system explainability. However, the improvement comes with a price of reducing the user perception of control (Q8) and the sense of ease of use (Q7). We confirmed this finding in the analysis of SEM that shows the time spent in inspecting the social recommendations was negatively correlated with the factor of *Perceived Control*, a possibly overwhelming amount of information caused the users to decrease the perception of controllability. Although we didn't find a direct effect between providing an explaining icon and the user perception of transparency, it nonetheless plays a crucial role in contributing to the factor of user satisfaction.

The finding of controllability and explainability trade-off is surprising, but not an uncharted area in the field of HCI. In explaining recommendations, one main goal is to provide completeness of information so the users can gradually improve the mental model while interacting with the system [15]. However, a detailed, full explanations may be "excessive" to the users [16], which had a negative impact on user confidence and enjoyment [19]. To overcome this problem, based on the context of information-seeking tasks, only the filtered "relevant and important information" should be presented as explanations [6]. In this paper, we asked the study participants to find conference attendee in different scenarios, e.g., "with close connection with your research group". In this case, the essential information is those recommendations with high "Co-Authorship Similarity", which can be done easier with the controllable sliders. The additional explanations may be attractive, but not mandatory. When the overwhelming amount of information was provided, especially for those who didn't adopt the explanation interfaces, it impaired the user perception on controllability.

6 LIMITATIONS

Our work has some limitations. First, it is a small-scale user study (N=33). Second, in a semi-controlled online study, we found only half of the subjects explored the explanation functions (manipulated aspect), which may hurt the significant effect on the transparency factor in our SEM analysis. Third, user rating and post-stage question ordering may be biased by the rating tendency of each subject, and might be better to normalize them. Fourth, there are too many variables in our experimental design. Further investigation will be required to control the interaction effects. All these issues will be addressed in our future work with a larger-scale, lab controlled study to confirm the findings and model robustness.

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