Diversity Exposure in Social Recommender Systems: A Social Capital Theory Perspective

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ABSTRACT
Meeting other scholars at conferences is often a stochastic, intuition-driven process. Social recommender systems can support identifying new collaboration partners that one might not naturally choose. However, to boost the accumulation of social capital, such systems must be designed for diversifying social connections. This paper draws from the extant theory on social capital and diversity exposure in recommendation systems to discuss the importance of social diversity exposure and presents design directions for social recommender systems for building social capital. As preliminary empirical insights, we report the results of a field study of two diversity-enhancing interfaces in an academic conference. Interestingly, we identified contradictory results between the subjective user feedback on the user interface quality and the objective analysis of clicking and viewing the recommendations. This implies that assessing the overall quality of a diversity-enhancing social recommender system requires careful design of suitable measurements.

Author Keywords
Interactive Recommender Systems; Social Recommendation; Social Capital; User Interface; Diversity

CCS Concepts
•Human-centered computing → Field studies; User interface design; •Information systems → Social recommendation; Recommender systems;

INTRODUCTION
Academic conferences are socially vibrant events where new acquaintances are made and existing relationships are strengthened. Scholars with different cultural and scholarly backgrounds come together to discuss topics of their interests. From economic and sociological perspectives, conferences are thus not only about information dissemination but opportunities for building *social capital*. We subscribe to extant research stating that social capital is a key asset in knowledge work [5, 11, 22].

However, various human tendencies and cultural norms can hinder the process of finding the most relevant interaction partners for knowledge work [24]. Existing social structure, or the lack of one, tends to direct the emergence of new ties. For junior scholars and other newcomers just entering the conference community, the identification of relevant individuals or cliques is laborious and characterized by chance [23]. For more senior scholars, a key issue, perhaps counter-intuitively, is the existence of their strong connecting tissue to the core of the community that limits their networking capability.

In this light, conferences are seemingly fruitful contexts for deploying information technology that could introduce opportune new ties. Social recommender systems are recommender systems that, instead of items, seek to identify social connections, new or existing, relevant to the system user [15]. The objective of developing social recommender systems is to mitigate issues related to information overload by ranking the potential connections according to their relevance. However, these *relevance-first* social recommenders have been shown to narrow down users' recommendation selection diversity [16]. We argue that increasing social diversity is a meaningful goal in this context: the capability to create novel ideas and innovations has been shown to result from complementary viewpoints and heterogeneity of knowledge among a diverse group of actors [28]. To this end, we want to introduce two types of connections to the discussion on what could be *relevant ties*: *weak ties* that serve as bridging capital and *strong ties* for bonding capital [14, 27]. We see particular value in forming weak ties in social events such as academic conferences.

In this paper, we discuss the role of diversity exposure in social recommender interfaces for supporting the formation of new social connections in academic conferences. We believe that this line of research can help build social capital both for individual scholars (i.e., dyadic ties) as well as for the research community as a whole (i.e., the overall social fabric of the community). We claim that the objective to form weak ties

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is particularly important in serving both the conference core community and newcomers and give arguments to support the claim. Moreover, we demonstrate that taking a relevance-first approach to building social recommender interfaces will not support weak tie formation. The contribution of the paper is two-fold. First, the key contribution is a theory-based discussion on the design directions of diversity-exposing social recommender interfaces. Second, we present and discuss the findings of a preliminary field study of two visual interfaces built to expose users of social recommender systems to social diversity, that is, social connections that are outside their existing social circles.

THEORETICAL FRAMEWORK AND RELATED WORK

Social Capital in Knowledge Work

Social capital is one of the components of human capital or broader cultural capital [5]. In their seminal article (cf., [29]), Nahapiet and Ghoshal [22] define *"social capital as the sum of the actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit"* and point to previous research stressing the importance of including both the social network and the resources available through the network under social capital [5]. Social capital is embedded in the social network and exists *"in the relations among persons"* [11].

More specifically, two types of social capital are identified in extant research, bonding and bridging [27, 7]. Conceptually, bonding and bridging social capital are close to strong and weak ties [14], respectively. Bonding capital consists of strong ties, i.e., actor's strong connections to close colleagues, family, and friends. Bridging capital is based on weak ties, connections beyond daily social life that form between clusters or groups of social actors.

Why is social capital important in knowledge work? Simply put, social capital makes *"possible the achievement of certain ends that in its absence would not be possible"* [11]. Social capital is argued to be a key driver of organizational advantage [22]. Bridging capital has a particular role for individual actors, organizations, and communities. Weak ties, although limited in their bandwidth, serve as important conduits for novel information [14]. Weak ties form across structural holes in social networks and put the connecting actors in the role of a broker. Brokerage *"between groups provides a vision of options otherwise unseen, which is the mechanism by which brokerage becomes social capital"* [8]. Further, weak ties are shown to improve the innovativeness of managers [28].

Social Capital Accumulation

We agree with Dobson [12] and Archer [3] that social structure is dynamic and evolves over time, that social structure is a key driver of social activity, and that social activity is a key driver of the evolution of social structure. Bourdieu [5] highlights the processual nature of social capital, stating that *"The existence of a network of connections is not a natural given, or even a social given, constituted once and for all by an initial act of institution [...] It is the product of an endless effort at institution."*

From social psychological perspective, the formation of new connections is governed by two key mechanisms, namely *choice homophily* and *triadic closure*. Homophily refers to the preference to connect to individuals that are similar [19, 21]. Similarity in background, knowledge, and interests contributes to the ease of forming a connection and starting a meaningful exchange of views and information. Triadic closure states that new connections are likely to form between actors that share a strong tie, e.g., between friends of friends [14]. In combination, these two mechanisms produce "*striking patterns of observed homophily*" [19] and form echo chambers [31], that is, groups of densely interconnected actors that have limited connections to other such groups.

An individual builds social capital one connection at a time. Both strong and weak ties have their role in sourcing information [2]. We see particular value in forming weak ties in social events such as academic conferences. First, for system level benefits, weak ties connect existing social clusters and support the flow of information. Second, as networking strategy, forming weak ties serves both the community core members and newcomers through the spread of ideas and knowledge. Optimizing for weak ties points new connections away from the community core, toward newcomers.

Social Recommendations at Academic Conferences

Starting in early 2000, some pioneer conference support systems offered conference attendees an opportunity to create profiles that provide relevant information about themselves and to explore profiles of other attendees [30, 10, 4]. This functionality is now offered by many commercial conference support systems, but support to social exploration remains limited due to the passive nature of these systems and continued challenges to find and recognize relevant attendees among hundreds. To increase attendees' chances to learn about each other, some conference systems offered more proactive solutions. For example, public displays and their combination with sensors were used to stream information about random delegates or those who are nearby [30, 10]. Public displays were also used to allow two or more people to examine common topics of interest and future co-authors [18, 20].

More recently, recommender systems emerged as an attractive approach to make the process of accumulating social capital at academic conferences more proactive [1]. Recommender systems are valuable in a time-sensitive conference context due to their ability to adapt to users' interests and select list of most relevant items or people from a large pool of candidates. While the majority of research on recommendation in conference context focused on paper recommendations, a number of projects explored various approaches for people recommendation [9, 26, 34, 35]. The increased popularity of this topic brought the issue of diversity in attendee recommendation to the research agenda, e.g., social recommendations [15, 34]. We examine this issue in the next subsection.

APPROACH

Next, we move to describe our proposed solution to increasing social diversity exposure in academic conferences. We claim that a straightforward strategy to depart from the two key mechanisms of social connection formation, that is, homophily and triadic closure, is to maintain similarity as the key relevance criteria and increase the social distance between the active user and recommendations. If successful, this strategy will also support the accumulation of bridging social capital because the connections between socially distant actors are by definition weak ties. However, instead of taking an algorithmic approach to limit the users focus on actors that are similar and socially distant, we propose that social recommendation system designers should focus on increasing the controllability and transparency of the system as means to carefully *nudge* the user toward options with potential long-term benefits for both the individual and the entire community.

We test two alternative user interface designs, *Scatter Viz* and *Relevance Tuner*, to explore how might these interfaces expose the active user to social diversity. The two interfaces were originally proposed by [34, 35, 36] who evaluate their usefulness in devising recommendation selection in controlled user studies at conferences. The interfaces are designed from alternative perspectives to enhance recommendation selection diversity. *Relevance Tuner* is a straightforward extension of the ranked list. *Scatter Viz* follows a more exploratory approach.

Interface 1: *Scatter Viz* (Figure 1) combines a scatter plot visualization with a standard ranked list to present recommendations. The scatter plot view presents the recommended item in two dimensions defined by the active user and has been shown useful in helping people in the analysis of the large datasets [25]. The design concept is supporting the user's perception of two dimensions of a multi-relevance recommendation. By selecting different dimensions to X-axis and Y-axis, the user can correlate multiple types of relevance among the social recommendation.

Interface 2: *Relevance Tuner* (Figure 2) takes an alternative approach to help the user to inspect the multi-relevance social recommendations. The user interface provides five relevance sliders that allow the active user to adjust the weighting of the features and, by doing so, re-ranking the social recommendations with a standard ranked list. The user can tune the weighting for each recommendation feature and the ranked list will reorder on the fly. Next, we will put these designs into play in a real-life setting to see what kinds of social diversity exposure patterns their use results in.

EXPERIMENT: FIELD STUDY

Study Design

To explore the social diversity exposure impact of the two interface designs, *Scatter Viz* and *Relevance Tuner*, we organized an in-the-wild experiment as a field study in EC-TEL 2017 conference held in Tallinn, Estonia in September 12–15, 2017. The two interfaces are integrated into *Conference Navigator (CN3)* [33], a social recommendation system for academic conferences. The recommendations are mostly based on data collected by the CN3 system [6]. To mitigate the cold start problem that occurs when users have no publications or co-authorship information related to the event for which the recommendations are produced for [33], the system integrates the AMiner dataset [32]. The live system is available at http://halley.exp.sis.pitt.edu/cn3/.

Table 1: Post-experiment survey questions

Q1	The interface helps me to explore various interesting people in the conference.
Q2	It is helpful to see people attributes like Title, Country and Position when exploring interesting people in the list
Q3	The interface helps me to perceive the diversity of explored attendees.
Q4	The interface helps me to improve my trust in the people recommendation result.
Q5	The interface helps me to understand why specific attendees were recommended.
Q6	I like the people recommendation result from the system.
Q7	I became familiar with the system very quickly.
Q8	Overall, I am satisfied with the system.
Q10	It was useful to see the explanation of scores produced by different recommendation components.
Q11	It is fun to use the system.
Q12	The system has no real benefit for me.

This demonstration will extend the evaluation to explore the role of the two interfaces in exposing the active user to more diverse social connections in a real-world context through A/B testing. That is, how does the proposed interface design lead to social exposure and the possible change in social capital? Moreover, we are interested in users' subjective experience of the two proposed interfaces in terms of diversity exposure. Following the discussion earlier in this paper, we defined two research questions for the demonstration as follows: **RQ1:** How is the effect of social diversity exposure perceived by users? **RQ2:** What are the social exposure patterns implied by the two proposed user interfaces in an academic conference?

Study Procedure

1) We sent out an invitation email three days before the conference date to introduce the social recommendation feature available in CN3 to all the 170 attendees of the conference. The email contained the login and ID/Password information, so the conference attendees can click and link to the experimental system. 2) The subjects were assigned to the Scatter Viz (*Scatter group*) and Relevance Tuner (*Tuner group*) interface, respectively. We equally split the conference attendees into the two groups based on the system-generated user ID (odd or even), resulting to 85 users in each group with a customized link to the assigned testing interface. 3) The assigned users were free to explore the system for four days during the conference event. We collected the system log for the four conference days. The log data includes the frequency of users logging in to the system, clicking on the social recommendations, and the duration of each session. 4) A post-experiment

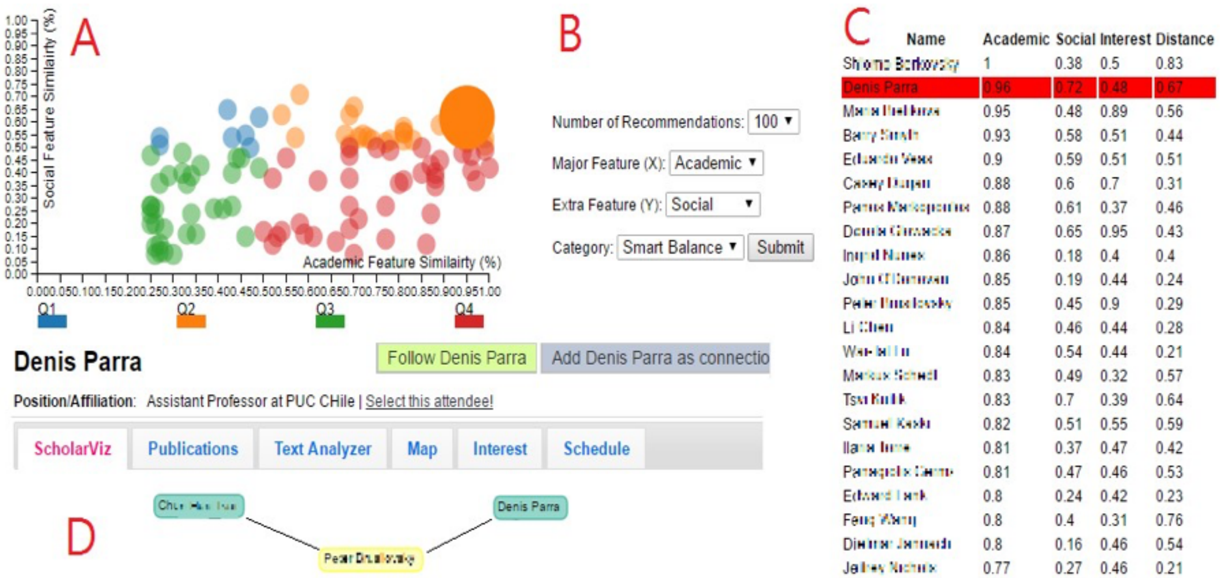

Figure 1: *Scatter Viz*: (A) Scatter Plot; (B) Control Panel; (C) Ranked List; (D) User Profile Page. The user can inspect the recommendations with two relevance dimensions in the scatter plot.

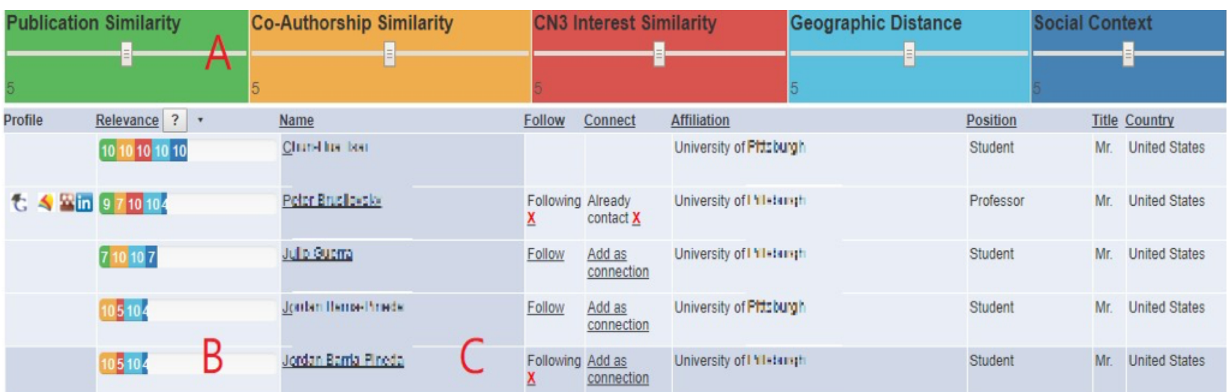

Figure 2: *Relevance Tuner*: (a) Relevance Sliders; (B) Stackable Score Bar; (C) User Profiles. The user can inspect the recommendations with multi-relevance dimensions.

online survey (5-point scale) was sent three days after the conference date to collect the subjective feedback from the users.

Data Analysis and Measurements

The social recommender systems should support the accumulation of social capital, but it is hard to measure the effects that the system had to this end, particularly in such a lively empirical context. We assumed the user must first find and view the profile of a potential connection in the social recommendation system. Hence, for the purposes of this experiment, we operationalize "social exposure" as *clicks* on the social recommendations that inspecting the profile of the recommended scholars. That is, if the user clicks on the scholar who is recommended by the system, we will consider it as social exposure.

Social network analysis provides an expressive way to investigate complex interaction patterns at a macro level [37]. We take a visual network analytic approach [17] to investigate the diversity exposure implied by the two interfaces. The approach allows the investigators to observe patterns in social structure and to share their findings [13]. We create and visualize users' pre-existing social networks and project their social exploration on top of this network. The resulting network visualization enables inspecting the patterns of existing and new social links. Here we define the "existing social connections" using the co-authorship of the conference publications. We assume that conference paper co-authors have an existing social connection. Moreover, we define "new social connections" using user clicks logged when the users were using the CN3 system. The click pattern helps to observe the social exposure of new connections and their topological placement in the network.

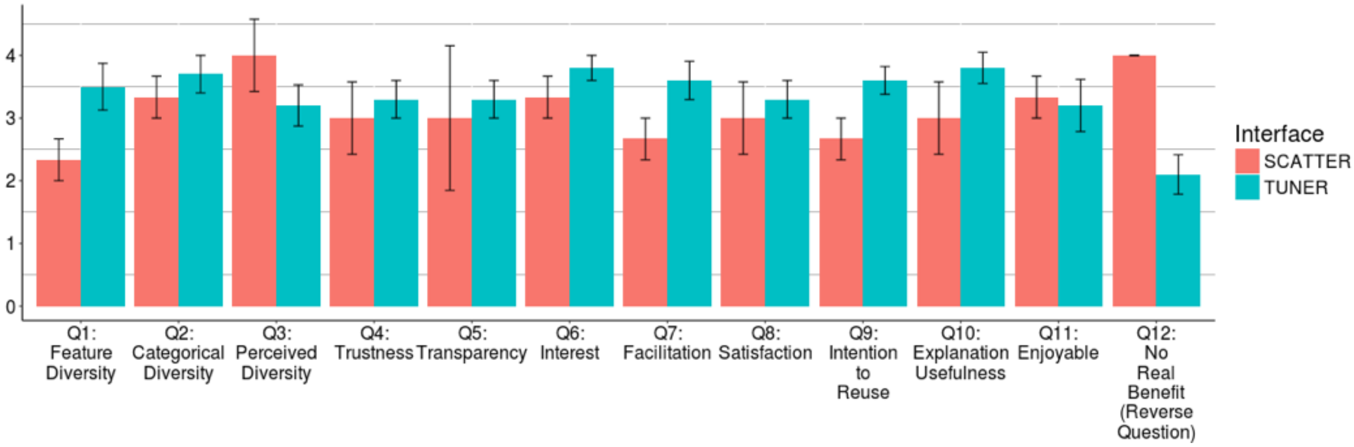

Figure 3: Post-Experiment Survey result shows that the Relevance Tuner interface was preferred by users in almost all aspects except perceived diversity. We did not perform significance tests due to the small sample size.

RESULTS

The demonstration produced a total of 97 social recommendation clicks by 32 participants that used the system under the two different treatments. There were 21 active users in Scatter Group with 75 observations (M=3.33, SD=3.92) and 11 active users in Tuner Group with 22 observations (M=2.00, SD=1.48; M=mean, SD=standard deviation) within a four-day period (period of the main conference events). The data shows that the Scatter Viz users performed more clicks when exploring the social recommendation compared to Relevance Tuner users. The demonstration results are consistent with the previous study in that Relevance Tuner requires fewer clicks to explore the desired conference attendees [34]. We found the users in Scatter Group tended to try a few clicks to interact with the visualized interface. This result also supports our assumption on the steeper learning curve of the Scatter Viz interface, due to the higher number of clicks required to look up information on recommended scholars.

User Perception: We sent out the post-experiment questionnaire three days after the conference and received a total of 13 responses, three from Scatter Group and ten from Tuner Group. Interestingly, the response rate of the Tuner Group is much higher than the Scatter Group (14% vs. 90%). The response rate may indicate the usability of the user interface—users may be more likely to submit their feedback when the user experience is positive. The post-experiment survey (shown in Table 1) gives further support for the usability of the Relevance Tuner over Scatter Viz. However, post-experiment survey results also suggest that users self-reported to perceive higher social diversity using the Scatter Viz.

Social Exposure Pattern: In order to explore their actual behavioral patterns, we project the clicks that the users made to recommended scholars on the conference co-authorship network. Figure 4a & 4b represents the social diversity exposure pattern for Scatter Viz and Relevance Tuner, respectively. The visualization can be interpreted by the color and size of network nodes representing the scholars: 1) *Dark nodes* represent authors in the conference and *dark edges* are their co-authorship. 2) *Green nodes* are active users in the experiment and *green edges* are the clicks of social recommendations (social exposure). 3) *Light gray nodes* are conference attendees that were clicked during the experiment. 4) *Edge weight* encodes the number of clicks and co-authored papers. The network is directed with edges pointing from the active user to the scholars they clicked. 5) *Node size* is proportional to its weighted indegree, that is, the sum of the weights of connections pointing to a node. Indegree is the simplest network metric for authority.

The visual network analytic can be summarized in four-fold. First, the identical pattern in the two networks is the high density of the co-authorship network. In such a network, should the social recommender system follow the relevance-first approach, the active users would be more likely to get exposed to the scholars at the core of the network. For newcomers, this is not a major issue because most of the conference participants are new to them. However, senior scholars would be likely to get exposed to each other, resulting in triadic closure and choice homophily.

Second, compared to Relevance Tuner, the clicking pattern in Scatter Viz is more visible. A few of the conference attendees that have not co-authored a paper are brought in through clicks; the click-based connections form a couple of new bridges into the already densely connected network. However, it is possible that the difference in the pattern is first and foremost a function of the number of clicks.

Third, the few clicks that the Relevance Tuner users performed do not merit any analysis. However, an interesting contradiction is that the Relevance Tuner users did not view essentially any of the recommendations and yet the questionnaire indicated a preference toward Relevance Tuner.

Fourth, the visible structural differences in the two networks also show in network metrics. The Scatter Viz network has 4 components and 103 nodes in total out of which 96 (93.2%) in the giant component. The Relevance Tuner network has 10

(a) Social exposure with Scatter Viz

(b) Social exposure with Relevance Tuner

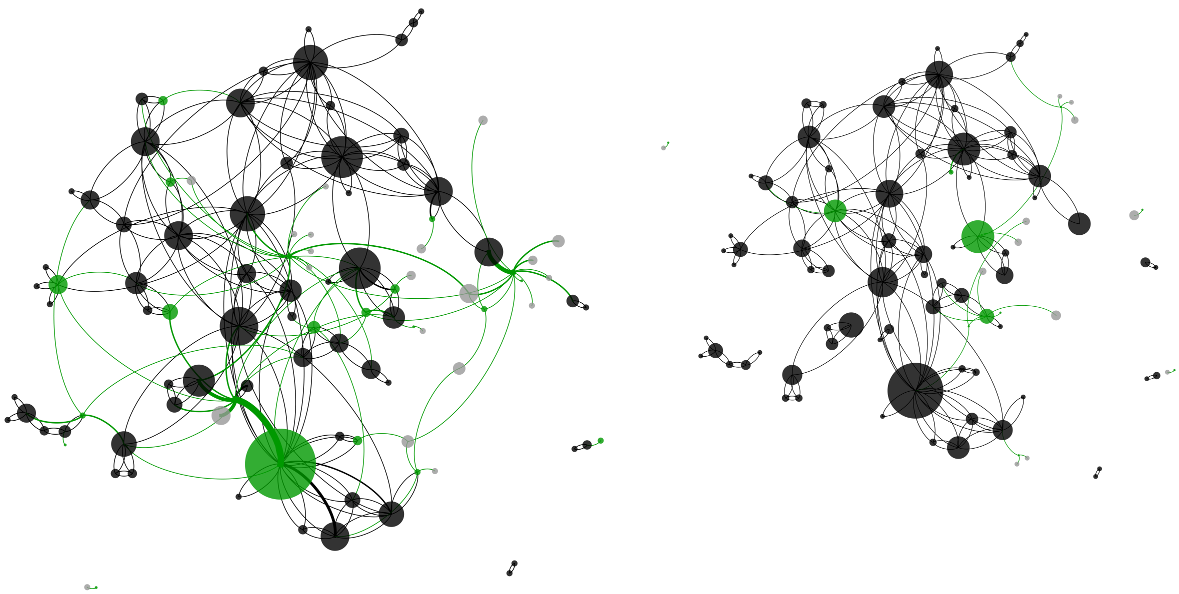

Figure 4: Conference Co-Authorship (pre-existing network) and Click Networks (new social exposure)

components and 94 nodes in total out of which 71 (75.5%) in the giant component.

DISCUSSION

The field study results hint that users might be prone to favor the Relevance Tuner, an interactive extension of the ranked list, that is, the relevance-first approach for implementing a social recommendation system. At the same time, the observed social diversity exposure pattern in Scatter Viz seems to better meet our design objective to support social diversity exposure and weak tie formation. This contradiction might suggest that the perceived usability and familiarity of the user interface weigh more in the overall estimation of the system quality. Operationalizing the social effect as questionnaire statements about the interface is challenging particularly in this context: the participants seem to have focused on the quality of the interface as a decision-support system, while the notion of social effect would call for objective measurements like the click analysis in Figures 4a and 4b. However, drawing conclusions requires further research and new ways of studying both the subjective perceptions and objective measurements about the long-term effects of providing social recommendations.

The click-based new connections seem to form in bridging positions and draw in peripheral scholars, including newcomers and attendees without a paper at the conference. However, it is noteworthy that the two interface solutions are based on different types of information architecture and interaction flows, which means that different numbers of clicks are required for the same actions. The Scatter Viz interface allows the user to explore the social recommendation in two dimensions. This interface design required the user to click more for inspecting social recommendations. The network visualization showed that the click pattern is visible on both strong and weak ties. The Relevance Tuner interface enables the user to re-rank social recommendations according to five recommendation features. The users can diversify the recommendation exposure through re-tuning the sliders. A table style presentation decreased the interface learning costs as well as the clicks on the recommendations. These findings help to provide design directions for diversity-exposing user interface in social recommender systems.

CONCLUSION

In this paper, we discussed and explored the ways social recommender systems, in particular their user interfaces, impact social diversity exposure, and therefore the accumulation of social capital. Although the small size of the population that took part in the experiment, we argue that focusing on the formation of weak ties is a recommendation strategy that should be explored further. For conference newcomers, the lack of an existing network implies that new connections are weak ties by default. For senior scholars, weak ties provide an opportunity to escape their existing dense web of connections. We point to extant literature for evidence on the importance of weak tie-based bonding capital in knowledge work. We make two main contributions. First, we draw from extant theory on social capital and diversity exposure in recommendation systems to suggest design directions for social diversity exposure in social recommendation systems. Second, we run an in-the-wild online field study in an academic conference to reflect on our theoretical discussion and to guide the design of controlled user experiments and the future user interface design of social systems.

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