Enhancing Recommendation Diversity Through a Dual Recommendation Interface

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ABSTRACT

The beyond-relevance objectives of recommender system are drawing more and more attention. For example, a diversity-enhanced interface has been shown to positively associate with overall levels of user satisfaction. However, little is known about how a diversity-enhanced interface can help users to accomplish various real-world tasks. In this paper, we present a visual diversity-enhanced interface that presents recommendations in a two-dimensional scatter plot. Our goal was to design a recommender system interface to explore the different relevance prospects of recommended items in parallel and to stress their diversity. A within-subject user study with real-life tasks was conducted to compare our visual interface to a standard ranked list interface. Our user study results show that the visual interface significantly reduced exploration efforts required for explored tasks. Also, the users' subjective evaluation shows significant improvement on many user-centric metrics. We show that the users explored a diverse set of recommended items while experiencing an improvement in overall user satisfaction.

KEYWORDS

Recommender System; Diversity; Beyond Relevance; User control

1 INTRODUCTION

Recommending *people* in a social system is a challenging task. The user may look for other people for a range of reasons; for example, they may wish to re-connect with an acquaintance or to find a new friend with similar interests [5]. This diversity among user needs makes it difficult to generate a ranked list that fits all cases.

A specific case in which a single ranked list might not work well is in a parallel hybrid recommendation system that fuses several recommendation sources. In this case, different sources might be preferred for different needs (i.e., social similarity could work best for finding known friends while content-based similarity could be used to find people with similar interests). Several authors argued that the best approach in this situation is to offer users the ability to control the fusion by choosing various algorithms [5, 6] or data sources [2]. However, it is not clear whether a casual user with no computer science background can fine-tune the provided interface to adjust the results to their exploration interests. Providing a visual interface that makes the process of fusion more transparent - for example, by showing recommender sources and their overlaps as set diagrams [16, 26] - could further address this problem. However, the set-based approach has limited applicability, since it ignores the strength of relevance (which is a continuous variable). In this paper, we attempt to overcome the limitations of set-based visual fusion by exploring a visual fusion approach that represents the continuous nature of relevant aspects while keeping the fusion process transparent.

When selecting a visual metaphor for the transparent fusion of recommendation sources, we focused on better informing users about the diversity of the recommender results. It has been demonstrated that a proper user interface could promote diversity in information exploration. A diversity-enhancing interface evaluated in [8] led to higher user satisfaction than the ranking list interface. Several attempts to design a diversity-focused interface using a dimension reduction technique to present opinion similarity by latent distance have been presented in [7, 20, 27]. However, the clustering distance was not easily interpreted, and as a result, a user was unable to make a personalized judgment.

In this paper, we attempted to use a scatter two-dimensional plot visualization to present recommendations with several dimensions of relevance. A scatter plot is an intuitive way to present multidimensional data [10]. In our context, the scatter plot interface was used to help users combine different aspects of relevance for each recommended item. The user can further filter the recommendation results within each dimension. We conducted a user study during an international conference to compare the ranking list and scatter plot interface. Our user study results show that the new visual interface did reduce exploration efforts on the proposed tasks. Also, the users' subjective evaluation shows significant improvement on many user-centric metrics. We provide empirical evidence that the user explored a diverse set of recommended items while improving the overall levels of user satisfaction.

2 RELATED WORKS

The social recommender system should provide more diverse content for the user to extend the social connection outside of the personal bubble. However, not every user equally values the diversity with the same standard [1]. The level of diversity-seeking is an existing individual difference. For instance, [14] classified people into two group the group of "Diversity Seeking" and the group of "Challenge Averse". The author described the difference between stratification and level of diversity exposure among the two groups. It explained the individual difference in the information seeking process. A social recommender system with enhanced diversity needs a different interface to fit the need of their prior conviction.

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Furthermore, to only present the different information may not facilitate users to interact with diverse contents. A reinforce effect may happen if the user feels threat on the unfamiliar information [11].

Providing visual interface is an approach to improve the recommendation diversity. There are some previous works has been conducted. For example, adopting a visual discovery interface can increase click-through rate (CTR) across different item categories in an e-commerce website [20]. The user can explore the new or relevant products without the need for search queries. The key factor of the interface is to provide the controllability to the user of filtering the recommendation contents. [17, 27] proposed a user-controllable interface for the user to interactively change the ranking or feature weighting, for a better-personalized ranking. [7, 8] proposed interfaces to show the various recommendation result which promotes the user perceive the diversity of recommendation. The study of [23] shown a more diverse exploration pattern when the user was adopting a two-dimension interface, versus the standard ranked list.

There is some design principle from the literature review. The study of [27] adopted the dimension reduction techniques to project the multidimensional data in two or three for the visualization purpose. However, the user can not distinguish the meaning of each axis, which pushes the user to explore the closer items around them [7]. [3] argues for considering a "diverse conceptions of democracy" when we design a diversity enhancing tool or application. The literature showed that to only presenting the comparison between the difference was not enough to help the user to explore more diverse results. Besides, the design should create the perception of the difference of the recommendation items. That is, a useful diversity enhances interface should provide the controllability to the users and make the filtered result is interpretable.

3 BEYOND THE RANKING LIST

We propose a recommender system to help conference attendees to find other relevant attendees to meet with a dual interface, which includes a ranking list and visual scatter plot components. The ranking list is a classic way of presenting recommended results in a single dimension, listed from high to low relevance. The scatter plot was added as a diversity-promoting interface to show the recommended result in two dimensions, with the second dimension used to reveal the overall diversity. Figure 1 illustrates the design of the dual interface.

Section A is the proposed scatter plot. The interface presents each item (a conference attendee) on the canvas as a circle. The user can move the mouse over the circle to highlight the selection. Section B shows the control panel with which the user can interact. The user can select the number of recommendations to display, and both the *major feature* and the *extra feature* to visualize the recommendations on the scatter plot. The major feature is used to rank the results along the X axis and in the ranked list (section C), while the extra feature shows the diversity of results in the selected aspect along the Y axis. To further investigate the diversity of the displayed recommendations, the user can also use a single aspect of the data as a *category* to color-code the results. The default category was *Smart Balance*, which color codes in the four quadrants with a 0.5 ratio. Section C is the standard ranking list. More exactly is a combination of four ranked lists produced by four recommender engines explained below. To make four dimensions more clear, a normalized relevance of each user to the target user generated by each recommender engine is shown on the right side of the ranked list. Section D presents more detailed information about the person selected in either the visualization or the ranked list. Among other aspects, four of the six tabs visually explain how each recommender engine calculates the relevance of the selected user to the target user. The design detail of the explanation functions can be found in the work of [24].

3.1 Personalized Relevance Model

To rank other attendees by their relevance to the target user, the system uses four separate recommender engines that rank other attendees along four dimensions that we call *features*: text similarity of their *academic* publications, *social* similarity through the co-authorship network, current *interests* of CN3 activities, and the *distance* of their affiliated place to the target user. Each of the features is defined as below:

(1) The Academic feature is determined by the degree of publication similarity between two attendees using cosine similarity [12, 25]. The function is defined as:

$$Sim_{Academic}(x, y) = (t_x \cdot t_y)/\|t_x\|\|t_y\| \tag{1}$$

where t is word vectors for user x and y.

(2) The Social feature approximates the social similarity between the target and recommended users by combining co-authorship network distance and common neighbor similarity from publication data. We adopted the depth-first search (DFS) method to calculate the shortest path p [19] and common neighborhood (CN) [15] for the number n of coauthor overlapping in two degrees.

$$Sim_{Social}(x, y) = p + n \tag{2}$$

for user x and y.

(3) The Interest feature is determined by the the number of co-bookmarked papers and co-connected authors within the experimental social system.The function is defined as

$$Sim_{Interest}(x, y) = (b_x) \cap (b_y) + (c_x) \cap (c_y) \tag{3}$$

where b_x, b_y represent the paper bookmarking of user x and y; c_x, c_y represents the friend connection of user x and y.

(4) The Distance feature is simply a measure of geographic distance between attendees. We retrieve the longitude and latitude data based on attendees' affiliation information. We used the Haversine formula to compute the geographic distance between any pair of attendees [25].

$$Sim_{Distance}(x, y) = Haversine(Geo_x, Geo_y) \tag{4}$$

where Geo are pairs of latitude and longitude coordinates for user x and y.

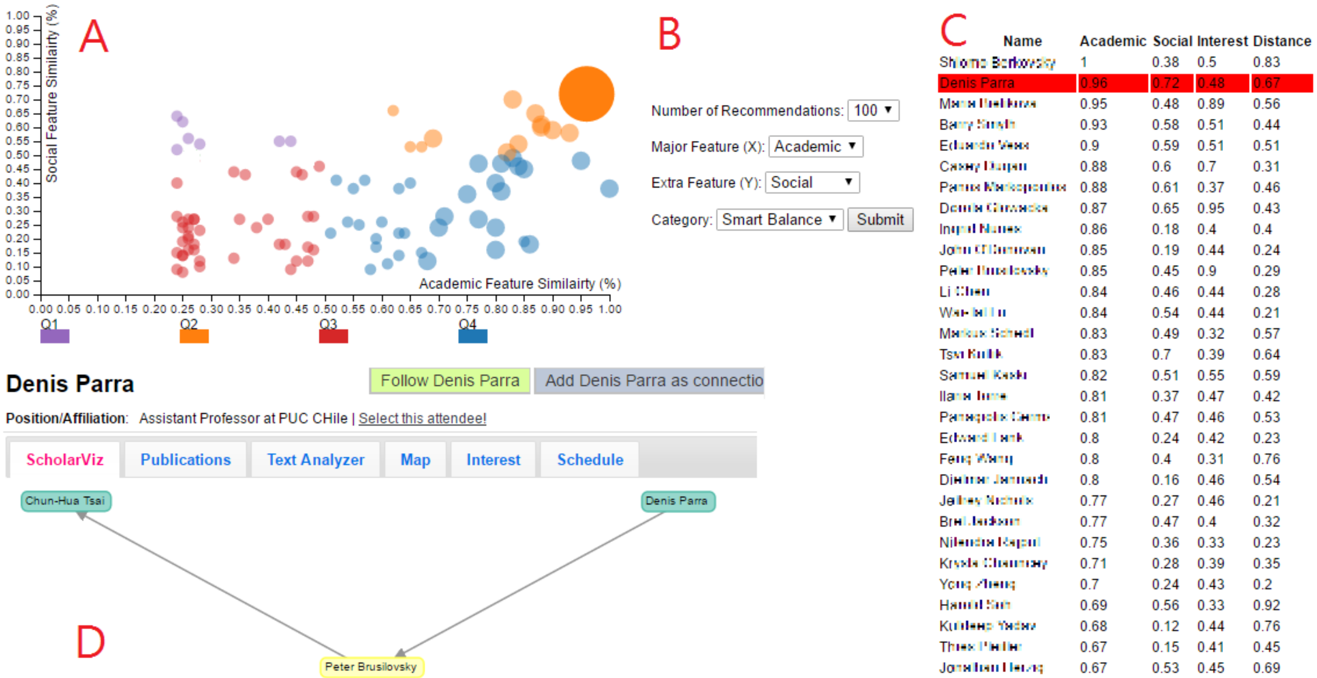

Figure 1: (A) Scatter Plot; (B) Control Panel; (C) Ranking List; (D) User Profile Page.

3.2 Diversity Navigation Model

The system determines the personalized relevance score for all conference attendees. Instead of ranking the recommended people by ensemble value, the user can filter the items based on multiple aspects of relevance through our system. There are two kinds of diversification.

1) Feature diversification: the user can select any two pairs of proposed features and spot the recommended items from the relevance intersection. All of the proposed features were calculated on a different scale. For example, the distance feature is the physical distance in miles, while the academic feature is calculated as a percentage. To enable comparison of diverse features, we adopted a standard Z-score to normalize all the features to the same scale from 0 to 1. The function was defined as:

$$ZScore = \frac{x_i - u_j}{\sigma_j} \tag{5}$$

where x_i is ith recommended item and j represents the corresponding features from 1 to 4. Then, we use the standard Z-table to convert the $ZScore$ to the corresponding percentile p_{ij}. Hence, we can list all the features on the same scale for presentation in a ranking list or scatter plot diagram.

2) Coverage diversification: a diversification model to help the user select the recommended item from a different category. [9]. In the SCATTER interface, we color-code the item from different categories, such as title, position, and country. In the RANK interface, we listed the category as one column for a user to access.

We can then measure the user selection diversity through the two diversification model. We observe the user interaction with items from different "quadrants" (feature intersections) [21], such as high academic and high social features, or high academic and low social features. The range of diversity is measured by:

$$Entropy : d_u = -\sum_{i=1}^{4} p_i log_4 p_i \tag{6}$$

where p_i is the probability for a particular quadrant (feature or category) and the proportion of all of the user's selections [13].

4 EXPERIMENT

4.1 Data and Participants

The recommendations produced by all four engines are mostly based on data collected by the Conference Navigator 3 (CN3) system [4]. The system has been used to support 38 conferences at the time of writing this paper and has data on approximately 6,398 articles presented at these conferences, 11,939 authors, 6,500 users (attendees of these conferences), 28,590 bookmarks, and 1,336 social connections. To mediate the cold start issue for academic and social engines that occurs when users have no publications or co-authorship within CN3 [22], we used the Aminer dataset [18]. This dataset includes 2,092,356 papers, 1,712,433 authors, and 4,258,615 authors with co-authorship.

A total of 25 participants (13 female) were recruited for the user study. All of the participants were attendees at the 2017 Intelligent User Interfaces Conference (IUI 2017). Since the main goal of our system was to help junior scholars connect with other people in the field, we specifically selected junior scholars, such as graduate students or research assistants. The participants came from 15 different countries; their age ranged from 20 to 50. All of them could be considered as knowledgeable in the area of the intelligent interface for at least one academic publication from IUI 2017. To control for any prior experience with the recommender system, we included a question about in the background questionnaire. The average answer score was 3.28 on a five-point scale.

4.2 Experiment Design and Procedure

To assess the value of the diversity visualization, we compared the dual interface with the scatter plot and the ranked list (SCATTER) with a baseline interface using only a ranked list (RANK) with part A removed. The study used a within-subjects design. All participants were asked to use each interface consecutively for three tasks and to fill out a post-stage questionnaire at the end of their work with each interface. At the end of the study, participants were asked to explicitly compare interfaces along of their preference. The order of using interfaces was randomized to control for the effect of ordering. In other words, half of the participants started the study with the SCATTER interface. To minimize the learning effect (getting familiar with data), we used data from two years of the same conference: the SCATTER interface used papers and attendees from IUI 2017, while the RANK interface used the same data from IUI 2016.

Participants were given the same three tasks for each interface.

$Task1$: Your Ph.D. adviser asked you to find four Committee Member candidates for the dissertation defense. You need to find candidates with expertise close to your research field while trying to lower the travel cost to the defense.

$Task2$: Your adviser asked you to meet four attending scholars, preferably from different regions across the world, with a close connection to your research group.

$Task3$: You want to find four junior scholars (not yet faculty members) with reasonably similar interests among the conference attendees to establish your networking.

The participants were asked to pick suitable candidates among conference attendees based on their best judgment in each task. When designing the tasks, we attempted to make them realistic, yet focused on multiple aspects of relevance, as many real tasks are. We consider that task 1 is relevance-oriented and tasks 2 & 3 are diversity-oriented. For a relevance-oriented task, we expect to see if the proposed interface helps the user to filter the desired target efficiently. For the diversity-oriented task, in contrast, we expect to see the user interact with the recommendation result diversely, compared to the baseline interface.

5 ANALYSIS OF RESULTS

5.1 User's Objective Evaluation

The result of the users' click pattern is shown in Figure 2. The arc diagram shows a different click pattern when the user is using the two interfaces. The users click to a more diverse recommendation through the scatter plot interface. This finding supports the design of dual interfaces can facilitate users to explore the recommendation result beyond the top rankings. Table 1 shows the system usage for two interfaces. The data indicate that participants extensively used both the control panel and explanation tabs to complete the tasks. There is no significant difference between the interfaces, although, in the SCATTER interface, the users tend to use the explanation functions less.

	Control Panel Usage		Explanation Tab Usage	
	RANK	SCATTER	RANK	SCATTER
Task 1	3.88	4.12	8.56	8.56
Task 2	2.88	2.88	6.56	4.8
Task 3	2.56	2.84	8.12	6.76
Overall	9.32	9.84	23.23	20.12

Table 1: Usage Analysis: control panel usage (the frequency of user change and submit the setting of control bar), explanation tab usage (the frequency of the user switch the tab on User Profile Page). Column 2 & 3 shows the comparison of user clicks between RANK / SCATTER interfaces.

	Hover	Click	Time	Engage
Task 1	-37.16%	-69.71%(*)	+9.21%	+161.7%(*)
Task 2	-59.53%(*)	-63.67%(*)	-11.91%	+115.2%(*)
Task 3	-55.51%(*)	-66.45%(*)	+50.14%	+179.6%(*)
Overall	-48.35%(*)	-67.07%(*)	+9.47%	+134.8%(*)

Table 2: Efficiency Analysis: the frequency of hover, click, task time (seconds for finish each task) and engage time (seconds between each click). All columns show incremental changes between RANK and SCATTER interfaces. (*) indicates statistical significance at the 0.05 level.

	Diversity	Coverage - Country	Coverage - Position
Task 1	-20.4%(*)	-6.42%	-15.10%
Task 2	+24.29%(*)	+46.59%(*)	-17.16%
Task 3	+35.8%(*)	+45.45%(*)	-23.07%

Table 3: Diversity Analysis: the test of diversity and coverage with two category variable. All columns show incremental changes between RANK and SCATTER interfaces.

Table 2 shows the work efficiency comparison between the two interfaces. We counted how many mouseovers (hovering) and clicks the users made to complete each task and expressed the number of actions done in the SCATTER interface as a percentage increase or decrease from the RANK interface. The data shows that with the SCATTER interface, users completed the same tasks with 40-60% fewer mouseovers and about 66% fewer clicks. At the same time, we found no significant difference in the time spent on the tasks. The data hints that each action taken in the SCATTER interface delivered more interesting information to explore. Indeed, we found that with the SCATTER interface, the users spent significantly more time engaged in analyzing results.

Table 3 shows the diversity analysis for each task and interface. We found that the diversity and coverage measurement shows the task difference. All three tasks are with a significant feature diversity difference between two interfaces but in the different aspect of features. Task 1 (relevance-oriented) shows less diversity on academic/distance features and less coverage on the country and position variables. The SCATTER interface helped users to more accurately explore the attendees with multiple types of relevance.

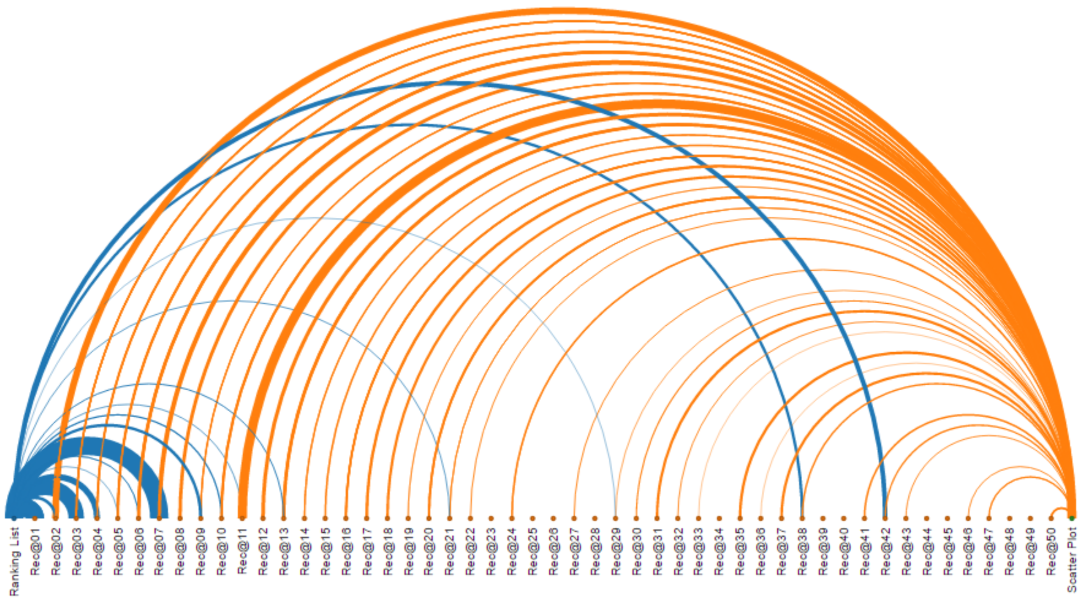

Figure 2: Arc Diagram of Top 50 Recommendation: this figure shows the users' click pattern of the two interfaces. The blue color (left-hand side) links indicate the click from Ranked List (RANK). The orange color (right-hand side) links mean the click from Scatter Plot (SCATTER). The node in the middle means the ranking position of each recommended item (from 1 to 50, smaller number is in the top of the order). The width of the edge represents the clicks frequency from each interface.

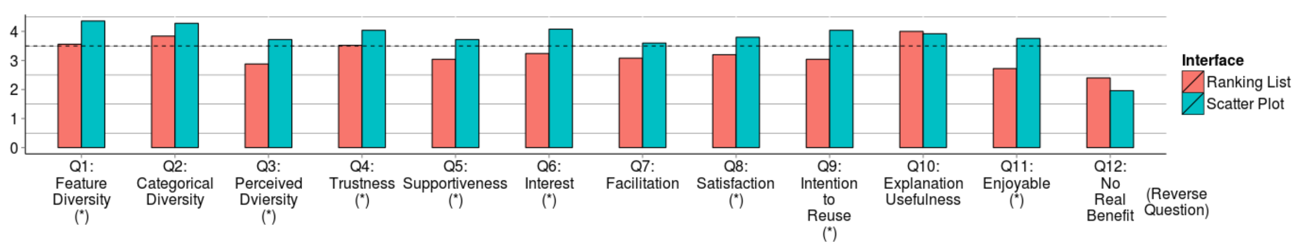

Figure 3: Usability and user satisfaction assessment results. A cut off value at 3.5 on the 5 point scale. (*) means significant differences at the 5% level (p-value $<$ 0.05)

Tasks 2 & 3 (diversity-oriented) show more diversity in the interest/distance and social/distance features, respectively, as well as higher coverage in the country category. The result shows the user response to the same task with a different pattern of exploration on diversity and coverage.

5.2 Subjective Evaluation

To compare subjective feedback, responses to the post-stage questions were analyzed using paired sample t-tests. The result of this analysis is shown in Figure 3. We compared the eight aspects of subjective feedback from the participants. Among them, the SCATTER interface received a significantly higher rating for six aspects: Trust (Q4), Supportiveness (Q5), Interest (Q6), Satisfaction (Q8), Intention to Reuse (Q9), and Enjoyable (Q11). In two questions, facilitation (Q7) and the control-reversed Benefit Question (Q12), the SCATTER interface scored higher, but not significantly. It is interesting to see that the RANK interface scored a bit higher (though not significantly) on explanation usefulness, which hints that the lack of visualization made explanations more important in the RANK interface. In the final preference test, the SCATTER interface received much stronger support than the RANK interface in the user preference feedback (Figure 4). Most importantly, a majority of users (84%) considered the SCATTER interface to be a better system for recommending attendees and a better help in diversity-oriented tasks, as well as better for recommending.

6 CONCLUSION

In this paper, we presented a dual visual interface for recommending attendees at a research conference. A research conference context introduces several dimensions of attendee relevance, such as social, academic, interest, and distance similarities. Due to these factors, a traditional ranked list makes it difficult to express the diversity

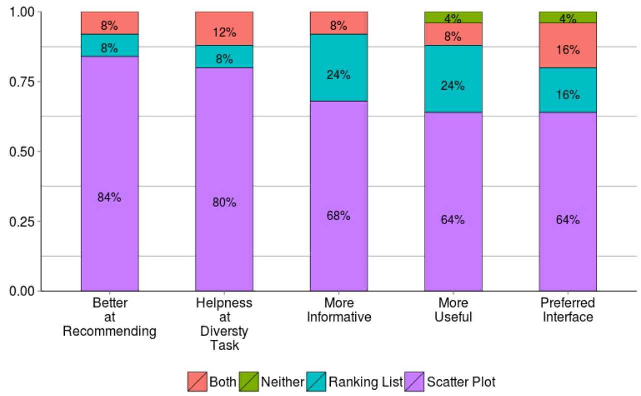

Figure 4: Preference Results: the final preference test after user experienced the two interfaces.

of recommended items (attendees). By spreading ranking over two dimensions, the suggested interface helps users in exploring recommendations and recognizing their diversity in several aspects. Our approach can be applied to any recommender system with multiple relevance features and item categories. To assess the visual approach, we conducted a user study in a real conference environment to compare our interface (SCATTER) with a traditional ranked list (RANK) in three practical tasks.

Our experimental result shows the tangible incremental impact the metrics of system usage, efficiency, and diversity. We found that the SCATTER interface benefits more on the aspect of perceived tasks and helps enhance diversity tasks. Results from the final preference survey show a strong preference for the SCATTER interface. Interestingly, we also found that users of the SCATTER interface benefited more from the feature diversity tasks. The user feedback suggests that it would be easier to find and categorize variables through the RANK interface. However, even the user feedback indicates an ease of use for selecting and inspecting an item by category through the RANK interface. The users of the SCATTER interface still show significantly higher coverage measurement between tasks.

The main contribution of this paper is to prove that the enhanced diversity interface not only helps the user to perceive diversity [8], but also helps the user to improve usability in the real world beyond simple relevance tasks. We provide empirical evidence on how to design a recommender system interface for users to explore a diverse set of recommended items while simultaneously improving the user stratification.

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