Beyond Lists: Studying the Effect of Different Recommendation Visualizations

Denis Parra
School of Information Sciences
University of Pittsburgh
135 North Bellefield Avenue,
Pittsburgh, PA, USA
+1 412 6249437
dap89@pitt.edu

ABSTRACT

Recommendation Systems have been studied from several perspectives over the last twenty years –prediction accuracy, algorithmic scalability, knowledge sources, types of recommended items and tasks, evaluation methods, etc. - but one area that has not been deeply investigated is the effect of different visualizations and their interaction with personal traits on users' evaluation of the recommended items. In this paper, I survey visual approaches that go beyond presenting the recommended items as a textual list or as annotations in context. I also review related literature from recommendations' explanations. In this thesis, I aim to understand how different visualizations and some personal traits might influence users' assessment of recommended items, particularly in domains where multidimensional data or contextual constraints are involved. I present the prototype of 2 recommendation visualizations and then briefly propose the research approach of this investigation.

Categories and Subject Descriptors

H.3.3 [**Information Search and Retrieval**]: Information Filtering. H.5.2 [**User Interfaces**]: Interaction Styles, User-centered design.

General Terms

Design, Experimentation, Human Factors.

Keywords

Recommender Systems, Adaptive Interfaces, Visualization of Recommendations.

1. INTRODUCTION

Recommendation Systems (RS) aim to provide users relevant items from a crowded information space. RS have become popular commercially and as a research field in the latest 10 years as evidenced by online contests such as the Netflix Prize, and by the interest in related conferences like ACM RecSys.

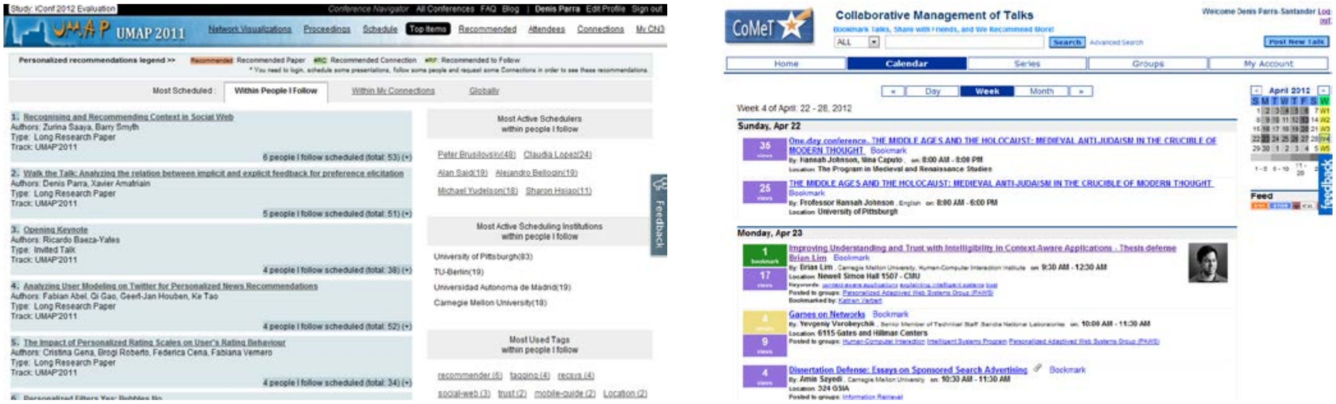
RecSys'12, Month 1–2, 2010, Dublin, Ireland.

On the research field, among the several issues that has been investigated over the years –prediction accuracy, algorithmic scalability, knowledge sources, types of recommended items and tasks, evaluation methods, etc. - the effect of different visualizations and their interaction with personal traits over users' preference on recommended items has been studied but not at the same extent as the aforementioned issues. One can identify three main reasons that make this an important area of research: a) *Recommendation Transparency*: Explaining how the recommendations were generated to RS users has shown to have a positive effect in users' trust in the RS [1], and visualizations of recommendations can provide better ways than textual lists to comprehend how recommendations were generated. b) *Multivariate Data*: most current state-of-the-art recommender systems rely not only on one dimension of user feedback –such as user ratings-- but also on implicit feedback, time, location, and many other forms of contextual information. In addition, some domains such as Event Recommendations pose additional constraints, such as the limited life time of the items. Visualizing recommendations beyond textual lists might facilitate incorporating several dimensions [2] when presented to users to make sense of the recommendations. c) *The Effect of Personal Traits*: Considering human traits as factors affecting how users evaluate recommendations has been studied [3, 4], but not their interaction with rich visualizations as those implemented in [5-7].

In this research proposal, I aim to bridge the lack of investigation on the effects of rich visualizations, interface interactions and some traits of users upon how users' evaluate recommendations: users' perceived relevance, novelty and serendipity, users' satisfaction, and users' trust on the recommendation process. In section 2, I survey related work about visualizing and explaining recommendations. Then, in section 3, I introduce two systems that will be used to test the influence of different visualizations. In section 4 I briefly describe my research plan, and in section 5 I summarize the challenges and expectations of this research proposal.

2. RELATED WORK

Research on visualizing recommendations beyond a textual list or as *annotation in context* [8] is not abundant. Some of these studies have shown the positive effect on user satisfaction of visualizing recommendations and allowing richer interaction [5-7, 9]. PeerChooser [5] was introduced by O'Donovan et al. to show movie recommendations interactively. The active user was depicted as the center node in an ego-network, and PeerChooser's users could explore their nearest neighbors, movie genres, and check their recommendions in different ways.



a) b)

Figure 1. Screenshots of a) Conference Navigator 3, and b) CoMeT.

The recommended movies were presented as top-N, clusters and rating predictions on user-selected items. A study with 25 users that compared four recommendation methods showed that adding user interaction significantly improved the system's rating predition and users' satisfaction. On a different domain, Gotz and Wen [9] developed an approach called Behavior-Driven Visualization Recommendation (BDVR), by which they detect patterns of user behavior in a data analysis system called HARVEST. Based on the detected behavioral patterns, HARVEST recommend other visualizations to analyze the data. A user study with 20 users, that considered two different tasks per user on three possible scenarios, showed that using the BDVR on HARVEST decreased the average time needed to complete the tasks and also the error rate, compared to those users that were assigned to the group without BDVR support. Despite its novel approach, BDVR innovates in the way that recommendations are identified based on user behavior, rather than the way in which the recommendations are presented to the user –a link blinking that suggest another way to analize the data to the user. Another interesting work using visualizations to show user recommendations is SmallWorlds [6], a visual recommender system implemented as a Facebook application that utilizes the profiles of the active user and her connections to generate recommendations. A user study allows the authors of SmallWorlds sustaining that system's transparency and interface interaction increases user satisfaction, and even under the constraints of the Facebook API –that allows to get information only from the user's direct connections– the recommendations enhanced by pre-existing friends information boost the users' satisfaction on recommendation predictions. The main limitation of this study is the assessment based only on user preferences of movies, although Facebook profiles provides various other types of items for recommendation. More recently, in the music domain, Gou et al. present SFViz [7] present a sunburst visualization to allow users exploring and finding friends interactively under a context of interest. Their visualization and iteraction method is novel, and although they introiduce a case study using the social network and tags of a last.fm dataset, no user study is presented to empiricially assess their design.

The second related area of research is explaining recommendations to users and how visualizations help increasing users' trust in the system and overall user satisfaction. Zhao et al. [10] present Pharos, a content-centric system able to recommend items, people and communities. They try to tackle the cold-start problem and also explain the recommendations by visualizing a social map with terms organized in latent communities. A within subjects study with ten users shows that Pharos helped the subjects to complete exploratory tasks faster and better than BlogCentral, an existent tool. Although user knowledge and tasks were considered and they didn't affect the significant differences between Pharos and BlogCentral, the small amount of subjects calls for a larger user study to generalize these results. Another drawback of this system is the lack of personalization. The social map displayed the same communities and terms to every user, and users' feedback suggests adding this feature in an future version. Zhang et al. [11] go beyond textual explanation by presenting a visual interface for a critiquing-based RS. In an e-commerce system, they present various critiques by a set of meaningful icons, and their results show how the visual presentation and the aided interaction improves users' shopping experience. However, the visualizations are not rich visualizations as those presented in [5-7].

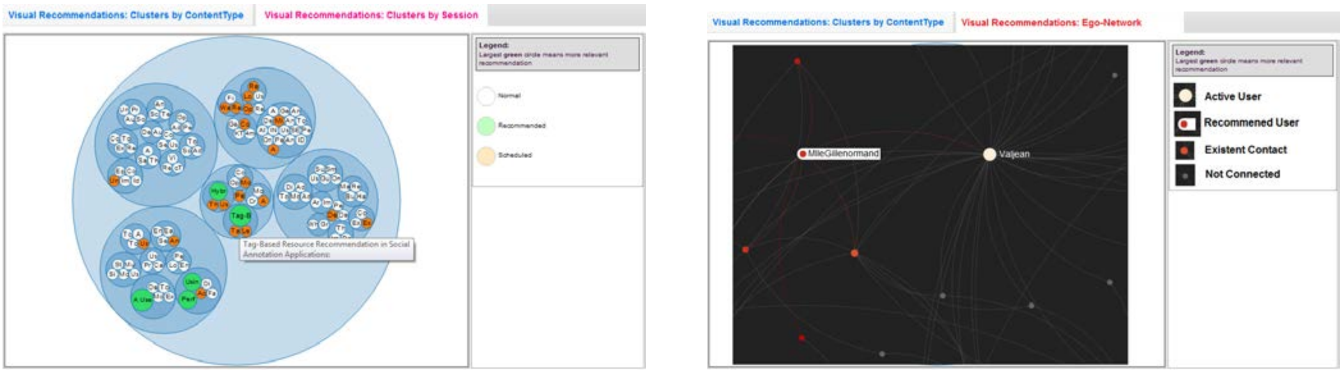
The main limitation of the aforementioned studies, excepting Pharos [10], is the absence of users' traits in the analysis of factors interacting with visualizations on users' perceived relvance of the recommendations. The importance of users' traits on recommendation peformance is shown in [3, 4]. Knijnenburg et al. [3], shows that the users' domain knowledge is a factor influencing what kind of interaction method they prefer in an energy-saving RS. Tkalcic et al. [4] shows how affective parameters, based on users' emotive responses, improve the performance of a recommender system. These two studies don't neglect user traits but they don't consider rich visualizations (such as ego-network graphs, sunburst plots, circle packs, etc.) in their evaluations. Building on the results of these articles, I will consider the users' domain knowledge and the type of visualization

3. WORK UP-TO-DATE

I plan to test the effect of rich recommendation visualizations and their possible interaction with user's domain knowledge in two systems developed in the PAWS lab[1] at the University of Pittsburgh: Conference Navigator –a system that supports academic conferences-- and CoMeT (Collaborative Management of Talks) –a system designed to share information of open lectures

[1] http://adapt2.sis.pitt.edu/wiki/

and talks in the area of Pittsburgh, but mainly from the University of Pittsburgh and Carnegie Mellon University.



a) b)

Figure 2. Screenshots of a) recommendations as a circle pack using d3.js b) ego-network visualization based on sigma.js.

3.1 Conference Navigator

Conference Navigator[2], shown in Figure 1.a), is a system which supports attendees at academic conferences. It provides usual information about a conference such as the list of papers with authors and abstract, the schedule of the conference, details of each talk and in some occasions the list of attendees.

Conference Navigator allows users scheduling the talks they are interested to attend, and in addition, it allows users connecting each other as followed/follower, and also as reciprocal connections. Furthermore, Conference Navigator has useful features that present aggregated users' behavior, such as the ranking of the most scheduled papers, the most active contributors, the institutions of the most active contributors, a cloud of the tags which users have attached to papers, and a feature similar to Amazon.com about papers: "people who scheduled paper X also scheduled paper Y". Conference Navigator also provides a personalized textual list of recommended talk constructed upon content and tag-based algorithms. Since the talks are part of a larger event, the conference, they can be classified inside days or sessions. Moreover, talks present characteristics such as popularity or whether they are recommended that make them prone to be presented in a richer visualization than a list.

3.2 CoMeT

CoMeT[3], shown in Figure 1.b), stands for Collaborative Management of Talks. It is a system that aggregates information about open academic lectures and talks in the Pittsburgh area, mainly at the University of Pittsburgh and at Carnegie Mellon University. Some of the talks are manually entered to the system by users and the rest are automatically collected by web crawlers. CoMeT provides socially aggregated data about the talks: how many people has viewed, bookmarked and e-mailed each one. CoMeT features the most popular talks of each day in its homepage, but it also provides different ways to navigate and search throughout all the talks available. Although some talks are entered as isolated events, they usually belong to series of talks or to special department events, what makes them good candidates to be grouped and classified under several categories. The social activity associated to talks, and their temporal restrictions, makes them good candidates to be recommended and presented in visualization richer than lists. Currently, CoMeT provides users a textual list of recommended talks by e-mail once a week.

4. RESEARCH PLAN

4.1 Prototypes of Recommendation Visualizations

4.1.1 Circle Pack Layout

Considering a layout that shows concentric circles helps visualizing a tree, which is one of the possible ways to structure the contents of a conference consecutively as days, sessions and talks. Figure 2.a) shows a prototype of talk recommendation for Conference Navigator, where the largest circle represents the conference, the largest circles inside represent days, and inside them, sessions and talks. The talks which the user has scheduled to attend are presented with orange color, the ones not scheduled with white, and the recommended talks with green. The different size of the recommended talks (the green circles) represent their recommendations score: the larger the recommendation score, the larger the circle. Planned interaction will allow the users clicking on a circle and obtaining additional information of the day, session or talk clicked. Furthermore, they will be able to rate the recommended talks and we will track user interactions with the system.

4.1.2 Ego-Network Layout

This model has been already explored in [5, 6] and a prototype implemented in Conference Navigator is shown in Figure 2.b). The active user will be represented as the central node in a network, and every node in the network will be at most 3 hops away from the central user. The other nodes will represent neighbors, articles, and in some cases users' tags –depending on the method used to provide the recommendations: content-based or tag-based.

4.2 User Study

In the user study, I plan comparing the 2 aforementioned layouts (Circle Pack and Ego-Network) with a textual list of

[2] http://halley.exp.sis.pitt.edu/cn3/

[3] http://halley.exp.sis.pitt.edu/comet/

recommendation, and a recommendation list enhanced with facets in both Conference Navigator and CoMeT. The reason for comparing with a faceted list comes for the advice given by Hearst in [12], where faceted lists provide support to present multivariate data beyond lists, that is difficult to overcame by other richer visualizations in terms of user performance to complete search tasks.

5. DISCUSSION AND FUTURE WORK

The proposal presented in this paper is ongoing work, in an early stage of development, but it highlights the importance of this work and introduces the research and initial evaluation plan.

I have outlined the reasons, surveyed the related work, and presented an initial description of the approach to investigate the influence of visualizations in users' perception of recommendations. First, regarding the reasons, there is a lack of research that integrates the influence of different visualizations, interactions and user traits in recommender systems. Moreover, the need of transparency in recommendations, the multivariate nature of the data, and the lack of studies incorporating the effect of personal traits makes this research and important area. The related work highlights the positive effect of different interaction on user satisfaction, but it presents limitations. They are restricted to recommend movies [5, 6]–an area already deeply investigated whose results cannot be generalized to other fields, such as event recommendations--, their recommendation visualizations are not rich in interaction [9], their user studies have few users [10] or they completely lack a user study [7].

The expected number of subjects for the study in Conference Navigator and CoMeT is around 20 and 30. However, a power analysis is necessary to establish the minimum number of users needed to detect an effect in case it exists. This analysis will be conducted in the next stage of this research.

6. ACKNOWLEDGEMENTS

I appreciate the feedback provided by Roman Bednarik to clarify some terms that might lead to confusion, and some ideas to describe better the purpose of this research.

7. REFERENCES

[1] Tintarev, N. and Masthoff, J. Designing and Evaluating Explanations for Recommender Systems. Recommender Systems Handbook. Springer US, City, 2011.

[2] Knijnenburg, B. P., Reijmer, N. J. M. and Willemsen, M. C. Each to his own: how different users call for different interaction methods in recommender systems. In Proceedings of the Proceedings of the fifth ACM conference on Recommender systems (Chicago, Illinois, USA, 2011). ACM, [insert City of Publication],[insert 2011 of Publication].

[3] Tkalčič, M., Burnik, U. and Košir, A. Using affective parameters in a content-based recommender system for images. User Modeling and User-Adapted Interaction, 20, 4 2010), 279-311.

[4] O'Donovan, J., Smyth, B., Gretarsson, B., Bostandjiev, S. and H\"ollerer, T. PeerChooser: visual interactive recommendation. ACM, City, 2008.

[5] Gretarsson, B., O'Donovan, J., Bostandjiev, S., Hall, C. and Höllerer, T. SmallWorlds: Visualizing Social Recommendations. Computer Graphics Forum, 29, 3 2010), 833-842.

[6] Gou, L., You, F., Guo, J., Wu, L. and Zhang, X. L. SFViz: interest-based friends exploration and recommendation in social networks. ACM, City, 2011.

[7] Herlocker, J. L., Konstan, J. A., Terveen, L. G. and Riedl, J. T. Evaluating collaborative filtering recommender systems. ACM Trans. Inf. Syst., 22, 1 2004), 5-53.

[8] Gotz, D. and Wen, Z. Behavior-driven visualization recommendation. ACM, City, 2009.

[9] Zhao, S., Zhou, M. X., Yuan, Q., Zhang, X., Zheng, W. and Fu, R. Who is talking about what: social map-based recommendation for content-centric social websites. ACM, City, 2010.

[10] Zhang, J., Jones, N. and Pu, P. A visual interface for critiquing-based recommender systems. In Proceedings of the Proceedings of the 9th ACM conference on Electronic commerce (Chicago, Il, USA, 2008). ACM