Let Me Show You You: Personalized Preference Profiles for Self-Actualization

Bart P. Knijnenburg and Sushmita Khan, Clemson University

Although recommender systems claim to learn users' preferences by tracking their consumption or purchase behaviors, research shows that such preferences are usually heuristically constructed on-the-fly [1, 2, 5]. This leaves recommender systems particularly vulnerable to trying to solve a very common but impossible task: trying to recommend things to a user who does not know what they want. Explanations increase users' understanding of the recommendation process, which supports their preference construction [6, 7, 14, 17]. Systems that *visualize* the recommendation process take a step further by allowing users to critically appraise the origin of recommendations and even take control over the recommendation process [3, 9, 10, 16].

We propose Personalized Preference Profiles (PPPs) that help users reflect on their preferences in a way that meaningfully supports their preference construction process. PPPs visualize users' *preferences* rather than the recommendation process, which allows users to realign their preferences with their long-term goals.

The information visualization field provides useful guidance on how to design visualizations of preferences. "Infographics" leverage visual representations to amplify human cognition [4]. Recent advances in big data have allowed developers of commercial systems (e.g., OkCupid, Uber, The EchoNest) to share compelling infographics on their company blogs, highlighting surprising preference dynamics that give insights into their customers' tastes. Note that although some infographics provide information broken down by gender, age or other demographics, they are not tailored to a specific user. Preliminary efforts visualize topic coverage [12, 13] and potential blind spots in users' interests [15], but these works do not leverage the unique capability of recommendation algorithms to distinguish between the common (what can be predicted by an algorithm) and unique (what algorithms get wrong) sides of users' preference profiles. We therefore propose a specific preference visualization that juxtaposes the user's likes and dislikes against a reference group. We anticipate that we will face the following challenges when building PPPs:

- **Reference group selection:** What reference group would be the most meaningful to juxtapose the user's preferences against? We may consider a reference group that consists for all other users, a set of users that shares a particular characteristic (e.g., age or gender), or a set of users with similar preferences.
- **Data representation:** Should the visualization consider expressed or predicted preferences? Expressed preferences (e.g. an item rating the user entered into the system) are arguably more accurate, but less granular than predicted preferences. On the other hand, predicted preferences can be calculated for all items, and can be more granular than expressed preferences.
- **Likes and dislikes selection:** Which items should be presented in the visualization? We argue that it is most useful for users to discover items that they (are predicted to) like much better or much worse than the reference group. On the other hand, a baseline agreement on many items can serve as a common ground between the user and their reference group.
- **Visualization complexity:** Many visualizations in the RecSys field can be criticized for being too complex for most "regular users" to understand. We want to make a concerted effort to create visualizations that are intuitive for all users.

We look forward to discussing PPPs at the workshop, where we are happy to present our ideas for how to implement and study them.

References

[1] Joseph W. Alba and J. Wesley Hutchinson. 1987. Dimensions of Consumer Expertise. *J. Consum. Res.* 13, 4 (March 1987), 411. https://doi.org/10.1086/209080

[2] James R. Bettman, Mary Frances Luce, and John W. Payne. 1998. Constructive Consumer Choice Processes. *J. Consum. Res.* 25, 3 (December 1998), 187–217. https://doi.org/10.1086/209535

[3] Svetlin Bostandjiev, John O'Donovan, and Tobias Höllerer. 2013. LinkedVis: Exploring Social and Semantic Career Recommendations. In *Proceedings of the 2013 International Conference on Intelligent User Interfaces* (*IUI '13*), 2013. ACM, New York, NY, USA, 107–116. https://doi.org/10.1145/2449396.2449412

[4] Stuart K. Card, Jock D. Mackinlay, and Ben Shneiderman (Eds.). 1999. *Readings in Information Visualization: Using Vision to Think*. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.

[5] Eloïse Coupey, Julie R. Irwin, and John W. Payne. 1998. Product Category Familiarity and Preference Construction. *J. Consum. Res.* 24, 4 (March 1998), 459–468. https://doi.org/10.1086/209521

[6] Gerhard Friedrich and Markus Zanker. 2011. A Taxonomy for Generating Explanations in Recommender Systems. *AI Mag.* 32, 3 (June 2011), 90–98. https://doi.org/10.1609/aimag.v32i3.2365

[7] Fatih Gedikli, Dietmar Jannach, and Mouzhi Ge. 2014. How should I explain? A comparison of different explanation types for recommender systems. *Int. J. Hum.-Comput. Stud.* 72, 4 (April 2014), 367–382. https://doi.org/10.1016/j.ijhcs.2013.12.007

[8] Anthony Jameson, Martijn C. Willemsen, Alexander Felfernig, Marco de Gemmis, Pasquale Lops, Giovanni Semeraro, and Li Chen. 2015. Human Decision Making and Recommender Systems. In *Recommender Systems Handbook*. 611–648.

[9] Pigi Kouki, James Schaffer, Jay Pujara, John O'Donovan, and Lise Getoor. 2017. User Preferences for Hybrid Explanations. In *Proceedings of the Eleventh ACM Conference on Recommender Systems* (*RecSys '17*), 2017. ACM, New York, NY, USA, 84–88. https://doi.org/10.1145/3109859.3109915

[10] A. Lex, N. Gehlenborg, H. Strobelt, R. Vuillemot, and H. Pfister. 2014. UpSet: Visualization of Intersecting Sets. *IEEE Trans. Vis. Comput. Graph.* 20, 12 (December 2014), 1983–1992. https://doi.org/10.1109/TVCG.2014.2346248

[11] H. A. Maslow. 1943. A theory of human motivation. *Psychol. Rev.* 50, 4 (1943), 370–396. https://doi.org/10.1037/h0054346

[12] Stuart E. Middleton, Nigel R. Shadbolt, and David C. De Roure. 2003. Capturing Interest Through Inference and Visualization: Ontological User Profiling in Recommender Systems. In *Proceedings of the 2Nd International Conference on Knowledge Capture* (*K-CAP '03*), 2003. ACM, New York, NY, USA, 62–69. https://doi.org/10.1145/945645.945657

[13] Emily Sullivan, Dimitrios Bountouridis, Jaron Harambam, Shabnam Najafian, Felicia Loecherbach, Mykola Makhortykh, Domokos Kelen, Daricia Wilkinson, David Graus, and Nava Tintarev. 2019. Reading News with a Purpose: Explaining User Profiles for Self-Actualization. In *Proceedings of 27th Conference on User Modeling, Adapation & Personalization Adjunct*, June 09, 2019. Larnaca, Cyprus. https://doi.org/10.1145/3314183.3323456

[14] Nava Tintarev and Judith Masthoff. 2012. Evaluating the effectiveness of explanations for recommender systems. *User Model. User-Adapt. Interact.* 22, 4–5 (October 2012), 399–439. https://doi.org/10.1007/s11257-011-9117-5

[15] Nava Tintarev, Shahin Rostami, and Barry Smyth. 2018. Knowing the Unknown: Visualising Consumption Blind-spots in Recommender Systems. In *Proceedings of the 33rd Annual ACM Symposium on Applied Computing* (*SAC '18*), 2018. ACM, New York, NY, USA, 1396–1399. https://doi.org/10.1145/3167132.3167419

[16] Katrien Verbert, Denis Parra, Peter Brusilovsky, and Erik Duval. 2013. Visualizing Recommendations to Support Exploration, Transparency and Controllability. In *Proceedings of the 2013 International Conference on Intelligent User Interfaces* (*IUI '13*), 2013. ACM, New York, NY, USA, 351–362. https://doi.org/10.1145/2449396.2449442

[17] Jesse Vig, Shilad Sen, and John Riedl. 2009. Tagsplanations: Explaining Recommendations Using Tags. In *Proceedings of the 14th International Conference on Intelligent User Interfaces* (*IUI '09*), 2009. ACM, New York, NY, USA, 47–56. https://doi.org/10.1145/1502650.1502661