Psychology-informed Recommender Systems Tutorial

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ABSTRACT

Recommender systems are essential tools to support human decision-making in online information spaces. Many state-of-the-art recommender systems adopt advanced machine learning techniques to model and predict user preferences from behavioral data. While such systems can provide useful and effective recommendations, their algorithmic design commonly neglects underlying psychological mechanisms that shape user preferences and behavior. In this tutorial, we offer a comprehensive review of the state of the art and progress in *psychology-informed recommender systems*, i.e., recommender systems that incorporate human cognitive processes, personality, and affective cues into recommendation models, along with definitions, strengths and weaknesses. We show how such systems can improve the recommendation process in a user-centric fashion. With this tutorial, we aim to stimulate more ideas and discussion with the audience on core issues of this topic such as the identification of suitable psychological models, availability of datasets, or the suitability of existing performance metrics to evaluate the efficacy of psychology-informed recommender systems. Besides, we present takeaways to recommender systems practitioners how to build psychology-informed recommender systems. Previous versions of this tutorial were presented, among others, at The ACM Web Conference 2022 and the ACM SIGIR Conference on Human Information Interaction and Retrieval (CHIIR) 2022.

KEYWORDS

recommender systems, cognitive models, affect, emotion, personality, human decision-making

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1 MOTIVATION AND TOPIC IMPORTANCE

The increasing availability of online social networks and online marketplaces has resulted in an abundance of information and items. Recommender systems (RSs) have been introduced to guide users in their decisions in this overloaded information space. Correspondingly, research on RSs has been a very active and growing field for the past twenty years.

Most of today's RSs are data-driven and use advanced machine learning algorithms to model and predict user preferences. While these RSs can generate useful recommendations, they often lack interpretability and are black-box models, which do not incorporate psychological mechanisms that shape user preferences and behavior. With this tutorial on *psychology-informed recommender systems*, we aim at bridging this gap in computer science and psychology. We provide the attendees with an overview of recent work that leverages psychological constructs and theories to model and predict user behavior and improve the recommendation process. We follow an interdisciplinary direction, aiming to connect the research communities of recommender systems and psychology.

The tutorial is based on a recent long survey article published by the tutorial presenters in the Foundations and Trends in Information Retrieval journal [14]. Similar to this article, in the tutorial, we discuss three categories of psychology-informed RSs: cognition-inspired, personality-aware, and affect-aware RSs. Since RSs are fundamental tools to support human decision-making, in the tutorial, we also outline the relationship between human decision-making and RSs, as well as decision biases that shape the users' interactions with a RS.

We hope that our tutorial inspires a discussion on our vision for future RSs research: *"to draw from the decent knowledge of psychology and the social sciences in the entire workflow of creating and evaluating RSs to adopt a genuinely human-centric perspective"* [14].

2 SUBJECT MATTERS

- **Overview of traditional recommender systems:** Content-based, collaborative filtering, context-aware, and hybrid RSs.
- **Taxonomy of psychology-informed recommender systems:** Categorization of recommendation approaches that utilize psychological models to improve the recommendation process into cognition-inspired, personality-aware, and attention-aware RSs.
- **Cognition-inspired recommender systems:** Cognitive models and architectures, and how to exploit cognitive models of memory, stereotypes, and attention for RSs.
- **Personality-aware recommender systems:** Modeling personality, acquiring personality traits, relation between personality and item preferences, approaches that leverage personality traits for recommendation.
- **Affect-aware recommender systems:** Definition of major affective concepts (mood and emotion), modeling mood and emotion, acquiring affective cues, approaches that leverage affective cues for recommendation.

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2.1 Cognition-inspired Recommender Systems

Cognition-inspired RSs leverage cognitive models from cognitive psychology to create and improve recommendations. Cognitive psychology is a subfield within psychology that investigates the human mind and human mental processes such as memory, attention, or learning. Previous work on human decision making and RSs has shown that such mental processes strongly influence a user's preferences and interaction with a recommender system [11].

Most related works utilize cognitive models of human memory, attention, and competence; in addition, case-based reasoning (CBR) RSs are early forms of cognition-inspired RSs. Works that leverage cognitive models of human memory to model and predict user preferences show that human memory decay functions are effective models of user preference shifts and help improve personalization (e.g. [12, 24, 30]). Other works incorporate cognitive models of attention into the recommendation process to rerank recommendations based on the user's current attentional focus [28]. While numerous works investigate attention mechanisms in deep learning-based architectures, to the best of our knowledge, these works do not relate their experiments to psychological theory. Other types of cognition-inspired recommender systems include case-based reasoning RSs [13] - which mimic how humans base their reasoning on previous learning episodes when solving new problems, as well as competence-based recommender systems, which are typically utilized in learning scenarios [20], or to recommend activities and resources [5].

Overall, cognitive models of human mental processes are incorporated into the recommendation process to give further insights into user behavior grounded in human cognition. Also, resulting algorithms allow for improved personalization. Furthermore, the algorithms are typically interpretable and transparent.

2.2 Personality-aware Recommender Systems

Personality is a fundamental psychological concept that has been studied for decades in psychology research. Unlike affective cues such as mood or emotion, personality traits are human characteristics that are largely stable over a human's lifetime.

As such, they are independent of a particular context or stimulus. In addition, several studies have revealed that personality traits are correlated with user-specific information that RSs exploit (e.g., preferences for movies [9], music [8], or books [25]. Further correlations have been identified between personality and users' preferences for recommendation diversity, popularity, and serendipity (e.g. [3, 17, 29]). All of these characteristics make personality traits particularly suited for personalization purposes in RSs.

While there exist various models to describe personality traits, the most commonly adopted one in RSs research is the OCEAN (or Big Five) model [15], which describes an individual along five dimensions: Openness to experience (conventional vs. creative thinking), Conscientiousness (disorganized vs. organized behavior), Extraversion (engagement with the external world), Agreeableness (need for social harmony), and Neuroticism (emotional stability). To characterize a user's personality, each dimension of OCEAN can be quantified either by well-established psychological instruments such as questionnaires (e.g., the International Personality Item Pool[1]), or by applying machine learning techniques to user-generated data (e.g. [2, 7, 10]).

The main reasons why personality traits are incorporated into the recommendation process are to mitigate cold start for new users (e.g. [1, 29]), to improve personalization, for instance, by adjusting diversity of recommendation lists (e.g. [29]), and in group recommendation scenarios to improve the quality of group decisions and increase user satisfaction (e.g. [16, 21, 23]).

2.3 Affect-aware Recommender Systems

Affective cues, such as emotion and mood, play an important role in everyone's life. While the former is an affective response to a particular stimulus and lasts only for a short time (typically minutes), the latter is an affective experience of lower intensity but longer duration (commonly hours). Similar to personality, emotion and mood are fundamental human features that have been researched intensely in the field of psychology. They correlate with human preferences, as shown for instance in the domains of music [8], video [18], movies [9], fashion [19], and books [25]. Moreover, they impact how much diversity in recommendation lists users prefer [3, 29]. Due to their more dynamic behavior than personality, mood and emotion have been used as a contextual attribute in context-aware RSs.

To describe a user's affective state, three categories of models exist: categorical, dimensional, and hybrid. Categorical models describe affect using a fixed vocabulary of terms, for instance, Ekman's universal emotions [6], i.e., anger, surprise, disgust, enjoyment, fear, sadness, and contempt.[2] Dimensional models delineate affect along a continuous scale, most commonly defined in two dimensions: valence and arousal, where valence refers to pleasantness (positive vs. negative) while arousal refers to intensity (high vs. low). A prominent example is Russell's Circumplex model [26]. Hybrid models combine both approaches by describing affect on a continuous scale, but instead of using the two dimensions valence and arousal, such models leverage a set of basic affects, e.g., in the Geneva Emotion Wheel [27].

Compared to personality, affect has been less frequently addressed in the RSs literature. When it is used, the common reason is to tailor recommendations to a particular context. Typically, users and items are both described in a fixed dimensional affect space in which they are matched, as for instance demonstrated for point-of-interest recommendation [22] and music recommendation [4].

3 TARGET AUDIENCE

We target an audience of researchers and practitioners who are interested to delve into psychological aspects of RSs. Particular prerequisite knowledge or skills are not required from the audience, except for a basic understanding of the main concepts in RSs, user modeling, and machine learning. The purpose of this tutorial is to provide the attendees with an overview of recent work on psychology-informed RSs and hands-on knowledge on how to design, improve, and evaluate RSs based on a variety of psychological models and theory. After attending this tutorial, the participants will know how to: (1) create RSs based on cognitive models, (2) model personality and mood according to psychological theories

[1]https://ipip.ori.org

[2]https://www.paulekman.com/universal-emotions

and results of empirical studies, (3) acquire personality- and affect-related user traits from user-generated data and questionnaires, and (4) integrate personality and affective information into RSs.

4 TUTORIAL PRESENTERS

Elisabeth Lex (https://elisabethlex.info) is an associate professor at Graz University of Technology, Austria. Besides, she is the head of the Recommender Systems and Social Computing Lab. Her research focuses on applied machine learning, in particular, recommender systems, user modeling, information retrieval and computational social science, with a particular focus on cognition-inspired recommender systems, quantifying and mitigating bias in recommender systems, human decision making and recommender systems, privacy in recommender systems, and music consumption behavior. Elisabeth has (co-)authored more than 120 peer-reviewed publications and has served as a co-organizer of the Workshop on Interfaces and Human Decision Making for Recommender Systems (IntRS), co-located with ACM RecSys 2021, and as a track chair at The ACM Web Conference 2023 for user modeling and personalization, at ACM UMAP 2022 for intelligent user interfaces, and at ACM Hypertext and Social Media 2020 for recommender systems and social media. She has been senior PC member of ACM RecSys, The ACM Web Conference, ACM IUI, or Social Informatics. She has given tutorials, among others, at the Web Conference 2022, CHIIR 2022, and SIGIR 2022.

Markus Schedl (http://www.mschedl.eu) is a full professor at the Johannes Kepler University Linz, affiliated with the Institute of Computational Perception, leading the Multimedia Mining and Search group. In addition, he is head of the Human-centered AI group at the Linz Institute of Technology, AI Lab. His main research interests include recommender systems, user modeling, information retrieval, machine learning, multimedia processing, and trustworthy AI, with a particular focus on detecting and mitigating bias in retrieval and recommendation algorithms and on psychological models for recommendation. He (co-)authored more than 250 refereed conference papers, journal articles, and book chapters, and served as a program co-chair for the International Society for Music Information Retrieval (ISMIR) conference in 2020. He has given numerous tutorials in top venues, including ACM Recommender Systems (2018), ACM Multimedia (2013), SIGIR (2013, 2015, 2022), CHIIR (2022), and the Web Conference (2022).

5 TUTORIAL MATERIALS

The tutorial is supported by a GitHub repository.[3] The repository contains the tutorial slides with references to all relevant works, software, and datasets. Furthermore, we share with attendees the long survey article published in the Foundations and Trends in Information Retrieval journal [14].

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[3]https://socialcomplab.github.io/pirs-psychology-informed-recsys

REFERENCES

[1] N. Y. Asabere, A. Acakpovi, and M. B. Michael. 2018. Improving Socially-Aware Recommendation Accuracy Through Personality. *IEEE Transactions on Affective Computing* 9, 3 (2018), 351–361.

[2] Shlomo Berkovsky, Ronnie Taib, Irena Koprinska, Eileen Wang, Yucheng Zeng, Jingjie Li, and Sabina Kleitman. 2019. Detecting Personality Traits Using Eye-tracking Data. In *Proc. CHI*.

[3] Li Chen, Wen Wu, and Liang He. 2013. How Personality Influences Users' Needs for Recommendation Diversity?. In *Proc. CHI EA*.

[4] Shuiguang Deng, Dongjing Wang, Xitong Li, and Guandong Xu. 2015. Exploring User Emotion in Microblogs for Music Recommendation. *Expert Systems with Applications* 42, 23 (2015), 9284–9293. http://www.sciencedirect.com/science/article/pii/S0957417415005746

[5] Sebastian Dennerlein, Dieter Theiler, Peter Marton, Patricia Santos Rodriguez, John Cook, Stefanie Lindstaedt, and Elisabeth Lex. 2015. Knowbrain: An online social knowledge repository for informal workplace learning. In *European Conference on Technology Enhanced Learning*. Springer, 509–512.

[6] Paul Ekman. 1992. An Argument for Basic Emotions. *Cognition & Emotion* 6, 3–4 (1992), 169–200.

[7] Bruce Ferwerda and Marko Tkalcic. 2018. Predicting users' personality from instagram pictures: Using visual and/or content features?. In *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*. 157–161.

[8] Bruce Ferwerda, Marko Tkalcic, and Markus Schedl. 2017. Personality Traits and Music Genres: What Do People Prefer to Listen To?. In *Proc. UMAP*.

[9] Jennifer Golbeck and Eric Norris. 2013. Personality, Movie Preferences, and Recommendations. In *Proc. ASONAM*.

[10] Jennifer Ann Golbeck. 2016. Predicting personality from social media text. *AIS Transactions on Replication Research* 2, 1 (2016), 2.

[11] 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*. Springer, 611–648.

[12] Dominik Kowald and Elisabeth Lex. 2016. The influence of frequency, recency and semantic context on the reuse of tags in social tagging systems. In *Proceedings of the 27th ACM Conference on Hypertext and Social Media*. 237–242.

[13] D.B. Leake. 2001. Problem Solving and Reasoning: Case-based. In *International Encyclopedia of the Social & Behavioral Sciences*, Neil J. Smelser and Paul B. Baltes (Eds.). Pergamon, Oxford, 12117 – 12120. https://doi.org/10.1016/B0-08-043076-7/00545-3

[14] Elisabeth Lex, Dominik Kowald, Paul Seitlinger, Thi Ngoc Trang Tran, Alexander Felfernig, and Markus Schedl. 2021. Psychology-informed Recommender Systems. *Found. Trends Inf. Retr.* 15, 2 (2021), 134–242. https://doi.org/10.1561/1500000090

[15] Robert R. McCrae and Oliver P. John. 1992. An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality* 60 (6 1992), 175–215. Issue 2. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x

[16] T. N. Nguyen, F. Ricci, A. Delic, and D. G. Bridge. 2019. Conflict resolution in group decision making: insights from a simulation study. *User Model. User Adapt. Interact.* 29, 5 (2019), 895–941.

[17] Tien T Nguyen, F Maxwell Harper, Loren Terveen, and Joseph A Konstan. 2018. User personality and user satisfaction with recommender systems. *Information Systems Frontiers* 20, 6 (2018), 1173–1189.

[18] Claudia Orellana-Rodriguez, Ernesto Diaz-Aviles, and Wolfgang Nejdl. 2015. Mining Affective Context in Short Films for Emotion-Aware Recommendation. In *Proc. HT*. 185–194.

[19] Alexander Piazza, Pavlina Kröckel, and Freimut Bodendorf. 2017. Emotions and Fashion Recommendations: Evaluating the Predictive Power of Affective Information for the Prediction of Fashion Product Preferences in Cold-start Scenarios. In *Proc. WI*. 1234–1240.

[20] Frans J Prins, Rob J Nadolski, Adriana J Berlanga, Hendrik Drachsler, Hans GK Hummel, and Rob Koper. 2008. Competence Description for Personal Recommendations: The importance of identifying the complexity of learning and performance situations. *J Educ Techno Soc* 11, 3 (2008), 141–152.

[21] L. Quijano-Sanchez, J. A. Recio-Garcia, and B. Diaz-Agudo. 2010. Personality and Social Trust in Group Recommendations. In *Proc. ICTAI*. 121–126.

[22] Logesh Ravi and Subramaniyaswamy Vairavasundaram. 2017. Learning recency and inferring associations in location based social network for emotion induced point-of-interest recommendation. *J Comput Inf Sci Eng* 33 (1 2017), 1629–1647.

[23] J. A. Recio-Garcia, G. Jimenez-Diaz, A. A. Sanchez-Ruiz, and B. Diaz-Agudo. 2009. Personality Aware Recommendations to Groups. In *Proc. RecSys*.

[24] Markus Reiter-Haas, Emilia Parada-Cabaleiro, Markus Schedl, Elham Motamedi, Marko Tkalcic, and Elisabeth Lex. 2021. Predicting Music Relistening Behavior Using the ACT-R Framework. In *Proc. RecSys*. 702–707.

[25] Peter Rentfrow, Lewis R. Goldberg, and Ran Zilca. 2011. Listening, Watching, and Reading: The Structure and Correlates of Entertainment Preferences. *Journal of Personality* 79 (4 2011), 223–258. https://doi.org/10.1111/j.1467-6494.2010.00662.x

[26] James A. Russell. 1980. A Circumplex Model of Affect. *Journal of Personality and Social Psychology* 39, 6 (1980), 1161–1178.

[27] Klaus R. Scherer. 2005. What are emotions? And how can they be measured? *Social Science Information* 44, 4 (2005), 693–727.

[28] Paul Seitlinger, Dominik Kowald, Simone Kopeinik, Ilire Hasani-Mavriqi, Tobias Ley, and Elisabeth Lex. 2015. Attention please! a hybrid resource recommender mimicking attention-interpretation dynamics. In *Proc. WWW*. 339–345.

[29] Wen Wu, Li Chen, and Yu Zhao. 2018. Personalizing Recommendation Diversity Based on User Personality. *User Modeling and User-Adapted Interaction* 28, 3 (8 2018), 237–276.

[30] Zhenning Yang, Jingsha He, and Siyuan He. 2019. A Collaborative Filtering Method Based on Forgetting Theory and Neural Item Embedding. In *Proc. ITAIC*. 1606–1610.