Modeling User Personality Traits for Recommender Systems

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Abstract

In recent years, some research have been done on integrating user personality traits into recommender systems. The use of this type of psychological dimension could help to predict user preferences for several factors and enhance personalization in recommendation tools. The goal of this work is to investigate the adoption of personality traits in recommender systems. In the paper, some challenges of this research area are addressed, including the development of new methods to automatically predict the user Big Five personality traits, the exploration of novel ways to leverage them in user models, and the assessment of benefits deriving from the adoption of this type of information in recommender systems.

Keywords

user modeling, recommender systems, personality traits, personality computing

1. Introduction and related work

In recent years, there has been a lot of research on improving personalization in recommender systems. The latter play a crucial role in supporting users' decision-making processes by suggesting items people may like and helping to reduce the time spent on information seeking [1]. Modeling user preferences in a comprehensive way is essential to provide better recommendations. Enhancing the personalization of a recommender system means also to identify what factors influence people's decision-making process and to model a user profile able to deal as much as possible with the complexity of human cognition [2]. In recent years, the research community started to consider that people's personality can provide important information on users' preferences, since it has been shown to be related to the actual or potential behaviour patterns of an individual [1]. Personality-aware recommender systems recently emerged as a new category of tools that leverages this type of cognitive facet to enhance user satisfaction and help to tackle some of the well known issues encountered by these systems, such as the lack of data about user preferences [3].

Works that try to experiment the integration of personality information into recommender systems usually model it according to the theory of Costa and McCrae [4], which identifies five dimensions, also know with the acronym OCEAN (Openness to experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism). Although there are already few examples of projects that follow this trajectory, there are still serious obstacles to overcome. The inclusion

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of personality as a factor within the user profile poses complexities that need to be carefully addressed. Indeed, its integration in the user profile does not come without challenges, since this psychological dimension represents a complex factor to be modeled, whose possible applications have not yet been thoroughly explored [3].

The personality assessment phase represents a major problem. Traditional techniques consisting in text-based questionnaires (e.g., the BFI-10 [5] or the Ten Item Personality Inventory [6]) are not always suitable for recommendation purposes. Requiring people to self-assess their personality traits can be bothering to users who may not want to spend time in this task or may fill the questionnaire inaccurately [3]. Automatic personality recognition for the recommendation domain is currently considered an emerging research field whose findings could facilitate and enhance the adoption of personality information in several contexts. Recently proposed methods include detection from audio, text and visuals [7]. Given the increasing amount of multimedia contents on social media, the latter seem to be a particularly promising source. Indeed, some research [8] has shown that personality traits correlate with visual patterns, influencing what images are liked by the user. Few works [9], [10], [11], [12], [13] have tried to infer Big Five from personal aesthetic preference on one image. However, much research still needs to be done to improve this task (e.g., experimenting the detection from multiple images) and to assess its effectiveness in real-world recommender systems.

Once the information on the user personality is available, it is necessary to identify the best ways in which it can be incorporated in the user model and to uncover all the possible exploitation. Some works [14],[15] experimented the use of personality to compute similarity between users in the collaborative filtering approach, basing on the assumption that people with similar psychological traits are expected to share similar interests. However, in many recommendation tools, acquired data are used to derive further knowledge on the user expected preferences for specific attributes of items [16]. It is thought that a wide range of preference factors may be predicted from the user personality profile. For example, some recent works found relevant correlations in various domains, such as in recommendation for music [17], movies [18] or tourist attractions [19]. Further research is needed to investigate other possible applications, such as the use of personality to predict preference on contextual factors, which represents a topic that still needs to be fully explored.

By addressing these challenges and exploring novel approaches, recommender systems can harness the power of personality to provide even more tailored recommendations, potentially enhancing user satisfaction and engagement.

2. Goals and Objectives

The aim of this study is to investigate and experiment the integration of Big Five personality traits in recommender systems. To do so, some goals have been defined, which try to address problems related to the various phases involved in the creation of personality-aware models. In particular, we are interested in addressing the following problems:

- **Personality recognition:** exploring new methods to detect personality that could be suitable to various recommendation domains. We want to propose techniques to automatically predict scores for the Big Five personality traits such as to make the personality acquisition process as less bothering as possible for users.

- **Prediction of preferences from personality:** investigating the use of personality traits to infer user preferences on several factors, including dimensions relative to context, interpreted as a set of factors that are relevant to the situation of an item. The objective is to determine if it is possible to correlate contextual factors to this psychological dimension.

- **Recommender system design:** devising and testing a model which integrates an automatic personality recognition module and, given the personality trait prediction as input, produces recommendations personalized in several aspects. This experimentation could help to demonstrate how automatically detected personality traits can be integrated in a real-world recommender system and to provide insights into the practical implementation and benefits of adopting personality-aware user profiles.

By addressing these key challenges, the study aims to contribute to the broader understanding and practical implementation of personality-based recommender systems.

3. Approach and expected contributions

First, we developed a model to detect Big Five personality traits based on the user's aesthetic preference (e.g., the images a user likes). The proposed system exploits Resnet50, a convolutional neural network, to automatically extract image features and then fits five independent regressors on the output to predict scores for personality traits. The model was trained to complete the task starting from one to five images given as input. As the training dataset, we used PsychoFlickr[1], a corpus containing the Big Five personality profile of 300 people and 60'000 images they labeled as "favourite" on the social media Flickr [8]. We evaluated the performance of the model, comparing the results obtained with the different numbers of images. The system achieved good performances, outperforming the relater state-of-the-art works that use the same dataset. To test the model on heterogeneous images, we also created a new dataset. The latter includes self-assessed personality traits of 100 users, resulting from both the Ten Item Personality Inventory and the BFI-10 questionnaires. Furthermore, users' preferences were collected asking them to choose five images from predefined sets. Images were selected checking their content to ensure that it was not violent or questionable. The model showed to be less effective when applied to other data. Further analysis is necessary to assess why in this experimentation the performance was not as good as in the first test. The promising results suggest that some improvements are needed in future works, starting from the augmentation of the training data pool with the new proposed dataset.

[1]https://github.com/raoulg/PsychoFlickr

A paper describing more accurately the methods and results of this work is nearing completion and will be soon submitted for publication.

The model we developed could be used in several scenarios as a support to a recommender system. For example, it could be utilized to predict users' personality based on the images they favor on social media, if this type of data is available. Alternatively, visual-based personality tests could be devised and administered employing gamification strategies to users, asking them, for example, to select some images from predefined collections.

Second, we thought about the possible application of this personality recognition system and reasoned about how it could be used to improve personalization. Given the abundance of possible application areas, we chose to start the research from itinerary recommendation, since it is known to be one of those domains in which the problem of modeling subjective preferences is particularly complex. Indeed, the activity of planning travels is considered a multi-criteria decision problem, involving a wide range of needs that are considered by the user during the decision-making process [20]. Starting from the literature, we identified relevant factors that the user may take into account while planning an itinerary, including preference on contextual factors such as the availability of free time, the avoiding of crowded places, the visit duration, etc. These do not concern directly the recommended places to visit, but instead the ways in which itineraries can be constructed, such as the time-related dimensions or the user planning style. Then, a survey-based study was carried out on 101 participants to explore possible correlations between these factors and Big Five Personality traits for young adults (19-24 years old) who are generally accustomed to the use of digital services. All the participants were provided with a consent form including a description of the experiment structure and their rights. People were asked to complete a personality questionnaire and to assess the importance of the itinerary factors assigning a score from a 5-point Likert scale. Statistically significant correlations were found for some of the itinerary dimensions through correlation analysis and linear regression. We used the findings to propose some guidelines that we hope will help other designers to understand how to exploit information on personality in their recommender systems.
Further details about this research are described in our published article [21]
The results suggest that information on personality traits could not only be used to infer user preference for types of items (e.g., the attraction to visit) but could also contribute to develop context-aware recommender systems.

As furure work, we plan to assess the results achieved so far building a real-world recommender system, which automatically recognizes the user personality from aesthetic preferences and personalizes the suggested items accordingly. This work will be carried out during the third and last year of doctoral research plan. Some aspects to be defined include but are not limited to establishing a method for integrating personality data with other information in the user profile, as well as determining the technique to be employed for generating recommendations. Being already explored in our previous study, itinerary recommendation could be retained as the application domain for this part of the PhD research project. The development of the recommender system will be followed by an evaluation phase aimed at assessing whether users feel satisfied with the produced recommendations. Additionally, we will compare the performance of the proposed system with a similar recommender that does not include information on personality traits in its user model. The purpose of this comparison is to measure the effective contribution of using personality traits information in the user profile, relative to more traditional recommendation strategies.

With this project, we hope to be useful to the research community, helping to reduce some of the problems this field presents and contributing to bring advances and progresses in the realization of increasingly personalized systems.

4. Ethical implications

Despite the expected contribution of this work, some ethical implications need to be discussed. In the case of integrating personality traits, various issues may arise from the application of our approach to the real-world. Indeed, in our opinion, the use of personality information in recommender systems should be scrutinized with particular attention, since it implies user data collection, automatic preference prediction and personalization of suggested contents. The first and most obvious issue that is to be considered concerns the data collection phase. The recommendation domain is known to be a research field that deserves an accurate assessment of privacy concerns [22]. Explicit consent should always be obtained by users before acquiring the information for recommendation purposes. In the case of our work, informed consensus should include clear statements about the data usage purposes and the recommendation objectives.
Concerning the integration of personality traits into recommender systems, a further exploration may be necessary to assess whether inferred preferences really reflect the profile of heterogeneous groups of people in order to avoid great discrepancies between personalized recommendations and the actual user taste. A user study could be conducted on a sample including participants with different characteristics.
Furthermore, future works will discuss problems related to the recommender system explainability. When presenting the suggestions to users, it is important to provide the latter with some simple description of the reasons for which they receive a specific type of personalized recommendations.

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References

[1] R. Karumur, T. Nguyen, J. Konstan, Personality, user preferences and behavior in recommender systems, Information Systems Frontiers 20 (2018). doi:10.1007/s10796-017-9800-0.

[2] E. Lex, M. Schedl, Psychology-informed recommender systems tutorial, in: Proceedings of the 16th ACM Conference on Recommender Systems, RecSys '22, Association for Computing Machinery, New York, NY, USA, 2022, p. 714–717. URL: https://doi.org/10.1145/3523227.3547375. doi:10.1145/3523227.3547375.

[3] S. Dhelim, N. Aung, M. A. Bouras, H. Ning, E. Cambria, A survey on personality-aware recommendation systems, Artif. Intell. Rev. 55 (2022) 2409–2454. URL: https://doi.org/10.1007/s10462-021-10063-7. doi:10.1007/s10462-021-10063-7.

[4] R. R. McCrae, P. T. Costa, Validation of the five-factor model of personality across instruments and observers, Journal of Personality and Social Psychology 52 (1987) 81–90. URL: http://search.ebscohost.com/login.aspx?direct=true&db=pdh&AN=psp-52-1-81&site=ehost-live. doi:10.1037/0022-3514.52.1.81.

[5] B. Rammstedt, O. P. John, Measuring personality in one minute or less: A 10-item short version of the big five inventory in english and german, Journal of Research in Personality 41 (2007) 203–212. URL: https://www.sciencedirect.com/science/article/pii/S0092656606000195. doi:https://doi.org/10.1016/j.jrp.2006.02.001.

[6] S. D. Gosling, P. J. Rentfrow, W. B. Swann, A very brief measure of the big-five personality domains, Journal of Research in Personality 37 (2003) 504–528. URL: https://www.sciencedirect.com/science/article/pii/S0092656603000461. doi:https://doi.org/10.1016/S0092-6566(03)00046-1.

[7] Y. Mehta, N. Majumder, A. F. Gelbukh, E. Cambria, Recent trends in deep learning based personality detection, CoRR abs/1908.03628 (2019). URL: http://arxiv.org/abs/1908.03628. arXiv:1908.03628.

[8] M. Cristani, A. Vinciarelli, C. Segalin, A. Perina, Unveiling the multimedia unconscious: Implicit cognitive processes and multimedia content analysis, in: Proceedings of the 21st ACM International Conference on Multimedia, MM '13, Association for Computing Machinery, New York, NY, USA, 2013, p. 213–222. URL: https://doi.org/10.1145/2502081.2502280. doi:10.1145/2502081.2502280.

[9] Z. Halim, A. Zouq, On identification of big-five personality traits through choice of images in a real-world setting, Multimedia Tools Appl. 80 (2021) 33377–33408. URL: https://doi.org/10.1007/s11042-021-11419-5. doi:10.1007/s11042-021-11419-5.

[10] S. C. Guntuku, W. Lin, J. Carpenter, W. K. Ng, L. H. Ungar, D. Preoţiuc-Pietro, Studying personality through the content of posted and liked images on twitter, in: Proceedings of the 2017 ACM on Web Science Conference, WebSci '17, Association for Computing Machinery, New York, NY, USA, 2017, p. 223–227. URL: https://doi.org/10.1145/3091478.3091522. doi:10.1145/3091478.3091522.

[11] C. Segalin, A. Perina, M. Cristani, A. Vinciarelli, The pictures we like are our image: Continuous mapping of favorite pictures into self-assessed and attributed personality traits, IEEE Transactions on Affective Computing 8 (2017) 268–285. doi:10.1109/TAFFC.2016.2516994.

[12] S. C. Guntuku, J. T. Zhou, S. Roy, W. Lin, I. W. Tsang, 'who likes what and, why?' insights into modeling users' personality based on image 'likes', IEEE Transactions on Affective Computing 9 (2018) 130–143. doi:10.1109/TAFFC.2016.2581168.

[13] L. Li, H. Zhu, S. Zhao, G. Ding, W. Lin, Personality-assisted multi-task learning for generic and personalized image aesthetics assessment, IEEE Transactions on Image Processing 29 (2020) 3898–3910. doi:10.1109/TIP.2020.2968285.

[14] R. Hu, P. Pu, Enhancing collaborative filtering systems with personality information, in: Proceedings of the Fifth ACM Conference on Recommender Systems, RecSys '11, Association for Computing Machinery, New York, NY, USA, 2011, p. 197–204. URL: https://doi.org/10.1145/2043932.2043969. doi:10.1145/2043932.2043969.

[15] Z. Hafshejani, M. Kaedi, A. Fatemi, Improving sparsity and new user problems in collaborative filtering by clustering the personality factors, Electronic Commerce Research 18 (2018). doi:10.1007/s10660-018-9287-x.

[16] F. Cena, S. Likavec, A. Rapp, Real world user model: Evolution of user modeling triggered by advances in wearable and ubiquitous computing: State of the art and future directions, Information Systems Frontiers 21 (2019). doi:10.1007/s10796-017-9818-3.

[17] M. Onori, A. Micarelli, G. Sansonetti, A comparative analysis of personality-based music recommender systems, in: EMPIRE@RecSys, 2016.

[18] J. Golbeck, E. Norris, Personality, movie preferences, and recommendations, in: 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2013), 2013, pp. 1414–1415. doi:10.1145/2492517.2492572.

[19] P. Alves, P. Saraiva, J. a. Carneiro, P. Campos, H. Martins, P. Novais, G. Marreiros, Modeling tourists' personality in recommender systems: How does personality influence preferences for tourist attractions?, in: Proceedings of the 28th ACM Conference on User Modeling, Adaptation and Personalization, UMAP '20, Association for Computing Machinery, New York, NY, USA, 2020, p. 4–13. URL: https://doi.org/10.1145/3340631.3394843. doi:10.1145/3340631.3394843.

[20] A. K. Theo Arentze, P. Aksenov, Recent trends in deep learning based personality detection, Information Technology Tourism 19 (2018). URL: https://doi.org/10.1007/s40558-018-0105-z. doi:10.1007/s40558-018-0105-z.

[21] F. Cena, L. Console, S. Likavec, M. Micheli, F. Vernero, How personality traits can be used to shape itinerary factors in recommender systems for young travellers, IEEE Access 11 (2023) 61968–61985. doi:10.1109/ACCESS.2023.3285258.

[22] S. Milano, M. Taddeo, L. Floridi, Recommender systems and their ethical challenges, AI & SOCIETY 35 (2020) 957–967. URL: https://doi.org/10.1007/s00146-020-00950-y. doi:10.1007/s00146-020-00950-y.