On the Exploitation of User Personality in Recommender Systems

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Abstract. In this paper we revise the state of the art on personality-aware recommender systems, identifying main research trends and achievements up to date, and discussing open issues that may be addressed in the future.

Keywords: recommender systems, collaborative filtering, personality.

1 Introduction

Human personality, as defined in psychology, is a combination of characteristics or qualities that form an individual's style of thinking, feeling and behaving in different situations [24]. Among the existing models proposed to characterize and represent human personality, the Five Factor model [4] states that there are five main factors that allow describing an individual's personality: *openness*, *conscientiousness*, *extraversion*, *agreeableness*, and *neuroticism*.

Personality influences how people make their decisions [18]. Recent research has shown that correlations between user personality traits and preferences exist in different domains, such as music [2, 20, 21, 22], movies and TV shows [2, 3, 19, 21], books and magazines [2, 21], and websites [15]. These correlations can be used to enhance personalized information access and retrieval [10, 17]. Specifically, in recommender systems, the exploitation of user personality information has enabled address *cold-start situations* [25], facilitate the *user preference elicitation process* [8], mitigate the *sparsity problem* [11], and improve the *accuracy of collaborative filtering* [5, 23].

Despite these achievements, the exploitation of user personality in recommender systems is a challenging and still largely under explored topic.

2 Open Issues in Personality-aware Recommender Systems

Similarly to user preferences, personality factors can be inferred explicitly, e.g. by means of psychometric questionnaires [1, 4, 8], or implicitly, e.g. by analyzing digital footprints [14], linguistic features of user texts [23], and by correlating personality traits with patterns of social network use, such as posting, rating, establishing friendship relations, and participating in user groups [1, 12]. Whereas explicit questionnaires are more accurate than techniques inferring personality from user

generated contents, they require the users' effort to fill them. Note that the well known IPIP [7] proxy for Costa and McCrae's NEO-PI-R test [4] may have between 60 and 240 items. Hence, innovative techniques to efficiently **acquire user personality** in recommenders have to be developed, and may be incorporated into the user preference elicitation process [8].

Once extracted, it is needed to **model user personality**. Most of existing personality-aware recommenders deals with a vector representation composed of the numeric values of personality factors [5, 8, 11]. This, nonetheless, may not be the best choice. There are works that have considered using discrete value intervals of the personality factors [5], sets of predefined personality categories – e.g. *reflective* and *energetic* people [22], and *aesthetic*, *cerebral*, *communal*, *dark*, and *thrilling* contents [21] –, and personality-based stereotypes [2, 16]. In this context, a balance between recommendation accuracy and comprehension (explicability) could be important. Moreover, instead of broad user personality representations, using more fine-grained information provided by the IPIP tests, such as the facets of each personality factor [9] may help achieve better recommendations; Note e.g. that a particular individual with a high overall *openness* score, may have high *imagination* and *artistic interests*, but may not have a high level of *adventurousness*. Finally, the modeling task is even more challenging if we account for variables that could influence particularities of an individual's personality. In this case, special attention should be given to the users' age, gender, and educational attainment, as pointed out in [2, 3, 5].

Assuming that user personality can be inferred and modeled by a recommender system, another set of open issues is related with the particular **exploitation of user personality** for making recommendations. In general, simple approaches have been investigated so far, from content-based [23] to collaborative filtering [5, 8, 11, 17] heuristics. There is plenty of room for alternative, more sophisticated methods. In particular, we envision matrix factorization as a powerful model in which user personality information can be easily integrated with content-based and collaborative filtering user profiles. Moreover, in addition to user preferences, contextual signals may have an important role in personality-aware recommendations. In a particular context, people with distinct personalities react differently. The identification and exploitation of relations between context and personality is thus of special interest in recommender systems. In fact, the user's current mood is one of the contextual signals that has been shown as directly related with personality [18, 19]. It is known that an individual's personality influences her mood changes due to external emotional stimuli [13], and these stimuli may be generated by received recommendations. In all the above cases, we may go beyond the accuracy of personality-aware recommendations, and deal with other metrics, such as novelty and diversity [20]; Note, for example, that *open-minded* people may appreciate diverse and serendipitous recommendations, while *introverted* people may prefer recommendations much more related with their past preferences. Finally, we would like to highlight the fact that exploiting personality could also help address new recommendation scenarios, such as those of cross-domain recommender systems [2], in which information from a source domain is used to enhance or generate recommendations in a different target domain, where the user's preferences may not be available [6, 26].

Acknowledgements

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