# Personality-Based Recommendations: Evidence from Amazon.com


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## ABSTRACT

In this paper, we evaluate the accuracy of personality-based recommendations using a real-world data set from Amazon.com. We automatically infer the personality traits, needs, and values of users based on unstructured user-generated content in social media, rather than administering questionnaires or explicitly asking the users to self-report their characteristics. We find that personality characteristics significantly increase the performance of recommender systems, in general, while different personality models exhibit statistically significant differences in predictive performance.



## Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval - Information filtering

## Keywords

Recommendations; Personality traits; Big Five; Values; Needs


## 1. INTRODUCTION

Personality traits have been found to influence various aspects of individual behavior, including job performance [5], academic motivation [17], and romantic relationships [25]. Despite the initial promising evidence in various academic fields and applications, including recommender systems (RSes), personality traits are still not frequently used in predictive modeling, mainly because they usually require users to complete long questionnaires and hence they cannot be easily applied at a large scale. In this study, we automatically infer cognitive and social characteristics of users based on different personality models in psychology, including Big Five, Values, and Needs, and present a comparative analysis.

## 2. RELATED WORK

Tapping into the recent advances of data mining, various studies have successfully attempted to automatically derive personality traits from text based on the established relationship between word use and personality [11, 14, 27]. Exploring the feasibility of deriving personality traits from social media text, [19] demonstrated that computational models based on derived personality traits perform better than models using self-reported traits. In addition, [7] found that predicted personality traits had the same effects as the traits measured by traditional personality questionnaires.

In RSes, the use of personality traits is a promising but under-explored research direction. Among the most relevant works, [10, 15] explicitly measure users' personality based on quizzes aiming at alleviating the cold-start problem. Using also questionnaires, [13] finds correlations between personality and movie preferences, while [6] studies the relationship between personality and preferences in multiple entertainment domains using explicit psychometric tests. There are several characteristics though that differentiate this study from the related work. For instance, apart from the Big Five model [9, 20] that the aforementioned studies employ, we also use the personality models of needs [12, 18] and values [22]. Besides, rather than administering questionnaires or explicitly asking the users to self-report their characteristics as in previous studies in RSes, we automatically infer the personality characteristics, needs, and values of users based on unstructured user-generated content in social media.



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## 3. PERSONALITY MODELS

The *personality traits* [9, 20], *needs* [12, 18], and *values* [22] of the users in this study are automatically inferred based on a textual analysis of user-generated unstructured data. In particular, for each user we analyzed the content of all the messages that there were publicly posted over time on the social network of Twitter as well as the user-defined description of their accounts. From the messages of the users analyzed are excluded all the private messages between the users as well as non-English messages. In addition, we excluded any messages that were not written by the specific target user each time (e.g., re-tweets) as those messages do not correspond to the linguistic style of the specific user and hence might not reflect her/his personality. After the pre-processing of the corpus of user-generated content, there were on average $26,568$ words per user; this number is much higher than the typical number of words in other studies (e.g., [13]) and can lead to more accurate results. The messages and the rest of the user-generated of each target user are merged into a single "document" and the personality traits, intrinsic needs, and values of individuals are then derived using linguistic analytics. In particular, the tokens of the user-generated content -after some pre-processing of the words, which includes removal of stop-words and non-English words, stemming, and fuzzy matching- are matched with the Linguistic Inquiry and Word Count (LIWC) psycholinguistic dictionary, which has been developed over several years and currently includes almost 4,500 words and word-stems associated with one or more personality categories [21], to compute relative scores in each dictionary category. Afterwards, based on [27], a weighted combination is estimated based on the coefficient between category scores and characteristics, using coefficients that were derived by comparing personality scores obtained from surveys with LIWC category scores from text [23, 27]. Similarly, user values are derived based on the same approach [8] whereas for automatically inferring user needs a statistical model was employed based on ground-truth scores and a custom dictionary [26]; a publicly available implementation of the employed approach is available by [16].

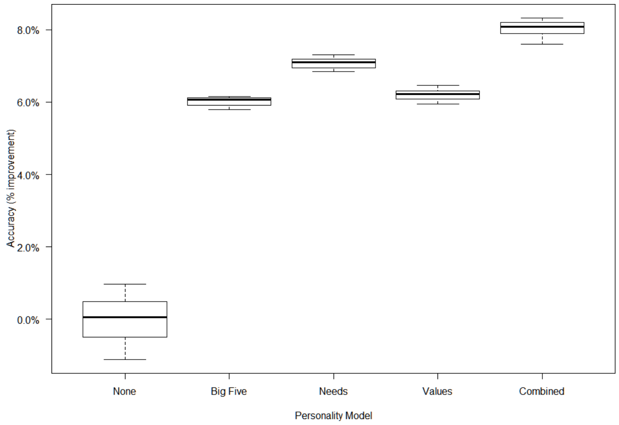


Figure 1: Predictive performance of different personality models.

# 4. EXPERIMENTAL RESULTS

To empirically evaluate the employed approach, we build a factorization model incorporating the information of *personality traits*, *needs*, and *values* as well as item attributes. In particular, the user preferences are modeled as:

$$
\begin{aligned}
y(\mathbf{x}) &= y(u; i; \alpha_1^u, \ldots, \alpha_m^u; \alpha_1^i, \ldots, \alpha_n^i) \\
&= w_0 + w_u + w_i + \sum_{j=1}^{m} w_j \alpha_j^u + \sum_{l=1}^{n} w_l \alpha_l^i + \langle \mathbf{v}_u, \mathbf{v}_i \rangle \\
&\quad + \sum_{j=1}^{m} \alpha_j^u \langle \mathbf{v}_j^u, \mathbf{v}_i \rangle + \sum_{l=1}^{n} \alpha_l^i \langle \mathbf{v}_u, \mathbf{v}_l^i \rangle + \sum_{j=1}^{m} \sum_{l=1}^{n} \alpha_j^u \alpha_l^i \langle \mathbf{v}_j^u, \mathbf{v}_l^i \rangle,
\end{aligned}
$$

where the input vector $\mathbf{x} \in \mathbb{R}^{|U|+|I|+m+n}$ contains binary indicators for the user and item, the user attributes $\boldsymbol{\alpha}^u = (\alpha_1^u, \ldots, \alpha_m^u)$ capturing the personality characteristics of the users, and item attributes $\boldsymbol{\alpha}^i = (\alpha_1^i, \ldots, \alpha_m^i)$ capturing the item categories, prices, etc.; the factorization of users $\mathbf{v}_u$, items $\mathbf{v}_i$, and attributes $\mathbf{v}_j^u, \mathbf{v}_l^i$ is of dimensionality $k$.

Our data set was collected as in [1, 24] and contains 906,277 purchases of 138,536 distinct products on Amazon.com from 81,475 users who shared their purchases on Twitter as well as the account information and the user-generated content on the social network of Twitter for the same users. As our data set includes only implicit ratings, for each user we randomly select an equal number of non-rated items (based on the frequency of ratings of each item) as negative examples in order to increase the accuracy of our predictions. We use MCMC inference with Gibbs sampling to learn our factorization model. Moreover, we employ a holdout evaluation scheme with 80/20 random splits into training and test sets without filtering any ratings and we evaluate each model in term of classification performance based on accuracy.

Figure 1 shows the experimental results. We see that personality characteristics increase the performance of RSes and that different personality models can result in different predictive accuracy. Interestingly, the under-explored personality models of needs [12, 18] and values [22] resulted in better predictive performance compared to the more popular model of Big Five traits [9, 20]. We also see that combining the attributes of the different personality models results in even better performance and, hence, has the potential to further increase the business value of recommendations [2, 3].

# 5. CONCLUSIONS

In this study, we automatically infer the personality traits, needs, and values of users based on unstructured user-generated content in social media and build different RS models. Using data from Amazon.com, we find that personality characteristics can increase the performance of RSes and we identify a specific model of personality that significantly outperforms the remaining models achieving promising performance.

The main advantage of the employed approach is that automated methods for personality assessment are more efficient and objective [11]. In particular, the traditional way of measuring personality, which requires people to complete long questionnaires, does not allow to obtain personality traits at a large scale for the population of interest [7]. Besides, user-generated content is more reflective of users' actual personalities, not "idealized" versions of themselves [4].

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