Design and User Issues in Personality-based Recommender Systems

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ABSTRACT
Recommender systems have emerged as an intelligent information filtering tool to help users effectively identify information items of interest from an overwhelming set of choices and provide personalized services. Studies show that personality influences human decision making process and interests. However, little research has ventured in incorporating it into recommender systems. The utilization of personality characteristics into recommender systems and the exploration of user perception to such systems are the focuses of my thesis. The overall goal is to develop an efficient personality-based recommender system and to arrive at a series of design guidelines from the perspective of human computer interaction. In this paper, I present my up-to-date results on a proposed personality-based music recommender prototype, user perception investigations, and my ongoing research about addressing new user problem by utilizing personality characteristics. Finally, I shall present future works.

Categories and Subject Descriptors
H.5.2 [**Information interfaces and presentation**]: User Interfaces – *evaluation/methodology, interaction style*; H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *information filtering*

General Terms
Algorithms, Performance, Design

Keywords
Personality, Recommender System, User Experience

1. INTRODUCTION
The ubiquity of the web brings an explosive increase of accessible information in our life. To deal with this problem, recommender systems have emerged as an intelligent information filtering tool to help users effectively identify information of interest from such an overwhelming amount of choices and provide personalized services [20]. Variations of recommendation algorithms have been widely studied and incorporated in a wide range of online commercial websites [1]. The resources most used to build user interest profiles include ratings (e.g., collaborative filtering and content-based filtering [1]), item attributes (e.g., critiquing-based methods [18] and content-based filtering) and tags [11]. Despite the success of current recommenders, they rarely take human factors, such as personality, into account when generating recommendations.

Research has shown that personality is an enduring and primary factor which determines human behaviors and that there is a significant connection between personality and people's tastes and interests. Studies have found the relations between personality and tastes in perceiving or interpreting art works, such as fine arts, music, and literature [12]. Kemp reveals a coherent general personality portrait of musicians and preliminarily explores the links between personality and music preferences [13]. Rentfrow and Gosling find that personality, self-views, and cognitive abilities could all have roles to play in formation and maintenance of music preferences. [19]. In addition, marketing researchers have tried to relate purchasing behavior, media choice, innovation, and other marketing phenomena to personality, with varying degrees of success [4]. Recently, several websites have begun using personality quizzes to build users' interest profiles and recommend movies or music accordingly, such as Whattorent (whattorent.com) and Yobo (yobo.com). Our informal survey showed that this elicitation method receives a rather positive acceptance level among users whom we surveyed. Some users even reported that they prefer this method of revealing their tastes, especially when the product domain involves entertainment products such as movies, music, and so on.

This research was motivated to combine human personality into recommender systems so as to improve current recommendation mechanisms. Since it is a new research topic, there are still plenty of open issues. The main focus of my thesis is to investigate how to make personality-based recommender systems more efficient (design) and widely accepted (user issues), especially from the perspective of human computer interaction. The first expected outcome is a personality-based recommender system which makes advantage of personality characteristics to make recommendations. The main problem is how to build the model linking personality types to items characteristics, which haven't been dealt with in current recommender systems. For example, for an extravert, what kind of items should a system suggest for him? The second outcome would be a collection of design principles from the perspective of human computer interaction. A series of user studies will be conducted in this part to explore the factors which influence user perceptions to personality-based recommender systems, so as to arrive at design guidelines.

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2. RELATED WORKS

According to Burger [3], personality is defined as a "consistent behavior pattern and intrapersonal processes originating within the individual". It is relatively stable and predictable. Studies also show that personalities influence human decision making process and their interests [12, 13, 14, 19]. Drawing on the inherent inter-related patterns between users' personalities and their interests/behaviors, personality-based recommender systems are designed with the potential ability to better predict users' needs and improving the services of information/service provider systems. As this is still an emerging trend, not much research and user validation work has yet been done on this topic.

Lin and Mcleod [14] proposed a temperament-based filtering model incorporating human factors, especially human temperaments (Keirsey's theory), into the processing of an information recommendation service. Their model categorizes the information space into 32 temperament segments. Combining with the content-based filtering technique, their method aims at recommending the information units which best matched both users' temperaments and interests. Even though the system utilizes personalities to model user profiles, they don't really take psychological relations between human personalities and information items into account. In addition, user issues have not been explored in their study, for example, user perception, satisfaction and trust with respect to the proposed system.

Whattorent provides the service of movie recommendation in terms of users' personality and mood. The developers of this site said it was built based on the "LaBarrie Theory", which states that "movie viewers emotionally interact with a film in the same manner that they interact with other human beings". According to this theory, the developers designed a personality quiz which includes 20 scene-oriented questions which put users in situations that they have been in before or can easily imagine experiencing. The designers hope that by asking about seemingly unimportant life experiences they will get honest responses from users. Yobo is a Chinese music recommender website, providing several psychological questions to find out users' "music DNA" or users' musical preferences and make music recommendations. Even though these personality-based systems have been used in industry, any research reports regarding the methods used behind have not been open yet.

3. RESEARCH WORK UP-TO-DATE

3.1 Personality-based Music Recommender Prototype

According to the work of Rentfrow [19], we proposed a framework for personality-based music recommender systems [8]. Generally, the recommendation problem can be formalized as follows [1]. Let U be the set of all users and let P be the set of items or categories to be recommended. PF is defined as a prediction function that measures the possibility of one item p is liked by user u, i.e., $PF: U \times P \rightarrow R$, where R is a totally ordered set (e.g., nonnegative integers or real numbers within a certain range). Then for each user $u \in U$, we want to choose such item $p_u^{'} \in P$ that maximizes the inferred preference value. More formally,

$$\forall u \in U, \quad p_u^{'} = \operatorname{argmax}_{p \in P} PF(u,p). \tag{1}$$

In the following, we propose a general algorithm framework for inferring liked musical preference in terms of user personalities. The possibility of one musical dimension p is liked by user u is predicted by considering two factors: the personality of user u and the relations between the personality and four musical preference dimensions. More specifically, we present personality characteristics described in the Big-Five model [6] as a vector $\mathbf{ps_u} = (ps_u^o, ps_u^c, ps_u^e, ps_u^a, ps_u^n)^T$ for user u. Here, ps_u^o, ps_u^c, ps_u^e, ps_u^a and ps_u^n represent the values in the dimension of openness to new experience, conscientiousness, extraversion, agreeableness and neuroticism respectively. Their values are normalized to the range [-1, 1]. The user preference model is described as $\mathbf{mp_u} = (mp_u^{rc}, mp_u^{ir}, mp_u^{uc}, mp_u^{er})^T$, where, mp_u^{rc}, mp_u^{ir}, mp_u^{uc} and mp_u^{er} represent the extent to which the user u like reflective and complex, intense and rebellious, upbeat and conventional, and energetic and rhythmic music respectively. Therefore, user preference model $\mathbf{mp_u}$can be calculated as

$$\mathbf{mp_u} = W \cdot \mathbf{ps_u} \tag{2}$$

, and

$$W = \begin{bmatrix} w_{11} & \cdots & w_{15} \\ \vdots & \ddots & \vdots \\ w_{41} & \cdots & w_{45} \end{bmatrix}.$$

W is a 4-by-5 weighting matrix. The value of w_{ij} means the strength of the relation between personality trait j and musical preference dimension i, and w_{ij} is also normalized in the range of [-1,1]. The positive value represents a positive relationship between a personality trait and a musical preference dimension. That is, a user have a higher value in the personality trait j, will like the music preference dimension i with a higher possibility, vice versa. On the other hand, the negative w_{ij} indicates a negative relationship between personality trait j and musical preference dimension i. The magnitude of w_{ij} represents the strength of such relations. The larger is this value, the stronger dominates the personality trait j on the musical preference dimension i. In our current prototype system, we assign w_{ij} with the correlation value between music preference dimension i and personality trait j reported in [19].

Then, all values in the vector $\mathbf{mp_u}$ are ordered. The musical preference dimension mp_u^k, $k \epsilon \{rc, ir, uc, er\}$, with the maximal value is the one which user u might most like. The genres in that dimension can be chosen and recommended to the user. As an alternative to increase recommendation diversity, the musical preference dimensions whose corresponding values in $\mathbf{mp_u}$ are more than a defined threshold r are picked out and the number of songs in these dimensions are in proportion to the predicted preference values. In our study, we adopted the second strategy.

3.2 User Perception Evaluation

3.2.1 General Investigation

In order to understand whether the personality quiz-based preference elicitation process can achieve high subjective opinions from the users, as well as whether it can be an alternate way to help users to build their preference models, we conducted a user study that compared one personality quiz-based system (Whattorent.com) with one baseline rating-based system (MovieLens) [9, 10].

Three criteria were used in this comparative study: perceived

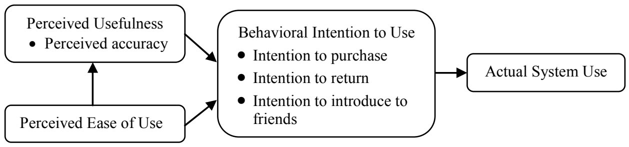

Figure 1. Technology Acceptance Model (TAM)

accuracy, user effort and user loyalty. Results show that the perceived accuracy in two systems is not significantly different. However, users expended significantly less effort, both perceived cognitive effort and actual task time, to complete the preference profile establishing process in the personality quiz-based system than in the rating-based system. Additionally, users expressed stronger intention to reuse the personality quiz-based system and introduce it to their friends. After using these two systems, 53% of users preferred the personality quiz-based system vs. 13% of users preferred the rating-based system, since most users thought the former is easier to use.

Furthermore, we utilize a well-studied intention model, the technology acceptance model (TAM) [5], to explore potential user acceptance issues of personality-based recommender systems, especially those based on personality quizzes [9]. In TAM, two particular beliefs, perceived usefulness and perceived ease of use, were postulated to determine an individual's intention to use a system. Perceived usefulness was also seen as being directly influenced by perceived ease of use (see Figure 1). The results validate the fact that perceived usefulness and perceived ease of use are two significant factors affecting users' acceptance to the personality-based recommender systems.

3.2.2 Influence of Prior Domain Knowledge

We further investigated the influence of domain knowledge to user perception to personality-based recommender systems [8] in the experimental platform described in section 3.1. The results show that prior domain knowledge does influence users' perception of the system. Domain novice and medium users had significantly more positive perceptions than expert users, and further higher intention to use and return to the system. On the other hand, domain expert users scored moderately higher on perceived helpfulness when using the system to find songs for friends than for themselves. It is indicated that the way of using personality quizzes to build user profiles cannot satisfy the advanced needs of domain expert users. There is a need to design adaptive personality-based recommender systems. For example, for expert users, we could integrate other modeling methods to increase user control, e.g., leveraging rating-based methods to update user preference models. For novice users, systems with simple operating interfaces and low requirements on domain knowledge could be more helpful.

3.2.3 User Perception to Different Usage

We further investigated the feasibility of using personality quizzes to build user profiles not only for an active user but also his or her friends [8]. From the results of objective measure, we could see that in both cases, about ¾ of the recommended songs are rated as acceptable and half of them are rated as to be liked. There is no significant difference between two compared scenarios. Regarding the subjective evaluation, participants, in general, expressed that users enjoyed using personality quizzes to get recommendations and satisfied with the overall functions in both cases. The finding that the personality quiz-based recommender systems were strongly perceived to be easy to use was revalidated in the present study. It is surprising to see that, while active users perceive the recommended items to be more accurate for their friends, they enjoy more using the system to find songs for themselves.

3.3 New User Problem Alleviation

The basic idea behind Collaborative filtering (CF) method is that it gathers the opinions of other users who share similar interests with a target user (referred to as the "*active user*") and assist this active user to identify items of interest based on these *neighbors*' opinions. Despite the overall success of CF systems, they suffer one serious limitation, namely the *new user* problem [1]. Before a recommender system can present a user with reliable recommendations, it should know about this user's preferences, most likely from a sufficient number of behavior records, e.g., ratings or log-archives [7]. Therefore, a new user, having few records in a system, cannot get accurate recommendations. To address the new user problem, most studies present hybrid recommender systems that combine both content information and ratings data [15, 21] to circumvent the problem, where content-based similarity is used for new users or new items. In most currently used systems, only demographic information is used as users' attributes to calculate content-based similarity [16].

We are working on how to address the new problem by utilizing personality information in user-based CF systems. We treat users' personality characteristics as a vector as rating records. For each user u, his/her personality descriptor $p_u = (p_u^1, p_u^2, \ldots, p_u^n)^T$ is a n-dimension vector. Consequently, the similarity between two user u and v can be computed as the Pearson correlation coefficient of their personality descriptors.

$$simp(u, v) = \frac{\sum_k (p_u^k - \overline{p_u})(p_v^k - \overline{r_v})}{\sqrt{\sum_k (p_u^k - \overline{p_u})^2 \sum_k (p_v^k - \overline{p_v})^2}}, \quad (3)$$

where, $\overline{p_u}$ is the average value of p_u. Our first trial compared the proposed personality-based user similarity measure with the traditional rating-based similarity measure and their hybrid in different cold start settings. The results positively support the advantage of the personality-based similarity measure in improving recommendation quality, at least in the case of sparse dataset, for new users (see Figure 2).

Figure 2. Comparison results on MAE in different start-up settings. X-axis represents of percentage of training set sizes.

4. FUTURE PLANS

As future plans, I am going to validate the personality-based recommender framework proposed in section 3.1 by comparing it with other current recommendation algorithms, such as collaborating filtering and content-based methods. Various measurements will be employed. Except recommendation quality (e.g., accuracy, diverity), I will consider more about user perceptions to different recommender systems.

In addition, I am going to explore ways to implement a system recommending cross-domain items employing personality characteristics as linkage. Cross domain recommendation is a novel topic in recommender systems. For current technologies, if one user wants to get recommendations of two products, such as movies and CDs, from a recommender, the system needs to have users' records on both products respectively. These records are used separately, and cannot be transformed into each other. That is, ratings on movies cannot be used to recommend CDs, nor vice versa. Considering personality can be linked to various kinds of products, it is reasonable to believe that human personality could be used as a media connecting different item domains. Figure 3 shows an example. In this case, two different domains with a bunch of items are connected by personality type A. We can realize that there are two ways in which users could get recommendations from different domains. One way is that the system knows a user belongs to personality type A. Then, it can recommend him $P3$ and Pn from domain 1, or $Q1$ and $Q2$ from domain 2 based on the learned relationship between personality and domain items. The other way is that the system first infer the user's personality type (e.g., type A) according to his preferences in domain 1, and then make recommendations $Q1$ and $Q2$ from the other domain, vice versa. Therefore, single recommender systems would be connected into a recommender network, sharing information among individuals. Additionally, user perception to such cross-domain systems need to be evaluated afterwards.

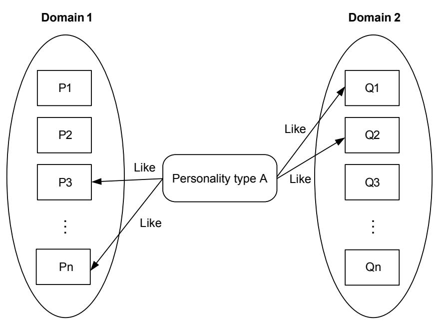

Figure 3. Cross domain recommendation via personality.

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6. REFERENCES

[1] Adomavicius, G. and Tuzhilin, A. 2005. Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. *IEEE Trans. Knowledge and Data Eng.*, 17, 6(2005), 734-749.

[2] Ahn, H. J. 2008. A new similarity measure for collaborative filtering to alleviate the new user cold-starting problem. *Information Sciences* 178:37-51.

[3] Burger, J. M. 2008. Personality (7th ed.). Belmont, CA: Thomson/Wadsworth.

[4] Carl, J. Psychological Types. New York, Harcourt Brace, 1923.

[5] Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. 1989. User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35(8), 982-1003

[6] Gosling, S. D., Rentfrow, P. J., and Swann, Jr. W.B.2003. A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, 37, pp. 504--528.

[7] Hofmann, T.2004. Latent semantic models for collaborative filtering. *ACM Trans. Info. Syst.*, vol 22(1):89-115.

[8] Hu, R. and Pu, P. 2010. A Study on User Perception of Personality-Based Recommender Systems. In: *P. De Bra, A. Kobsa, and D. Chin (Eds.): UMAP 2010*, LNCS 6075, pp. 291–302.

[9] Hu, R. and Pu, P. 2009. Potential Acceptance Issues of Personality-based Recommender Systems. *In Proceedings of RecSys'09*, New York City, NY, USA, October 22-25.

[10] Hu, R. and Pu, P. 2009. A comparative user study on rating vs. personality quiz based preference elicitation methods. *In Proceedings of IUI'09*, pages 367-372, Sanibel Island, Florida, USA, February 08 - 11.

[11] Jaschke, R., Marinho, L. B., Hotho, A., Schmidt-Thieme, L., and Stumme, G. 2007. Tag recommendations in folksonomies. In PKDD, pages 506–514.

[12] Jung, C.G., translated by Hull, R. F. C. 1997. The Sprit in Man, Art, and Literature. Princeton University Press.

[13] Kemp, A. E. 1996. The Music Temperament: Psychology and Personality of Musicians. Oxford University Press, New York

[14] Lin, C. and McLeod, D.2002. Exploiting and Learning Human Temperaments for Customized Information Recommendations. *IMSA*, 218-233.

[15] Park, S.-T., Pennock, D. M., Madani, O., Good, N., and DeCoste, D.2006. Naive filterbots for robust cold-start recommendations, in: *Proceedings of KDD'06*, ACM, Philadelphia, PA, USA

[16] Pazzani, M.1999. A Framework for Collaborative, Content-Based, and Demographic Filtering. *Artificial Intelligence Rev.*, pp. 393-408, Dec.

[17] Picard, R.W., 1997. Affective Computing. MIT Press, Cambridge, MA.

[18] Pu, P. and Chen L. 2008. User-Involved Preference Elicitation for Product Search and Recommender Systems. *AI Magazine* 29(4), pp. 93-103, Winter 2008.

[19] Rentfrow, P. J. and Gosling, S. D.2003. The do re mi's of everyday life: The Structure and Personality Correlates of Music Preferences. *Journal of Personality and Social Psychology*, 84, 1236—1256.

[20] Resnick, P. and Varian, H. R.1997. Recommender Systems. *Commun. ACM 40*, 56-58.

[21] Schein, A. I., Popescul, A., Ungar, L. H., and Pennock, D. M. 2002. Methods and metrics for cold-start recommendations, in: Proceedings of SIGIR'02, ACM, Tampere, Finland, pp. 253–260.