How Personality Influences Users' Needs for Recommendation Diversity?

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Abstract
The existing approaches for enhancing diversity in online recommendations neglect the user's spontaneous needs that might be potentially influenced by her/his personality. In this paper, we report our ongoing research on exploring the actual impact of personality values on users' needs for recommendation diversity. The results from a preliminary user survey are reported, that show the significantly causal relationship from personality factors (such as conscientiousness) to the users' diversity preference (not only over the item's individual attributes but also on all attributes when they are combined). We further present our plan for the follow-up work and discuss its practical implications.

Author Keywords
Recommender Systems; Diversity; Personality Factors; User Survey.

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Diversity Studies in Recommenders

It has been recognized that being accurate alone is not enough to judge the effectiveness of a recommender system [8]. Some researchers have endeavored to achieve the optimal balance between the two objectives, similarity and diversity, from the algorithm's perspective. For example, Smyth and McClave proposed the bounded greedy selection algorithm and proved that it can improve the diversity of recommendations, without significantly compromising their similarity [10]. Hurley and Zhang regarded the tradeoff between similarity and diversity as a binary optimization problem and defined a controller to explicitly tune the two metrics [5]. Ziegler *et al.* developed the topic diversification, which is a heuristic algorithm based on taxonomy similarity to increase recommendation diversity [12]. However, it was rarely studied whether users would be affected by their own personality in terms of the need for recommendation diversity.

Introduction

In recent years, recommender systems have been found in many modern web applications with the primary aim of eliminating users' information overload and providing recommended items that are personalized to users' interests. Recently, more attentions have been paid to generate diverse recommendations in a single display, so as to effectively learn users' interests via their feedback and allow them to discover unexpected items that they might be interested in [8]. Unfortunately, though diversity has emerged as an important metric, the challenging issue regarding its ideal balance with similarity is still not well solved. Existing approaches usually adopted a fixed strategy to adjust the diversity degree within the set of *N* (*N* > *1*) recommendations [5, 10, 12] (see more details in the left bar), which however is not adaptive to individual users' spontaneous needs. As another branch of research, as being motivated by prior studies done in the area of psychology that showed personality can likely affect users' attitudes, tastes and behavior, a few researchers have started to build the so called personality-based recommender system [4, 9, 11] (see more details in the next page's left bar). However, most of existing personality-based works just emphasize studying the effect of personality on users' preference over a single item/ attribute (e.g., music type), but few have in-depth investigated whether and how it impacts users' impression when they face multiple recommendations at once.

Therefore, given these limitations, we are motivated to study whether people, with different personality values, would have different needs for recommendations' diversity degree. The outcome of our work can hence be suggestive of developing more personalized diversity in recommender systems. In this paper, we report the preliminary results from a user survey that we lately conducted. By studying 181 subjects' responses, we found that some personality factors have significant impact not only on users' diversity need in respect of individual attributes (such as the movie's director, country, or actor/actress), but also on the overall diversity within multiple recommendations when all of the item's attributes are addressed together. Inspired by these findings, we present the plan for a follow-up work that aims to develop a recommender system of explicitly embedding the personality, as a moderating factor, to adjust the diversity degree within the set of recommendations. We are also interested in performing evaluation on the system, with the purpose of demonstrating an effective solution to take personality into account for producing diverse recommendations.

Experimental Approach: User Survey

To reduce the gap between the aforementioned two separate branches of research: diversity studies and personality studies, we have been driven to empirically identify the causal relationship from users' personality factors to their spontaneous needs for recommendation diversity. The concrete research question that we are interested in answering is: *would users' personality have big impact on their preference over the diversity within a set of recommendations?* In order to solve this question, we have conducted a user survey by means of collecting users' item selections (i.e., the movies in our experiment) and their personality information.

Totally 181 participants (94 females) volunteered to take part in the survey. All of them are Chinese. As the incentive, there was a lottery draw with 20 awards (at

Personality Studies in Recommenders

The relationship between personality factors and users' preference on music genre was studied in [9], which shows that extravert people are likely to prefer energetic and rhythmic music, while individuals who are relatively conventional tend to listen to upbeat and conventional music. Moreover, it was stated that personality can be leveraged into solving the cold-start problem of user-based recommender systems. As the typical method, Tkalcic and Kunaver integrated personality into enhancing the nearest neighborhood measure in collaborative filtering systems [11]. Hu and Pu further found that recommender systems that consider users' personality are more effective in terms of increasing users' loyalty towards the system and decreasing their cognitive effort, relative to the non-personality based systems [4].

total cost of 2000RMB). Table 1 shows these participants' demographic properties. For each user, we obtained a set of her/his movie choices. Such information was retrieved via two channels: we first asked each subject to name ten movies that s/he recently watched and liked; we then asked her/ him to choose ten new movies that s/he is prepared to watch. For the latter, we provided a movie database system, Douban Movie (http://movie.douban.com/) being popular in China, for users to check movies' information and select interesting ones. Concretely, an online procedure was implemented to collect users' personal information, personality values, and movie choices. In addition, all questions were accompanied with Chinese translations, in order to avoid any misunderstandings.

Gender	Female (94); Male (87)
Age	<20 (21); 20-30 (149); 30-40 (10); >40 (1)
Education level	Bachelor (75); Master (75); PhD (30); Others (1)
Job domain	Student (119); Enterprise (39); Institution (9); Others (14)

Table 1. Demographic profiles of participants (the number of users is shown in the bracket).

Measure of Personality

The user's personality values were assessed based on the popular big-five factor model [7] that defines personality as five factors: *Openness to Experience* (O), *Conscientiousness* (C), *Extroversion* (E), *Agreeableness* (A), and *Neuroticism* (N). Each factor is concretely measured via 5 sub-factor questions [3] (i.e., the factor's score is the average of scores on these five questions; see Table 2). Specifically, according to [7], ***Openness to Experience*** (O) factor can distinguish people from imaginative, creative (with high score) to down-to-earth, conventional (with low score). ***Conscientiousness*** (C) factor inherently leads a person to become prudent (with high score) or impulsive (with low score). As for ***Extroversion*** (E), it is to judge whether a person is extrovert (with high score) or introvert (with low score). ***Agreeableness*** (A) mainly determines the person's cooperation and social harmony. People with high agreeableness score tend to be friendly and cooperative while people with low score will be suspicious and aggressive. The last factor according to the big-five factor model is ***Neuroticism*** (N): people with high neuroticism score will be more sensitive and nervous than ones with low score.

Measure of Diversity

The diversity was measured in terms of both individual attributes and the whole set of attributes. That is, among the set of movies that a user selected, we first evaluated their diversity degree in respect of each attribute. Using the diversity calculation for "genre" as an example, we assign n to be the number of all movies selected by the user, m to be the number of distinct genres that appear in the user's selections, and $p(j)$ to be the proportion of a genre j (e.g., action movie) in the user's movie selections. The diversity formula based on Gini-index [2] is hence:

$$Div(genre) = (1/(\frac{1}{m}\sum_{j=1}^{m}(2*j-m-1)*p(j)+\alpha))*\frac{m}{n} \quad (1)$$

where $p(1), p(2), \ldots, p(m)$ are in the ascending order and α is an adjustment coefficient in order to avoid the result of Gini-coefficient being zero (it is set as 0.1 in the experiment). Similar formulas are applied to calculate the diversity regarding other attributes, such as director, country, and release time (e.g., 1990s,

Factor 1: *Openness* (O)
Sub-factors: Imagination (Q3); Artistic Interests (Q8); Liberalism (Q13); Adventurousness (Q18); Intellect (Q23).
Factor 2: *Conscientiousness*(C)
Sub-factors: Orderliness (Q5); Cautiousness (Q10); Self-discipline (Q15); Self-efficacy (Q20); Dutifulness (Q25).
Factor 3: *Extroversion* (E)
Sub-factors: Gregariousness (Q2); Cheerfulness (Q7); Assertiveness (Q12); Friendliness (Q17); Excitement-Seeking (Q22).
Factor 4: *Agreeableness* (A)
Sub-factors: Modesty (Q4); Altruism (Q9); Morality (Q14); Cooperation (Q19); Trust (Q24).
Factor 5: *Neuroticism* (N)
Sub-factors: Anxiety (Q1); Vulnerability (Q6); Depression (Q11); Anger (Q16); Self-Consciousness (Q21).

Table 2. Personality quiz questions for assessing five factors (the question number is referred to the quiz defined in [3]). Each question is responded on a 5-point Likert scale. For example, for Imagination (Q3), it is rated from 1 "No-Nonsense" to 5 "A Dreamer".

2000s).

As for actor (and actress), Gini-coefficient is not so suitable because the value of *m* (i.e., the number of distinct attribute values) would be too large (since each movie normally has more than 5 actors/actresses). Therefore, its diversity calculation is based on the Jaccard coefficient [1]:

$$Div(actor) = \frac{2}{n(n-1)} \sum_{i=2}^{n} \sum_{j=1}^{i-1} (1 - Sim(i,j)) \quad (2)$$

where *Sim(i,j)* gives the similarity between two movies in terms of the concerned attribute ($Sim(i,j) = \frac{|A \cap B|}{|A \cup B|}$, e.g., A is the set of actors contained in movie *i*, and B is the set of actors in movie *j*), and *n* is the number of movies selected by the user.

We then measured the overall diversity among the user's choice set, when all attributes are combined together. Considering that users usually place different weights on attributes (for example, "genre" may be more important than other attributes for some users), we generated several typical sets of weights in reference to [6] (e.g., one set is {0.4, 0.1, 0.1, 0.2, 0.2} assigned to the five major attributes {genre, director, country, release time, actor/actress}; the sum of these attributes' weights is equal to 1). The overall diversity is thus calculated as follows:

$$OverDiv = \sum_{i=1}^{k} W_i * Div(attr_i) \quad (3)$$

where W_i is the weight on *i-th* attribute ($0<W_i<1$, $\sum_i W_i=1$), *k* is the total number of attributes (which is 5 in our experiment), and $Div(attr_i)$ is the *i-th* attribute's diversity value (via Formula (1) or (2)).

Results: Impact of Personality on Recommendations' Diversity w.r.t. Individual Attributes

We first calculated each attribute's diversity score within the set of movies that a user selected. We then computed the Spearman's rank correlation coefficient in order to reveal the diversity score's correlation with the user's five personality values respectively. The results are shown in Table 3. It can be seen that there are significant correlations between some values. For instance, the "director" is significantly positively correlated with the personality factor *neuroticism*, which suggests that more reactive, excited and nervous person is more inclined to choose diverse directors. In addition, it is significantly related to *extraversion* in the negative way. As for the demographic values, the "director" is significantly correlated to *education* and *gender*. The former is in the negative relationship, indicating that people with lower education level are more subject to choose movies with diverse directors, while for the gender, female users more prefer diverse directors than male users.

The analysis respecting other attributes (i.e., the movie's country, release time, actors/actress) also returns some significant results. Particularly, the "country" is negatively significantly correlated to the personality factors *agreeableness* (indicating that its diversity is preferred by suspicious/antagonistic users) and *conscientiousness* (i.e., preferred by unorganized/impatient users). The higher "country" diversity is also related to lower *education* level and *female* gender. As for "release time", it is positively correlated to *conscientiousness* (suggesting that its diversity is preferred by efficient/organized users), and for "actor/actress", it is positively correlated to *openness* (i.e., its diversity is preferred by imaginative

Annotation to Table 4

It suggests that, in general, users who are more flexible, spontaneous, disorganized, and lack of patience will be subject to choose diverse movies. According to the psychological study reported in [7], the corresponding *conscientiousness* personality factor is actually concerned with the way in which persons control, regulate and direct their impulses. Usually, people with high conscientiousness value tend to be prudent, while those with low value tend to be impulsive. This may explain why users with lower conscientiousness score are shown being more willing to choose diverse movies in our survey, whereas self-disciplined people spontaneously do not like much diversity.

Moreover, the significant correlation between overall diversity and age/education implies that people who are younger and/or with lower education level will more likely prefer diverse movies.

	Div(genre)	**Div(director)**	**Div(country)**	**Div(release_time)**	**Div(actor/actress)**
Neuroticism (N)	-0.04	**0.17***	0.06	-0.08	0.09
Extraversion (E)	0.02	**-0.15***	-0.15	-0.14	-0.07
Openness (O)	0.10	0.07	0.07	-0.07	**0.20***
Agreeableness (A)	-0.04	-0.17	**-0.18***	-0.04	-0.10
Conscientiousness (C)	-0.12	-0.16	**-0.15***	**0.15***	-0.10
Age	**-0.18***	0.13	-0.14	-0.05	-0.01
Gender	-0.13	**0.24****	**0.23****	-0.12	0.10
Education	-0.10	**-0.20****	**-0.20****	0.06	-0.04

Table 3. Correlation coefficient between diversity (w.r.t. single attribute) and personality/demographic values (*p<0.05 and **p<0.01).

/creative users). Thus, it shows that the five personality factors are all somewhat significantly influential to users' diversity needs as for individual attributes of the movie. Moreover, users' demographic properties, including age, gender, and education level, also initiate certain effects.

Results: Impact of Personality on Recommendations' Overall Diversity

Then, we computed the correlation between the overall diversity (see Formula (3)) and the user's personality values via Spearman's rank correlation coefficient. The results are presented in Table 4. It indicates that no matter how the attributes' weights are varied, the overall diversity is consistently significantly correlated with one personality factor *conscientiousness*, and two demographical factors *age* and *education level*, in the negative way (see discussions in the left bar).

Future Work

For the next step, we plan to perform user evaluation on a proof-concept system that can incorporate

	OverDiv1	**OverDiv2**	**OverDiv3**	**OverDiv4**
N	0.071	-0.017	0.016	0.113
E	-0.112	-0.035	-0.070	-0.135
O	0.057	0.065	0.069	0.086
A	-0.137	-0.088	-0.112	**-0.177***
C	**-0.162***	**-0.148***	**-0.161***	**-0.192***
Age	**-0.237****	**-0.212****	**-0.214****	**-0.182***
Gender	-0.007	-0.066	-0.015	0.091
Education	**-0.152***	**-0.148***	**-0.159***	**-0.165***

Note:
OverDiv1: weight assignment {0.2, 0.2, 0.2, 0.2, 0.2} on the five attributes {genre, director, country, release time, actor/actress};
OverDiv2: weight assignment {0.4, 0.1, 0.1, 0.2, 0.2};
OverDiv3: weight assignment {0.3, 0.1, 0.2, 0.2, 0.2};
OverDiv4: weight assignment {0.1, 0.1, 0.2, 0.3, 0.3}.

Table 4. Correlation coefficient between the overall diversity and personality/demographic values (*p<0.05 and **p<0.01) (note that we tested six more various sets of weight assignment, which returned similar phenomena. To save space, those results are not listed in this table).

personality, as a moderating factor, into adjusting the diversity degree within the set of multiple recommendations, so as to be personalized to individual users' spontaneous needs. We are currently developing such a system by using the content-based recommending technique, for which the diversity adjusting strategy is based on the above reported user survey's results.

Specifically, the next question we are engaged in solving is: *how to accordingly adjust the recommendations' diversity degree by meeting with individual users' needs?* We plan to compare our developed system to a variant that adopts personality in the negative way (i.e., recommending less diverse items though the user spontaneously requires higher level of diversity according to her/his personality values). Through this comparison, we may identify whether users would perceive our system more accurate and satisfying. The practical implication is to validate how to adapt recommendations' diversity degree to individual users' personality values. Furthermore, since the current survey mainly involved Chinese, in the future, we will verify the findings in the global context by recruiting subjects from other countries. We will also examine the results' validity in other product domains, except for movies.

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