Identifying Dominators and Followers In Group Decision Making Based on The Personality Traits

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ABSTRACT
Human factors, such as emotions, personality traits and trust network, have been proved to play an important role in the decision making process. The impact by personality in individual and group decision making is still under investigation, especially in the area of educational learning. In this paper, we propose two approaches to distinguish the "*dominator*" and "follower" in group decision making by using an educational data. Our experiments also show that the characteristics of these two user roles can further be utilized in group recommender systems to produce better item recommendations.

Author Keywords
recommender system, personality, group decision

INTRODUCTION
Human factors, such as emotions, trust and personality, have been recognized as influential factors in the recommender systems. For example, *emotional reactions* [18] can be treated as strong implicit feedbacks that can represent user tastes. *Trust network* [8] can provide additional property to infer the user preferences. *User personalities* [10, 16] may directly affect a user's decision, since people with different personalities may present distinct behavior patterns and preferences in the real world.

Recently, the importance of personality is realized not only for predicting the individual tastes, but also the group preferences. For example, a group of users may decide which dishes should be ordered for a group lunch. Or, a group of tourists would like to make a decision about the list of points of interests for tomorrow's trip. Researchers [15, 12] find out that user personality is one of the key factors in group decisions. For instance, some users (i.e. *followers*) in the group may yield their choice to group decisions, but some of other users (i.e., *dominators*) may play a dominant role in group decision making.

The impact by personality in *individual and group decision making* is still under investigation, especially in the area of educational learning. For example, team work becomes more and more popular in the educational learning. Students may be suggested to work together on the assignments or projects. Decision making is involved in such a scenario, e.g., how will the students build the team, or which materials or topics should a team select to start learning, etc. Furthermore, it is also interesting to understand which group of the users may yield to group decisions. In this paper, we discuss our analysis to distinguish followers and dominators in the group decision by using an educational data. Our contributions can be summarized as follows:

- We propose two approaches to identify the dominators and followers in the group decision making.
- We discover and summarize the characteristics of these user roles in terms of the personality traits.
- We infer the pattern in team building.
- We demonstrate that these characteristics are useful to improve the quality of group recommendations.

RELATED WORK
Personality has been successfully applied to improve decision making in different areas, such as tourism [2, 14], trading [3], career [4], etc. For example, the analysis on economics behaviors by Ertac, et, al. [3] helps us understand the role of personality in group decisions. Particularly, they found that openness, agreeableness and conscientiousness are the major three personality traits that can affect the group decisions by distinguishing the user roles as leaders and non-leaders. Furthermore, the personality traits are found to be useful in recommender systems, e.g., Delic, et, al. [2] observe significant patterns in user behaviors based on the personality traits which can improve the group recommender systems.

In educational learning, personality has been proved to be influential. Komarraju, et al. [6] identify the impact of personality on the academic achievements, such as GPA. Vedel, [17] focuses more on the group differences

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across academic majors. However, there are limited work that explore the impact of personality on individual and group decision making in the learning environment.

In this paper, we are particularly interested in distinguishing the follower and dominators. *Dominator(s)* is defined as one or more members in a group who could be the decision leaders. By contrast, *follower(s)* can be viewed as the member who may yield to the group decisions. The notions are inspired by Recio-Garcia, et al. [13]. They propose five different modes for responding to conflict situations – competing, collaborating, avoiding, accommodating and compromising. The dominator in our paper is the user role in the competing mode, while the follower represents the user role in the compromising mode. However, their work relies on the Thomas-Kilmann Conflict Mode Instrument (TKI) test. The subjects are required to take the test in order to be classified into these five modes. In our paper, we ignore the TKI test and try to distinguish the dominator and followers by the rating characteristics in the data.

ITMLEARNING PLATFORM

The impact of personality on individual and group decisions is under investigation in the area of educational learning. But unfortunately, there are no available data sets for public research in this domain. Even in the general area of group recommendations, most of the research may use the MovieLens data – the evaluation is usually based on the simulated groups. In this case, we start collecting our own data for the research purpose.

ITMLearning platform is built for the department of information technology and management (ITM) at the Illinois Institute of Technology in USA. The platform is a technology-enhanced learning system which aims to: a) suggesting appropriate learning materials (e.g., books, articles, tutorials, videos); b) recommending job positions; c) assisting instructors in the teaching.

One of the ongoing projects from this platform is collecting students' preferences on the topics of the projects in order to better support learning and assist teaching [19]. We start from three courses (i.e., database, data mining and data analytics) which require students to complete a project as the final evaluations. Students have their own choice to select a topic for the project, and each student can complete the project by himself/herself or by a team work. We ask student volunteers to complete the questionnaires, in order to collect the subjects' personality traits and their preferences on the topics of the projects. More specifically, the questionnaires are designed to collect both individual and group tastes:

- **Topics of The Projects**: First of all, we provide a list of potential topics for each course respectively. Take data analytics course for example, we provide the information about 50 data sets that are available on Kaggle.com. Students should select one of them, define the research problems, and figure out solutions by using the data analytics skills.
- **Collection of Individual Preferences**: At the beginning, each student is required to fill the questionnaire by himself or herself. Each subject should select at least three liked and disliked topics of the projects, and provide an overall rating to them. In addition, they are asked to rate each selected project on three criteria: how interesting the application area is (i.e., App), how convenient the data processing will be (i.e., Data), how easy the whole project is (i.e., Ease). The rating scale is from 1 to 5.
- **Collection of Group Preferences**: Finally, each student has to decide whether they will complete the project individually. For the team work, they need to find partners and build the team by themselves. Each team will fill the same questionnaire from the perspective of a team based on the group discussions.

In addition to these preference data, we collect demographic (e.g., age, gender, marriage status, home country) information and personality traits of each student. We choose the Big Five Factor (Big5) [9] which is the most popular framework to represent the personality traits. In the Big5 framework, the personality traits can be described by five dimensions [6]: Openness (O) is reflected in a strong intellectual curiosity and a preference for novelty and variety. Conscientiousness (C) is exemplified by being disciplined, organized, and achievement-oriented. Extraversion (E) is displayed through a higher degree of sociability, assertiveness, and talkativeness. Agreeableness (A) refers to being helpful, cooperative and sympathetic towards others. Neuroticism (N) indicates the degree of emotional stability, impulse control, and anxiety. To collect the Big5 traits, we use the well-known Ten-Item Personality Inventory (TIPI) [5].

The full questionnaire includes the ten statements that are listed below, and the subjects are asked to give a rating in scale 1 (strongly disagree) to 7 (strongly agree) to each of them.

- I see myself as extraverted, enthusiastic.
- I see myself as critical, quarrelsome.
- I see myself as dependable, self-disciplined.
- I see myself as anxious, easily upset.
- I see myself as open to new experiences, complex.
- I see myself as reserved, quiet.
- I see myself as sympathetic, warm.
- I see myself as disorganized, careless.
- I see myself as calm, emotionally stable.
- I see myself as conventional, uncreative.

At this moment, we have collected data for a full year – we obtain a data set with 194 individuals and 122 groups. 81 out of 122 groups are composed of more than one members. More specifically, 60% of these 81 groups are composed of two members, and the remaining groups are composed of three or four members. The individuals leave 1951 ratings on the topics of projects, while the groups leave 745 ratings in total. In addition to the overall ratings, we collect their ratings on three criteria as introduced above. For the purpose of personalization, this data is available for traditional recommender systems (i.e., recommendations for individuals), group recommender systems (i.e., recommendations for each group), and multi-criteria recommender systems (i.e., recommendations based on multi-criteria decision making), as well as context-aware recommendations (i.e., semester, year, course can be viewed as the context information). The project is still ongoing and we expect to collect more data gradually.

ANALYSIS AND DISCUSSIONS

Personality Traits by Gender

In our data, 42% of the subjects are female. We'd like to explore whether there is a significant difference in their personality traits in comparison with males. Table 1 presents the mean and standard deviation (SD) of the scores in the Big5 factors for the overall, male and female individuals respectively.

Table 1. Statistics About The Personality Traits (* indicates significance at 95% confidence level by gender)

		O	C	E	A	N
Overall	Mean	5.22	5.05	4.63	4.85	4.11
	SD	1.28	1.34	1.49	1.47	1.53
Male	Mean	5.15	4.89*	4.52	4.64*	4.12
	SD	1.23	1.38	1.4	1.49	1.44
Female	Mean	5.32	5.27	4.78	5.14	4.1
	SD	1.34	1.26	1.61	1.39	1.66

In addition, we also observe that the standard deviations in neuroticism and extraversion are significantly larger than other personality factors. The two-independent sample hypothesis tests reveal that the difference on conscientiousness and agreeableness between males and females are significant at the 95% confidence level.

Team Building

We further analyze the 81 groups which are composed of at least two members. Students actually find their own partners and build the team without intervention by the instructors. We are pretty interested in how they build a team or what are the most important criteria for them to select partners. More specifically, we try to measure the intra-group similarities.

First of all, each subject can be represented by the Big5 vector. Cosine similarity, as shown by Equation 1, can be used to produce the similarity between two subjects U_a and U_b in a same team. The vectors $\overrightarrow{V_a}$ and $\overrightarrow{V_b}$ are the Big5 vectors for U_a and U_b respectively. We obtain similarity values of each pair of the subjects in a team, and the mean similarity is viewed as the intra-group similarity.

$$Sim(U_a, U_b) = \frac{\overrightarrow{V_a} \cdot \overrightarrow{V_b}}{||\overrightarrow{V_a}||_2 \times ||\overrightarrow{V_b}||_2} \quad (1)$$

Furthermore, each subject is required to provide the individual preferences (i.e., user ratings) on the topics of the projects. Alternatively, we can represent each subject by his or her rating vector. The rating vector can be filled by the overall rating or the multi-criteria ratings on app, data and ease respectively. In other words, $\overrightarrow{V_a}$ and $\overrightarrow{V_b}$ could be rating vectors based on the overall rating or the multi-criteria ratings. The similarity between two subjects can be obtained by the Equation 1 accordingly.

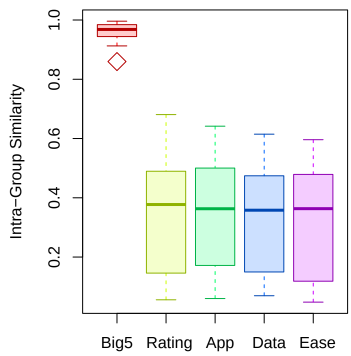

Figure 1. Comparison of In-Group Similarities

As a result, we are able to produce the intra-group similarities by representing a user as the Big5 vector or a rating vector. We further analyze the distribution of these intra-group similarities, and visualize them as box plots in Figure 1. It is clear that the intra-group similarity is significantly higher by the representations based on the Big5 factors than the ones based on user's rating vectors. It implies that the subjects prefer to find the team members by the personality traits, even if their tastes on the projects may be different. The average intra-group similarity based on the rating vectors is actually below 0.5, which is surprising.

Distinguish Dominators and Followers

It has been recognized that personality can affect group decisions. Our goal is to find out distinct individuals who react differently in group decisions. More specifically, we define *dominator(s)* as one or more members in a group who are the decision leaders, and *follower(s)* as the member who may yield to group decisions. We try to these two user roles from the perspective of *user-group similarities* and *user-group conflicts* which can be further discussed as follows. Also note that our following analysis is based on the 81 groups which is composed of at least two team members.

By User-Group Similarities

We have both individual and group preferences on the topics of the projects. Each individual and group can be represented by the rating vectors. In this analysis, we focus on the overall rating only and ignore the multi-criteria ratings for simplicity. The similarity between a group and an individual in the group can be computed by the cosine similarity of the representations based on the

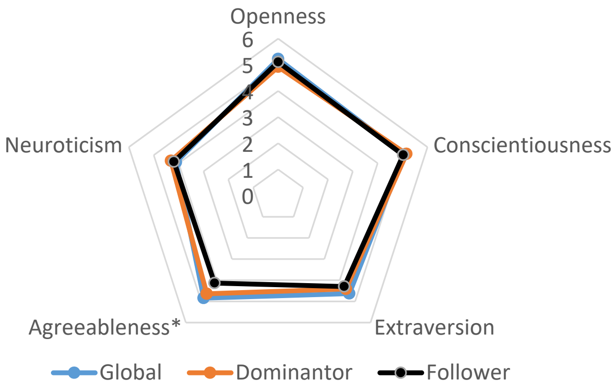

Figure 2. Identifying User Roles by Rating Vectors

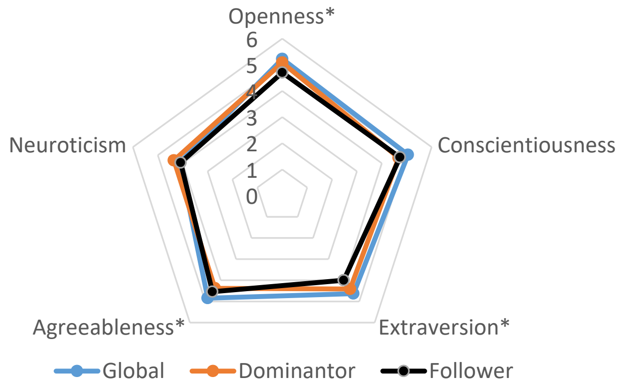

Figure 3. Identifying User Roles by Latent Vectors

rating vectors. If this similarity value is relatively low, it implies that this subject yields to the group decisions. Subjects with higher user-group similarity can be viewed as the "dominator", while the subjects with user-group similarity smaller than a threshold can be the "follower".

We have two strategies to define the thresholds:

- We can use the average value of the user-group similarities as a single threshold. The subjects will be split into dominators and followers.

- Or, we will set two thresholds. For example, we obtain the 1^{st} and 3^{rd} quartile of the user-group similarities. The subjects with user-group similarity larger than 3^{rd} quartile will be viewed as dominators, while the users with user-group similarity smaller than 1^{st} quartile will be considered as the followers.

We found that the second way was better, therefore we only present these results in the following sections.

Afterwards, we computer the mean Big5 vector for the subjects as dominators and followers which can be depicted by the radar chart as shown in Figure 2. We use "Global" to represent the mean Big5 vector of all the subjects. The "*" denotes a significant difference (two-independent sample test at 95% confidence level) in a specific personality trait between dominators and followers. We can observe that the significant difference only shows up in agreeableness, while dominators actually have larger degree of agreeableness. It sounds surprising to us, since we expect the followers may yield to the group decisions and they should present relative larger degree of agreeableness.

After a further investigation, we realize that the cosine similarity based on the rating vectors relies on the number of co-ratings by a team and an individual in the team – the similarity may be not reliable if the number of co-rated items is limited. In our data, the average value of co-ratings by the teams and the team members is 3.33 with standard deviation 2.45. We believe the results in Figure 2 are not reliable due to the limited number of co-ratings between a team and team member.

We figure out a way to alleviate this problem. More specifically, we blend user ratings and group ratings together, while each group is viewed as a special user. We utilize a matrix factorization model based on this rating matrix to find the best model which can minimize the squared prediction errors in the ratings. Finally, each user and each group can be represented by a latent vector which is learned by the matrix factorization model. The user-group similarity, therefore, can be calculated by the cosine similarity of two latent factors. In our work, we use the biased matrix factorization [7] as the algorithm, and assign 10 latent factors so that each user and group will be represented by a vector with size 10.

Figure 3 presents new comparisons of the BIG5 traits. The dominators and followers are identified based on the same method as mentioned above, where we represent a team and a team member as the latent vectors learned based on the matrix factorization model. We can observe that there are significant differences between dominators and followers in openness, agreeableness and extraversion based on the two-independent sample test at 95% confidence level. More specifically, dominators present higher values in the openness and extraversion, while the agreeableness value is relatively higher in the followers who may yield to the group decision. It is not surprising to see that a dominator could be more extraverted since he or she may be a talkative, confident and assertive person. In terms of the openness, one explanation could be that dominator is usually the first person to start the discussions in a team, and they may produce novel ideas and lead the group decisions. By contrast, the followers present larger degree of the agreeableness, which may infer that they tend to accept the group decisions even if they have different opinions.

By User-Group Conflicts

Alternatively, we can distinguish dominators and followers based on the notion of "conflicts". Recio-Garcia, et al. [13] summarized five different modes for responding to conflict situations in their work – competing, collaborating, avoiding, accommodating and compromising. The dominator in our paper is in the competing mode, while the follower is in the compromising mode. However, the work by [13] relies on the Thomas-Kilmann Conflict Mode Instrument (TKI) test. In our work, we try to figure out another way to define the conflicts and avoid additional human efforts in the TKI test.

More specifically, we define conflict as either the false positive or the false negative case. A "false positive" case can be described as the situation that a subject presents positive preference on one item, but his or her group finally made a negative decision on the same item. Accordingly, the scenario that being positive on one item by group decision but negative by a team member will result in a "false negative" case. In our experiment, we use a rating threshold to define whether it is positive or negative. More specifically, it is positive when individual or group rating on one project is larger than 3. We compute the total number of conflicts (including both false positive and false negative cases) for each team member in a team. We find out that only 22.5% of the subjects present the conflicts in our data.

Accordingly, we obtain the mean, 1^{st} and 3^{rd} quartile of the number of conflicts, and set the threshold to distinguish the followers and dominators. The process is similar to the one we used to identify different user roles by using the user-group similarities – we can use a single threshold or two thresholds. In our experiments, we finally use the mean value of the number of conflicts as the threshold to split the subjects to dominators and followers.

The sparsity problem is involved again since the number of co-ratings by a team and a team member is limited. We use matrix factorization model to make predictions on the unknown ratings for both subjects and teams. As a result, 97% of the subjects present the conflicting behaviors. We use the single threshold to separate the subjects to dominators and followers, while the comparison in BIG5 can be depicted by Figure 4. We can observe that the statistical significance only presents in the agreeableness, while the followers usually have higher values in agreeableness.

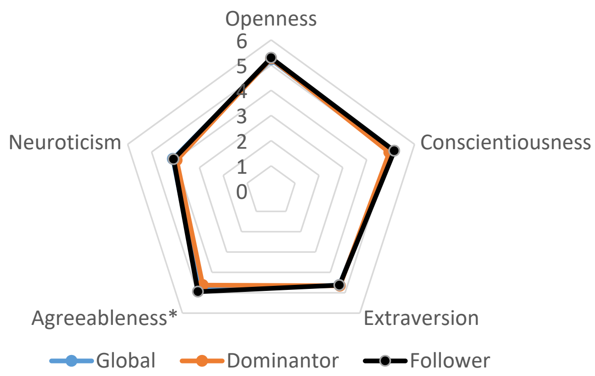

Figure 4. Identify User Roles by Conflicts

Summary

We try to distinguish the dominators and followers in the group decision making by two proposed approaches – one is by the similarity between the team and its team members, another one is by the conflicts between individual and group preferences. We find that openness, agreeableness and extraversion are the three influential factors to recognize the dominator and followers by using the user-group similarities. By contrast, agreeableness is the only crucial factor we find by using the method based on the conflicts.

Some previous research have also identified the important personality traits in the group decisions. For example, Ertac, et, al. [3] tried to distinguish users as leaders and non-leaders, and they found that openness, agreeableness and conscientiousness are the three major personality traits which affect the group decisions. But the openness only takes effect if the person is a leader. Our findings are basically consistent with Ertac's work. Neuroticism is also pointed out as a key factor by [1, 4]. But we did not confirm its importance in our data.

RECOMMENDATIONS

Once we identify the dominators and followers, we further exploit whether and how these findings are helpful in producing the group recommendations. There are 515 ratings associated with the 81 groups which are composed of at least two team members. We conduct a 5-fold cross validation based on these ratings – we split the 515 ratings into 5-folds. For each round evaluation, we select one of the five folds as the testing sets, the remaining four folds plus the data of individual ratings, information about group members and the user's BIG5 traits will be considered as the corresponding training set. We simply examine the recommendation performance by rating predictions and use mean absolute error (MAE) as the evaluation metric. The rating prediction for a group g on an item t is represented by $P(g,t)$. We adopt the following strategy in the group recommendations:

- Average (AVG): $P(g,t)$ is the average predicted rating by all of the team members on the same item t.
- One user choice (ONE): $P(g,t)$ is equivalent to the preference by the dominator on the item t. If there are more than one dominators, we use their average rating predictions [1]. We set up a baseline setting for the ONE method – assuming that we do not know the dominators, $P(g,t)$ will be the preference by a random team member on the item t.
- Least misery (LM): It is used to minimize the misery for the group members. $P(g,t)$ is the minimal predicted rating by the team members.
- Most pleasure (MP): It tries to maximize the happiness or pleasure for the group members. $P(g,t)$ is the maximal predicted rating by the team members.

For the purpose of rating predictions, we use the biased matrix factorization [7] as the recommendation model. Recall that we figure out two ways to identify the dominators and followers, we finally adopt the ones shown

[1]Note that this does not happen in our experiments.

by Figure 3 and 4 – we simply name them as "By Similarity" and "By Conflicts" in the following discussions. To take advantage of the identified dominators and followers, we simply ignore the contributions by the followers when we execute the four recommendation strategies mentioned above. Take the AVG recommendation method for example, we will ignore the ratings by the identified followers when we try to calculate the average value of the member's rating predictions. Similar operations can be applied to other recommendation strategies, while the ONE method will not be affected, since there are no followers involved. Additionally, we add another simple baseline – matrix factorization (MF) based on the ratings given by the teams only without considering any dominators or followers.

Table 2. Comparison of MAE

	MF	AVG	ONE	LM	MP
Baseline	0.899	0.889	0.892	0.911	0.906
By Similarities	N/A	0.874*	0.881	0.916	0.882*
By Conflicts	N/A	0.871*	0.891	0.92	0.894

The recommendation performance based on the MAE metric can be presented in Table above. We can observe that the AVG method is the best one among all of the baseline approaches. By incorporating the identified dominators and followers, the method by user-group similarities can offer significant improvement for the AVG and MP strategies. The method by conflicts obtains improvements for the AVG method only. Note that the significance test was examined at the 90% confidence level. Unfortunately, there are no significant improvements at the 95% level, and the improvement is relatively small.

Furthermore, the method by user-group similarities presents significant improvements in MP rather than LM. It implies that the followers may leave false positive contributions to the group decisions in our data. It is because the performance can be improved if we ignore the followers in the MP method.

CONCLUSIONS & FUTURE WORK

In this paper, we try to distinguish the dominators and follows in group decision making by using user-group similarities and conflicts. We further take advantage of the identified dominators and followers in different group recommendation strategies. And we find that we are able to obtain significant improvements by ignoring the followers in the group recommendations. Furthermore, we find that students with similar personality tend to work together in our data.

This paper presents our initial work, while there are plenty work to do. For example, the identification method by using user-group conflicts relies on the user ratings. However, user bias should be taken into account in the process to define the false positive and false negative cases. The approach by user-group similarities is dependent with the recommendation algorithms, since we use the algorithm to fill in the unknown ratings. We will further explore the corresponding solutions in the future. Furthermore, we evaluate the recommendation performance based on simple group recommendation strategies, but there are several advanced work which can directly incorporate personality in the group recommenders, such as the work by [11]. We will figure out how to incorporate the identified dominators and followers into these advanced group recommendation models.

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