Exploring User Roles In Group Recommendations: A Learning Approach

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ABSTRACT

Personality, as one of the human factors, has been demonstrated as an influential factor in decision making. Particularly, personality traits can be utilized to identify decision leaders and followers in the context of group decision making. In this paper, we propose an approach to learn user roles (i.e., decision leaders and followers) to improve the performance of group recommendations. More specifically, we utilize the binary particle swarm optimization as the method to assign and learn user roles in each group. Our experimental results based on an educational data reveal that the proposed approach is able to improve group recommendations. However, the learned user roles may not present expected characteristics in terms of the personality traits.

CCS CONCEPTS

• **Human-centered computing** → **User models**; • **Information systems** → **Recommender systems**;

KEYWORDS

decision making; personality; educational learning; recommender systems

1 INTRODUCTION

Recommender systems are effective tools to assist decision making by suggesting item recommendations. Recently, researchers realize the importance of human factors, such as emotions, trust and personality. For example, *emotional reactions* [18, 23] can be treated as strong implicit feedbacks that can represent user tastes. *Trust network* [11] can provide additional property to infer the user preferences. *User personalities* [13, 16] may directly affect a user's decision, since people with different personalities may present distinct behavior patterns and preferences in the real world.

Particularly, personality-based recommender systems [13, 14, 16] have been built to better assist both individual and group decisions. Our recent work [19] proposed to identify the roles of group members (i.e., leaders and followers) by intra-group similarity or conflicts to assist group recommendations. More specifically, we found that the identified group leaders and followers would present significant different in specific personality traits, such as agreeableness, extraversion and openness. The quality of group recommendations can be improved if we incorporate these user roles into the recommendation strategies. However, the proposed may suffer from sparsity problem, if the number of co-rated items by individuals and their group is limited.

In this paper, we propose to use a learning and optimization approach to learn user roles in the group recommendations. It is another way to explore user roles in the groups in comparison with our previous work [19]. More specifically, we employ the binary particle swarm optimization to learn whether a user is a group leader in the group decisions by optimizing the predictions errors in the group recommendations. Our experimental results demonstrate the effectiveness of the proposed method in the group recommendations. However, they finally did not present any significant differences in terms of the personality traits.

2 RELATED WORK

Personality has been successfully applied to improve decision making in different areas, such as tourism [2, 15], trading [4], career [5], etc. There are many frameworks which describe the personality traits. Big Five Factor (BIG5) [12] is the most popular one to represent the personality traits, where the personality traits can be described by five dimensions [10]: 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.

The effect of personality in group recommendations has been discovered by existing research [2, 4]. We are particularly interested in distinguishing the follower and dominators. *Dominator(s)* or *leader(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. [14]. 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 to be classified into these five modes. In our paper, we try to avoid these human efforts to identify user roles in the groups.

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In our previous work [19], we assume that a group leader will share most of the interests with group decisions, while a group follower may yield his or her decision to the group preferences. Therefore, a group follower may present lower similarity of preferences or more conflicts in comparison with the group decisions. The workflow in [19] can be summarized in this way:

- Step 1). Distinguish user roles by intra-group similarity or intra-conflicts.
- Step 2). Confirm the identified leaders and followers present significant differences in the personality traits.
- Step 3). Incorporate these user roles into group recommenders to examine whether the recommendation performance can be improved.

In this paper, we conduct research in a reversed way – we learn user roles by optimizing the performance of group recommendations. Afterwards, we analyze these user roles in terms of the characteristics and personality traits.

3 PROPOSED APPROACH

3.1 Data

To better introduce the proposed approach, it is necessary to introduce the data used in our research. There are very limited available data for group recommendations, not to mention we also need the information about the personality traits. In this case, we continue to the data in our previous work [19, 20] which was collected from user surveys from the educational domain.

Students are required to complete a project by the end of the semester. They need to find a topic for the project, define research problems, and utilize the knowledge and skills in the class to solve the proposed research problems. In addition, students may choose to work on the project by a team work or by themselves. We pre-define a list of potential topics by giving a list of data sets on Kaggle.com. The questionnaires are designed to collect both individual and group tastes:

- **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.
- **Group Preferences**: Finally, each student must 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 preferences, we collect demographic information (e.g., age, gender, marriage status, home country) and personality traits of each student. We use the Ten-Item Personality Inventory (TIPI) [6] to collect their personality traits in the BIG5 framework. At this moment, we obtain a data set with 194 individuals and 122 groups. 81 out of 122 groups are composed of more than one members, while there are 28 groups which 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.

3.2 Methodology

Theoretically, there could be three user roles in the group decisions: leader(s), follower(s) and other members who are neither leaders nor followers. To simplify the problem, we assume there are only group leaders and followers in the group. Our previous work [19] also demonstrates that these two roles are helpful to improve the group recommendations. We will leave the identification of three user roles in our future work.

Our research problem becomes a binary selection challenge – given a user, we attempt to learn whether he or she is a group leader (i.e., value one) or follower (i.e., value zero). The ultimate goal is to improve the group recommendations by learning these user roles. We adopt the following four group recommendation strategies, while the rating prediction for a group g on an item t is represented by $P(g, t)$.

- Average (AVG): $P(g, t)$ is the average predicted rating by all 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. Without the information about the group leaders, we will randomly select one team member as the dominator.
- 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 happiness (MH): It tries to maximize the happiness or pleasure for the group members. $P(g, t)$ is the maximal predicted rating by the team members.

Once we identify or learn the group leaders and followers, the corresponding updates on these four strategies can be described as follows:

- Average (AVG): $P(g, t)$ is the average predicted rating by the non-followers on the same item t. Note that there may be more than one group leaders.
- One user choice (ONE): $P(g, t)$ is equivalent to the preference by the dominator on the item t. We will randomly select a dominator if there are more than one group leaders.
- Least misery (LM): $P(g, t)$ is the minimal predicted rating by the team members who are not followers.
- Most happiness (MH): $P(g, t)$ is the maximal predicted rating by the team members who are not followers.

It is clear that a non-linear optimization method is required to solve the binary selection problem. We propose to utility the binary particle swarm optimizations (BPSO). Particle swarm optimization (PSO) [7] is a kind of swarm intelligence which was originally introduced by Eberhart and Kennedy in 1995. It is a population-based optimization approach inspired by social behaviors in swarming and flocking creatures like bees, birds or fish. It was introduced to the domain of information retrieval [3] and recommender system [1, 17, 22] recently as a way for feature weighting. Binary particle swarm optimization (BPSO) [8] is a discrete binary version of the technique introduced in 1997, which is used to fit our binary selections for contexts and feature relaxation in this paper.

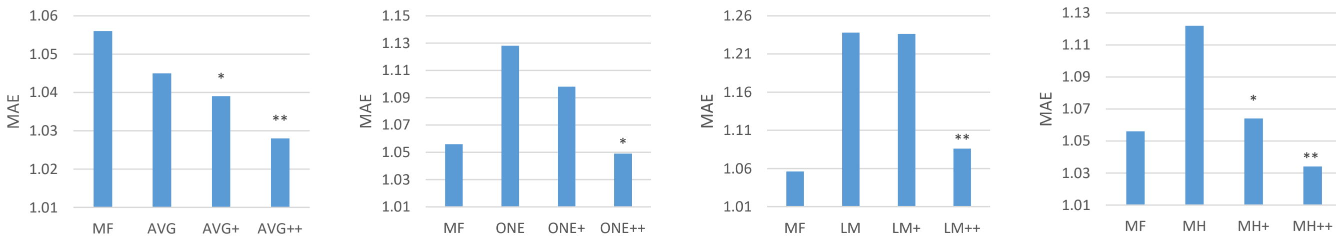

Figure 1: Experimental Results By Each Group Recommendation Strategy

We use an improved version of BPSO which was proposed by Mojtaba *et al* [9]. It was successfully applied on differential context relaxation [21] for a purpose of binary feature selection in context-aware recommender systems. In our work, BPSO will assign multiple particles to learn the binary values as user roles in the group decisions. It is an iterative learning process, where each particle can learn from its own history (i.e., previous iterations) and the global history (i.e., the best solution by all the particles). The fitness in the learning process is set as the sum of the squared errors in the rating predictions, since we have the item ratings by each group in our data. For more details about the BPSO, refer to our previous work on context-aware recommendations [21]. We use the same empirical parameter settings as the ones in [21], and vary the number of learning iterations from 20 to 100 with an increment of 10 in each step, also change the number of particles from 5 to 20 with an increment of 5.

4 EXPERIMENTAL RESULTS

4.1 Data and Evaluations

We use the data described in Section 3.1. The group size is one of the concerns in our research. The research results may not be reliable if the group size is too small. Therefore, we only utilize the groups with at least three team members. Finally, the data becomes relatively small – there are 28 groups with 243 ratings by the groups. These groups are associated with the 85 individual students who gave 582 ratings to the 70 topics of the projects.

We utilize a 5-fold cross validation for evaluation purpose. The training set will also contain the individual ratings and their personality traits. We utilize the mean absolute error (MAE) to measure the performance of group recommendations, since the BPSO will find the optimal solutions by minimizing sum of the squared prediction errors.

4.2 Baseline Approaches

We first employ the biased matrix factorization (MF) on the group preference data (with group, item, rating information only) to produce the rating predictions. In addition, we utilize the four group recommendation strategies mentioned above. Particularly, we use the intra-group similarity method [19] as other baselines to identify the group leaders and followers which will be incorporated into the group recommendations, in order to compare the performance by the learning approach proposed in this paper.

4.3 Results and Findings

Figure 1 presents the experimental results by using each group recommendation strategy – AVG, ONE, LM and MH. “MF" represents the baseline approach based on the group preferences only. A “+" method indicates the method that we incorporate identified group leaders and followers by the intra-group similarities [19] into group recommendations, while the “++" approach represents the group recommendations by using the learned user roles based on the BPSO we proposed in this paper. For example, “AVG" represents the group recommendation strategy “Average" without considering user roles. “AVG+" utilizes the user roles identified by the intra-group similarities [19], while “AVG++" incorporates the learned user roles by BPSO into the group recommendation strategy “Average". In addition, we perform significance test between the “+" or “++" approach and the recommendation strategy without considering user roles at the 95% confidence level, as well as the test between the “+" and “++" approach. We use “*" to indicate the significance.

Based on the results described by Figure 1, we can observe that the proposed methods in this paper are able to outperform the algorithms based on different group recommendation strategies. More specifically, AVG++, LM++ and MH++ can produce significant lower MAE in comparison with the corresponding group recommendation strategies without considering user roles and with considering user roles identified by the intra-group similarities [19]. ONE++ can present significance advantages over the ONE approach, but failed the significance test with the ONE+ method. Additionally, the methods based on the LM strategy failed to outperform the MF method which is the basic matrix factorization applied on group preference data. This result is consistent with the ones in our previous work [19], where we found that MH works much better than LM methods. It implies that the followers may leave false positive contributions (i.e., they may give higher ratings to the items than other members) to the group decisions in our data.

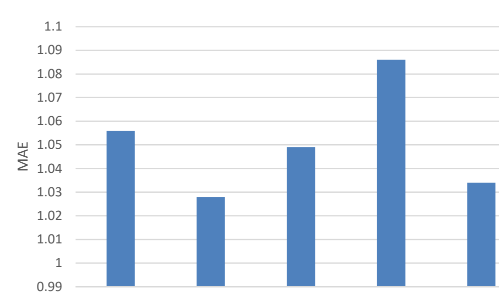

Figure 2: Comparison of Best Performing Methods

Figure 2 presents a comparison among the MF method and the best performing group recommendation strategies. We can discover that the AVG++ and MH++ methods work the best. Unfortunately, there is no significance difference on the MAE values by these two approaches.

To seek more insights about the user roles in the groups, we plot the distribution of the number of leaders by difference approaches, as shown by Figure 3. "SIM" is used to denote the approach by using intra-group similarities. We can observe that the successful solutions, such as AVG++ and MH++, have similar distributions of the group leaders – most of the groups may have two leaders. The underperformed methods, such as LM++ and SIM, may indicate more leaders (such as 3) in the groups. This plot may also explain the reason why the approach based on the intra-group similarities do not perform better than the proposed approach in our work.

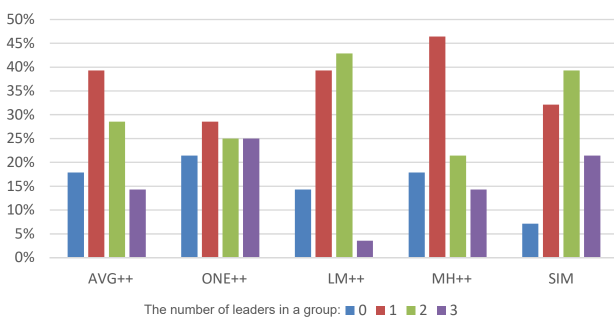

Figure 3: Distribution of User Roles In The Groups

We successfully identify or learn the user roles by the intra-group similarities [19] and the learning approach based on BPSO respectively. And we demonstrate the learning approach can produce better group recommendations. We also explore the difference between the identified group leaders and followers in terms of the personality traits. More specifically, we employ a two-sample hypothesis testing to the BIG5 personality traits of the group of leaders and followers. We find out that the followers have significant higher values in the agreeableness than the leaders, if we utilize the intra-group similarities to identify leaders and followers. By contrast, we did not find any significant differences in the personality traits, if we learn the user roles by the proposed BPSO approach.

There are two possible reasons: the collected personality traits by user surveys are not accurate; or, the optimal solution by BPSO failed to guarantee different personality traits in the learned group leaders and followers. One potential solution to alleviate this issue is to assign the constraints of personality traits in the BPSO learning process which we will consider in our future work.

5 CONCLUSIONS & FUTURE WORK

In this paper, we propose to learn user roles (i.e., group leaders and followers) by using the BPSO approach. We demonstrate that the proposed approach can help produce better group recommendations. But the learned leaders and followers failed to present significant differences in the personality traits. In our future work, we will incorporate more constraints into the BPSO approach to learn a solution which can not only improve group recommendations but also help identify user roles which present significant different characteristics in the personality traits.

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