

# Evaluating User's Personality and Social Interactions for Groups Recommendations

Francesco Barile<sup>1</sup>, Francesco Cervone<sup>2</sup> and Silvia Rossi<sup>2</sup>

<sup>1</sup> Dipartimento di Matematica e Applicazioni,  
Universita' degli Studi di Napoli "Federico II", Napoli, Italy  
francesco.barile@unina.it

<sup>2</sup> Dipartimento di Ingegneria Elettrica e Tecnologie dell'Informazione,  
Universita' degli Studi di Napoli "Federico II", Napoli, Italy  
silvia.rossi@unina.it

**Abstract.** Common approaches to provide group recommendations are based on the aggregation of the recommendations that are provided, for each group's member, by an individual recommendation system, using social choice functions. These techniques do not consider factor like social interactions, roles, influences, and group members' personality that model real group's decision-making process. Recent approaches tried to include these factors by introducing social-based weights in the aggregation of preferences or social aware utility functions. On the basis of these evaluations we propose two possible approaches, one based on the study of user's personality, in particular, on the *agreeableness* factor, and a second one based on the analysis of social interaction between group's members on a social network, to determine a dominance factor for each user in the group. The conducted pilot studies show that these approaches can increase the goodness of the recommendation provided and the satisfaction of group's members with respect to standard aggregation mechanisms.

**Keywords:** Group Decision Making, Social Choice, Group Recommendation, Small Groups, Social Networks.

## 1 Introduction

Group recommendation approaches rely either on building a single group profile, resulting from the combination of the profiles of all the users, or on merging the recommendation lists generated for each individual users, at runtime, using different group decision strategies. In this case, we talk about *Social Choice* functions. These strategies, according to [14], can be classified as majority-based (mainly implemented as voting mechanisms to determine the most popular choices among alternatives), consensus-based (that try to average among all the possible choices and preferences), and role-based (that explicitly take into account possible roles and hierarchical relationships among members). Examples of these techniques are illustrated in [9], the most common approaches are based on the average satisfaction and least misery techniques.

Nevertheless, many of these techniques do not consider social relationships among the group members [7], while the design and implementation of group recommendation

systems, and, more generally, of decision support systems, should take into account the type of control in the group decision-making process, and the diversity and the dynamics of relationships, roles and mutual influences among the group members [7]. For example, the decision of a group member whether or not to accept a given recommendation may depend not only on the own evaluation of the content of the recommendation, but also on the beliefs about the evaluations of the other group members [2].

PolyLens [11] has been one of the first approaches to include social characteristics within a group recommendation system. A more recent example is represented by the work of [7], where the Authors started to evaluate the group members' weights, in terms of individual members' importance or influence in a group, for movie recommendations. The defined group consensus function relies on the concept of "expertise" and "group dissimilarity". Also, it introduces the idea of diversifying the social choice strategy to use on the basis of the characteristics of the group. The Authors calculate a "social value" on the basis of social interactions between group members and, then, use this value to discriminate the strategy to apply for the group.

Another way to use interactions between group members is presented in [13]. Here, the authors introduce the concept of *empathetic utility* on social networks: the satisfaction of an individual depends from both his intrinsic utility and his *empathetic utility* deriving from the happiness of his neighbors in the social network [13]. Based on this idea, individual preferences are aggregated in a weighted social choice function that takes into account local relationships with neighborhoods in the network. However, in [13] the Authors do not specify how to evaluate such numerical relationships, while they focus on computational aspects of scaling up with large networks of friends.

## 2 A Personality based Social Utility Function

In our opinion, a key factor that can influence the group decision in a realistic scenario is user's personality. Some people could rarely change their minds because they believe that their decision is the best for everyone, or simply because they do not want to reduce their utility in favor of others. Other types of people instead, can be worried about the satisfaction of all the other members, at the cost of the personal one. To involve these elements, a study of users' personalities through some models proposed in human sciences area is necessary. One of the most common is the Five-Factor Model (FFM), that summarize the behavioral features of a person into five factors, also called Big-Five: *openness*, *conscientiousness*, *extraversion*, *neuroticism* and *agreeableness* [5]. In particular, we focused on the role of the *agreeableness* factor in the definition of a utility function that models altruistic behavior. While the role of personality has been addressed before, in literature, to improve the performance of Recommendation Systems [10, 8], up to our knowledge, this is the first attempt to introduce personality factors in group decision making through the use of social choice functions.

We start assigning a *utility* to the items for each user that takes into account both the personal and the group satisfaction, depending on an altruistic factor (i.e., the agreeableness). It can be described as "the satisfaction of the user if the recommendation system chooses that item for the group". Once the new utilities are evaluated, the goal is to recommend items that maximize the *social welfare*. We used a model developed

by [4] and a *Mini-IPIP* (Mini International Personality Item Pool) [6] to evaluate the agreeableness level of individual users.

To evaluate this approach, we conducted a user study on movie recommendations, where we compare the results of our social function with a simple Least Misery strategy (LM). Results showed that for small groups a LM performs slightly better. In particular, for two people groups LM is the best choice; in the other cases the two methods are comparable and show similar performances. Our utility function improves its effectiveness proportionally to the group size: the larger is the group, the greater will count altruism in the final decision.

### 3 Dominance Weighted Social Choice Functions

According to [9], users involved in real interaction seem to care about fairness and to avoid misery. In [12], we decided to use a fairness strategy and one based on average satisfaction and to weigh such functions with a measure of the influence of each user on the other group's members, and, consequently, on the group's final decision. To make this, we evaluate the weight of the relationship between pairs of users from the analysis of the interactions on an OSN. We are interested in the analysis of the strength and the directionality of online social interactions in order to gather useful information on intra-group relationships, and use the strength of the different pairwise relationships in an aggregated manner in order to evaluate the power/dominance of each single member on the whole group. To compute the users' ranking, we decided to use a simple "non-semantic" approach defined in our previous work [3]. Such popularity values are obtained implementing an extension of the well-known *PageRank* algorithm [1] starting from the users' interactions on the social network *facebook.com*. These dominance values are used as weights for the average satisfaction strategy, while, for the fairness strategy, we proposed to use the dominance values to provide a ranking and to sort the users.

To evaluate our approach, we conducted two pilot studies with real users involved in the task of planning a trip in a city, and compare the results of our weighted functions with respect to their standard not-weighted implementations. Results showed that the weighted functions had better performances. In particular, in the first user study with binary selections (e.g., no rating provided), a bigger improvement was noted for the average satisfaction function, which also performed better than the fairness that suffers more of random choices. On the contrary, in the second one, which involved POI rankings, fairness strategy has a bigger acceptance rate and appreciation evaluation.

### 4 Conclusions

In this work, we introduced two approaches that include factors like user's personality, social roles and influences in the process of preferences aggregation for group recommendations. We evaluated these approaches through pilot user studies that show encouraging results, in particular, for the dominance weighted social choice functions. Nevertheless, a more deep analysis is necessary, involving a greater number of users and groups of larger dimensions.

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## References

1. Brin, S., Page, L.: The anatomy of a large-scale hypertextual web search engine. *Comput. Netw. ISDN Syst.* 30(1-7), 107–117 (1998)
2. Cantador, I., Castells, P.: Group recommender systems: New perspectives in the social web. In: *Recommender Systems for the Social Web*, Intelligent Systems Reference Library, vol. 32, pp. 139–157. Springer (2012)
3. Caso, A., Rossi, S.: Users ranking in online social networks to support pois selection in small groups. In: *Extended Proceedings of the 22nd Conference on User Modelling, Adaptation and Personalization - UMAP 2014*. pp. 5–8 (2014)
4. Charness, G., Rabin, M.: Understanding social preferences with simple tests. *Quarterly journal of Economics* pp. 817–869 (2002)
5. Costa, P.T., MacCrae, R.R.: Revised NEO Personality Inventory (NEO PI-R) and NEO Five-Factor Inventory (NEO FFI): Professional Manual. *Psychological Assessment Resources* (1992)
6. Donnellan, M.B., Oswald, F.L., Baird, B.M., Lucas, R.E.: The mini-ipp scales: tiny-yet-effective measures of the big five factors of personality. *Psychological assessment* 18(2), 192 (2006)
7. Gartrell, M., Xing, X., Lv, Q., Beach, A., Han, R., Mishra, S., Seada, K.: Enhancing group recommendation by incorporating social relationship interactions. In: *Proc. of the 16th ACM International Conference on Supporting Group Work*. pp. 97–106. ACM (2010)
8. Hu, R., Pu, P.: Enhancing collaborative filtering systems with personality information. In: *Proceedings of the Fifth ACM Conference on Recommender Systems*. pp. 197–204. *RecSys '11*, ACM (2011)
9. Masthoff, J.: Group recommender systems: Combining individual models. In: *Recommender Systems Handbook*, pp. 677–702. Springer US (2011)
10. Nunes, M.A.S., Hu, R.: Personality-based recommender systems: An overview. In: *Proceedings of the Sixth ACM Conference on Recommender Systems*. pp. 5–6. *RecSys '12*, ACM, New York, NY, USA (2012)
11. O'Connor, M., Cosley, D., Konstan, J.A., Riedl, J.: Polylens: A recommender system for groups of users. In: *Proc. of the 7th European Conf. on CSCW*. pp. 199–218 (2001)
12. Rossi, S., Caso, A., Barile, F.: Combining users and items rankings for group decision support. In: *Trends in Practical Applications of Agents, Multi-Agent Systems and Sustainability, Advances in Intelligent Systems and Computing*, vol. 372, pp. 151–158. Springer International Publishing (2015)
13. Salehi-Abari, A., Boutilier, C.: Empathetic social choice on social networks. In: *13th International Conference on Autonomous Agents and Multiagent Systems*. pp. 693–700 (2014)
14. Senot, C., Kostadinov, D., Bouzid, M., Picault, J., Aghasaryan, A., Bernier, C.: Analysis of strategies for building group profiles. In: *User Modeling, Adaptation, and Personalization, LNCS*, vol. 6075, pp. 40–51 (2010)