Generating Natural Language Explanations for Group Recommendations in High Divergence Scenarios

Shabnam Najafian
Delft University of Technology
Delft, the Netherlands
s.najafian@tudelft.nl

ABSTRACT

In some scenarios, like music or tourism, people often consume items in groups. However, reaching a consensus is difficult as different members of the group may have highly diverging tastes. To keep the rest of the group satisfied, an individual might need to be confronted occasionally with items they do not like. In this context, presenting an explanation of how the system came up with the recommended item(s), may make it easier for users to accept items they might not like for the benefit of the group. This paper presents our progress on proposing improved algorithms for recommending items (for both music and tourism) for a group to consume and an approach for generating natural language explanations. Our future directions include extending the current work by modeling different factors that we need to consider when we generate explanations for groups e.g. size of the group, group members' personality, demographics, and their relationship.

CCS CONCEPTS

• **Information systems** → **Recommender systems**; • **Human-centered computing** → **User studies**; **Empirical studies in HCI**.

KEYWORDS

explanations; group recommendations; preference aggregation strategies; human-centered computing user studies

ACM Reference Format:
Shabnam Najafian. 2020. Generating Natural Language Explanations for Group Recommendations in High Divergence Scenarios. In *25th International Conference on Intelligent User Interfaces Companion (IUI '20 Companion), March 17–20, 2020, Cagliari, Italy.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3379336.3381512

1 INTRODUCTION

Recommender systems (RSs) can help users cope with an abundance of items to try or buy by offering those items the user is likely to find interesting [2]. The main focus of current RSs is to propose items to individual users. However, in many domains (e.g., music, tourism) people often consume items in groups rather than individually.

IUI '20 Companion, March 17–20, 2020, Cagliari, Italy

ACM ISBN 978-1-4503-7513-9/20/03.
https://doi.org/10.1145/3379336.3381512

Group recommendation typically can be generated either by aggregating individual recommendations or by aggregating user profiles [3]. Recommending to groups is challenging as different members of the group may have highly diverging tastes (*high divergence scenarios*). Previous work suggests strategies for combining users' individual preference models into a preference model of the group [3], however, there is no optimal way to do this; every feasible aggregation method has some disadvantages [1]. We suggested some improvements on these strategies especially focusing on high divergence scenarios [4].

To keep the rest of the group happy, an individual might need to be confronted occasionally with items they do not like, in this context, presenting an explanation of how the system came up with the recommended item(s), can fulfill the explanatory goal of *transparency* and may make it easier for users to accept items they might not like for the benefit of the group [7]. Although there exists many studies on group recommendations, only a few of them focus on *generating explanations* in the context of group recommendations. For example [4, 5, 8] reveal the underlying mechanisms of preference aggregation strategies to generate the recommended items. Although initial approaches for explaining group recommendations have already been proposed, explanations for groups, can have further goals, as they should consider certain aspects of group dynamics. For example *privacy* is an explanation goal that arises in groups, but not for single users.

Research questions. The ultimate goal of the project is to "facilitate reaching consensus for groups especially on high preference divergence scenarios". We divided that into the following two main components or research questions, so the second component will be generated based on the results from the first component:

RQ1. How to generate *recommendations for groups* that best help to increase perceived group satisfaction, fairness, and consensus?

RQ2. How to define *explanations for groups* that best help to achieve consensus, fairness, and privacy?

Two domains will be used in this research: *music* and *tourism.*

2 RESEARCH PROGRESS UP TO DATE

The use case scenario in Figure 1 represents the main components of my work. Consider situations when no best option exists and trade-offs occur. For instance when people in a group listening to a playlist together on a road trip have different preferences. This scenario contains two main components: a preference *aggregation strategy*; these strategies decide what is best for a group given the ratings of individuals which is Fairness strategy in this case (see Section 2.1), and (2) *explanations*; which is any information we provide for users to make the strategy behind group recommendations transparent and help people comprehend how these

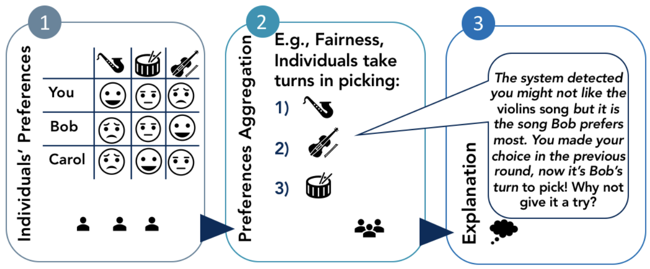

Figure 1: Use case scenario in music domain.

recommendations are generated (see Section 2.2). These strategies and explanations both aim to help users with different preferences reach an acceptable consensus.

2.1 Aggregation strategies

To mitigate the disadvantages of the state-of-the-art aggregation strategies and avail their advantages, we have proposed new aggregation strategies to combine some of the existing aggregation strategies [4]. For example, if recommendations to the group are aggregated based on a single social choice theory function such as Most Pleasure strategy which considers maximum ratings from each user then the recommender system is ignoring the items which a particular user doesn't like. For example, by combining Most Pleasure with Least Misery and Without Misery, we try to ensure that we avoid extreme low ratings, but support extreme high ratings at the same time.

As we mentioned earlier, there is no strategy that outperforms all other strategies in all situations [1]. Therefore, recommending to groups requires a better understanding of group dynamics and other concepts that play an important role in group decision-making processes. I focused on a specific, and yet crucial concept, relationship strength (strong, weak) between group members and will expand these to consider other important attributes in group decision making.

2.2 Explaining for groups in RSs

To study how to best formulate explanations for groups to increase their perceived satisfaction, I proposed two explanation categories (repairing versus reassuring) comparing two scenarios. Repairing category describes the scenario where group members have conflicting preferences. Reassuring category describes the scenario where all group members agree on the recommended item. I evaluated these explanation styles in structured interviews with users (n=16) in terms of user-perceived satisfaction [4].

This paper gave an empirical basis for explaining recommendations to groups in two different scenarios. In the next work, I proposed an automated pipeline consists of two main parts: (1) automatically generating group explanations in the tourism domain by explaining underlying preference aggregation strategies and, (2) crowd-sourcing part which utilizes the wisdom of crowds to improve the quality of the initial proposed explanations in order to increase the satisfaction of users with group recommendations. This allowed us to refine our initial proposed explanations [5].

I also did a study which is under review, to investigate which information people would like to disclose in explanations for group recommendations in the *music* domain especially when group members have conflicting preferences. Intuitively, in high preference divergence scenarios, privacy seems to matter more. We presented a framework which is adapted to users' privacy preferences to (dynamically) generate natural language explanations in the context of group recommendations. The study allowed us to compare users' privacy preferences for different low consensus scenarios, with a high consensus scenario.

Apart from their styles, explanations can be represented in different ways, e.g., as textual representations, or as graphical representations. The most frequent way of presenting explanations is by far Natural language generation (NLG) [1]. I also use NLG techniques to generate explanations in my work.

3 FUTURE DIRECTIONS

I designed several studies with hypothetical recommendations, and held the group size constant. In my next steps, I plan to conduct a user study with a live recommendation setting, with real groups of various sizes.

Besides, based on the findings a further component of "group dynamics" in interaction with both research questions should be added. I plan to study the effects of size of the group, personality and demographics of group members and relationship between group members on selecting the right aggregation strategy and corresponding explanation's style. I will study these in two domains to study the domain effects as well and comparing explanation styles for two domains.

Ultimately, I aim to develop theories and models about which aspects of explanations styles are important and how they tied to different aggregation strategies for groups. The outcome should answer what different factors (e.g. privacy preferences, personality, and group composition) are that we need to consider when we generate explanations for groups.

REFERENCES

[1] Kenneth J Arrow. 1950. A difficulty in the concept of social welfare. *Journal of political economy* 58, 4 (1950), 328–346.
[2] Robin Burke. 2002. Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction* 12, 4 (2002), 331–370.
[3] Judith Masthoff. 2015. Group recommender systems: aggregation, satisfaction and group attributes. In *recommender systems handbook*. Springer, 743–776.
[4] Shabnam Najafian and Nava Tintarev. 2018. Generating Consensus Explanations for Group Recommendations: an exploratory study. In *Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization*. ACM, 245–250.
[5] Vincent Robbemond Soumitri Vadali Shabnam Najafian Nava Tintarev Öykü Kapcak, Simone Spagnoli. 2018. TourExplain: A Crowdsourcing Pipeline for Generating Explanations for Groups of Tourists. In *ACM RecSys Workshop on Recommenders in Tourism*.
[6] Ehud Reiter and Robert Dale. 1997. Building applied natural language generation systems. *Natural Language Engineering* 3, 1 (1997), 57–87.
[7] Nava Tintarev and Judith Masthoff. 2012. Evaluating the effectiveness of explanations for recommender systems. *User Modeling and User-Adapted Interaction* 22, 4-5 (2012), 399–439.
[8] Thi Ngoc Trang Tran, Müslüm Atas, Alexander Felfernig, Viet Man Le, Ralph Samer, and Martin Stettinger. 2019. Towards Social Choice-based Explanations in Group Recommender Systems. In *Proceedings of the 27th ACM Conference on User Modeling, Adaptation and Personalization*. ACM, 13–21.

[1] NLG is a sub-field of artificial intelligence and computational linguistics used for producing understandable texts in English or other human languages from a given set of text or data [6].