Group Dynamic and Group Recommender Systems for Decision Support

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Abstract

Making a choice that equally satisfies all group members is challenging and time-consuming. In fact, group decision making is a complicated and time-consuming process that may involve group members with different preferences and personalities. To deal with this challenge, novel types of group recommender systems are emerging. The main objective of our research is to develop technologies that can help groups to make *justifiable* and *fair* choices, in a short amount of time (*limited costs*). We are therefore addressing three questions related to group recommender systems: (i) how to predict a group choice by leveraging data related to the group dynamic, (ii) how to design a conversational system that can help groups to make better choices, and (iii) how to support groups while the state of the group and the group/system interaction is evolving. We believe that a conversational group recommender system can use the predicted group choice to interact more effectively with the group. But, in order to do that the system should understand the dynamic of the group and in particular how the group preferences evolve during the group discussion. The conversational group recommender system should use this information to support the groups in different *dynamically evolving states*. Our research attempts to address these questions.

Keywords

Recommender System, Group Recommender System, Decision Making, Group Decision Making

1. Introduction

Recommender Systems (RSs) are software tools and techniques that recommend relevant and specific items to each user [1]. These tools have been designed to help people cope with information overload in their individual decision-making (DM) processes. However, there are circumstances in which DM is performed by a group of people, while searching for items that may suit the whole group, like finding a movie to watch with some friends or parents. Groups require some specific support during their DM process. To help such groups, *Group Recommender Systems* (GRSs) have been introduced, with the initial goal to recommend relevant items to a group of people [2].

For several decades, small groups have been the research subject of *social psychologists* [3]. Social psychologists have shown that though two minds are better than one, the group discussion may end up with a wrong decision due to *decisional biases*, *unshared information*, and *groupthink* [4]. A *wrong* decision can be defined as one that does not meet the group expectation [4]. Therefore, groups need some support in their DM process to tackle these problems, whereas

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most of the existing GRSs overlook these problems and they just generate recommendations for items.

GRSs have been proposed to help groups in different domains, like music and movies [5, 6]. But, another limitations of these state of the art applications is related to the fact that group members' preferences are considered to be constant during the DM process. But, as already indicated many years ago by Masthoff et al. [7], group members' preferences and satisfaction can change during the group discussion, before the decision is made. Hence, a group profile should evolve during the discussion, and to successfully support groups, GRSs must take into account *group dynamics* in their methods. Forsyth [4] divides the process of a group DM into four stages: *Orientation* (defining the problem), *Discussion* (conducting a discussion), *Decision* (making a decision), *Implementation* (carrying out the decision).

Hence, to effectively support groups, the GRS should initially create group profiles and, while monitoring the group activity, revise the group members' profiles, based on the members' actions and the new elicited preferences. STSGroup [8] is one of a few applications that monitor the group during the group discussion and support the group members in their DM process. This system exploits short-term and long-term preferences to help groups by recommending relevant items and exploits an aggregation method to rank the items for producing new recommendations. One of the drawbacks of this system is that it supports groups by only suggesting relevant items and recommending one of the suggested items as the group's final choice. Although ranking items and recommending them is important, as explained in [4, 9], recommendations are not the only support that a group requires. Groups need to be helped during *orientation* and *discussion* stages in addition to *decision* stage.

A good choice for a group must have the following criteria (i) *Good outcomes* (minimizing group members' dissatisfaction), (ii) *Limited costs* (shorter time), and (iv) *Justifiability* (explanation of why the choice is good for group) [9]. Additionally, the system should decrease the unfairness of the group choice. Fairness can be defined as the variance of group members' dissatisfaction with respect to an item [10].

In our research[1], we aim at the following goals: (i) to predict a group choice by leveraging data related to the group dynamic, (ii) to design a conversational system that can help groups to make better choices, and (iii) to support groups while the state of the group and the group/system interaction is evolving. Conversational GRSs can use the predicted choice of the group to interact more effectively with groups, for instance, by reducing the candidate set to the items that are not significantly different from the predicted choice, thereby reducing the DM time. Conversational GRSs, in addition to suggesting items in several rounds, can capture the group dynamic and produce new recommendation in each round to increase the group satisfaction. The supporting functionalities of the developed conversational RS should take the group dynamic into account to better support groups. In other words, the provided support should be adapted to the group dynamic for effectively supporting groups.

[1]This paper is a summary of our previous paper [11]

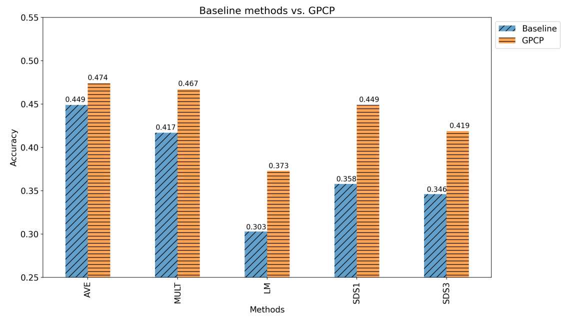

Figure 1: Comparing the ML-based methods accuracies with standard aggregation methos

2. Results and Contributions

In the first step of our research, we propose to use Machine Learning (ML) for predicting the group choice. We note that classical preference aggregation methods (such as Borda count or Copeland rule) can also be used to predict a group choice by first computing group's scores, i.e., a score for each option that represents how much the considered preference aggregation strategy estimates that the option may suit the group. Then, the option with the maximum group score is predicted as the group's final choice. These strategies do not consider the evolution of preferences during the discussion and the effect of the discussion stage. On the other hand, Social Decision Scheme (SDS) theory [12] tries to predict group choice using some basic ingredients: individual preferences, group profile, social influence, and collective responses. This method considers group influence that can happen during the group discussion and predict group choice by taking into account this influence.

In our proposed ML-based method, the system learns (predicts) the social decision schema that determines the group choice by relying on a data set of observed groups discussions and choices (individual preferences for options and final choice of the group). In our approach, the group profiles constructed by one of the aggregation methods and group final choices are used to train a model to predict the final choice of the group. Hence, the group profiles, created by a standard aggregation, are the input of the model, and group choices are the output classes (Logistic regression model). Next, the trained model is used to predict the choice of a new group, when only the individual preferences of the group members are known. This is clearly different from the mechanical application of the preference aggregation methods that aggregate the individual preferences and predict item with the maximum group score as the final choice.

We evaluate our methods using data collected by Delic et al. [13]. This dataset includes 79 groups and 282 participants and contains individual ratings and groups' choices. We found that all our proposed ML-based models perform better than the corresponding baseline strategies (Figure 1). We used three standard aggregation methods and two additional methods motivated by SDS theory to create group profiles: (i) Average (AVE): averaging individual ratings, (ii) *Multiplicative* (MULT): multiplying individual ratings, (iii) *Least misery* (LM): selecting the minimum rating of group members for an option as group score, and (iv) *SDSk*: a group's score for an option is calculated by counting the number of times that item is among the most k preferred one by the group members. Figure 1 shows that for all of the methods, the accuracy of the proposed variants of our choice prediction model (called GPCP, for Group Profile Choice Prediction) performs better than the corresponding baseline method.

3. Conclusion and Future Work

In this research, we aim to address three questions regarding group decision-making and the usage of group recommender systems: (i) how to predict a group choice by leveraging data related to the group dynamic, (ii) how to design a conversational system that can help groups to make better choices, and (iii) how to support groups while the state of the group and the group/system interaction is evolving. Conversational group recommender systems can use the predicted group choice to interact more effectively with groups. Thereby, the system can help groups to reduce decision-making costs (e.g., time). Conversational group recommender systems are conjectured to be better than other approaches in the capability to capture the group's dynamic state, since group members express various types of feedback during their interaction with the system. The supporting functionalities can use this information to help groups in different group dynamic states. In the future, we want to extend our prediction model to be used when we have many options for groups. We also aim to develop a conversational GRS which is able to detect group dynamic. Then, we want to unobtrusively detect important group members' roles, namely, leaders, influencers, and experts. This roles will be used to effectively and efficiently support groups based on the group members' roles and current dynamic state of groups.

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