Combining Long-term and Discussion-generated Preferences in Group Recommendations

Thuy Ngoc Nguyen
Free University of Bozen-Bolzano
Piazza Domenicani 3
Bolzano, Italy
ngoc.nguyen@unibz.it

Francesco Ricci
Free University of Bozen-Bolzano
Piazza Domenicani 3
Bolzano, Italy
fricci@unibz.it

ABSTRACT

In this abstract we discuss how long-term and discussion-generated preferences can be appropriately combined in supporting group decision making. We measure the quality of a group recommendation model by varying the importance given to these two types of preferences in different group scenarios, where the group setting may impact on user's behavior. The results of a simulation experiment illustrate that when users' preferences are not influenced by the group, the preference aggregation model should weigh more the long-term preferences. In contrast, when discussion-generated preferences tend either to align with each other or to diverge due to the group setting, it is beneficial to take into account more the discussion-generated preferences, which help to capture the newly arising interests of the users.

CCS CONCEPTS

• **Information systems → Recommender systems**;

KEYWORDS

Recommender Systems; Group Recommendations; Conversational Systems; Preference Elicitation.

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1 INTRODUCTION

Group Recommender Systems (GRSs) are tools that aim at supporting groups of users in making decisions when considering a set of alternatives [4, 5].

While a considerable amount of research on GRSs has focussed on algorithmic solutions for computing high quality group recommendations on the base of the individuals' preferences, the dynamic aspect of group decision making has been so far explored much less. In fact, researchers in social sciences have pinpointed that the recommendation needs of groups go beyond the bare identification of items that fit the aggregation of individual preferences [5]. In a recent observational study on group decision processes the authors has further shown that group preferences are constructed during the group decision making process [2]. For these reasons, it is necessary to analyse and model the interactions between users and the system, in order to collect preferences emerging in the group discussion and help the group members in reaching a consensus.

In a previous work, we attempted to exploit the user interactions with the system by introducing a group recommendation model that is based not only on individual long-term preferences but also session-based preferences, i.e., the discussion-generated preferences that can be inferred from users' feedback on the considered options, during the group session. The proposed model was implemented in a GRS that provides a chat environment in which a variety of decision support and recommendation functions are integrated [6]. Even though the results obtained from a controlled live user study showed that the proposed system has a very good usability and perceived recommendation quality, the user study itself was inadequate to fully assess the system performance, which requires to be examined in different situations where users are likely to go through in a group setting.

Motivated by this challenge, in the study reported in this abstract, we have designed a generic simulation process to analyze the appropriateness and the efficacy of the proposed recommender while using three different preference combination schemes: when the importance of the long-term and session-based preferences is equal; when a much stronger importance is given to the long-term preferences; and when greater importance is given to the session-specific preferences. These approaches were assessed in three different group dynamics scenarios, which are inspired by the three typical kinds of social impacts on users' behavior [3]: (a) *independence* - the group has no effect on the user preferences; (b) *conversion* - the group setting nudges group members to be more similar to each other; and (c) *anti-conformity* - the group setting pushes the group members to be more divergent. We hypothesize that the more the users disclose their preferences, the better the group recommendations become. Thus, we measure the quality of group recommendations when the amount of elicited preferences grows.

The results of our study show that the proposed model can correctly capture the changes in user preferences, and as more feedback is acquired in the simulated group session, the efficacy of the model raises. Our results show that: in the scenarios (a), a GRS requires less discussion-generated preferences while in the scenario (b) and (c) it must cater for the session-based preferences to faster identify the preferences of the group.

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Table 1: The rank position of the group choice in the recommended ranking list - random groups of 5 users.

	Independence			Conversion			Anti-conformity		
t	$\sigma = 0.1$	$\sigma = 0.5$	$\sigma = 0.9$	$\sigma = 0.1$	$\sigma = 0.5$	$\sigma = 0.9$	$\sigma = 0.1$	$\sigma = 0.5$	$\sigma = 0.9$
1	5.3	3.5	1.3	4.6	2.4	1.6	11	10.8	12
2	4.8	3	1.3	4.5	2.3	1.5	10.3	10.5	11.7
3	3.9	2.6	1	4.3	1.6	1.4	8.3	10.4	11
4	3.2	2.5	1	3.3	1.2	1.4	8.2	10.2	10.2
5	2.7	2.4	1	2.5	1.1	1.3	8.2	9.6	9.8
6	2.5	2.3	1	2.2	1	1.3	7.7	8.8	9.7
7	2.4	1.6	1	1.6	1	1.2	7.1	8.7	9.2
8	2.3	1.5	1	1.5	1	1.1	6.3	8.5	9.1
9	2.2	1.3	1	1.1	1	1	6.1	8.4	8.8
10	2	1.3	1	1	1	1	5.7	8.1	8.5

2 GROUP RECOMMENDATION MODEL

We call $w^{(u)}$ and $w_G^{(u)}$, the utility vector that represents the preferences of user u expressed before and during a discussion of group G, respectively. Utility functions are defined by these vectors and are linear in the features of the items. The vector $w^{(u)}$ is learned by using pre group discussion item ratings and a content-based approach [6]. Next, the system searches for the utility vectors of the group members $w_G^{(u)}$ $(u \in G)$ that satisfy the constraints in $\phi_G^{(u)}$, on the session-based user preferences, and maximize the cosine similarity of these vectors with the vector $w^{(G)}$, which is the aggregated utility vector of the group. Here, $\phi_G^{(u)}$ is the set of constraints on the preferences of the user u inferred from her evaluations of the items discussed in the group discussion [1, 7]. For instance if a user liked an item we assume that the utility of this item for her is larger than the utility of an item that she did not like. The resulting optimization problem is formulated as follows:

$$w_G^{(u)} = \arg\max \cos(w_G^{(u)}, w^{(G)}) \text{ s.t. } w_G^{(u)} \text{ sat. } \phi_G^{(u)} \tag{1}$$

Each user utility vector $w^{(u)}$ is continuously updated by a linear combination of the long term and short term utility vectors (which changes as new session-based preferences are revealed):

$$w^{(u)} = \sigma w^{(u)} + (1 - \sigma) w_G^{(u)}, \sigma \in [0, 1] \tag{2}$$

The final recommended items are generated by using the group model that aggregates the group's members preference models; in our case, we use the *Average* aggregation function.

3 EXPERIMENTS AND RESULTS

We generated groups randomly to simulate heterogeneous groups. Next, we simulated items that the users propose to their group and their evaluations (e.g., liked or disliked) for the proposed items, in the following three scenarios: *independence*, *conversion* and *anti-conformity*. Item proposals and evaluations are simulated by assuming that the users have, while interacting in a group, new utility functions that depend on the scenario. For instance in the conversion scenario the utility functions of the group members are more similar than they were before the discussion. In each scenario, we investigated the effect of the parameter σ (see Eq. 2) on the recommendation quality when the number of proposed items t grows, i.e., when the number of elicited preference constraints increases. We have studied the following cases: $\sigma = 0.1, 0.5$, and 0.9. Note that when larger values of σ are used the recommender weighs more the long-term preferences of the users.

In the *independence* scenario, Table 1 shows that the rank of the group choice in the recommendation list is approaching the top as more items are evaluated (t grows). As expected, the system learns better and better the users' preferences. Moreover, when $\sigma = 0.9$, the recommender can immediately rank the group choice in the top position even with a small number of evaluated items. When $\sigma = 0.5$ and 0.1 the recommender needs more user feedback to rediscover the unchanged user preferences from the group discussion.

In the *conversion* scenario, since the users have more similar preferences, the ranking position of the group choice, when $\sigma = 0.5$ and 0.1, is higher than when the same values are used in the *independence* scenario, but this does not hold for $\sigma = 0.9$. In particular, when $\sigma = 0.9$, the recommender requires the evaluations of at least 5 proposed items from each group member to position the group choice at rank 1.3, while in the first scenario only one discussed item was needed to achieve that rank position.

In the *anti-conformity* scenario i.e., when the group members express preferences that are more diverse, it is harder for the learning process to rank the group choice in the top position. In fact, in this case for all the considered values of σ, the group choice goes below the top 10 (when $t = 1$). In contrast to the first two scenarios, we notice that in this case a smaller value of σ is more effective.

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