Research article

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Supporting Informed Negotiation Processes in Group Recommender Systems

Abstract: Group recommender systems make suggestions to groups of users who want to share experiences or products. Despite their high potential for helping users, GRS face diverse challenges that can be clustered into two groups: predictions and processes. Generating predictions of the goodness of the fit of recommendations to the group has been seen as a core challenge of recommender systems from their beginning, while supporting the processes of discussion for reaching consensus on the item to pick is a more recent challenge. In this paper I report on a base platform for GRS with powerful algorithms for generating and explaining recommendations with high predictions, and an easy and effective process model for GRS.

Keywords: Group Recommender Systems, Prediction, Algorithm

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1 Introduction

Recommender systems (RS) help single users to identify adequate goods or services by offering suitable items from a broad range of alternatives (e. g., suggesting book recommendations to online shoppers). Ricci et al. [16] define the following RS domains: entertainment (e. g., movie or music recommendations); content (e. g., personalised news or Web pages); e-commerce (e. g., book recommendations); and services (e. g., travel service recommendations). They describe the advantages of RS for: 'individuals who lack sufficient personal experience or competence to evaluate the potentially overwhelming number of alternative items' [16, p. 1].

Group recommender systems (GRS) extend the scope to make suggestions to groups of users who want to share experiences or products. O'Connor et al. motivate GRS in their classical paper on the early PolyLens GRS by pointing out: 'A group recommender is more appropriate and useful for domains in which several people participate in a single activity, as is often the case with movies and restaurants.' [15, p. 199]. GRS have the potential to help groups choosing a favourable shared item in two ways: first they can inform a group with a manageable selection of items from a potentially vast amount of items, and secondly they can facilitate the group process of choosing an item from this selection that finds the strongest consent in the group.

Despite their high potential, GRS face diverse challenges that can be clustered into two groups: processes and predictions. Processes reflect the need for concepts for the interaction of group members with each other and with the GRS; examples from the GRS literature are helping group members to arrive at a consensus on the item to choose among the recommended ones [9, 10]; handling social dynamics among group members, offering negotiation mechanisms, and having an adequate user interface [3]; not neglecting usability of the system [13]. Predictions refer to the degree to which the items satisfy all members of the group; relevant aspects from the GRS literature are generating recommendations and aggregating them to group recommendations, presenting recommendations to group members [9, 10]; providing explanations of the recommendations to the group members [3].

This paper addresses both groups of challenges, the group negotiation process, and the predictions that are the foundation of this group negotiation process. In fact, despite the great research in GRS these challenges have been solved—as Salamo et al. rightly point out: 'many group recommenders do not explicitly support consensus negotiation' and 'consensus remains an open issue for group recommenders.' [17, p. 599]. The paper is structured as follows: in the next section I glance at related work, then I present our GroupRecoPF GRS platform, and our AGReMo process model. I show how we verified them. I report on ongoing research with respect to proactive process support. Finally, the last section provides a summary and an outlook.

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2 Background

In the last few years many concepts and systems for GRS have been developed. I first provide some general background of GRS, and then discuss groups and group processes, and finally address predictions of recommendations.

2.1 GRS in General

Amongst the comprehensive surveys of GRS are [10] as well as [12]. Jameson and Smyth [10] identify four domains for GRS: Web and news pages, where groups get Web pages and news items; tourist attractions, where groups who are planning a trip get suggestions or groups who are actually tourists get restaurants or exhibits in museums; music, where music stations or individual songs or sequences of songs are either suggested or played without explicit consent form the groups; and entertainment, where groups get movies and shows on television. Masthoff [12] uses different dimensions to classify GRS, which she specifies as dichotomies: prespecification versus evolution of individual preferences of group members; multiple recommendations to choose from versus one item automatically picked by the system; system aggregation of group recommendations versus user aggregation of recommendations to individual group members; and single item versus multi-item sequence recommendation.

2.2 Groups in GRS

In order to better understand group processes we now have a look at groups and their properties relevant to GRS. Groups in GRS are two or more users who want to receive recommendations that fit all members' preferences. In the GRS different types of groups are distinguished: 'established groups' who are formed explicitly and remain over time (e. g., the members of a fitness club); 'occasional groups' who are formed by a shared short-term interest (e. g., the one-time visitors of a museum); 'random groups' who are formed by change and for a short time (e. g., co-present people in a train station); and 'automatically identified groups' who are generated by the system based on commonalities in individual user profiles [2].

Groups in GRS can have strong effects on members' user experience. Masthoff [12] identifies two main processes based on social psychology. Emotional contagion refers to the fact that persons and their emotional expressions influence each other both in a positive (e. g., a smiling person can make other persons smile) and a negative way (e. g., a crying person can make other persons sad). As a side comment it should be mentioned that the strength of contagion differs between individuals. The second process is conformity and basically means that the members of a group often follow majorities either through normative influence where members adapt their voiced opinions to the opinion of others or through informational influence where the information provided by the group impacts its members' point of view. Other effects from social psychology on group identification, group norms, and social roles are introduced below where I present our work building on [8].

2.3 Group Processes in GRS

Group negotiation processes in GRS mainly start after the system has presented the recommendations to the group and the group members want to reach consensus with each other [9]. Many factors can influence these processes—for instance, a negative example is an individual group member's knowledge of the opinion of other group members that is used to adapt the discussion and voting tactics [18]. So, it is in this phase where the social dynamics happen and guidance during the negotiations is required. As Jameson and Smyth [10, p. 622] point out: 'With individual recommenders, ... the decision process ... typically takes place within the mind of a single person. With a group recommender, extensive debate and negotiation may be required, which may be especially problematic if the members are not able to communicate easily.' and 'Group recommender systems have tended not to provide explicit support for the process of arriving at a final decision.'. Therefore, the authors suggest some mechanisms for GRS to support reaching consensus such as voting one group member who takes the final decision, or specifying a threshold of prediction value over which one is ready to accept the recommendation without debate, or voting and deriving the choice from the aggregated votes.

2.4 Predictions in GRS

In the GRS literature a recommendation's prediction refers to its anticipated satisfaction to the group. The very notion emphasises the fact that RS apply algorithms and heuristics to the data on its items and users in order to arrive at items that might fit the group—without any guarantee of actually fitting. Despite the magnitude of algorithms and heuristics, most approaches fall into two categories: the wide-spread collaborative filtering RS leverage on data on user profiles and preferences and compare items based on these data, whereas the less used content-based RS have data on the features of the items and generate recommendations by comparing features. Some approaches extend collaborative filtering with data on demographics of the users, data on the domain, or data on friends of the users. Hybrid RS combine several approaches into one [16]. In GRS specifically, the system needs to move from recommendations and predictions for individual users to group recommendations and predictions. This can be reached by either aggregating single-user models or single-user predictions. Aggregating user models into a group preference model has some advantages (e. g., less privacy issues, since individual user profiles do not need to be stored), but is less common and not further explored here [10]. For the aggregation of single-user predictions various strategies can be applied, some examples are: plurality voting (i. e., item with most votes is chosen); average (i. e., item with highest prediction value); least misery (i. e., maximises minimum of individual predictions to avoid individual user frustration); and most pleasure (i. e., maximum individual prediction) [12].

The precision of the predictions of GRS depends not only on the algorithms used, but clearly also on the data available that can be processed by the algorithms. Effective and efficient preference elicitation thereby aims at getting the information needed for the algorithms from the users while keeping the users' effort of specifying their preferences to a minimum. This is a particular challenge in GRS, since here the system requires a whole group of users to specify their preferences [14].

So, there is great previous work with respect to group processes and predictions in GRS, but it is insulated. In the next section I present our GRS base platform, which is the foundation of the process model that is introduced afterwards.

3 A GRS Platform as Base Technology

Early on in our GRS research we decided that a generic GRS platform provides us with support for building user-friendly and scalable GRS and allows us to explore alternative prediction and process concepts.

The point of departure was that on the one hand literature shows the advantages of GRS for groups and their performance [10, 12], but on the other hand GRS entail new challenges with respect to base technology. The requirements we identified are two-fold: algorithms, and performance. First, algorithms need to respect the diverse taste of a group in the generation of recommendations. So, a multitude of aggregation strategies that depart from single-users and their preferences and come up with recommendations for groups need to be available [6, 19]. And, secondly, with respect to the performance of the GRS adequate distribution and scalability need to be addressed in the software architecture [5]. Group recommender systems typically have a distributed architecture and need to address scalability of user- and system-generated requests as well as user- and system-triggered use and re-use of sessions.

3.1 Aggregation Strategies of the GroupRecoPF Platform

The algorithms of the GroupRecoPF platform include three standard aggregation strategies, but can also easily be extended with others. The three strategies include two for recommending items to users and one for recommending users to users for company:

Weighted maximum average: the group predictions are the weighted average of the individual user predictions. The item with the highest group prediction is recommended. Here the overall group satisfaction should be high, but individual group members could be disappointed. A more formal description of this strategy is the following (where in the following three formula, M represents the set of movies that are available to the group, with m_j as a specific movie therein; U denotes the set of users in a group, with u_i as an individual group member; the generated user prediction for a given movie and a given user is denoted as the function $p(u_i, m_j)$; the group weight factor w_{u_i} for a user u_i describes the user's influence in the group recommendation generation; and F denotes the set of users on the friend list of a given user, with f_i as a specific friend):

$$\underset{m_j \in M}{\arg\max} \left\{ \sum_{u_i \in U} \omega_{u_i} \cdot p(u_i, m_j) \right\} \; with$$

$$\omega_{u_i} = \frac{w_{u_i}}{\sum_{\omega_{u_k} \in W} w_{u_k}}$$

Weighted maximum minimum: the group predictions are selected as minimal user prediction of all user predictions for each item. The item with the maximal group prediction is recommended. Here individuals do not run the risk of high frustration, but the group's overall satisfaction is not optimised. A more formal description of this strategy is the following:

$$\underset{m_j \in M}{\arg\max} \left\{ \min_{u_i \in U} \left(\omega_{u_i}^{-1} \cdot p(u_i, m_j) \right) \right\}$$

Maximum maximum: the group predictions are selected from the maximal user prediction of all user predictions for each item. The user with the maximal individual predictions becomes the companion recommendation. The group is suggested according to the best overall satisfaction. A more formal description of this strategy is the following:

$$\underset{f_i \in F}{\arg\max} \left\{ \max_{m_j \in M} (p(f_i, m_j)) \right\}$$

Switching between aggregation strategies can be done by means of an integrated graphical editor—so, no programming and no restart is necessary and the chosen strategy becomes active at runtime.

3.2 Performance Optimisation of the GroupRecoPF Platform

The performance of GRS largely depends on efficient request management, because the collaborative filtering approach relies on a huge number of single-user queries that are aggregated. The client-server software architecture of the GroupRecoPF platform optimises client and service requests. Client requests are handled as follows. Unique session containers encapsulate data on the group members, movies, merging strategies, etc. Session containers store these data. All containers can be accessed directly and in parallel. Sessions are kept persistently and can be accessed later (e. g., when users want to browse through the recommendations they received in the past). Consequently, no recalculations are necessary, even if users access the system from multiple devices. Service requests that the server might send to the clients or other servers are multi-threaded and parameterised. Caching mechanisms reduce data traffic (esp. when the server fetches movie background data from outside). A semantic distinction between lifetime caches that are kept without expiration or update, and time-relevant caches that might expire or need a refresh further optimises data handling.

The GroupRecoPF platform provides interfaces to diverse clients. For instance, interfaces to mobile clients provide more aggregated data to optimise the payload, while interfaces to full-fledged desktop applications provide fully detailed data. Standard protocols are supported (i. e., REST/JSON, XML-RPC).

The GroupRecoPF platform is extensively used in our research group in teaching. Our experience shows that, indeed, even undergraduate students who do small research projects in our lab are able to use the platform and build GRS prototypes. The platform allows students to easily demonstrate their ideas for GRS by building GRS on top of GroupRecoPF without profound knowledge of distributed systems.

Details on technical aspects of the software architecture and the functionality of its components can be found in [4].

4 A GRS Process Model for Ad-Hoc Groups and Movies

Based on a thorough GRS literature research—and particularly the challenges with respect to finding consensus on the suggested item to choose in groups—we devised a process model for GRS in the movie domain. The aim was to stimulate the active participation of all group members while keeping the user effort and negotiation time within reasonable limits.

The AGReMo (Ad-hoc Group Recommendations Mobile) process model was conceived to serve as a blueprint for the GRS applications to be developed and to guide developers in the design of the negotiation process. It was devised based on various exploratory GRS prototypes that were informally tested with groups of users.

It consists of three principal phases (cf. Figure 1):

- The Preparation Phase has the purpose of starting the system and providing the data needed to estimate predictions and generate recommendations. The individual group members create personal profiles by rating movies they have already seen. The group then meets and elects an agent who interacts with the GRS for the group (i. e., the assumption is that the whole group meets face-to-face and therefore only needs one GRS client). Then the group can optionally pre-select cinemas and movies in the region, it can also optionally specify vote weights (i. e., the default is that all group members have equal influence on the recommendation generation, but the group can assign stronger weights to a member, for instance, as a courtesy). The agent then requests recommendations, and the system generates group recommendations.
- In the Decision Phase the group gets the recommendations presented with the best prediction on top. The group recommendations are ranked according to the least misery aggregation strategy (i. e., maximising the minimal prediction in the group). The group can check details of each recommendation, and may also have a look at lower recommendations.

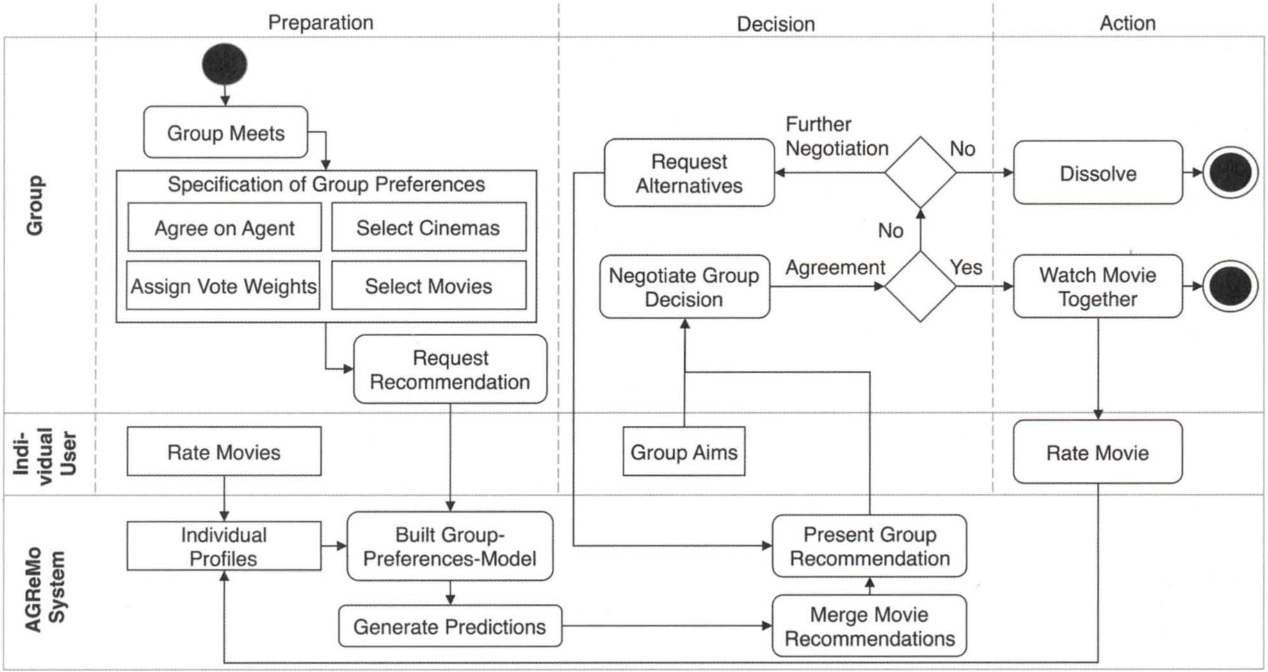

Figure 1: The AGReMo process model. Source: [1].

They can discuss face-to-face and eventually come to a conclusions.

- In the Action Phase the group normally goes to the cinema together and each member is then asked to rate the watched movie to further develop their own profile. The group might also dissolve if no consensus can be reached.

5 Verifying the Process Model

The platform and the process model have been verified in various ways. In particular, we developed an iPhone app to test the platform and the process model, and we also did a through literature study on socio-psychological concepts to corroborate the process model with respect to the group negotiation.

5.1 User Study

In order to test the acceptance of the AGReMo process model, we first conceived a mobile application implementing the processes, and then tested it with users. The AGReMo mobile app was developed for the iPhone according to the standard Apple productivity application guidelines. It is based on an agent approach. The group's agent starts the app and initiates the recommendation process. Various parameters are entered, most of which are optional, so the minimal threshold of receiving recommendations is low, while the ceiling of more intense tailoring is high. Basically, the system suggests cinemas in the area of the users' current position, where the agent can request details of the cinemas and also deselect cinemas the group does not want to go to. The date and time of the start of the movie screening can be entered with pre-defined items of various timeframes (e. g., this evening, today, this week). The agent then formally defines the group in the system by adding users from the friend list. Then recommendations are requested and generated and presented immediately.

The app was tested in a user study. For this purpose, we recruited 15 participants (age between 23–30 years) from a course at our university who received a bonus in the course in compensation. Before the test they needed to build individual user profiles by rating a minimum of 150 movies they had already seen. Informed consent was a pre-condition. During the test, they were randomly assigned to groups of three persons who had the task of agreeing on a movie that they would want to watch together after the negotiation. We first presented the process model, asked them to identify a group agent, and then gave them the AGReMo mobile app. After they had come to a decision, we asked them to fill-in a post-test questionnaire with 15 items on the process model, the actual process, the app, and their skill with touch-based applications.

Overall all five groups came to a conclusion and provided positive comments in the questionnaires. Three groups agreed on the top recommendation, two groups chose an alternative. All groups handled the essential attributes easily—agreement was found quickly. The groups used optional attributes differently: three groups included all cinemas suggested, only two groups excluded some cinemas. No group adjusted the vote weights of its members. All groups looked closely at the movie list. Four groups excluded some suggested movies, while one group just checked the movies included.

All participants commented positively on the general process model and its implementation in the app. We received several comments that pointed out that the recommended movies and the background information provided eased the process compared to a situation where they would have needed to choose a movie without AGReMo support. Participants also addressed the complexity of the process and the information provided and that it is very important for them to get an overview and details upon request. While this is a general human-computer interaction challenge that has been addressed with concepts and principles such as focus and context as well as details on demand, I still think that it is very important for GRS as well.

Several participants addressed performance issues—some had negative comments about the speed of the app. This shows two things. First the app, which was only a proof-of-concept implementation for the user study, was not reactive enough on the client side. Secondly, the point that I made above—describing the platform—about the importance of the performance and scalability of GRS was corroborated.

5.2 Literature Study

Besides the general literature research, the development of the platform and process model and exploration of them in the user study, we did a specific study of concepts from social psychology that influence the group process in a GRS.

Satisfiers and dissatisfiers from Keyton [11] were used as a starting point and matched with core concepts from social psychology [esp. 8]. The three essential concepts derived are group identification, group norms, and social roles.

Group identification can be defined as the individual members' awareness of and attraction to the group with affective (i. e., the process of interpersonal attraction), cognitive (i. e., the process of self-categorisation), and behavioural (i. e., the process of interdependence) components. Group identification in GRS can be positively influenced by making similarities among group members salient. So, for instance, a GRS could compare user profiles and include similarities in its explanation of the recommendations at hand. GRS can also gently remind users of their interdependence—in most negotiations compromise is reached by reminding the parties involved that everybody should give in to some extent.

Group norms can be seen as group members' agreement on thinking and behaviour in the group with aspects such as communication rules. They contribute to the formation of a group identity, and can be descriptive or prescriptive. They include—amongst others—attribute formation in group members' building of beliefs and feelings, as well as communication rules about the group members' social interaction with each other. With respect to making group members aware of group norms multi-client GRS where each user has their own client might monitor individual activity levels and influence users towards balanced activity levels in each group (e. g., give personal hints to passive users).

Finally, social roles can be seen as specific expected behaviour of individual group members. They include, for instance, shared cognition in the form of thoughts, attitudes, knowledge, beliefs, and expectations shared by group members, as well as expertise in the form of competency of individual group members in specific areas. GRS might analyse group members' history and duration and intensity of use of the system and provide friendly background information on this collected expertise (e. g., making the group aware of newbies vs. long-time users).

While all these concepts are important background information when developing fine-grained concepts for the concrete steps to be taken in the consensus finding endeavour, they did not turn into hard design rules or similar. Details were reported in [7].

6 Pro-Active Extension of the Process Model

At the moment we are developing a pro-active extension of the process model, which reflects the concepts from social psychology from the previous sub-section. The basic motivation stems from the literature research and from our own observations of users—in particular, we learned that negotiation processes and GRS have a considerable share of commonalities, but also have individual characteristics. It is our goal to extend the process model towards pro-active support of the negotiation. So, ideally, a GRS would provide recommendations and then monitor the decision process (i. e., the users' input into the system). The GRS could then pro-actively influence the negotiation process—for instance, it might not interrupt users while it has the impression that users are actively using the system, but might pro-actively

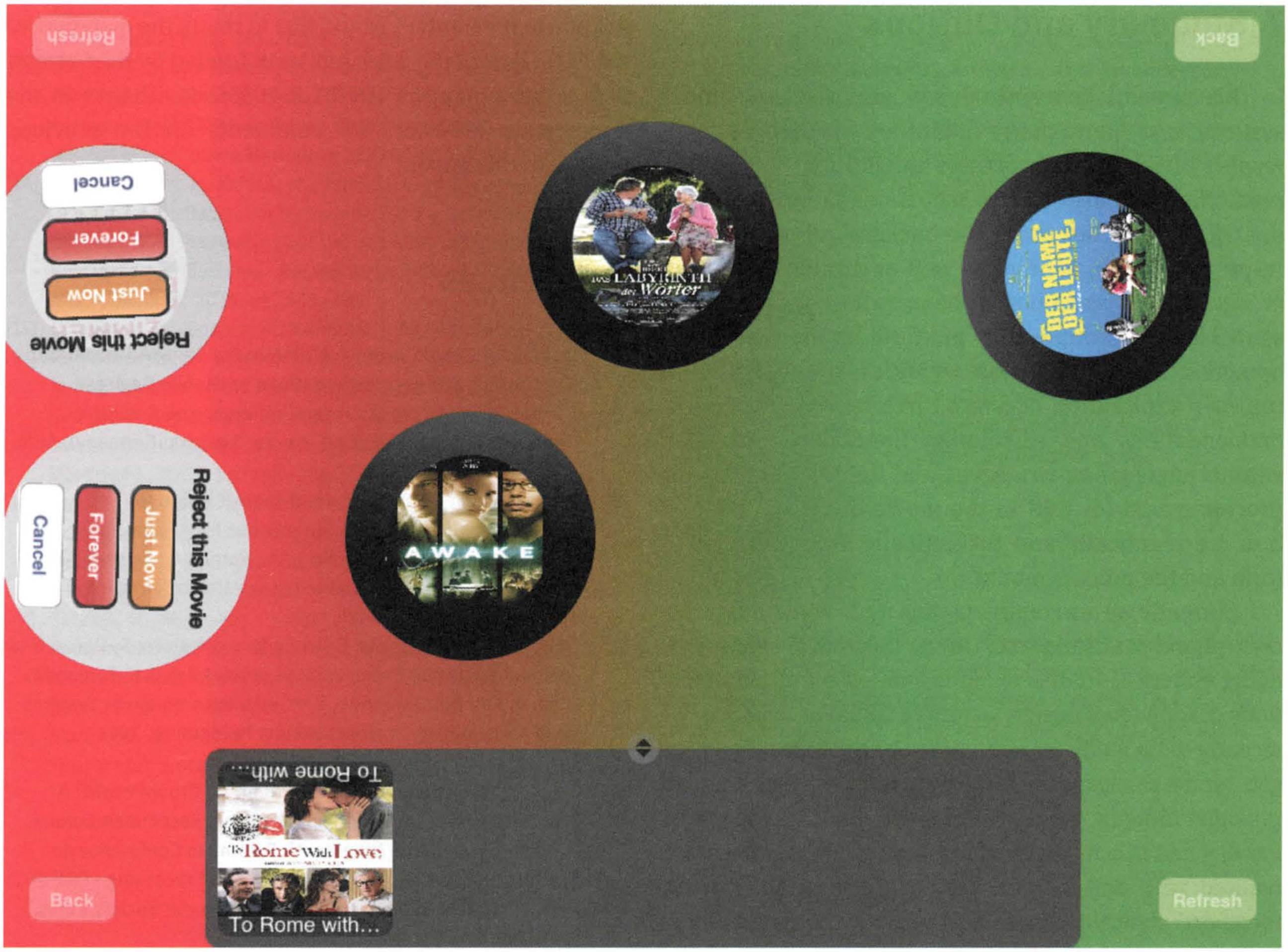

Figure 2: The RecoUIE user interface showing the groups movies on a background from intense green on the right to intense red on the left side; with one favourite movie on the right side, two medium in the centre, two less favourite on the left, and one in the grey bar on the bottom, which means it will be recommended on the next occasion.

provide further information under other circumstances (e. g., more recommendations, or more background information depending on the current state of the negotiation).

As a first step in this direction we built a prototype that simulates pro-active support for a group negotiating movie recommendations for the iPad, where the group shares an iPad on a table and follow the three phases above. Please note that an iPad is used just from matters of practicability of prototyping—in the future, the system might be based on an interactive table. In this RecoUI app (cf. Figure 2) the recommended movies are presented in circles in the centre of the screen and can be moved to the positive green side on the very right, or the negative red side on the very left, or on the grey bar on the bottom to be considered in the next group meeting. The RecoUI has for the first version some very simple hard-coded rules that allow the system to capture the group's current appreciation of the recommended movies at hand: it simply analyses the positions of the movie circles, aggregates the current overall state, and reacts accordingly. For instance, when the group has all of its current movie circles on the left red negative side, the system might pro-actively suggest additional movies. Likewise, if the group has two movies on the green side and has been acting passively for some time, the system might pro-actively provide additional background information on these two most appreciated movies.

The RecoUIE was demonstrated and informally tested on various open house events. Visitors and users liked it and found it easy and intuitive to use. They appreciated that it uses real data of cinemas in the neighbourhood and actual show times. However, as with most systems that follow an approach of active adaptivity, it is clear that users might quickly feel manipulated by the system—so, careful pro-activity needs to be combined with well-thought concepts for making the pro-active behaviour of the system understandable and acceptable to the users. And, it can also be anticipated that many groups will not want to have any type of pro-activity in their negotiation.

7 Summary and Outlook

In this paper I have introduced group recommender systems and particularly identified challenges with respect to the group processes in GRS and aggregated predictions as bases for the recommendations made by the GRS. I have discussed the background of GRS with respect to GRS in general as well as groups and group processes, and predictions. The contributions that I presented are the GroupRecoPF platform for the easy development of usable GRS systems with a special focus on the easy exploration of alternatives for generating recommendations and calculating predictions based on various aggregation strategies, and the AGReMo generic process model for GRS in the movie domain. I showed how we practically and theoretically verified the platform and the process model.

Currently we are continuing this route with further theoretical and practical steps. On the theoretical side we are doing empirical studies exploring the effect of manipulations of individual design factors of GRS. For instance, we recently did a study manipulating the time that the group gets for the consensus finding discussion. Furthermore, we provided different means of communication in the group. Parallel and synchronous voting of all group members was realised with and without feedback on the other group members' choice and with and without the possibility to revise the own choice. On the practical side we are continuing to explore the design space of pro-active mediation of negotiations in GRS, where we basically try to balance positive effects (resulting from actively providing the group with further information on movie descriptions and trailer, further recommendations, etc.) and negative implications (from the interruption caused).

So far, the results primarily apply to the movie domain. Here the groups experience rather easy decisions on single items (i. e., no sequences of items), and the complexity of the items is low to moderate (i. e., small number of parameters that influence the choice), and the investment of users is rather low (i. e., time and money). For the future it would be interesting to explore more complex domains such as GRS in the travel domain with multiple items, high complexity, and high investment.

Finally, the basic assumption underlying most GRS research so far is that group negotiations with GRS support are more effective and efficient than group negotiations without any technical support. It could be tested in a comparative study where in one setting the groups use a GRS, and in another setting the groups do not use one. It might be dependent on the domain and on the background knowledge of the users involved.

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