On the Intrinsic Challenges of Group Recommendation

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ABSTRACT

In group recommendation systems, recommendations may be given to arbitrarily composed groups that may not display any particular characteristics across group members. Since individual recommendation systems can assume that the users' previous behavior is sufficient for coming up with new recommendations, statistical analyses of user logs or user preferences is enough for computing new recommendations with some degree of certainty. Group recommendation systems face a substantially more complex situation, as group members may be so different that no single recommendation seem acceptable and group processes may alter the individual preferences when users discuss their options. This paper discusses some of the intrinsic challenges of group recommendation systems and argue that current approaches to group recommendations only address part of the problem. A framework for analyzing the critical issues in group recommendations is presented and related to common recommendation problems.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]:

Keywords

Group Recommendation System, Group Preferences, Recommendation system

1. INTRODUCTION

Recommender systems have emerged as a significant research area since the mid-1990s. Interest in this research area remains high [1] because on the one hand, the applications explicitly help general users find relevant items and on the other hand these systems are useful in retrieving items that cannot be accessed because users do not know of their existence. Examples of such applications include recommending movies [2, 17], news [9, 15] and books and other products on Amazon.com. Most of these techniques were defined to suggest items or services tailored to individual users' preferences [1]. However, there are situations, when a group of users participate together in a single activity like watching a movie together or sightseeing in the city. For cases like that, we need techniques that address the problem of identifying recommendations to a group of users and trying to satisfy, as much as possible, the individual preferences of all the group's members. Group recommendation [14, 16] aims at identify items that are welcomed by the group as a whole, rather than by individual group members. These groups can vary from established groups, to random groups requiring recommendations only occasionally. The two main strategies for group recommendations are; aggregation of individual preferences into a single recommendation list or aggregation of individual recommendation lists to the group recommendation list [14]. Different aggregation functions such as average, least misery, average without misery have been proposed [16]. Using these strategies, the systems have been able to transfer recommendation techniques for individuals into the realm of arbitrarily composed groups. However, research shows that group recommendation is a far more complex task than individual recommendation, and there are fundamental challenges with groups that prevent these traditional techniques from being efficient on recommending items to groups. In this paper we discuss some intrinsic challenges with group recommendation systems and argue that traditional techniques from individual recommendation systems can only be part of solution to our groups. Section 2 introduces recommendation systems and presents the most common approaches to group recommendation. In Section 3 we explain why group recommendation systems need more complex solutions than traditional recommendation systems, before we provide a classification of enhanced recommendation approaches in Section 4. Section 5 concludes the paper.

2. RECOMMENDATION APPROACHES

In this section, we introduce some related work on recommendation systems for single users as well as approaches to group recommendation.

2.1 Recommendation System

As an increasing amount of data is made available, new technologies are necessary for assisting users in retrieving resources of interest among the overwhelming number of items available. One promising technology for dealing with this information overload problem is the recommendation systems. Recommendation Systems (RSs) are tools and techniques that provide relevant suggestions to users that need some particular data. Examples of such applications include systems for recommending movies [2, 21] and news [9, 7] , as well as built-in functionality in Amazon.com, YouTube, and Netflix. Recommendation systems can be broadly categorized into Content-based filtering and collaborative filtering [6]. In content-based filtering, items are compared and ranked according to similar items that have been rated high by the user, while in Collaborative filtering, systems recommend items that users with similar preferences liked [1] . However, there are different situations, whereby a number of users participate together in a single activity, such as having dinner with family members, watching movies with friends, or selecting requirements to a system. Group recommendation aims at identify items that are suitable for the whole group beside of individual group members. Group recommendation has been designed for various domains such as web/news pages [20], tourism [11], music [8], and TV programs and movies [19, 24], and they provide additional complexity that calls for a reconsideration of traditional recommendation techniques.Traditional recommendation systems are based on three fundamental assumptions:

-**Convergence of user preferences**. Recommending products based on the user's previous behavior requires extensive statistical analyses of the user's logs and other representations of user's behavior. The intention is to recognize behavioral patterns that indicate the user's preferences and interests in particular items. However, if there is no pattern to extract due to non-convergent user interests, the characterization of the user's preferences will be so coarse-grained that no precise matching with item descriptions can be achieved.

-**Simplicity of user and item representations**. Representations of user preferences and items are usually based on very limited sources of information, e.g. representations of earlier items retrieved by the user and simple content characterizations of the items. Still, the assumption is that these representations are sufficient for coming up with appropriate recommendations, without making use of additional information about users and items.

-**Independence of strategy**. Even though there are numerous strategies for individual user recommendation, the assumption is that the chosen recommendation strategy is independent of users and items. This means that all users are subjected to the same strategy, and all items are analyzed independently of other relevant items. Recommendation systems are useful in situations, in which the users do not realize what information they need or are not able to formulate an appropriate query for retrieving the desired information. The question is to what extent the techniques from individual user recommendation are transferable to the realm of group recommendation.

2.2 Group Recommendation Approaches

In this section, the main components of group recommendation system are discussed.

-**Group**. A group may be formed at any time by a random number of people with different interests, a number of persons who explicitly choose to be part of a group, or by computing similarities between users with respect to some similarity functions and then cluster similar users together [18, 3].

-**Aggregation Strategies**. There are two dominant strategies for groups: (1) aggregation of individual preferences into a single recommendation list or (2) aggregation of individual recommendation lists to the group recommendation list [3, 5]. In other words, the first one creates a pseudo user for a group based on its group members and then makes recommendations based on the pseudo user, while the second strategy computes a recommendation list for each single user in the group and then combines the results into the group recommendation list.

In general, the second approach is usually deemed more flexible and offers opportunities for improvements in terms of efficiency [3].

-**Aggregation functions**. This component creates the k highest group-value item recommendation for the group of users G. In other words, the goal of group recommendation is to compute a recommendation score for each item that reflects the interests and preferences of all group members. For group recommendation, a widely adopted approach is to apply some aggregation function to obtain a "consensus" group ranking/score for a candidate item. Different popular aggregation function, namely average and least misery, and average without misery are proposed in [16]. The average aggregation method captures more democratic cases where the majority of the group members are equally important and the decisions made by users are independent and returns the average score. The Least misery aggregation method captures cases where strong user preferences act as a veto (e.g., do not recommend allergic food to a group when a person with allergy belongs to the group). The average without misery captures the preferences of all the group members in the group without these individual that score below a certain threshold δ. The *average* and the *Average without Misery* strategies perform best from the users' point of view [12] because they tend to lead to recommendations similar to those that emerge from group-discussions.

least-misery.

$$relevance(G, i) = min(relevance(u, i)$$

Average.

$$relevance(G, i) = \Sigma(relevance(u, i))/G$$

Average without misery.

$$relevance(G, i) = \Sigma(relevance(u, i))/G$$

where

$$relevance(u, i) >= \delta$$

3. WHY GROUP RECOMMENDATIONS ARE DIFFERENT

As we mentioned in section 2.2 recommending items for a single user have some characteristics which are absent in recommending items for a group of users, and one needs to define a fundamental research direction to keep making progress in the field. In the following the main challenges are discussed.

-**Non-convergence of group's preferences over time**
For a single user, we may safely assume that user logs over time converge into a representation of user preferences. However, group members may not necessarily have a lot in common, their user preferences will most likely not converge with respect to each other. For example, suppose we want to suggest a restaurant to a group of persons who participate in a conference; these persons share an environment in a

particular moment, without explicit food-interests that link them. Even though the system knows about the preference of each single user, the preference of groups may not converge into a representation of groups and we cannot assume that there is one recommendation strategy which satisfies all users' preferences. While in the some settings, like families or a group of friends, groups are very likely to share common characteristics, we may not say that their preferences always converge the same way as single user.

-**User dependencies**.There can be relationships between users in the group. Some users are in some groups the most influential, while other group members have hierarchical relationships. For example, for suggesting a recipe to the family probably the mother has an active and influential role relative to the children. In a hierarchical structure like a company, the president of the company has probable more influence than other employees. In these situations, we need to consider the following question: Do the view of all users have the same weight? Are there particular relationships between users that affect the group recommendation? Are there subgroups that should count as one unit? How can authority relationships be taken into account with respect to this recommendation?

-**User-Item authorities**.This is given by relationships between users and items. For example, suppose one of the members of a travel group who is especially familiar with Norway, expresses a strong preference for a given Norwegian ski resort. In this situation, we may need to take into account the following question: Who has the most recent or most extensive experience with these items? Who has the most experience with item alternatives? So, if some people know more about the items than others the system needs more comprehensive data to find out different user-item authorities.

4. SPECIALIZED GROUP RECOMMENDATION APPROACHES

The analysis from Section 3 indicates that single user recommendation approaches are unlikely to be sufficient in group recommendation systems. Since we cannot assume that preferences converge among group members, the idea of merging users or preferences to turn the group recommendation task into a simpler single user recommendation task, may not satisfactory. In principle, there will not be one consistent user profile or preference that is representative to the group, and there will always be group members that are not accommodated by a particular recommendation. Group recommendation is by nature a more complex challenge than single user recommendation.The intrinsic challenges of group recommendation deal with strategic issues, algorithmic issues, and user and item representation issues. Figure 1 show this high-level framework of Group recommendation. For each of these issues, there have been attempts at formulating more extensive group recommendation approaches that address the shortcomings of current technologies.

-**Strategic Layer**. On the strategic layer, we take into account that the structure of a group may reflect on the group recommendations. Structure is the underlying pattern of stable relationships among the group members. Four key structural components are roles, authority, attraction, and communication. Roles are sets of behaviors that are characteristic of persons in a particular social context; role differentiation, is the various role emergence and are often unique to a particular group; sometimes roles are more individually oriented or group oriented. For example, some people will be happy to follow the preferences of the group members with most experience. Some people may prefer items that have excited some group members, even though the average score may be lower than for other items that did not cause such excitement. Another criteria is authority. Authority Status relations often follows hierarchical or centralized patterns. Attraction focuses on the relationship between the rank and file group members. How this relates to member's attraction for each other and how the attraction is reciprocal. Fritz Heider developed the Balance Theory Attraction, stating that relations in groups are balanced when they fit together to form a coherent, unified whole[13]. For example a two person group is balanced only if liking or disliking is mutual. Furthermore, [4] confirmed that users which are more alike in the group, are more satisfied with the group recommendation. Communication deal with regular patterns of information exchange among members of the group. Like the other forms of structure communication networks are sometimes deliberately set in place when the group is organized. The finding in [23], for example, implies that for smaller groups, the social influence among group members plays a major role in item selection for the group. However, for larger groups, the group consensus aggregated from individual preferences may dominate the group decision. This finding is consistent with our common experience that in activity planning for a smaller group, one or two influencing members may significantly determine the activity venue. On the other hand, for a large group, the social influence from individuals may not have such a strong effect on the entire group.

-**Algorithmic Layer**. There is a wide range of additional data that may be taken into account in group recommendation systems [22] . This may involve the extent of experience of each group member, the recency of each group member's experience or any other statistical data that may affect the recommendation process. For example, [12] shows that groups with strong social relationships tend to maximize the satisfaction of users in the groups, while group with weak social relationships tend to minimize the misery of group members. Similarly, they formalize group disagreement in [3] and study how this disagreement can be resolved as part of the group recommendation computation process.

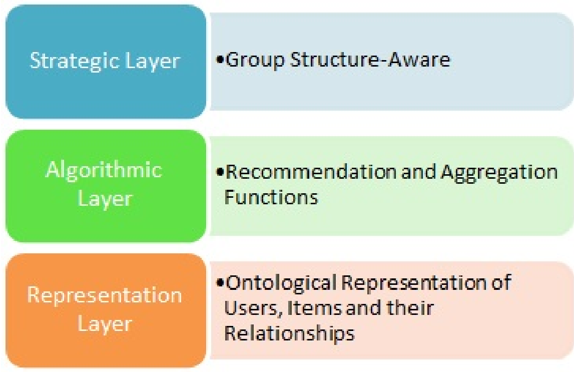

Figure 1: GRecSyF. Group Recommendation System Framework

-Representation Layer. Whereas single user recommendation techniques can be based on automatically created profiles of users and items, it is difficult to fully automate a group recommendation approach that takes into account the relationships among users and items. This information has to be modeled or extracted from other sources and typically constitutes ontologies of users and items. With these ontologies in place, the recommendation system can employ more advanced techniques that combine qualitative knowledge from ontologies with quantitative representations from statistics. For example, even though [10] shows good results with both the Average and the Average without Misery techniques, the quality of the techniques vary with both the domain and group characteristics. The results deteriorate when the volume of data is reduced or the items are classified with a more complex ontology, and the results are also badly affected when group members have rated so many items that there are not enough items left to recommend.

5. CONCLUSIONS

This research attempts to explorer intrinsic challenges of group recommendation systems, including the non-convergence of group preferences over time, user dependencies, and user-item authorities. Non-convergence of group preference refers to the phenomenon that group preferences will most likely not converge with respect to each other and since preferences do not converge, recommendation must not only reflect users' preferences on the item, but also users' preferences on the group decision process. Furthermore, in group recommendation, there are other issues such as relationship between users in the group, relationship between items and relationships between items and users. To address the shortcomings of current technologies, we attempts at formulating a framework for a group recommendation approaches; in this framework we suggest three layers such as strategic layer, algorithmic layer, and presentation layer. Basically, we think the current group recommendation algorithms provide a rather limited point of view and that an approach needs to fit into the bigger picture of group behavioral modeling.

6. REFERENCES

[1] G. Adomavicius and A. Tuzhilin. Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Trans. on Knowl. and Data Eng.*, 17(6):734–749, June 2005.

[2] M. Al-Shamri and K. Bharadwaj. A compact user model for hybrid movie recommender system. volume 1, pages 519–524, 2007.

[3] S. Amer-Yahia, S. B. Roy, A. Chawlat, G. Das, and C. Yu. Group recommendation: semantics and efficiency. *Proc. VLDB Endow.*, 2(1):754–765, Aug. 2009.

[4] L. Baltrunas, T. Makcinskas, and F. Ricci. Group recommendations with rank aggregation and collaborative filtering. RecSys '10, pages 119–126, New York, NY, USA, 2010. ACM.

[5] S. Berkovsky and J. Freyne. Group-based recipe recommendations: analysis of data aggregation strategies. RecSys '10, pages 111–118, 2010.

[6] R. Burke. Hybrid recommender systems: Survey and experiments. *User Modeling and User-Adapted Interaction*, 12(4):331–370, Nov. 2002.

[7] S. Cleger-Tamayo, J. M. Fernandez-Luna, and J. F. Huete. Top-n news recommendations in digital newspapers. *Know.-Based Syst.*, 27:180–189, Mar. 2012.

[8] A. Crossen, J. Budzik, and K. J. Hammond. Flytrap: intelligent group music recommendation. IUI '02, pages 184–185, 2002.

[9] A. S. Das, M. Datar, A. Garg, and S. Rajaram. Google news personalization: scalable online collaborative filtering. WWW '07, pages 271–280, 2007.

[10] I. Garcia, S. Pajares, L. Sebastia, and E. Onaindia. Preference elicitation techniques for group recommender systems. *Inf. Sci.*, 189:155–175, Apr. 2012.

[11] I. Garcia, L. Sebastia, and E. Onaindia. On the design of individual and group recommender systems for tourism. *Expert Syst. Appl.*, 38(6):7683–7692, June 2011.

[12] M. Gartrell, X. Xing, Q. Lv, A. Beach, R. Han, S. Mishra, and K. Seada. Enhancing group recommendation by incorporating social relationship interactions. *Inf. Sci.*

[13] F. Heider. The psychology of interpersonal relations. 1958.

[14] A. Jameson and B. Smyth. The adaptive web. chapter Recommendation to groups, pages 596–627. Springer-Verlag, Berlin, Heidelberg, 2007.

[15] H. Lee and S. J. Park. Moners: A news recommender for the mobile web. *Expert Systems with Applications*, 32(1):143 – 150, 2007.

[16] J. Masthoff. Group modeling: Selecting a sequence of television items to suit a group of viewers. *User Modeling and User-Adapted Interaction*, 14(1):37–85, Feb. 2004.

[17] B. N. Miller, I. Albert, S. K. Lam, J. A. Konstan, and J. Riedl. Movielens unplugged: experiences with an occasionally connected recommender system. IUI '03, pages 263–266, 2003.

[18] E. Ntoutsi, K. Stefanidis, K. Nørvåg, and H.-P. Kriegel. Fast group recommendations by applying user clustering. ER'12, pages 126–140, 2012.

[19] M. O'Connor, D. Cosley, J. A. Konstan, and J. Riedl. Polylens: a recommender system for groups of users. ECSCW'01, pages 199–218, 2001.

[20] S. Pizzutilo, B. De Carolis, G. Cozzolongo, and F. Ambruoso. Group modeling in a public space: methods, techniques, experiences. AIC'05, pages 175–180, 2005.

[21] N. Rattanajitbanjong and S. Maneeroj. Multi criteria pseudo rating and multidimensional user profile for movie recommender system. pages 596–601, 2009.

[22] K. Stefanidis, N. Shabib, K. Norvag, and J. Krogstie. Contextual recommendations for groups. 2012.

[23] M. Ye, X. Liu, and W.-C. Lee. Exploring social influence for recommendation: a generative model approach. SIGIR '12, pages 671–680, 2012.

[24] Z. Yu, X. Zhou, Y. Hao, and J. Gu. Tv program recommendation for multiple viewers based on user profile merging. *User Modeling and User-Adapted Interaction*, 16(1):63–82, Mar. 2006.