Iterative Voting under Uncertainty for Group Recommender Systems (Research Abstract)

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Abstract

Group Recommendation Systems (GRS's) assist groups when trying to reach a joint decision. I use probabilistic data and apply voting theory to GRS's in order to minimize user interaction and output an approximate or definite "winner item".

Research Question and Contribution

People are sometimes required to reach a joint decision. For example, family members who search online for a TV show to watch together or some acceptance committee who needs to jointly choose which applicants to accept.

Recommendation Systems and Social Choice are two domains that address these problems. A group recommendation system (GRS) typically provides recommendations for a group of users considering their specific tastes. In the social choice domain, research in voting theory deals with the similar problem of finding a winner item based on voters preferences (Konzak and Lang 2005). In both domains, it is required to interact with the users to obtain item preferences. Traditionally, it is assumed that an entire list of preferences is required in order to reach a joint decision. In practice, spares rating scenarios are common. Users may wish to state preferences only as necessary, particularly in cases of many available options. Also, bandwidth and communication costs may make it impossible to send all preferences of multiple voters. I therefore aim to keep user interaction at its necessary minimum. Research on GRS primarily focuses on outputting accurate recommendation (Garcia et.al. 2012). Aspects such as group decision making or minimizing communication received little attention. I propose to apply voting theory to GRS in order to determine a "winning item", an item that certainly suits the group.

My research addresses practical vote elicitation by modeling a GRS that uses voting rules to support group decision, minimizes user interaction, and facilitates uncertainty by creating and updating probability distributions. I assume the users preferences are unknown in advance, but can be acquired during the process, i.e., a user queried for her preferences is able to submit them.

There are four general challenges which motivate my work and contribute to the Group Recommender and the Social Choice research fields: The first is **group decision**; most existing GRS's output accurate recommendations to satisfy the group preferences but ignore the group joint decision making process. I believe that an important added value to a GRS would be an interactive process that helps the group to reach a final satisfying joint decision with minimal interactions. I propose to accomplish this by employing voting rules based on methods from the social choice domain. The advantage of voting rules lays in the fact that the rules guarantee a definite winning item. Thus I do not output a recommendation in the traditional sense, i.e. an item with some winning probability and some error margin, but rather output a definite winner, i.e., an item which certainly fits the group's preferences. The second challenge is **uncertainty**; most previous studies do not consider probabilistic knowledge of the distribution of the users' preferences for the items. I propose to use probabilistic knowledge to select the next user-item query pair, i.e., to query a certain user for his rating for a specific item. Probabilistic knowledge may not be a common assumption, but is important when attempting to reduce communication. I present an algorithm for estimating probabilistic knowledge so as to demonstrate the feasibility of the assumption. The third challenge is **communication cost-sensitive elicitation of preferences;** I aim to minimize the number of user-item queries and thus reduce communication costs. The last challenge is **repeated system usage**; a tradeoff exists between eliciting preferences that will lead to a recommendation of good quality now vs. repeated future recommendations. I propose to use active learning methods in order to develop a model that is useful for future recommendations as well as a standalone recommendation.

Related Work

Predefined probability distribution of the votes is assumed by Hazon et al. (2008). They evaluate the winning probability of each item in different protocols and show theoretical bounds for the ability to calculate the probability of an outcome. Bachrach et al. (2010) compute the probability of an item to win. Both papers focus on calculating an item winning probability, while I focus on practical vote elicitation, i.e., finding a winner using a minimal amount of queries. To the best of my knowledge, only Lu and Boutlier (2011) tackle vote elicitation using a minimal amount of queries. However they do not assume or use the probability vote distribution.

In the recommender domain, few papers have dealt with uncertainty (McCarthy et al. (2006) and De Campos et.al (2009)). None dealt with minimizing user interaction or with updating the user distribution. Koren and Sill (2011) propose a framework for finding probability distribution, which is used for rating prediction but not for preference elicitation. Their method is not updated when new ratings are revealed.

Research Plan

In (Naamani-Dery et.al 2010) I presented algorithms for practical voting elicitation. I focused on Range voting, where users assign items a rating within a specified range. The ratings for each item are summed, the winner being the item with the highest score. Range voting is relevant in existing recommender systems applications where users rate items within a specified range (e.g., Netflix).

Computing the optimal minimal set of queries that are required to determine a winner is computationally intractable, due to the combinatorial space of queries orders. Thus I proposed two heuristic approaches to address this challenge. Both approaches proceed iteratively, querying a selected user-item pair. To determine a user-item pair, the first algorithm heuristically computes the information gain of each potential query based on the entropy of the probability of the items to win. The query that maximizes the information gain is selected. The second algorithm uses the user's probability distribution to select the item most likely to win and the user that is expected to maximize the score of that item.

Experiments on a simulated meeting schedule domain and on real-world Netflix contest dataset show that the algorithms saves much communication while guaranteeing that a winning item will be found. On Netflix dataset the communication cost can be cut by more than 50%.

Currently, I have developed an algorithm for dealing with uncertainty. The algorithm computes a nonparametric probability distribution for each user's preferences of items. It then updates the distribution as new information is revealed. I have also extended my published work to the Borda voting protocol. The advantage of Borda is that users rank their preferences instead of rating items, which is sometimes an easier task for the user.

My future work plan consists of two steps. Step 1 includes approximating a winning item; there is a tradeoff between (1) finding the optimal winner and thus having an accurate result and (2) the number of queries needed for this process. I wish to study the correlation between user interaction and the winner approximation accuracy. Step 2 includes the development of an active learning algorithm; the goal of active learning is to effectively acquire the most informative rated items from users (Jin and Si 2004). I wish to extend this definition to GRS's: both users and items are actively selected, the goals being: (1) to improve the recommender model for future recommendations and (2) to further establish the current model hypothesis for a better current recommendation.

References

Bachrach Y., Betzler N., Faliszewski P. 2010. Probabilistic possible winner determination. In *Proceedings of 24th AAAI*.

de Campos, L., Fernández Luna, J., Huete, J., Rueda Morales, M. 2009. Managing uncertainty in group recommending processes. *User Modeling and User Adapted Interaction* 19:3:207 242.

Garcia, I., Pajares, S., Sebastia, L., Onaindia, E. 2012. Preference elicitation techniques for group recommender systems, *Information Sciences*, 189:155 175

Hazon, N., Aumann, Y., Kraus, S., and Wooldridge, M. 2008. Evaluation of election outcomes under uncertainty. *In proceedings of 7th AAMAS*, Richland, SC.

Jin, R. and Si, L. 2004. A Bayesian approach toward active learning for collaborative filtering. In *Proceedings of the 20th UAI,* AUAI Press, Arlington, Virginia, 278 285.

Konczak, K., and Lang, J. 2005. Voting procedures with incomplete preferences. In *Proceedings of 19th IJCAI Workshop on Advances in Preference Handling*.

Koren, Y. and Sill, J.. 2011. OrdRec: an ordinal model for predicting personalized item rating distributions. In *Proceedings of the 5th Recsys*. ACM, New York, NY, USA.

Lu T. and Boutilier C. 2011.Robust Approximation and Incremental Elicitation in Voting Protocols. In *Proceedings of the 22nd IJCAI,* Barcelona, Catalonia, Spain.

McCarthy, K., Salamó, M., Coyle, L., McGinty, L, Smyth, B., Nixon, P. 2006. Group recommender systems: a critiquing based approach. In *Proceedings of the 11th IUI*. ACM New York, USA.

Naamani Dery, L., Kalech, M., Rokach, L., and Shapira, B. 2010. Iterative voting under uncertainty for group recommender systems. In *Proceedings of the 4th.* ACM, New York, NY, USA.