On group recommendation supported by a minimum cost consensus model

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Group recommender systems (GRSs) have recently attracted the attention from researchers and industry. They focused on recommending items which satisfy the global preferences of a group, being TV programs and holidays packages typical examples of these scenarios. Although there have been established several basic approaches for GRSs, it has been also identified the limitation about dealing with conflicts about the recommendation within the groups and hence, the necessity of managing in a deeper way the consensus among the group members to improve the agreed satisfaction of the recommendations. The current contribution is focused on proposing the application of the minimum cost consensus model in the GRS scenario for achieving such objective. A case study will show that this consensus model positively influences the groups' satisfaction about the recommendations.

Keywords: Group recommender systems; minimum cost consensus reaching; recommendation performance.

1. Introduction

In the last few years, recommender systems (RSs) have become a necessary tool in several online scenarios to overcome the burden associated to overloaded search spaces, by providing users with the items that best fit their preferences and needs.[1] Therefore, RSs are frequently used in several domains such as e-commerce, e-learning, e-services, tourism, and so on.[2]

Furthermore, there is an important set of items, so called social items, which are usually consumed by a group of users and not by an individual. TV programs and holidays packages are clear examples of these kinds of items, where individual interests of the users in the same group can differ. In order to generate suitable item recommendations in these scenarios, group recommender systems (GRSs)[3,4] have recently attracted the attention from researchers and industry to recommend items which satisfy the global preferences of the group.

Specifically, the group recommendation task[3] has traditionally been performed using two main approaches as a extension of the individual recommendation task: (i) the rating aggregation approach, where individual's preferences are combined to obtain a unified profile that represents the group preference, and (ii) the recommendation aggregation approach, in which individual recommendations are generated at first and afterwards they are aggregated to obtain the final recommendation list.

Although these approaches have been extensively used in the last few years,[3,4] some recent works[5] have pointed out that it is necessary the development of researches beyond these basic aggregation approaches, because just aggregation could generate loss of information and biased recommendations, obtaining in turn low group satisfaction with recommendations. Therefore the study of managing the agreement among groups' members can improve group recommendations.

This contribution is focused on such an objective, by exploring the effect of applying a minimum cost consensus reaching model over the individual user preferences, that would obtain agreed group recommendations. Our aim is to process the individual user needs in a direct way, reducing the set of possible agreed recommendations by using the Borda voting system[6] and then limit our analysis to the recommendation aggregation approach.

The paper is structured as follows. Section 2 shortly reviews the necessary background on GRSs and consensus reaching process, regarding the current contribution. Section 3 presents an approach to integrate the mentioned consensus model in the GRS framework, which is evaluated in Section 4. Section 5 concludes the paper.

2. Background

This section briefly presents the necessary background for the development of the current research work. It is focused on GRSs, the Borda Count, and the Minimum Cost Consensus Model.

Group recommender systems, on its basic approaches, extend RSs for targeting recommendations to group of users ($G = \{g_1, ..., g_m\} \subseteq U$). Formally, GRSs focuses on finding the item (or set the items) that maximizes the preference predicted for the group of users:

$$Recommendation(I, G_a) = arg \max_{i_k \in I} Prediction(i_k, G_a) \quad (1)$$

There are two main approaches for group recommendation, supported by single user recommendation:[3]

- *Rating aggregation:* It is based on the creation of a pseudo-user profile that aggregates the preference of the group. This profile is used as the final target user for generating recommendations.
- *Recommendation aggregation:* It aggregates the individual recommendation list associated to each member, into a new recommendation list targeted on the group.

Borda count:[6] This well-known voting system in social choice computes a mapping from a set of individual ranking list associated to experts, to find a combined ranking of such lists. Specifically, each ranked item obtains 0 point for each last place vote received, 1 point for each next-to-last place vote, and so on, receiving M-1 points for each first place vote (being M the number of items). At last, items are downwardly ranked according to the sum of all associated ranks provided by each expert. Some of Borda count's advantages are its easy implementation, its intuitiveness, and its low computational cost.

Minimum cost consensus model:[7] This model is focused on minimizing costs associated to the modification of the independent experts' opinions to reach a consensus. Such minimum cost is obtained by solving a lineal programming model[8] (Equation 2).

$$\begin{cases} min \sum_{u=1}^{n} c_u |\bar{o_u} - o_u| \\ s.t. \bar{o} = \sum_{u=1}^{n} w_u \bar{o_u} \\ |\bar{o_u} - \bar{o}| \leq \epsilon, u = 1, 2, ..., n \end{cases} \quad (2)$$

The parameters involved in this model are:

- c_u: the cost of modifying the preferences of the expert u.
- o_u: the initial preferences of the expert u.
- $\bar{o}_u$: the final preferences of the expert u, after consensus reaching.
- $\bar{o}$: the collective preferences of the group of experts.
- ϵ: the maximum possible distance between collective and individual preferences.
- w_u: the weight of the expert u.

3. Minimum Cost Consensus in Group Recommendation

The use of the minimum cost consensus model in the context of group recommendation, to reach a higher consensus level in the final recommendations and improve the recommendation acceptance, consists of the following phases: (i) Individual recommendation generation, (ii) Borda count-based ranking, and (iii) Minimum cost consensus analysis.

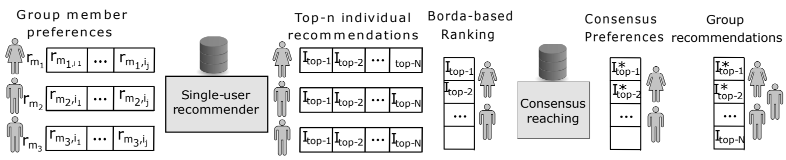

Fig. 1. General scheme of the proposal.

Individual recommendation generation: This phase computes the individual recommendations for each group's member. Here, it is applied a typical collaborative filtering recommendation approach to obtain such individual's recommendations. In our case study it will be considered the user-user and item-item neighborhood-based collaborative filtering approaches, [9] although any individual recommendation approach could be used in this scenario.

Borda count-based ranking: The Borda count-based ranking is applied here to shorten the possible set of recommended items that will be used in the consensus phase to reduce its computational cost. Therefore, only the top-k ranked common items according Borda will go to the consensus phase, to apply the minimum cost model over the individual's recommendations about these items.

The Borda count is applied to each group's member, and its individual ranking is obtained by downwardly sorting items according to the individual rating prediction performed in the previous step. Assuming that

$rank(i, R_u)$ returns the position of the predicted rating over the item i in the downwardly sorted list R_u of preference predicted for each user u member of the group G, then the average rank of i in the group G is formalized as follows:

$$Rank_i = \sum_{u \in G} rank(i, R_u). \tag{3}$$

Considering the downwardly sort list I of items according to $Rank_i$, and j the item at position k in such list, then the top-k ranked common items would be formalized as:

$$Top_k = \{i | \forall_{i \in I} Rank_i \leq Rank_j\}. \tag{4}$$

Minimum cost consensus model: This model is applied to the top-k common items obtained in the previous step. This phase receives individual's prediction values, and adjust the group recommendation to reach the consensus. As final output, the model recommends those items with highest agreed value to the group's members.

Specifically, the minimum cost consensus model is computed independently for each item i, considering the following assumptions for translating the consensus model notation into the GRS scenario:

- $\forall_{u \in G}(o_u = r_{ui})$ (each user preference on i is the expert's u opinion on i)
- $\forall_{u \in G}(c_u = 1)$ (the cost of modifying preferences of u is always 1)
- $\forall_{u \in G}(w_u = 1/n)$ (the expert's u weight is always $1/n$, being n the number of experts)
- $\epsilon = 0.2$.

The collective opinion $\bar{o}$ associated to each item i (see Equation 2) is considered as the group's preference prediction over such item.

4. Case Study

This section presents a case study developed over the well-known Movielens 100K recommender systems dataset[a] for evaluating the effect of applying the minimum cost consensus model in the final recommendation generation. Specifically, it is composed of 943 users, 1682 items, and 100000 ratings. The rating scale is in the range [1,5].

[a]https://grouplens.org/datasets/movielens/

In a similar way to previous works in GRS,[3,4] the group formation technique used is a random selection. Furthermore, a 20% item holdout is applied as validation technique, which is adjusted to be used in the GRS scenario by selecting the 20% of items evaluated by the current group as the test set, and the remaining ones as training set. Finally, Mean Absolute Error (MAE) and Area Under the receiver operating characteristic Curve (AUC)[10] are used as measures to evaluate the recommendation performance.

In the current case study, we focused our analysis in groups composed of five members, leaving to future works the evaluation with larger groups. In addition, the memory-based user-user (UKNN) and item-item (IKNN) collaborative filtering approaches are used as basic individual user recommenders,[9] needed in the phase 1 of the proposal.

We evaluate five group recommendation strategies to evaluate our proposal:

- *Cons Top-10:* It applies the minimum cost consensus model over the top-10 common items according to the Borda ranking, and obtains the final agreed rating value. For the rest of items, the aggregated value is obtained through the Mean aggregation strategy.
- *Cons Top-50*: The same strategy, but using the consensus model over the top-50 items.
- *Cons All*: It obtains the final agreed rating value through the minimum cost consensus model for all common items, disregarding the Borda ranking.
- *Mean*: It obtains the final aggregated rating value using the Mean aggregation strategy for all items.
- *Least Misery*: It obtains the final aggregated rating value using the Least Misery aggregation strategy for all items.[3]

For all cases, using the minimum cost model, consensus was reached in the optimization model.

Tables 1 and 2 present the performance associated to the five group recommendation strategies, according to AUC and MAE performance metrics. For both AUC and MAE measures, the best behavior was obtained for Cons Top-50 in the case of the UKNN individual recommender, and for Cons Top-10 in the case of the IKNN individual recommender. Globally, in the case of MAE the Least Misery strategy performs particularly worse. Another interesting finding was that for all cases the application of the consensus reaching only at some top-k ranked items according Borda, always leads to better performance in relation to the application of the consensus reaching to all items data.

Table 1. Evaluation results according to AUC. Larger values indicate better performance.

	Cons Top-10	Cons Top-50	Cons All	Mean	Least Misery
UKNN	0.6423	**0.6451**	0.6442	0.6428	0.6251
IKNN	**0.5576**	0.5498	0.5440	0.5527	0.5494

Table 2. Evaluation results according to MAE. Smaller values indicate better performance.

	Cons Top-10	Cons Top-50	Cons All	Mean	Least Misery
UKNN	0.7744	**0.7737**	0.7740	0.7742	0.8684
IKNN	**0.7969**	0.8032	0.8069	0.7995	0.9171

Overall, the performance values show that the consensus model could influence the GRS behavior, and that it could lead to the improvement of the recommendation performance. Further work will do a deeper exploration of the relation between the nature of the GRS data and the consensus reaching process to get a better justification of the obtained performance. Other consensus reaching models will be also explored.

5. Concluding Remarks

This paper introduced the use of the minimum cost consensus model in the GRS scenario. It is presented a case study that verifies that the proposal leads to a better recommendation accuracy in GRS. Our next future research will focus on the study of alternative consensus reaching models to be used in this scenario.

Acknowledgments

This research work was partially supported by the Research Project TIN2015-66524-P, a Scholarship for Young Doctors (2017) provided by the Advanced Center for Information and Communication Technologies at University of Jaén, Spain, and the Spanish FPU fellowship (FPU13/01151).

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