Group Recommender Systems-Evolutionary Approach Based on Consensus with Ties

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Abstract The issue regarding aggregation of multiple rankings into one consensus ranking is an interesting research subject in a ubiquitous scenario that includes a group of users. For minimizing the fitness value of Kendall tau distance (KtD), the well-known optimal aggregation method of Kemeny is used to generate an aggregated list from the input lists. A primary goal of our work is to recommend a list of items or permutation that can effectively handle the problem of full ranking with ties using consensus (FRWT-WC). Additionally, in real applications, most of the studies have focused on without ties. However, the rankings to be aggregated may not be permutations where elements have multiple choices ordered set, but they may have ties where some elements are placed at the same position. In this work, in order to handle problem of FRWT in GRS using consensus measure function, KtD are used as fitness function. Experimental result are presents that our proposed GRS based on Consensus for FRWT (GRS-FRWT-WC) outperforms well-knows baseline GRS techniques. In this work, we design and evolve an innovative method to solve the problem of ties in GRS based on consensus and results show that efficiency of group does not certainly reduce in which the group has similar-minded user.

Keywords Group recommender systems · Rank aggregation · Genetic algorithm · Kendall tau distance · Consensus

1 Introduction

Recommender systems (RSs) have evolved as a phenomenal mechanism which skillfully manages data excess issue which is generated by unmatched development of amenities accessible on the web. However, the most RSs [1] produce recommendations for single users, in many situations, the selected items (e.g., movies) are used by group

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of users. There has been much work done in group recommender systems (GRSs) with full ranking but full ranking with ties (list of items is ranked not clear) still remains a challenge [2, 3].

A recommendation system generates an item suggestion to a user focused on a study of interests. Such study is instructively developed from the single profile [4], built from the individual item evaluation made by this user, based on this interest profile [5]. For an example [6], situation related to recommendation for group's are-recommending repertories of songs for group of friends or online people, recommending a restaurant for group of people, a travel destination for family and movies for group of friends [7, 8].

Rank aggregation (RA) approach is being conveniently used in the domain of GRSs for aggregating group of users rankings [9]. Further, in actual approaches, the rankings which have to be aggregated are strictly ordered, but they do have ties explained in [10], where some elements are placed at the same position [1].

There is in GRS in general unique solution is not possible so optimization technique will be used [2]. And the genetic algorithm (GA) along with correlation is used to provide recommendations to the user. Optimization is the process to find that point or set of points in the search space and to making something better. The set of all possible solutions or values which the inputs can take make up the search space [11].

In specific circumstances where groups are formed randomly and thus the chances for heterogeneous random group results into consensus agreement failure.

Specifically, [12], this paper describes the notion of consensus measure which consists of two components, group ranking (Gr) and average pairwise dissimilarity (APD) between users for an item, and each of candidate item produce a single recommendation scores, higher the score means that items is for that particular group is highly consensus item and priority of that item should be first [13].

Section 2 reviews recommender systems for group ranking with ties and consensus strategy. In Sect. 3, we define formally the problem of recommendation for group ranking with ties and present an illustrative example of the functioning of the approach to a small number of users in a group; Sect. 4 discusses experimental results using consensus; and Sect. 5 finally shows some concluding states and future work.

2 Background and Related Work

Given a domain of choices (like books, movies, or CDs), user can express his preferences by ranking these choices, thus ranking serve as an approximate representation of users preferences, and the recommender system will match these rankings against rankings suggested by all other users.

There exist approaches [12, 13] which make use of consensus mechanism to reach a final item recommendation strategy accepted by the all users of group; recently, these approaches have also been called borderline and role-based strategy consensus used in Travel Decision form Collaborative Advisory Travel System [5].

A consensus ranking is not necessarily optimal solution of the problem; when a solution is optimal, it is explicitly signify as an optimal consensus. Different kinds of groups affect the way users evaluate the result of the adopted aggregation strategy.

2.1 Full Ranking with Ties (FRWT)

Full ranking means all users give their preferences for all the items in a group [10, 14]. It can be ties or without ties. A tie means a user give same preference of two items in a list so that items not clearly preferred to other. In this work, we expand a computationally efficient framework for ranking data which have same preference for more than one item. The framework starts by considering full ranking with Ties (FRWT) and for that we evaluate well-known notion of metrics, namely Kendall tau distance (KtD) [15].

Let σ, τ be two ranking with domain D and G = {{i, j}| i $\neq$ j and i, j D} be the set of district pairs of discrete elements. The Kendall tau distance will be equal to the number of exchanges needed in a bubble sort to convert one list of items to the other [2, 13].

2.2 Genetic Algorithms (GAs)

The genetic algorithm (GA) is based on a set of feasible resolution of the optimization problem which is needed to be solved. The representation of the candidate solution plays a Euclid role as it determines which genetic operators are to be employed. That represent a solution of the optimization problem, which we want to solve [11, 16].

They can be represented by the sets of symbols or the list of values for the continuous values, they are called as vectors. In case of combinatorial problems, the solutions often consist of character that appears in a list [17, 18]. Following are the pseudocode for genetic algorithms [19]:

1. Initial population,
2. Crossover and mutation,
3. Fitness computation,
4. Go to step 2 **until** population complete,
5. Selection of parental population, and
6. **Go to step 2 until** termination condition.

2.3 Consensus Measure (CM)

The goal of consensus measure (CM) in GRS is to compute a group ranking (Gr) for every item that reflects the interests and preferences of all members of the group. A CM for every item needs to be carefully represented because, in general, members of group may not have the same tastes [3, 4]. Intuitively, there are two main aspects to the CM which are as follows:

Average Pairwise Dissimilarity (APD). The dissimilarity of a group of user U over an item i, denote dis (U, i), indicate the score of consensus in the ranking score for item i among group members. We consider the following dissimilarity consensus methods:

$$dis(U,i) = \frac{2}{|U|(|U|-1)} \sum (|r(u,i) - r(v,i)|) \tag{1}$$

where r is ranking of user u and v for item i, and u $\neq$ v where u, v $\in$ U.

Group Ranking (GR). The ranking of an item i to group of user U, denoted Gr. There are several rank aggregation strategies used in group recommendation to aggregate the group rating.

Average. In this aggregation strategy for item i, the group ranking (Gr) is calculated as the average of the predicted ranking for the group of user U.

$$Gr(U,i) = \frac{1}{|U|} \sum (r(u,i)) \tag{2}$$

Least Misery. In this aggregation strategy for item i, the Gr is equal to the smallest predicted ranking in the group for i.

$$Gr(U,i) = Min(r(u,i)) \tag{3}$$

Most Pleasure. In this strategy for item i the Gr is equal to the largest predicted ranking for i in the group.

$$Gr(U,i) = Max(r(u,i)) \tag{4}$$

Borda_count. In this Strategy for each user u_j, the item with the highest satisfaction gets the rank 1, the next product gets rank 2, however, the satisfaction level of the two products are equal, and the rank values are averaged and then assigned to both the products.

$$Gr(U,i) = \sum_{j=1}^{m} (rank_{uj}^{i}) \tag{5}$$

The consensus measure function, symbolized CM (U, i), combines the group of users ranking Gr and the group dissimilarity of i for U into a single group recommendation score using the following fitness function for consensus measure (CM):

$$CM(U, i) = w_1 * Gr(U, i) + w_2 * (1 - dis(U, i)) \quad (6)$$

where w_1 and w_2 denote the relative importance of preferences and dissimilarity in the final decision, $w_1 + w_2 = 1$. Here, these two values for w_1 and w_2 (0.8 and 0.2, respectively) are chosen after observing the data that we have collected from our experiment [3].

So not only are the results stable across groups of different sizes for a single consensus list of recommended items but they also calculate the effectiveness of group of member using normalized discounted cumulated gain with different rank aggregation strategies [3].

3 Proposed Consensus-Based Recommendation

Consider a set G of all groups with at least two members that may be formed by group of users U. Consider, finally, $U \in G$ and |U| defined as the number m of group members U. If for instance, a group consists of user u_1, u_2, u_3, thus this can be expressed as $U = \{u_1, u_2, u_3\}$ and |U|.

Step 1. Group Generation.

First, we initiate synthetic groups of various set of different sizes [3]. We want to check the performance of proposed strategies change with varying group size. We randomly generated several groups and selected those set of groups which have ties with randomly generated different proportions. We have chosen a group with different data sets.

Let us consider a set of group of m users and n items.

$$\mathrm{U} = \{u_1, u_2, \ldots\ldots.u_m\}$$
$$\mathrm{I} = \{i_1, i_2, \ldots\ldots\ldots, i_n\}$$

Matrix on full ranking with ties is defined as follows:

item =	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}
u_i =	4	9	8	9	7	9	6	9	3	8
u_j =	10	5	2	7	9	7	5	6	7	6

Step 2. Fitness Function for GRS-FRWT (Sum-KtD).

The GRS problem is now to select group of n similar users and 15 items. We have to compare these matrix with full ranking with ties using fitness formula that is Kendall tau distance (KtD) that satisfies n users optimally.

Fitness Function. Let $\sigma\, and\, \tau$ both are full rankings with ties. Here, the fitness function is the *minimum sum of distance offer* which represents the sum of the distance for each individual in the group. We have to find the offer which is having minimum sum of the distance. In order to generate such an offer, sum of Kendall tau distance (Sum-KtD) formula is used. Similar to our definition we have to calculate KtD for every $\sigma\, with\, \tau_1, \tau_2, \ldots\ldots \tau_m$.

If $\sigma(i) \geq \sigma(j)\; and\; \tau(i) \geq \tau(j),\; or\; \sigma(i) \leq \sigma(j)\; and\, \tau(i) \leq \tau(j),\; than\, Ktd = 0.$

And If $\sigma(i) > \sigma(j)\; and\; \tau(i) < \tau(j),\; or\; \sigma(i) < \sigma(j)\; and\, \tau(i) > \tau(j)\; than\, Ktd = 1.$

And if $\sigma(i) \cong \sigma(j)\; and\; \tau(i) = \tau(j),\; or\; \sigma(i) = \sigma(j)\; and\, \tau(i) \cong \tau(j)$ than Ktd =0.5

Based on these cases, the *Kendall tau distance* is estimated as follows:

$$KtD(\sigma, \tau) = \sum\nolimits_{\{i,j\} \in \mathcal{P}} \bar{k}_{i,j}^{(p)}(\sigma, \tau) \tag{7}$$

$$\sigma = 5 \quad 1 \quad 3 \quad 10 \quad 2 \quad 9 \quad 6 \quad 10 \quad 1 \quad 5$$

Finally, GRS-FRWT recommends the list of items (minimum Sum-KtD) that satisfied n group of users optimally (Table 1).

Genetic Algorithm (GA). Genetic operators create new solutions, combine them with existing solutions, and select between solutions in order to maintain diversity. Here, we have to apply Crossover and Mutation for GRS-FRWT to retain the best chromosome from generation to generation.

Crossover. There are many popular crossover techniques exist (e.g., single point, two point). In a single-point crossover, single point on both parents' a set of list is selected. All data beyond that point in either set of list is swapped between the two parents. The resulting are the offspring. In this paper, we are using two-point crossover where the suitable crossover point is randomly chosen from the two parents (Fig. 1).

Mutation. In our model, we first select two randomly generated numbers out of possibilities and replace it by a randomly generated number ranging from 1 to 10. For example (Fig. 2) of mutation, 3 and 10 genes are replaced by a randomly generated number 8 and 4.

Table 1 Fitness function for group with ties (Sum-KtD)

Ranking		KtD
τ_1	10 4 3 6 10 9 6 8 10 8	25
τ_2	4 9 8 9 7 9 6 9 3 8	14
τ_3	10 5 2 7 9 7 5 6 7 6	21
τ_4	7 6 9 8 6 6 10 9 9 9	19
	Total distance Sum-KtD	79

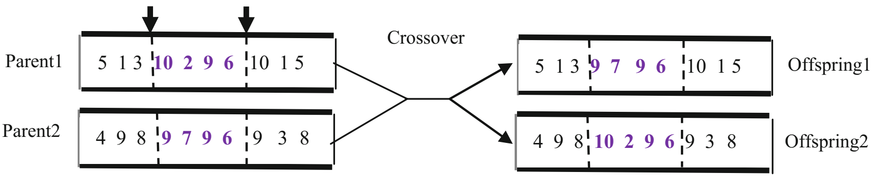

Fig. 1 A shadow of two-point crossover

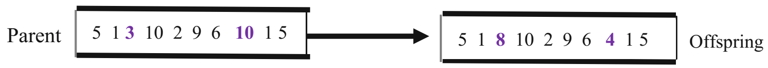

Fig. 2 A shadow of two-point mutation

Stopping Standard. In order to best individual may retain from generation to generation, we are using elitist approach. When there is no improvement in the fitness value after 30 consecutive generations, the evolution process stops.

Step 3. Fitness Function for Consensus Measure (CM).
When the system generates the recommendations, we measure consensus score using formulas (1 to 7) which described in Sect. 2 to reach a consensus between items which have ties on the recommendations made for a group. Final recommendation for this matrix is as follows:

$$\begin{array}{lcccccccccc} \mathrm{I}= & i_1 & i_2 & i_3 & i_4 & i_5 & i_6 & i_7 & i_8 & i_9 & i_{10} \\ \sigma = & 5 & 1 & 3 & 10 & 2 & 9 & 6 & 10 & 1 & 5 \end{array}$$

Possible permutation for this matrix is as follows: [4–8], 6, 7, [1–10], 3, 5, [2–9].

Here, we can see that there are ties in recommendation in between items 4, 8, and 1, 10, and 2–9. Calculate consensus for this recommendation list for using CM fitness function is as follows:

$$\begin{array}{lcccccccccc} I= & i_1 & i_2 & i_3 & i_4 & i_5 & i_6 & i_7 & i_8 & i_9 & i_{10} \\ CM = & 3.6 & 0.6 & 1.8 & 7.9 & 1.4 & 7.2 & 4.6 & 7.9 & 0.5 & 4.0 \end{array}$$

After consensus, permutation will be [4, 8, 6, 7, 10, 1, 3, 5, 2, 9].

Step 4. Effectiveness of a Recommend List of Ranking.
Using Consensus-based permutation can evaluate the effectiveness of recommendation of a ranked list and calculate the normalized discounted cumulative gain (nDCG) at rank k given below:

$$DCG_k^u = r_{up1} + \sum_{i=2}^{k} \frac{r_{up_i}}{\log_2(i)} \tag{8}$$

$$nDCG_k^u = \frac{DCG_k^u}{IDCG_k^u} \tag{9}$$

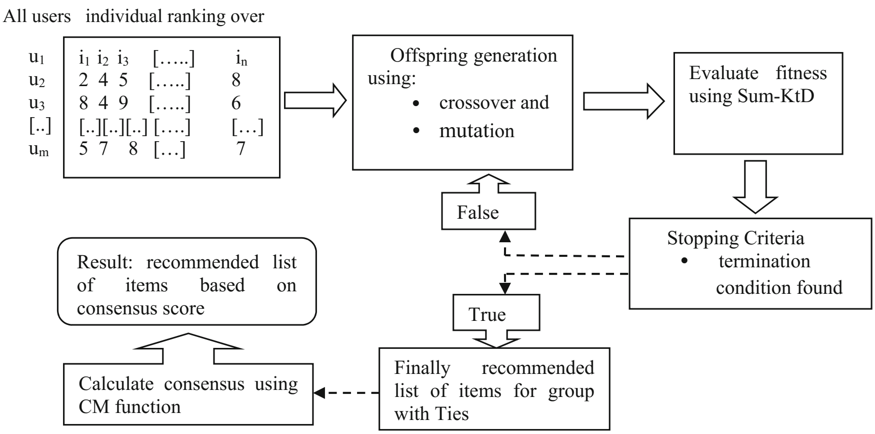

Fig. 3 A model recommendation aggregation scheme and consensus measure

where DCG is discounted cumulative gain, and IDCG is the maximum possible profit value for user u that is obtained from the optimal reorder of the k items in permutation p and n items I = 1, 2….. n. A model recommendation aggregation scheme and consensus measure is depicted in Fig. 3.

4 Experiments and Results

Data Set. The real data sets are not publicly available therefore we evaluate our proposed algorithms on a very large panel of carefully generated synthetic data set that has 15 items of different size of groups which have randomly generated ties. Experiments have been performed in order to compare the proposed approval with four states of art aggregation strategies.

Experiment 1. In this experiment, Sum-KtD is computed for different group sizes (G5, G10, G15, and G20). The results shown in Fig. 4 clearly indicates that for all group of different sizes GA meets near optimal solution after 200 generations.

Experiment 2. In this experiment, the proposed GRS-FRWT is compared with the different base line techniques. In order to compare performance of our proposed GRS-FRWT scheme with different baseline GRS techniques, we conducted experiments with groups of different sizes (G5, G10, G15, and G20). The results depicted in Fig. 5 clearly demonstrate that our scheme GRS-FRWT outperforms least misery, most pleasure, average, and Borda count.

Experiment 3. Here, we have compared the effectiveness of the group recommendation by our proposed scheme GRS-FRWT-WC with baseline techniques based on mean nDCG with varying group sizes. Results are shown in Fig. 6.

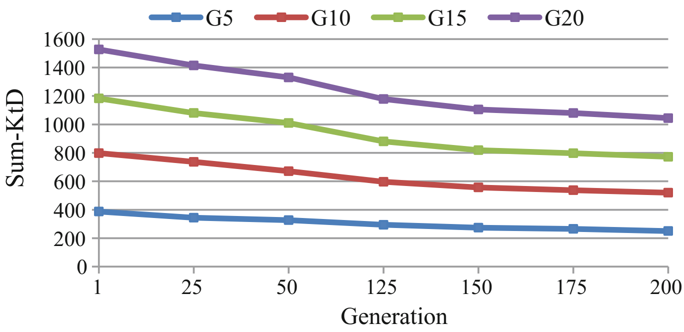

Fig. 4 The variation of Sum-KtD for group of different sizes

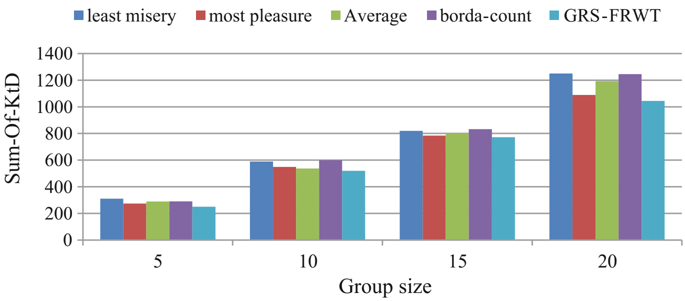

Fig. 5 The comparison of proposed GRS-FRWT to various baseline techniques for different group sizes

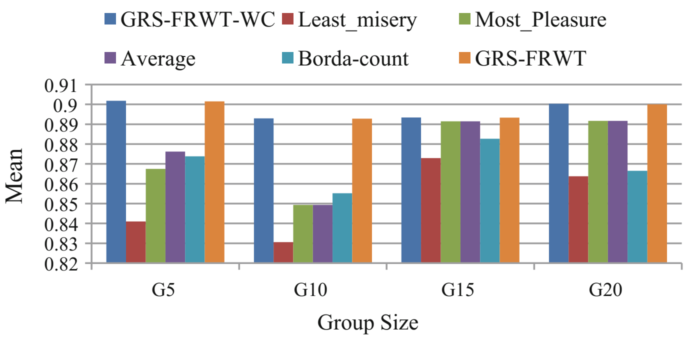

Fig. 6 The effectiveness of group recommendation with different rank aggregation techniques

5 Conclusions and Future Work

This paper provides a clear overview of the approached able to aggregate ranking with ties for selected randomly generated large number of data set with different size group of users, and finding an optimal consensus ranking in the context of ties. The purpose of this paper is that we have introduced the problem of ties using consensus in group recommender system where individuals have same preference for different items, how to solve the problem of ties in group recommender system. This system differs from normal personalized items to a group of users [18].

As a matter of feature work, we would like to experiment this strategy on real data (e.g., movie Lens, group Lens) set and to produce recommendations using trust-aware recommender systems and investigate incorporation of negotiation mechanism [20, 21].

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