Unified Group Recommendation Towards Multiple Criteria

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Abstract. In online social networks, a growing number of people are willing to share their activities with ones who have common interests. This motivates the research on group recommendation, which focuses on the issue of recommending items to a group of users. The existing methods on addressing the problem of grouping users and making recommendations for the formed groups simultaneously, however, often suffer from two defects. The first one is that they separate group partition and group recommendation, which often reduce the overall group satisfaction. The second one is that they tend to pursue a single objective optimum instead of making a balance between multiple objectives.

In this paper, we strive to tackle the key problem of grouping users and making recommendations for the formed groups simultaneously. It is a challenging problem due to the differences between user preferences over items, and how to make a trade-off among their preferences for the recommended items is still the main research point. To address these challenges, we present a Unified Group Recommendation (UGR) model, which intertwines the user grouping and group recommendation in a unified multi-objective optimization process that makes a balance between multiple criteria, including maximizing overall group satisfaction, social relationship density, and overall group fairness. Extensive experiments on two real-world datasets verify the effectiveness of our method.

Keywords: Group partition · Group recommendation · Multi-objective optimization

1 Introduction

As more and more people participate in group activities, group recommendation has been playing an important role in online social services, which aims to recommend interesting items to groups of users [13,32,33]. To fulfill group recommendation, two issues have to be overcome, i.e., reasonably partitioning users into groups and setting up an appropriate objective function [24,25,27]. First, the previous work [23] proposes a new framework that first extracts common-interest

This work was supported by the Sci. & Tech. Support Programs of Sichuan Province under Grant 2019YFG0213.

J. Shao et al. (Eds.): APWeb-WAIM 2019, LNCS 11642, pp. 137–151, 2019.
https://doi.org/10.1007/978-3-030-26075-0_11

user subgroups and then generates a recommendation list for each subgroup. After that, the final group recommendation is produced by a novel aggregation function to integrate the recommendation lists of all subgroups. Second, the previous work [16] proposes a Hidden Hierarchical Matrix Factorization (HHMF) method, which learns the hidden hierarchical structure from historical ratings to improve the performance of recommendation, where the group partition based on latent topics is accomplished. Although a few of works on group recommendation have been proposed, the existing methods often suffer from two drawbacks [1,2,31]. First, the existing methods tend to separate the grouping of users from the recommendation, where the recommendations are often made separately after users are partitioned into groups. However, as will be shown later in this paper, the separation of user grouping and recommendation would likely degrade the quality of group recommendation. Second, the existing methods often pursue a single objective when a recommendation is made. In real-world, however, the overall quality of group recommendation arguably depends on a trade-off of group satisfaction [2,6], social closeness of group members [11,12,26], and fairness between group members [22,27,30]. For example, in tourism, considering only group satisfaction may result in a high score for an attraction which is highly liked by the majority of group members but disliked by the others due to their preference disagreement. Such unfairness recommendation may make some users dissatisfied and slighted and spoil their experience. At the same time, assigning tourists who are familiar with each other to the same group would likely bring more enjoyment.

In this paper, we investigate the problem of making group recommendations in the absence of user group information, where three objectives are pursued simultaneously: group satisfaction, social relationship density, and fairness between group members. This is not a trivial task due to the following two challenges.

- **Integrating Group Partition and Recommendation.** As the quality of group recommendation heavily depends on the grouping of users, it is desired to integrate grouping and recommendation instead of separately handling them. However, the problem of user grouping is NP-Hard [2], so it is challenging to design a unified process by which the grouping and recommendation can both reach an acceptable optimal result.
- **Balance between Multiple Criteria.** For our target problem, we need to make group recommendations with respect to multiple criteria including group satisfaction, social relationship density, and fairness. However, it is hard for a solution to satisfy all the objectives simultaneously due to the conflicts between them [9]. Hence we need an appropriate optimal model and an optimization algorithm by which rational group recommendations can be made with a balance between the multiple criteria.

To address these challenges, we propose a novel Unified Group Recommendation (UGR) model. The main idea of UGR is to intertwine the user grouping and group recommendation in a unified multi-objective optimization process. UGR simultaneously generates the optimal user grouping and recommendations with

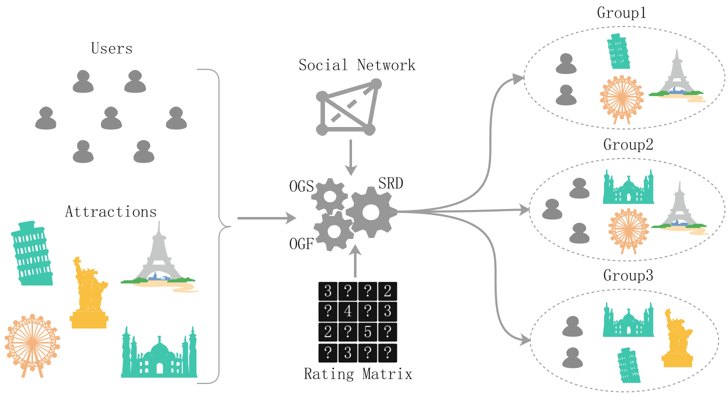


Fig. 1. Illustration of UGR

a fusion of historical ratings and the information extracted from social networks, where a trade-off between multiple criteria including Overall Group Satisfaction (OGS), Social Relationship Density (SRD), and Overall Group Fairness (OGF) is reached. Particularly, to fulfill the multi-objective optimization, we propose a novel alternate optimization algorithm which can facilitate the search of optimal solution via alternately adjusting the user memberships and recommendations at each iteration along the direction of increasing the objective function. Figure 1 shows an illustration of UGR, where tourists are partitioned into some non-overlapping groups and different packages of attractions are recommended to these groups.

The main contributions of this paper can be summarized as follows:

(1) We propose a Unified Group Recommendation (UGR) model that integrates the user grouping and group recommendation with a balance of multiple criteria.
(2) We propose a novel alternate optimization algorithm which facilitates the search of the optimal solution by alternately updating user grouping and recommendations.
(3) Extensive experiments conducted on real-world datasets verify that our approach is superior to the state-of-the-art methods.

In the rest of the paper, we review the related works in Sect. 2. We describe the detailed criteria of group satisfaction, social group density and fairness in Sect. 3. Section 3.2 introduces the problem formulation of group recommendation towards multiple criteria, and a novel alternate optimization algorithm is presented in Sect. 3.3. We analyze the experimental results in Sect. 4. We conclude in Sect. 5. Table 1 summarizes the notations used in this paper.

Table 1. Notations

Symbol	Description
U	The set of users
I	The set of items
K	The size of recommended items list
G	The set of the formed groups
T	The number of the formed groups
S	The social network
R	The rating matrix of user-item, $R \in \mathbb{R}^{\|U\| \times \|I\|}$
X	The group indicator matrix of users, $R \in \mathbb{R}^{\|U\| \times T}$
Y	The group indicator matrix of items, $R \in \mathbb{R}^{\|I\| \times T}$

2 Related Work

In this section, we briefly review the related work with our research, including collaborative filtering for groups and multi-objective optimization.

2.1 Collaborative Filtering for Groups

Many recommendation approaches are presented based on Collaborative Filtering (CF) [7,14,17,28] which is based on an assumption that a user may be interested in items liked by users who have similar preferences with her. In existing works [3–5], preference aggregation and score aggregation can be applied to group recommendation. When using the preference aggregation approach, preferences of individual users are aggregated into a group profile. Based on the group profile which can be treated as a pseudo user, collaborative filtering determines a ranking for each candidate item. When applying the score aggregation approach in combination with collaborative filtering, ratings can be determined for individual users and then aggregated into a final score for the group via a predefined aggregation strategy.

2.2 Multi-objective Optimization

Various approaches to multi-objective optimization have been proposed [10]. One key feature of multi-objective optimization is that there does not exist a solution that satisfies all the objectives simultaneously. Such problems are solved by a set of trade-off optimal solutions instead of a single optimum solution.

In personalized recommendation tasks, some existing methods [20,29,34] consider multiple objectives. In [34], multiple objectives including accuracy and diversity are considered simultaneously. [29] takes into account accuracy and long tail, and [20] regards spatial, temporal and social information as multiple objectives. They all aim to find a trade-off solution by optimizing a multi-objective function.

3 UGR

3.1 Multiple Criteria

Group Satisfaction. Intuitively, the group satisfaction is determined by the preferences of individuals within a group. The existing works have proposed several strategies to fuse the preferences of group members, such as Least Misery (LM), Maximum (MAX), and Average (AVG) [8]. For the sake of simplicity and convenience, we utilize AVG to aggregate the member preferences to evaluate the group satisfaction, which leads to the following definition:

Definition 1. ***Group Satisfaction.*** *Given the rating matrix R where R_{ui} represents the rating of item i given by user u, the Group Satisfaction of group g with a recommended item i (denoted as $Sat(g,i)$) is defined as*

$$Sat(g,i) = \frac{1}{|g|}\sum_{u\in g} R_{ui}, \tag{1}$$

where $|g|$ is the number of the members belonging to group g.

Since the historical rating data of users is extremely sparse, the missing entries need to be estimated. The existing works have proposed several effective approaches, such as MF [15], SVD [21], and PMF [19], which all serve our purpose. For convenience, we choose MF to infer the missing entries of a rating matrix.

Social Relationship Density. We propose the following metric called Social Relationship Density to evaluate the social closeness between group members with respect to an item. The higher relationship density of a group indicates that not only there are more friends in the group, but also they have higher collective preference to an item. Given the social network S where an edge $<u,v> \in S$ represents the friendship between users u and v, we can define the Social Relationship Density as follow:

Definition 2. ***Social Relationship Density.*** *The social relationship density of group g with respect to an item i is defined as*

$$SRD(g,i) = \frac{\sum_{\forall u,v\in g}(R_{ui}+R_{vi})\mathbb{1}(<u,v> \in S)}{|g|(|g|-1)}, \tag{2}$$

where $\mathbb{1}(x)$ is the indicator function whose value is 1 if x is true, otherwise 0.

Fairness. The fairness depicts how imbalanced the satisfaction of group members is. The existing work [30] presents several definitions of fairness in different forms, such as Least Misery Fairness, Variance Fairness, and Min-Max Ratio. Variance encourages the group members to achieve close satisfaction between each other, while Least Misery Fairness and Min-Max emphasise the gap between the least and highest satisfaction of group members. Despite the differences of the Fairness in definitions, the intuition of these metrics is to minimize the imbalance of the satisfaction of group members. In this paper, we introduce Variance Fairness [30] as follows:

Definition 3. ***Fairness.*** *The fairness of group g on item i is defined as*

$$F(g,i) = 1 - \frac{1}{|g|}\sum_{u\in g}|R_{ui} - \frac{1}{|g|}\sum_{v\in g}R_{vi}|. \tag{3}$$

The higher the function value, the higher the fairness within a group.

3.2 Optimization Framework

In this section, we formally introduce the optimization framework for the problem of group recommendation towards multiple criteria. We assign weights to each objective and use the weighted sum of different objective functions as a single objective for proximity:

$$\begin{aligned} J(X,Y) =& \alpha \sum_{g\in G}\sum_{u\in U}\sum_{i\in I} R_{ui}X_{ug}Y_{ig} \\ &+ \beta \sum_{g\in G}\sum_{u\in U}\sum_{i\in I} \frac{\sum_{v\in U}(R_{ui}+R_{vi})\mathbb{1}(<u,v> \in S)X_{ug}X_{vg}Y_{ig}}{\sum_{v\in U}X_{vg}(\sum_{v\in U}X_{vg}-1)} \\ &+ (\alpha+\beta-1)\sum_{g\in G}\sum_{u\in U}\sum_{i\in I}|R_{ui} - \frac{\sum_{v\in U}R_{vi}X_{vg}}{\sum_{v\in U}X_{vg}}|X_{ug}Y_{ig}, \end{aligned} \tag{4}$$

where three terms of the right side of the Eq. (4) represent the overall group satisfaction, social closeness, and fairness respectively; $X_{ug} \in \{0,1\}$ and $Y_{ig} \in \{0,1\}$ denote whether user u is assigned to group g and item i is recommended to group g.

Problem 1. Given a set of users U, items I, and the rating matrix R, we aim to divide all users into some non-overlapping groups and make recommendations for the formed groups so that the following objective function is maximized. The problem of the user grouping and recommendation can be formulated as follows:

$$\begin{aligned} &\arg\max_{X,Y} J(X,Y), \\ &s.t. \sum_{g\in G} X_{ug} = 1, \forall u \in U \\ &\quad \sum_{i\in I} Y_{ig} = K, \forall g \in G \\ &\quad X_{ug} \in \{0,1\}, \forall u \in U, g \in G \\ &\quad Y_{ig} \in \{0,1\}, \forall i \in I, g \in G \end{aligned} \tag{5}$$

Algorithm 1 *Alternate Optimization Algorithm*

Input:
the user rating matrix R, the set of users U and items I, step size θ,
the number of groups T, the size of recommended items list for each group K,
the threshold ϵ, the maximum number of iterations L, parameters α, β.
Output:
the group indicator matrix of users X, the group indicator matrix of items Y.
1: Initialize $X^{|U|\times T}$, $Y^{|I|\times T}$ with random values between 0 and 1;
2: Initialize $\mathcal{X}^{|U|\times T}$, $\mathcal{Y}^{|I|\times T}$ with random values between 0 and 1;
3: Set $l = 0$;
4: Calculate the initial value of objective function J^0 according to Equation (4);
5: Initialize $\Delta J^l = J^0$;
6: **while** $l < L$ and $\Delta J^l > \epsilon$ **do**
7:     **for** each user u **do**
8:         **for** each group g **do**
9:             Calculate the gradient $\partial_{X_{ug}} J$;
10:         **end for**
11:     **end for**
12:     $X = \min(\max(X + \theta * \partial_X J, 0), 1)$;
13:     **for** each group g **do**
14:         Calculate the top-K items for group g: $R(g, K)$;
15:         Assign them to $Y[:, g]$: $Y_{vg} = 1, \forall v \in R(g, K)$;
16:     **end for**
17:     $++l$;
18:     Calculate the l-th iteration of objective function J^l according to Equation (4);
19:     $\Delta J^l = J^l - J^{l-1}$;
20: **end while**
21: **for** each user u **do**
22:     Search the group index p of maximum value in $[X_{u1}, \cdots, X_{ut}]$;
23:     $\mathcal{X}_{up} = 1$;
24: **end for**
25: $X = \mathcal{X}$;
26: **for** each group g **do**
27:     Search the item indices $\mathcal{I}$ of top-K items in $[Y_{1g}, \cdots, Y_{kg}]$;
28:     $\mathcal{Y}_{ig} = 1, \forall i \in \mathcal{I}$;
29: **end for**
30: $Y = \mathcal{Y}$;

The main idea of the formula above is to repeat group partition process and group recommendation process until no user can get higher increase on the objective function by adjust the two processes.

3.3 Algorithm

In this section, we present an alternate optimization algorithm in Algorithm 1. Algorithm 1 gives the procedures of UGR, where a local optima of J is obtained through an iterative process of gradient descent. In detail, the initialization process is in the lines 1 to 5, followed by an alternate optimization process. First, we adjust user memberships according to the gradient. Second, the recommended packages are updated based on the current group partition. The two processed above are repeated until the objective function converges. Due to the entries of two optimized indicator matrices are non-integral value, we clarify the membership of users and the final recommendation results. For each user, she is assigned to the group corresponding to the maximum value. For each group, top-K items are chosen as recommendations.

Our proposed alternate optimization algorithm solves the constrained optimization problem. It first solves the problem with gradient descent and then maps the solution back into the feasible set if the solution is beyond the feasible set. In addition, the integer programming with discrete variables is usually NP-Hard and difficult to solve with an optimal solution. So, during optimization, we need to relax the binary constraint of integer variables to the range of 0 to 1.

4 Experiment

In this section, we conduct extensive experiments with the aim at answering the following two questions:

- **Q1** Does our proposed UGR method outperform the state-of-the-art group recommendation methods?
- **Q2** Is the multi-objective optimization helpful for improving the overall recommendation accuracy?

In what follows, we first present the experimental settings, and then describe the details of the experiments.

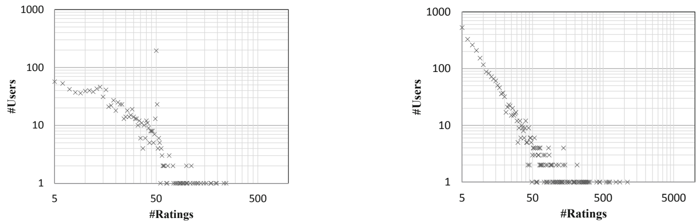
4.1 Experimental Settings

Dataset Description. Our experiments are conducted on two publicly accessible datasets: Filmtrust[1], CiaoDVD (See footnote 1). Figure 2 shows that the number of users follows a heavy-tailed distribution over the number of their rated items, which indicates the two datasets are nature. The characteristics of two datasets are summarized in Table 2. The ratings in CiaoDVD range from 1 to 5, and Filmtrust takes values from 0.5 to 4.

Table 2. The statistics of datasets

Dataset	#Users	#Items	#Interactions	#Trusts	#Density
Filmtrust	1508	2071	35497	1853	1.14%
CiaoDVD	17615	16121	72665	40133	0.03%

[1] https://www.librec.net/datasets.html.



(a) Filmtrust (b) CiaoDVD

Fig. 2. Overviews of datasets

Evaluation Metrics. To evaluate the performance of the group recommendation, we divide data into three parts, where 60% of the data are used for training, 20% of the data are used for validating, and 20% for testing. The performance of a ranking list is judged by $F1$ and *Normalized Discounted Cumulative Gain* ($NDCG$) [30].

Due to the conflict between precision and recall, we consider to reflect the overall performance of the recommendation by a single value. Therefore, we use $F1@K$ to evaluate our model:

$$Precision@K = \frac{\sum_{i=1}^{K} rel_i}{K}, Recall@K = \frac{\sum_{i=1}^{K} rel_i}{|y_u^{test}|}, \tag{6}$$

$$F1@K = 2 \cdot \frac{Precision@K \cdot Recall@K}{Precision@K + Recall@K}, \tag{7}$$

where $rel_i = 1$ if the item at rank i in the top-K recommendation list is in the test set, and 0 otherwise. y_u^{test} represents the items rated by user u in the test set.

However, $F1@K$ can not fully reflect the accuracy of recommendation because it does not take positions of hits in the ranking list into consideration. To address this problem, we adopt $NDCG@K$, which assigns higher scores to hits at top ranks:

$$DCG@K = \sum_{i=1}^{K} \frac{2^{rel_i} - 1}{log_2(i+1)}, NDCG@K = \frac{DCG@K}{IDCG@K} \tag{8}$$

The notion $IDCG$ means the maximum DCG through ideal ranking list. For both metrics, larger values indicate better performance. In the evaluation, we compute both metrics for each user in the test set and report the average score. Without special mention, we set K to 10 for two metrics.

Baselines. To justify the effectiveness of our method, we compare it with six baselines:

GRSE [1]. This method first proposes a formal semantics which accounts for item relevance to a group and preference consensus among group members.

LGM [31]. This method first introduces latent factor model into the group partition which is performed by clustering user latent factor vectors generated by MF. With the presentations of group members, the group presentations are produced by the predefined fusion strategies.

CGF [18]. This method generates groups and recommendations using network centrality concept that groups of users with similar preferences.

Greedy-Var [30]. This baseline investigates the group recommendation problem from the perspective of Pareto Efficiency, which tries to maximize the group satisfaction and the fairness simultaneously.

UGR-F. This is a variant of our UGR model by removing the criterion of relationship density. UGR-F is used for demonstrating the improvements by fusing social information.

UGR-R. This is another variant of our UGR model by omitting the criterion of fairness, which is used to verify that considering fairness in group recommendation leads to better performance.

Hyper-Parameter Setting. For hyper-parameter tuning, we determine α and β in Eq. (4) by the grid search in the range of [0,1] with a fixed step size of 0.1 on the validation set. We observe that $F1@K$ and $NDCG@K$ over the both two real-world datasets achieve the maximum when α=0.7 and β=0.2, therefore we choose the value 0.7, 0.2, and 0.1 as the weights of three criteria respectively in the following experiments. Without special mention following, the learning rate is set to 0.05.

4.2 Performance Comparison (Q1)

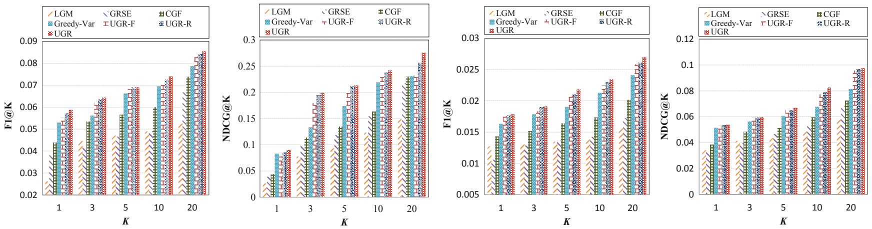
We first compare the recommendation performance of all methods on two real-world datasets with respect to both metrics, and then investigate the convergence of our methods.

Overall Comparison. We first compare the recommendation performance of all methods under different number of groups and then investigate the effect of package size on recommendation performance.

The performance comparison of all methods under different package sizes is presented in Fig. 3. The conclusions are threefold:

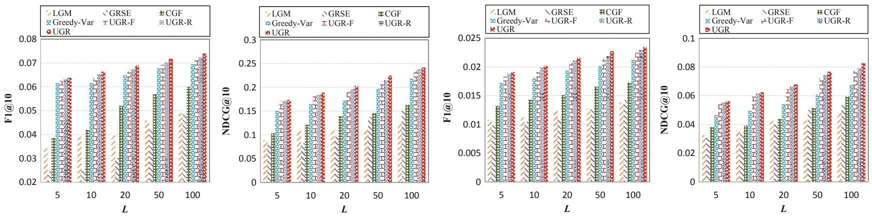
Firstly, our methods show significant improvements over other baselines. Specifically, both UGR-F and Greedy-Var take the satisfaction and fairness into consideration, but the improvement of UGR-F over Greedy-Var is significant. This verifies the effectiveness of integrating user grouping and recommendation into a same optimization process.

Secondly, compared to UGR-F and UGR-R, UGR obtains a relative improvement, which demonstrates that considering the fairness and relationship closeness within a group leads to better recommendation accuracy. It is an surprising discovery since fairness and relationship closeness are not directly related to recommendation accuracy. The reason is that fairness can alleviate the imbalance



(a) Filmtrust (b) Filmtrust (c) CiaoDVD (d) CiaoDVD

Fig. 3. Performance comparison of $F1@10$ and $NDCG@10$ *w.r.t* the package size on datasets of Filmtrust and CiaoDVD.



(a) Filmtrust (b) Filmtrust (c) CiaoDVD (d) CiaoDVD

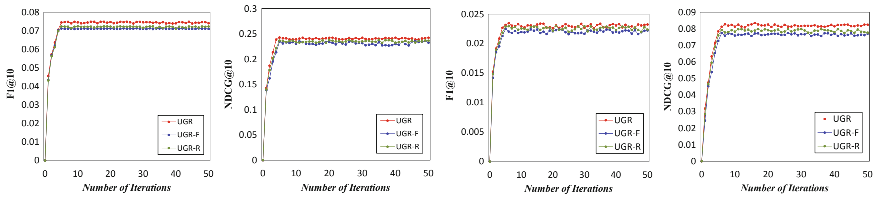
Fig. 4. Performance comparison of $F1@10$ and $NDCG@10$ *w.r.t* the number of formed groups on datasets of Filmtrust and CiaoDVD.

between satisfactions of users and the users who are less satisfied can get more items they like so that the overall recommendation accuracy increases. As such, considering assigning users with friendships or trusts to the same group also can make up for the imbalance between satisfactions of users. For example, an attraction with an amusement park intends to be chosen by a family with children because adults often make compromises for their children, which indicates that decision-making is influenced by relationships between group members.

Figure 4 shows the performance of all methods with respect to the number of formed groups via user grouping. From the two figures, we have following observations:

Firstly, our model UGR and its two simplified variants obtain better performance for group recommendation tasks. The reason is that the multi-objective optimization can effectively improve the recommendation accuracy and fusing user grouping and recommendation facilitates the search of optimal solution.

Secondly, as the number of formed groups increases, the recommendation accuracy keeps rising. The reason is that group members in a smaller group often have more decision-making power than those in a larger group, therefore the items chosen by the smaller group are more likely to satisfy their preferences. To see why the experimental results are reasonable, one can imagine that recommendation accuracy is optimal when all formed groups have only one user who needs to consider only her own tastes.



(a) Filmtrust (b) Filmtrust (c) CiaoDVD (d) CiaoDVD

Fig. 5. Recommendation performance of UGR, UGR-F, and UGR-R *w.r.t* the number of iterations on Filmtrust and CiaoDVD

Convergence. In this part, we empirically study the convergence of our method UGR and its two simplified variants. Figure 5 shows the recommendation performance at each iteration on datasets of Filmtrust and CiaoDVD. First, we can see that, with more iterations, the recommendation performance gets improved. Second, they converge quite fast and the most effective updates occur in the first 5 iterations, which indicates the efficiency of our framework of multi-objective optimization.

4.3 Is the Multi-objective Optimization Helpful? (Q2)

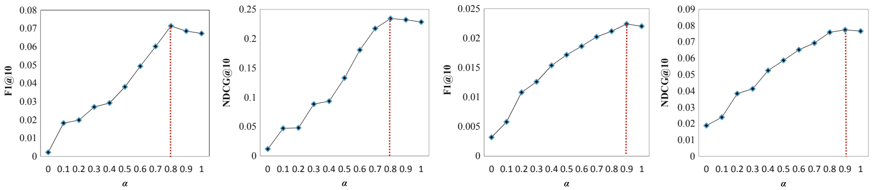
The overall performance comparison shows that UGR obtains the best results on two typical metrics, demonstrating the effectiveness of the multi-objective optimization for the group recommendation tasks. To further understand and analyse the effectiveness of components of UGR in contributing to the improvements of recommendation accuracy, we perform some ablation studies.

Fairness Effectiveness Study. In this subsection, we investigate the effectiveness of fairness by controlling the weights on satisfaction and fairness.

Figure 6 shows the results of the simplified variant UGR-F. As α rises, both two metrics gradually get improved, while they slightly decrease when α is over 0.8. This indicates that fusing fairness leads to better performance, but maximizing fairness alone tends to decrease the performance of recommendation. For example, when we recommend commonly disliked items to a group, the fairness is high but the overall group satisfaction is low.

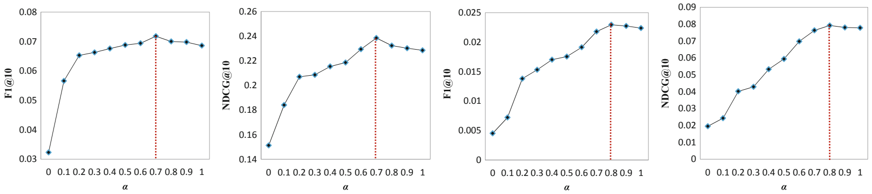
Relationship Closeness Effectiveness Study. UGR-R which removes the fairness effect is used to study the effectiveness of relationship closeness.

The results of the simplified variant UGR-R on two real-world datasets are presented in Fig. 7. The performance of UGR-R rises first and then decreases with the increase of the weight on relationship closeness. This reveals that relationship closeness has a positive impact on the performance of our model, while we do not obtain the best results when relationship closeness among group users is maximized alone.



(a) Filmtrust (b) Filmtrust (c) CiaoDVD (d) CiaoDVD

Fig. 6. Performance of UGR-F for each α on datasets of Filmtrust and CiaoDVD.



(a) Filmtrust (b) Filmtrust (c) CiaoDVD (d) CiaoDVD

Fig. 7. Performance of UGR-R for each α on datasets of Filmtrust and CiaoDVD.

5 Conclusion

In this paper, we address the group recommendation problem from the perspective of multi-objective optimization. We propose a novel Unified Group Recommendation model for group recommendation. Specifically, given n users, m items, the model assigns these users into l non-overlapping groups and respectively chooses k items with highest scores from candidate items as recommendations for each group. Different from existing works which separate group partition and recommendation, we integrate them into an optimization process and then alternatively adjust the group partition and recommendation by our proposed alternate optimization algorithm. Extensive experiments have been made on two real-world datasets. UGR consistently outperforms the state-of-the-art group recommendation models on two typical metrics. Moreover, we perform deep analyses of the components in UGR, which proves the effectiveness of our model.

By referring to existing methods of group recommendation, we adopt three criteria for designing the objective function. The reason is that we pay more attention to whether the performance can obtain the improvements by integrating group partition and recommendation. In the future, we will incorporate more criteria and additional contextual information to further improve the performance of our model.

References

1. Amer-Yahia, S., Roy, S.B., Chawlat, A., Das, G., Yu, C.: Group recommendation: semantics and efficiency. Proc. VLDB Endow. **2**(1), 754–765 (2009)
2. Basu Roy, S., Lakshmanan, L.V., Liu, R.: From group recommendations to group formation. In: Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data, pp. 1603–1616. ACM (2015)
3. Beckmann, C., Gross, T.: Towards a group recommender process model for ad-hoc groups and on-demand recommendations. In: Proceedings of the 16th ACM International Conference on Supporting Group Work, pp. 329–330. ACM (2010)
4. Boratto, L., Carta, S.: The rating prediction task in a group recommender system that automatically detects groups: architectures, algorithms, and performance evaluation. J. Intell. Inf. Syst. **45**(2), 221–245 (2015)
5. Boratto, L., Carta, S., Fenu, G.: Investigating the role of the rating prediction task in granularity-based group recommender systems and big data scenarios. Inf. Sci. **378**, 424–443 (2017)
6. Carvalho, L.A.M.C., Macedo, H.T.: Users' satisfaction in recommendation systems for groups: an approach based on noncooperative games. In: Proceedings of the 22nd International Conference on World Wide Web, pp. 951–958. ACM (2013)
7. Chen, C., Zheng, X., Wang, Y., Hong, F., Lin, Z., et al.: Context-aware collaborative topic regression with social matrix factorization for recommender systems. In AAAI, pp. 9–15 (2014)
8. De Pessemier, T., Dooms, S., Martens, L.: Comparison of group recommendation algorithms. Multimedia Tools Appl. **72**(3), 2497–2541 (2014)
9. Deb, K.: Multi-objective optimization. In: Burke, E., Kendall, G. (eds.) Search Methodologies, pp. 403–449. Springer, Boston (2014). https://doi.org/10.1007/978-1-4614-6940-7_15
10. Deb, K., Sindhya, K., Hakanen, J.: Multi-objective optimization. In: Decision Sciences: Theory and Practice (2016)
11. Fang, G., Su, L., Jiang, D., Wu, L.: Group recommendation systems based on external social-trust networks. In: Wireless Communications and Mobile Computing (2018)
12. Guo, C., Li, B., Tian, X.: Flickr group recommendation using rich social media information. Neurocomputing **204**, 8–16 (2016)
13. Guo, Z., Tang, C., Tang, H., Fu, Y., Niu, W.: A novel group recommendation mechanism from the perspective of preference distribution. IEEE Access **6**, 5865–5878 (2018)
14. Konstan, J.A., Miller, B.N., Maltz, D., Herlocker, J.L., Gordon, L.R., Riedl, J.: Grouplens: applying collaborative filtering to usenet news. Commun. ACM **40**(3), 77–87 (1997)
15. Koren, Y., Bell, R., Volinsky, C.: Matrix factorization techniques for recommender systems. Computer **8**, 30–37 (2009)
16. Li, H., Liu, Y., Qian, Y., Mamoulis, N., Tu, W., Cheung, D.W.: HHMF: hidden hierarchical matrix factorization for recommender systems. In: Data Mining and Knowledge Discovery (2019)
17. Linden, G., Smith, B., York, J.: Amazon.com recommendations: item-to-item collaborative filtering. IEEE Internet Comput. **1**, 76–80 (2003)
18. Mahyar, H., Ghalebi K, E., Morshedi, S.M., Khalili, S., Grosu, R., Movaghar, A.: Centrality-based group formation in group recommender systems. In: Proceedings of the 26th International Conference on World Wide Web Companion, pp. 1187–1196. International World Wide Web Conferences Steering Committee (2017)

19. Mnih, A., Salakhutdinov, R.R.: Probabilistic matrix factorization. In: Advances in Neural Information Processing Systems, pp. 1257–1264 (2008)
20. Özsoy, M.G., Polat, F., Alhajj, R.: Multi-objective optimization based location and social network aware recommendation. In: 2014 International Conference on Collaborative Computing: Networking, Applications and Worksharing (CollaborateCom), pp. 233–242. IEEE (2014)
21. Polat, H., Du, W.: SVD-based collaborative filtering with privacy. In: Proceedings of the 2005 ACM Symposium on Applied Computing, pp. 791–795. ACM (2005)
22. Qi, S., Mamoulis, N., Pitoura, E., Tsaparas, P.: Recommending packages to groups. In: 2016 IEEE 16th International Conference on Data Mining (ICDM), pp. 449–458. IEEE (2016)
23. Qin, D., Zhou, X., Chen, L., Huang, G., Zhang, Y.: Dynamic connection-based social group recommendation. IEEE Trans. Knowl. Data Eng. **PP**, 1 (2018)
24. Ribeiro, M.T., Lacerda, A., Veloso, A., Ziviani, N.: Pareto-efficient hybridization for multi-objective recommender systems. In: Proceedings of the Sixth ACM Conference on Recommender Systems, pp. 19–26. ACM (2012)
25. Rodriguez, M., Posse, C., Zhang, E.: Multiple objective optimization in recommender systems. In: Proceedings of the Sixth ACM Conference on Recommender Systems, pp. 11–18. ACM (2012)
26. Salehi-Abari, A., Boutilier, C.: Preference-oriented social networks: group recommendation and inference. In: Proceedings of the 9th ACM Conference on Recommender Systems, pp. 35–42. ACM (2015)
27. Serbos, D., Qi, S., Mamoulis, N., Pitoura, E., Tsaparas, P.: Fairness in package-to-group recommendations. In: Proceedings of the 26th International Conference on World Wide Web, pp. 371–379. International World Wide Web Conferences Steering Committee (2017)
28. Su, X., Khoshgoftaar, T.M.: A survey of collaborative filtering techniques. In: Advances in Artificial Intelligence (2009)
29. Wang, S., Gong, M., Li, H., Yang, J.: Multi-objective optimization for long tail recommendation. Knowl.-Based Syst. **104**, 145–155 (2016)
30. Lin, X., Zhang, M., Zhang, Y., Gu, Z., Liu, Y., Ma, S.: Fairness-aware group recommendation with pareto-efficiency. In: Proceedings of the Eleventh ACM Conference on Recommender Systems, pp. 107–115. ACM (2017)
31. Zeng, X., Wu, B., Shi, J., Liu, C., Guo, Q.: Parallelization of latent group model for group recommendation algorithm. In: IEEE International Conference on Data Science in Cyberspace (DSC), pp. 80–89. IEEE (2016)
32. Zhao, J., Liu, K., Tang, F.: A group recommendation strategy based on user's interaction behavior. In: 2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), pp. 1170–1174. IEEE (2017)
33. Zhu, Q., Wang, S., Cheng, B., Sun, Q., Yang, F., Chang, R.N.: Context-aware group recommendation for point-of-interests. IEEE Access **6**, 12129–12144 (2018)
34. Zuo, Y., Gong, M., Zeng, J., Ma, L., Jiao, L.: Personalized recommendation based on evolutionary multi-objective optimization [research frontier]. IEEE Comput. Intell. Mag. **10**(1), 52–62 (2015)