Group-Oriented Paper Recommendation With Probabilistic Matrix Factorization and Evidential Reasoning in Scientific Social Network

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***Abstract*—In recent years, the establishment of a substantial amount of academic groups on scientific social network has brought new opportunities for the collaboration among researchers. In this situation, conducting paper recommendation to these academic groups is of terrific necessity in that it can further facilitate group activities. However, when producing group recommendation, existing methods fail to make full use of the abundant group information, from which a great deal of valuable information can be inferred to facilitate the recommendation performance. In addition, those methods tend to assign an equal weight to each group member when aggregating their recommendations, which is unreasonable in practice. Although some improvements have been made to remedy this problem by assigning different weights to group members, they fail to take into account the reliabilities of group members. Therefore, a group-oriented paper recommendation method based on probabilistic matrix factorization and evidential reasoning (GPMF_ER) is proposed in this article to tackle these problems. More specifically, the group and paper content information are integrated into the probabilistic matrix factorization model to enhance the accuracy of individual recommendation. Afterward, evidential reasoning rule is introduced in the aggregation step to consider both the weights and reliabilities of group members. Extensive experiments have been conducted on the real world CiteULike dataset and the results demonstrate the effectiveness of the proposed method.**

***Index Terms*—Evidential reasoning (ER), group recommendation, paper recommendation, probabilistic matrix factorization (MF), scientific social network (SSN).**

I. Introduction

THE FLOURISHING development of information technology leads to the emergence of various social networking sites, among which scientific social network (SSN) is the one specifically designed for scientists and researchers. Some well-known examples of SSN include ResearchGate, Academia, Mendeley [8], and so forth. Registered users of SSN are allowed to create personal profiles, upload academic resources, build a library of research papers, and establish their own groups or participate in the existed ones. These online groups play an especially important role in facilitating researchers' research-related activities, such as collaborating with their colleagues, presenting and discussing trendy research topics, and keeping up with the current edge of their research fields [12]. This breaks the temporal and spatial barriers of the collaboration among researchers, and provides them with a more effective manner to conduct their research. In view of the tremendous benefits that groups can bring, it is necessary to explore paper recommendation for groups, which can further promote group activities by giving group members an immediate access to research papers, reducing their search efforts, and improving the share ability of information in groups. Nevertheless, this issue has not been paid enough attention by the academia.

As a matter of fact, recommending papers to academic groups essentially belongs to the group recommendation problem. Generally, group recommendation methods can be classified into two categories: 1) preference aggregation (PA) methods and 2) recommendation aggregation (RA) methods [15]–[17]. These two kinds of methods differ in the time of performing aggregation [20]. In particular, the PA methods first construct a group profile by consolidating preferences of group members, then treat the group as a pseudo-user and use traditional individual recommendation methods to generate group recommendation. Whereas the RA methods generate recommendation for each group member beforehand, and then merge those recommendations as final group recommendation. Actually, no matter which kind of method is adopted, the PA methods or the RA methods, there are totally two main issues need to be addressed when generating group recommendation. One is how to generate recommendations for individuals and the other is how to perform the aggregation.

With regard to generating individual recommendations, more specifically individual paper recommendations in this context, the methods that most existing studies use fall into one of the four categories: 1) content-based filtering (CBF) methods; 2) collaborative filtering (CF) methods; 3) graph-based methods (GB); and 4) hybrid methods [25], [26]. The CBF methods produce recommendations based on the content features of papers, whereas the CF methods produce recommendations based on the researcher-paper interactions [27]. In

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addition, the GB methods encode the information regarding researchers and papers into a graph, and based on which the relevance between them is calculated. There are some limitations when purely using one of these methods. Therefore, the hybrid methods are proposed to leverage the advantages of those methods and remedy their disadvantages at the same time. However, in spite of the fairly good performance of the hybrid methods in individual paper recommendation, they cannot solve the problem in this paper well. As a crucial component in group recommendation, it is far from enough for the hybrid methods to only generate recommendations from the perspective of individuals. On the contrary, they should consider the problem from the group perspective and make sufficient use of the ubiquitous group information. From the group information, a great deal of valuable information can be derived to facilitate recommendation. For example, if there is a large overlap between the groups two researchers have joined, then we can assume that these two researchers bear a similar interest. The same conclusion can be drawn if two researchers have participated in groups with a small group size together. Consequently, it is imperative to introduce group information into the recommendation process.

With regard to performing aggregation, several studies have given an elaborate description of the commonly used aggregation strategies, including average, least misery, most pleasure, Copeland rule, Borda Count, Fairness, and so on [28], [29]. Despite of the simplicity of these strategies, they tend to assign an equal weight to each group member when aggregating their ratings into a group rating, which is unreasonable in practice. In reality, there will be some members with relatively higher reputation and status than other members in a group. These group members with high prestige will have a considerable influence on the final group decision-making, such that they should be assigned a higher weight. Although some improvements have been proposed to remedy this problem by assigning different weights to group members, they fail to take into account the reliabilities of group members [4], [22]. The premise of an accurate aggregation result is that the individual ratings can characterize the preferences of group members perfectly. While in practice, there are some members in a group who always give the same rating to all items or just rate arbitrarily. Performing aggregation based on ratings from these unreliable members may result in inaccurate group recommendation. Therefore, when performing aggregation, not only the weights, but also the reliabilities of group members should be taken into account.

Considering the aforementioned problems, a group-oriented paper recommendation method based on probabilistic matrix factorization and evidential reasoning (GPMF_ER) is proposed in this article. For one thing, a hybrid method is proposed to predict the rating of each group member. Specifically, the valuable group and paper content information are used to calculate researcher similarity and paper similarity, which are subsequently incorporated into the PMF model by regularizing the researchers and papers, respectively. For another thing, the weight and reliability of each group member are redefined, and evidential reasoning (ER) rule is introduced to merge predicted ratings of group members into a group rating. Finally, top-K papers with the highest predicted ratings are added into the recommendation list for the target group. Extensive experiments have been conducted on the real world CiteULike dataset to validate the effectiveness of the proposed method. The results indicate that the proposed method consistently outperforms the baselines in terms of all evaluation metrics. In addition, ablation studies also demonstrate the necessity of taking into account the group information and the reliabilities of group members.

Our contributions can be summarized as follows.

1) The proposed GPMF_ER method can solve the problem of recommending papers for academic groups on SSN, which can facilitate the communication and collaboration among researchers, and help policymakers understand the latest research trends and formulate the national key R&D plan.
2) The group and paper content information are integrated into the PMF model, which enhances the accuracy of individual recommendation. In particular, the integrating of group information makes the individual recommendation method more adaptive to the group situation.
3) ER rule is first introduced to merge the predicted ratings of group members, which considers the weights and reliabilities of group members simultaneously.
4) Experiments have been conducted on the CiteULike dataset and the results demonstrate the effectiveness of the proposed method.

The remainder of this article is organized as follows. In Section II, we review the existing literature related to our research. In Section III, we introduce the framework and details of the proposed GPMF_ER method. We outline the experimental settings in Section IV. The experimental results and discussion are presented in Section V followed by the conclusion and future work in Section VI.

II. Related Work

In this section, we review pertinent literature from three aspects: 1) paper recommendation; 2) group recommendation; and 3) ER.

A. Paper Recommendation

Paper recommender systems are designed to recommend related papers for researchers. Hence researchers have no need to manually filter numerous papers themselves, which is a labor-intensive and time-consuming task [30]. In General, paper recommendation methods can be classified into CBF methods, CF methods, GB methods, and hybrid methods [25], [26]. Table I presents the selected previous studies with respect to paper recommendation.

The CBF methods produce recommendations utilizing the content features of papers, and researchers will be recommended papers similar to the ones he/she preferred in the past [27]. Many studies apply the CBF methods to generate paper recommendation [1], [3]. In spite of the wide application, the CBF methods suffer from the overspecialization problem that can only recommend similar papers and

TABLE I
SELECTED PREVIOUS STUDIES ABOUT PAPER RECOMMENDATION

Method	Study	Year	Individual or Group
CBF	Kodakateri Pudhiyaveetil *et al.* [1]	2009	Individual
	Nascimento *et al.* [3]	2011	Individual
CF	Bogers *et al.* [5]	2008	Individual
	Liu *et al.* [7]	2018	Group
GB	Zhou *et al.* [10]	2014	Individual
	Xia *et al.* [13]	2016	Individual
Hybrid	Ekstrand *et al.* [18]	2010	Individual
	Jiang *et al.* [21]	2012	Individual
	Tian *et al.* [23]	2013	Individual
	Wang *et al.* [24]	2018	Individual

fail to generate different but still appealing recommendations. Moreover, the new user problem is another impediment that significantly limits the performance of the CBF methods [31], [32].

Distinct from the CBF methods, the CF methods try to predict target researcher's ratings on unrated papers based on the rating information of other researchers and papers [32]. Typically, the CF methods can be divided into memory-based CF methods and model-based CF methods [31]. The memory-based CF methods generate recommendations mainly through K-Nearest Neighbor algorithms, which can be either user based or item based [27]. In contrast, the model-based CF methods use the collection of ratings to learn a predictive model, which is then used to make rating predictions [33]. One of the commonly used model-based CF methods is matrix factorization (MF), which has obtained much attention due to its high performance. The CF methods do not exist the over-specialization problem as their recommendations are content independent. However, when the rating matrix is extremely sparse, making effective predictions from the scarce available ratings becomes exceedingly challenging. Moreover, with the ever increasing number of researchers and papers, the demand of computational resources will become unacceptable, which is the so-called scalability problem [34], [35].

The main efforts of the GB methods are devoted to constructing a graph, where researchers and papers are considered as nodes, and the interactions or similarities among them are considered as edges. Then researcher-paper similarities can be calculated either by path-based or random walk methods to find relevant papers [26], [32]. Comparatively, the CBF and CF methods merely adopt one or two kinds of information, whereas the GB methods can exploit diverse information sources, like social relations, trust relations, etc.

The hybrid methods are the combination of the above two or more methods, to leverage the advantages of these methods and remedy their disadvantages at the same time. Several studies have shown that the hybrid methods can generate more accurate recommendations than purely using one of them [31]. Although the hybrid methods have achieved fairly good performance in personalized paper recommendation, from Table I we can observe that few of them have been applied to provide paper recommendation for group of researchers, which is a research area remains open.

B. Group Recommendation

As people tend to do things collectively (i.e., dining out with family members, watching movies with friends), there has been a proliferation of recommender systems that try to make recommendations for a group of people. These recommender systems are called group recommender systems (GRSs). Over the past few years, many remarkable GRSs have been developed and applied in various fields from music [36], movies [37], restaurants [38], TV programs [39], point of interests (POI) [40], to learning resources [41], and so forth.

Generating recommendations that can satisfy most group members with conflicting preferences is not a trivial task. Table II presents the selected previous studies with respect to group recommendation. In the literature, some studies make recommendations directly based on group-related information [42], [43], while some studies employ the negotiation techniques to simulate the process of human decision-making, so as to reach a consensus among group members [44], [45]. As a matter of fact, most studies with regard to group recommendation are based on specific aggregation technique, and these methods can be roughly divided into two categories: 1) PA methods and 2) RA methods [15]–[17]. The PA methods first construct a group profile by consolidating each group member's preference, then traditional individual recommendation methods can be used to generate group recommendation. Researches along this line mainly concentrate on the aggregation of individual ratings by different strategies, whereas some studies focus on the aggregation of member preferences. For example, Chen *et al.* applied the gene algorithm to learn the importance of each group member, then the weighted sum of group members' ratings was considered as the group rating on unrated items [2]. To compute group's latent factors, Ortega *et al.* designed three approaches that were after factorization (AF), before factorization (BF), and weighted BF (WBF), respectively. The AF approach merged the latent factors of members belonging to the group, whereas the BF and WBF approaches merged the ratings of group members before the MF process [6]. However, the PA methods may generate a biased group profile which cannot appropriately represent the whole group. This problem mainly stems from the extreme sparsity of the user-item matrix. Notoriously, it is often the case that the user-item matrix will be extremely sparse where 99% of its elements are absent. That is to say, there are only a few group members rate the same item [46]. Under this circumstance, by applying the PA methods, the group rating to that item is dominated by just a few members, which obviously cannot reflect the preference of the whole group.

In contrast, the RA methods generate prediction for each group member beforehand, and then merge those predictions as group recommendation. According to whether the prediction for individual group member is rating or list, the RA methods can be further classified into RA with rating (RAR) methods and RA with list (RAL) methods.

TABLE II
SELECTED PREVIOUS STUDIES ABOUT GROUP RECOMMENDATION

Aggregation	Study	Year	Strategy	Recommender	Weight	Group Info
PA	Chen *et al.* [2]	2008	Weighted Sum	item_CF	✓	×
	Wang *et al.* [4]	2016	Weighted Sum	user_CF	✓	×
	Ortega *et al.* [6]	2016	----	MF	×	×
RAR	Ghazarian *et al.* [9]	2015	AVE / LM	user_CF	×	×
	Wang *et al.* [11]	2018	AVE	Tensor Factorization	×	✓
PA、RAR	Berkovsky *et al.* [14]	2010	Weighted Sum	user_CF	✓	×
PA、RAL、RAR	Boratto *et al.* [19]	2017	Additive	item_CF、user_CF	×	×
PA + RAR	Wang *et al.* [22]	2019	----	MF	✓	×
----	Liu *et al.* [7]	2018	----	MF	×	✓

Ghazarian and Nematbakhsh presented an improved user-CF method to predict the rating of each group member, then the average and least misery strategies were adopted to generate group ratings [9]. Boratto *et al.* [19] implemented both the RAR and RAL methods for group recommendation in the context that only a limited number of recommendation lists can be produced. The RA methods can relieve the problem the PA methods faced by adding auxiliary information in the individual recommendation process. More specifically, by considering both the rating information and the auxiliary information in the individual recommendation process, the problem of data sparsity can be alleviated and relatively more accurate predicted ratings of individual members can be generated. In this way, the user-item matrix becomes a full-rating matrix in which the elements can reasonably characterize preferences of group members. At this point, the result of aggregation is the one that considers all group members' preferences, rather than only take a few members into account. Therefore, this article adopts the RA methods, more specifically the RAR methods, to provide paper recommendations to groups on SSN, considering the richer information included in the predicted ratings.

However, as can be seen from Table II, the existing methods, no matter the PA or RA methods, haven't make sufficient use of the group information, from which a great deal of valuable information can be derived to facilitate recommendation. What's more, Table II reveals that existing methods mainly adopt some heuristic aggregation strategies that tend to assign an equal weight to each group member, which is not in line with the reality. Although some improvements have been proposed to remedy this problem, they fail to take into account group members' reliabilities. Therefore, in this article, a novel group paper recommendation method, GPMF_ER, is proposed to tackle the aforementioned issues.

C. Evidential Reasoning Rule

ER rule is an uncertain reasoning method that was proposed by Yang *et al.* in 2013, for the combination of multiple pieces of independent evidence considering the weight and reliability of evidence [47]. It is based on the general framework of Dempster–Shafer (D–S) theory that originated from Dempster's research when he attempted to apply upper and lower probabilities to solve the multivalued mapping problem [48]. Afterward, Shafer extended the framework further and established a mathematical theory of evidence, which marks that the D–S theory has become a complete theory to deal with uncertainty [49]. Benefiting from the ability of flexibly and effectively dealing with uncertain information, and fusing these information under the same frame of discernment, the D–S theory had been widely employed in practical problems. However, the D–S theory will lead to counter-intuitive results when combining highly or completely conflicting evidence [50]. In addition, it assumes that all evidence is reliable and can veto any proposition, which means that a proposition will be ruled out completely if any piece of evidence does not support it, no matter how much support the proposition gets from other evidence. To tackle the above issues, Yang *et al.* developed ER rule that clearly distinguished the weight and reliability of evidence. In ER rule, weight reflects the relative importance of evidence when combining with other evidence. It is subjective and depends on the preference of the decision maker and the occasion of using the evidence. Reliability reflects the quality of evidence. It is objective and depends on the ability of the evidence source to provide accurate assessment for a given problem. Furthermore, by assigning the residual support to the power set of the frame of discernment instead of to the frame of discernment itself as in the D–S theory, ER rule maintains the specificity of evidence and can produce more reasonable fusion results.

In view of the aforementioned attractive features, ER rule had been applied in plenty of fields, such as fault diagnosis [51], financial investment [52], multiple attribute decision making [53], [54]. etc. However, ER rule has not been applied to the aggregation of member preferences in GRSs. It is also an information fusion process where not only the weight, but also the reliability of each group member should be taken into account. Therefore, in this article, ER rule is adopted to aggregate individual member's ratings into a group rating.

III. Group-Oriented Paper Recommendation Method With Probabilistic Matrix Factorization and Evidential Reasoning

The establishment of numerous academic groups on SSN has brought new opportunities for the collaboration among

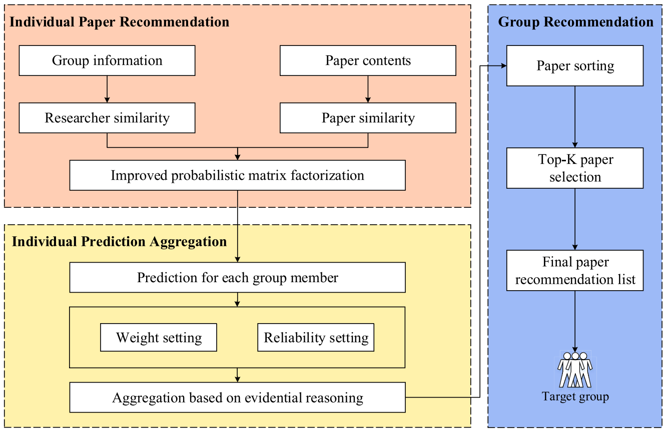

Fig. 1. Overview of the GPMF_ER Method.

researchers. In this situation, conducting paper recommendation to these academic groups is of terrific necessity to further facilitate group activities. However, existing group recommendation methods fail to make full use of the abundant group information when producing recommendations. In addition, they tend to assign an equal weight to each group member when aggregating their ratings into a group rating, which is unreasonable in practice. Therefore, in this article, a novel method termed as GPMF_ER is proposed to solve the above problems.

The overview of the GPMF_ER method is shown as Fig. 1. It contains three primary steps: 1) individual paper recommendation; 2) individual prediction aggregation; and 3) group recommendation. In the individual paper recommendation step, the researcher similarity and paper similarity are calculated, and then are embedded into the PMF model to enhance its performance and generate more accurate prediction for each group member. In the individual prediction aggregation step, the predicted rating of each group member is merged into a group rating by ER rule, where the weight and reliability for each group member are redefined to adapt to the paper recommendation situation. Finally, in the group recommendation step, top-K papers with the highest predicted ratings are recommended to the target group.

A. Problem Definition

For a clear presentation of the proposed method, the problem of recommending relevant papers to group of researchers on SSN is formally defined as follows. Let $u = \{u_1, u_2, \ldots, u_i, \ldots, u_M\}$ represent the set of researchers in which there are M researchers totally and u_i denotes the ith researcher, $v = \{v_1, v_2, \ldots, v_j, \ldots, v_N\}$ the set of papers in which there are N papers totally and v_j denotes the jth paper, $G = \{g_1, g_2, \ldots, g_l, \ldots, g_L\}$ the set of groups in which there are L groups totally and g_l denotes the lth group. Let $\mathrm{IR}_{M*N} = (r_{ij})_{M*N}$ represent the individual rating matrix where rows represent researchers, columns represent papers, and r_{ij} denotes the ith researcher's rating on the jth paper, $GR_{L*N} = (gr_{lj})_{L*N}$ the group rating matrix where rows represent groups, columns represent papers, and gr_{lj} denotes the lth group's rating on the jth paper. Our goal is to predict the rating $gr_{lj}(j = 1, 2, \ldots, N)$ for each target group g_l based on the observed ratings in IR_{M*N}, and $top - K$ papers with the highest predicted ratings will be recommended.

B. Individual Paper Recommendation Based on Improved PMF Model

The GPMF_ER method adopts the RAR methods to recommend papers for academic groups on SSN. The first step is to generate paper recommendation for each group member, which will be presented in this section. The individual paper recommendation method used in this article is mainly based on PMF, one of the most popular model-based CF methods that has been successfully applied in recommender systems. Nonetheless, the effectiveness of the original PMF model may be limited here since it neglects the valuable group information. Therefore, an improved method that integrating both the researcher similarities and the paper similarities with the PMF model, which is termed as improved PMF model thereinafter, is proposed, to make the individual predicted results more adaptive to the group situation. This section first introduces how to calculate researcher similarity and paper similarity, respectively. Then the improved PMF model is introduced to produce paper recommendation for each group member.

1) Researcher Similarity and Paper Similarity Calculation: For the measurement of researcher similarity, a variety of information has been used in previous studies, including co-authorship relations, researchers' research interests, researchers' affiliations, groups researchers have joined, and interactions between researchers on the social network, etc., [55]. Note that the focus of this study is to generate paper recommendation for academic groups. In order to make the individual paper recommendation method more adaptive to the group recommendation context, the group information is chosen to calculate researcher similarity, such that researchers from the same group can have similar feature vectors when performing MF. As for paper similarity, considering the TF-IDF technique is the most popular weighting scheme used in paper recommender systems [25], this study also employs the TF-IDF technique to extract features from papers and then calculate paper similarities.

The calculation of researcher similarity is mainly based on two assumptions. On the one hand, the more groups two researchers have joined together, the more similar they are. On the other hand, the smaller the size of a group, the higher the similarity among its members. A bipartite graph of groups and researchers is constructed to clearly depict the group-based researcher similarities. As shown in Fig. 2, the solid line indicates that researcher u_i has joined group g_l, while the dotted line means two researchers have joined common groups, on which the value refers to the number of common groups they have joined together.

Considering the effect of the first assumption, the similarity between two researchers u_i and u_h can be defined as (1), where G_i and G_h represent the groups researcher u_i and u_h have joined, respectively. $\mathrm{CG}_{i,h}$ represents the common groups researcher u_i and u_h have joined together. And $|\cdot|$ represents

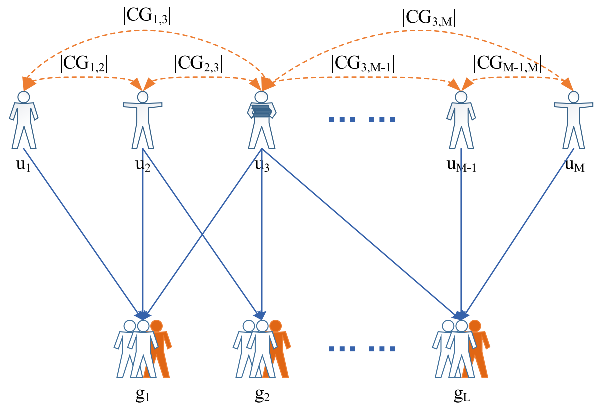

Fig. 2. Bipartite graph of groups and researchers.

the cardinality of set

$$\mathrm{SU}_{ih}^{(1)} = \frac{|\mathrm{CG}_{i,h}|}{|G_i| + |G_h|}. \tag{1}$$

The second assumption also plays an important part in measuring the similarity between researchers. Suppose researcher u_i and u_h jointly participate in a group of 1000 members, whereas researcher u_i and u_k jointly participate in a group of ten members. Apparently researcher u_i should have a higher similarity with u_k than with u_h because of the smaller size of the second group. Considering the effect of the second assumption, the similarity between two researchers u_i and u_h can be defined as (2), where cg is a certain group of $\mathrm{CG}_{i,h}$

$$\mathrm{SU}_{ih}^{(2)} = \frac{1}{|\mathrm{CG}_{i,h}|} \sum_{cg \in \mathrm{CG}_{i,h}} \frac{1}{|cg| - 1}. \tag{2}$$

By comprehensively considering the effects of the above two assumptions, i.e., the total number and the size of common groups, the final similarity between researcher u_i and u_h can be derived as

$$\mathrm{SU}_{ih} = \mathrm{SU}_{ih}^{(1)} \times \mathrm{SU}_{ih}^{(2)} = \frac{1}{|G_i| + |G_h|} \sum_{cg \in \mathrm{CG}_{i,h}} \frac{1}{|cg| - 1}. \tag{3}$$

This article similarity is calculated by TF-IDF, one of the well-known techniques in information retrieval for measuring keyword weight in a document. A keyword is important to a paper if it appears plenty of times in that paper while rarely appears in other papers. Typically, let $T = \{t_1, t_2, \ldots, t_w, \ldots, t_W\}$ represent the set of keywords in which there are W keywords totally and t_w denotes the wth keyword. The TF-IDF value of keyword t_w in paper v_j can be defined as

$$\mathrm{TI}_{w,j} = \frac{f_{w,j}}{\sum_{w=1}^{W} f_{w,j}} \times \log \frac{N}{1 + \left|\{v_j | v_j \in V, t_w \in v_j\}\right|} \tag{4}$$

where $f_{w,j}$ means the number of times that keyword t_w appears in paper v_j, N means the total number of papers, and $|\{v_j|v_j \in V, t_w \in v_j\}|$ means the number of papers including the keyword t_w.

After computing the TF-IDF value for all keywords in paper v_j, the content of paper v_j can be represented as a vector $\mathrm{Content}(v_j) = <\mathrm{TI}_{1,j}, \mathrm{TI}_{2,j}, \ldots, \mathrm{TI}_{w,j}, \ldots, \mathrm{TI}_{W,j}>$, and the similarity between paper v_j and v_k can be derived by the cosine similarity measure as (5), where $\cdot$ denotes the inner product operation of two vectors, and $||\cdot||$ denotes the norm of vector

$$\mathrm{SV}_{jk} = \frac{\mathrm{Content}(v_j) \cdot \mathrm{Content}(v_k)}{\|\mathrm{Content}(v_j)\| \times \|\mathrm{Content}(v_k)\|}. \tag{5}$$

2) Improved PMF Model With Similarity Information: The improved PMF model is mainly based on PMF, one of the variants of the MF models, which designs the model from the perspective of probability and place prior assumptions on both the observed ratings and the feature vectors [56]. In this section, we introduce how to integrate the researcher and paper similarity calculated above into the PMF model to form the improved PMF model, and then employ the improved PMF model to generate paper recommendation for each group member.

Concretely, let $U = (U_1, U_2, \ldots, U_i, \ldots, U_M)$ represent the researcher-specific feature matrix in which $U_i = < U_{i1}, U_{i2}, \ldots, U_{iD} >$ denotes the D-dimensional feature vector for researcher u_i, $V = (V_1, V_2, \ldots, V_j, \ldots, V_N)$ the paper-specific feature matrix in which $V_j = <V_{i1}, V_{i2}, \ldots, V_{iD}>$ denotes the D-dimensional feature vector for paper v_j. Suppose the researcher-paper matrix is subject to a Gaussian distribution with mean $g(U_i^T V_j)$ and variance σ_{IR}^2, then the conditional distribution over the observed ratings is defined as

$$P\left(\mathrm{IR}|U, V, \sigma_{\mathrm{IR}}^2\right) = \prod_{i=1}^{M} \prod_{j=1}^{N} \left[N\left(\mathrm{IR}_{ij} | g(U_i^T V_j), \sigma_R^2\right)\right]^{I_{ij}} \tag{6}$$

where $N(x|\mu, \sigma^2)$ is the probability density function of the Gaussian distribution with mean μ and variance σ^2. I_{ij} is the indicator function that is equal to 1 if researcher u_i has read paper v_j, 0 otherwise. And $g(x) = 1/(1 + \exp(-x))$ is the logistic function to bound the range of $U_i^T V_j$ within the interval [0, 1].

The zero-mean spherical Gaussian priors are placed on the researcher and paper feature vectors. In addition, as shown in Fig. 3, we assume that the researcher-specific feature vector U_i (paper-specific feature vector V_j) is also affected by the similar researchers' (papers') feature vectors at the same time. Consequently, the Gaussian prior distribution of feature matrix U and V are defined as

$$P\left(U|\mathrm{SU}, \sigma_U^2, \sigma_{\mathrm{SU}}^2\right) = \prod_{i=1}^{M} N\left(U_i | 0, \sigma_U^2 I\right) \times \prod_{i=1}^{M} N\left(U_i \Big| \sum_{u_h \in N(u_i)} \mathrm{SU}_{ih} U_h, \sigma_{\mathrm{SU}}^2 I\right) \tag{7}$$

$$P\left(V|\mathrm{SV}, \sigma_V^2, \sigma_{\mathrm{SV}}^2\right) = \prod_{j=1}^{N} N\left(V_j | 0, \sigma_V^2 I\right) \times \prod_{j=1}^{N} N\left(V_j \Big| \sum_{v_k \in N(v_j)} \mathrm{SV}_{jk} V_k, \sigma_{\mathrm{SV}}^2 I\right) \tag{8}$$

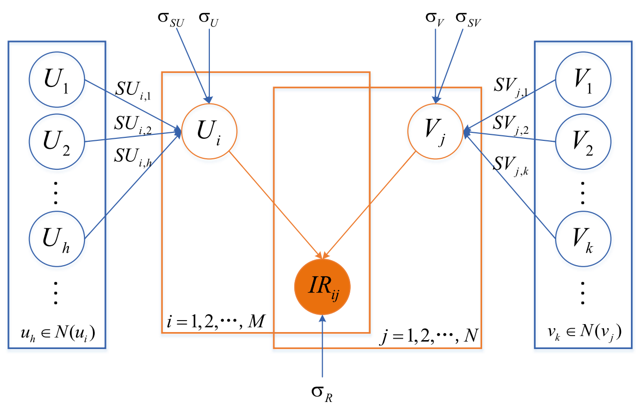

Fig. 3. Improved PMF model with group and paper content information.

where SU is the similarity matrix of researchers in which $SU_{i,h}$ is the similarity between researcher u_i and u_h computed by (3). Likewise, SV is the similarity matrix of papers in which $SV_{j,k}$ is the similarity between paper v_j and v_k computed by (5). And I is an identity matrix. $N(u_i)$ is the set of researchers who are similar to researcher u_i. $N(v_j)$ is the set of papers that are similar to paper v_j.

Through a Bayesian inference, the posterior distribution over the researcher and paper feature vectors is as

$$\begin{aligned}
&P\left(U, V|\mathrm{IR}, \mathrm{SU}, \mathrm{SV}, \sigma_{\mathrm{IR}}^2, \sigma_U^2, \sigma_V^2, \sigma_{\mathrm{SU}}^2, \sigma_{\mathrm{SV}}^2\right)\\
&\quad\propto P\left(\mathrm{IR}|U, V, \sigma_{\mathrm{IR}}^2\right)P\left(U|\mathrm{SU}, \sigma_U^2, \sigma_{\mathrm{SU}}^2\right)P\left(V|\mathrm{SV}, \sigma_V^2, \sigma_{\mathrm{SV}}^2\right)\\
&\quad= \prod_{i=1}^{M}\prod_{j=1}^{N}\left[N\left(\mathrm{IR}_{ij}|g(U_i^T V_j), \sigma_{\mathrm{IR}}^2\right)\right]^{I_{ij}}\\
&\times \prod_{i=1}^{M} N(U_i|0, \sigma_U^2 I)\prod_{i=1}^{M} N\left(U_i|\sum_{u_h\in N(u_i)}\mathrm{SU}_{ih}U_h, \sigma_{\mathrm{SU}}^2 I\right)\\
&\times \prod_{j=1}^{N} N\left(V_j|0, \sigma_V^2 I\right)\prod_{j=1}^{N} N\left(V_j|\sum_{v_k\in N(v_j)}\mathrm{SV}_{jk}V_k, \sigma_{\mathrm{SV}}^2 I\right). \qquad (9)
\end{aligned}$$

By taking the probability density function of the Gaussian distribution into (9) and simplifying the formula, we can obtain the log of the posterior distribution over the researcher and paper feature vectors

$$\begin{aligned}
&LnP\left(U, V|\mathrm{IR}, \mathrm{SU}, \mathrm{SV}, \sigma_{\mathrm{IR}}^2, \sigma_U^2, \sigma_V^2, \sigma_{\mathrm{SU}}^2, \sigma_{\mathrm{SV}}^2\right)\\
&\quad= -\frac{1}{2\sigma_{\mathrm{IR}}^2}\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij}\left(\mathrm{IR}_{ij} - g(U_i^T V_j)\right)^2\\
&\quad - \frac{1}{2\sigma_U^2}\sum_{i=1}^{M} U_i^T U_i - \frac{1}{2\sigma_V^2}\sum_{j=1}^{N} V_j^T V_j\\
&\quad - \frac{1}{2\sigma_{\mathrm{SU}}^2}\sum_{i=1}^{M}\left(\left(U_i - \sum_{u_h\in N(u_i)}\mathrm{SU}_{ih}U_h\right)^T \times \left(U_i - \sum_{u_h\in N(u_i)}\mathrm{SU}_{ih}U_h\right)\right)\\
&\quad - \frac{1}{2\sigma_{\mathrm{SV}}^2}\sum_{j=1}^{N}\left(\left(V_j - \sum_{v_k\in N(v_j)}\mathrm{SV}_{jk}V_k\right)^T \times \left(V_j - \sum_{v_k\in N(v_j)}\mathrm{SV}_{jk}V_k\right)\right)\\
&\quad - \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij}Ln\sigma_{\mathrm{IR}}^2 - \frac{1}{2}\mathrm{MDL}n\sigma_U^2 - \frac{1}{2}MDLn\sigma_{\mathrm{SU}}^2\\
&\quad - \frac{1}{2}\mathrm{NDL}n\sigma_V^2 - \frac{1}{2}NDLn\sigma_{\mathrm{SV}}^2 + C \qquad (10)
\end{aligned}$$

where C is a constant that does not depend on the parameters. And D refers to the dimension of the latent feature vectors that is far less than the dimension of the original rating matrix, i.e., M and N.

Our goal is to learn a reasonable feature matrix U and V by maximizing the log-posterior, and this is equivalent to minimizing the following objective function

$$\begin{aligned}
&E(U, V, \mathrm{IR}, \mathrm{SU}, \mathrm{SV})\\
&\quad= \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{N} I_{ij}\left(\mathrm{IR}_{ij} - g\left(U_i^T V_j\right)\right)^2\\
&\quad + \frac{\lambda_U}{2}\sum_{i=1}^{M} U_i^T U_i + \frac{\lambda_V}{2}\sum_{j=1}^{N} V_j^T V_j\\
&\quad - \frac{\lambda_{\mathrm{SU}}}{2}\sum_{i=1}^{M}\left(\left(U_i - \sum_{u_h\in N(u_i)}\mathrm{SU}_{ih}U_h\right)^T \times \left(U_i - \sum_{u_h\in N(u_i)}\mathrm{SU}_{ih}U_h\right)\right)\\
&\quad - \frac{\lambda_{\mathrm{SV}}}{2}\sum_{j=1}^{N}\left(\left(V_j - \sum_{v_k\in N(v_j)}\mathrm{SV}_{jk}V_k\right)^T \times \left(V_j - \sum_{v_k\in N(v_j)}\mathrm{SV}_{jk}V_k\right)\right) \qquad (11)
\end{aligned}$$

where $\lambda_U = (\sigma_{\mathrm{IR}}^2/\sigma_U^2)$, $\lambda_V = (\sigma_{\mathrm{IR}}^2/\sigma_V^2)$, $\lambda_{\mathrm{SU}} = (\sigma_{\mathrm{IR}}^2/\sigma_{\mathrm{SU}}^2)$, $\lambda_{\mathrm{SV}} = (\sigma_{\mathrm{IR}}^2/\sigma_{\mathrm{SV}}^2)$ are tradeoff parameters to regulate the influence of each matrix on the objective function. A local minimum of the objective function given by (11) can be found by performing the stochastic gradient descent (SGD) algorithm on U_i and V_j as (12) and (13), wherein $g(x)' = \exp(x)/(1+\exp(x))^2$ is the derivative of the logistic function $g(x)$

$$\begin{aligned}
\frac{\partial E}{\partial U_i} &= \sum_{j=1}^{N} I_{ij}\left(g\left(U_i^T V_j\right) - \mathrm{IR}_{ij}\right)g'\left(U_i^T V_j\right)V_j\\
&\quad + \lambda_u U_i + \lambda_{\mathrm{SU}}\left(U_i - \sum_{u_h\in N(u_i)}\mathrm{SU}_{ih}U_h\right)\\
&\quad - \lambda_{\mathrm{SU}}\sum_{u_h\in N(u_i)}\mathrm{SU}_{ih}\left(U_h - \sum_{u_k\in N(u_i)}\mathrm{SU}_{hk}U_k\right) \qquad (12)
\end{aligned}$$

$$\frac{\partial E}{\partial V_j} = \sum_{i=1}^{M} I_{ij}\big(g\big(U_i^T V_j\big) - \mathrm{IR}_{ij}\big)g'\big(U_i^T V_j\big)U_i + \lambda_V V_j + \lambda_{\mathrm{SV}}\left(V_j - \sum_{v_k\in N(v_j)} \mathrm{SV}_{jk}U_k\right) - \lambda_{\mathrm{SV}}\sum_{v_k\in N(v_j)} \mathrm{SV}_{jk}\left(V_k - \sum_{v_h\in N(v_j)} \mathrm{SV}_{kh}V_h\right). \quad (13)$$

After learning U and V, the predicted ratings on all papers can be estimated by $\widetilde{r_{ij}} = U_i^T V_j$ for each researcher. Table III shows the overall procedures of the individual paper recommendation method in this study.

C. Evidential Reasoning Rule for Individual Prediction Aggregation

After performing the individual paper recommendation method, each group member's predicted rating for all papers can be acquired. The next thing to do is to aggregate these member ratings into a group rating. The aggregation method used exerts a dramatic influence on final recommendation results. Most previous studies simply take the maximum, minimum, or average of member ratings as the group rating, without considering group members' different influences on final group decision. Although some improvements have been proposed to remedy this problem, they fail to take into account group members' reliabilities. Therefore, we introduce ER rule to merge member ratings by considering both the weights and reliabilities of group members. ER rule is an information fusion method which assigns weight and reliability to each piece of evidence to support multiple attribute decision analysis [47]. In the following, we first introduce the relevant concepts in ER rule, and redefine the weight and reliability to make ER rule adapt to the group paper recommendation context. Afterward, we describe how to apply ER rule to merge individual ratings into a group rating.

1) Redefinition of Weight and Reliability: We first give the definition of frame of discernment. The frame of discernment is an exhaustive set with mutually exclusive hypotheses. In this article, we define the hypotheses as the candidate papers to be recommended, and the frame of discernment can be represented as $\Theta = \{v_1, v_2, \ldots, v_j, \ldots, v_N\}$ where v_j denotes the *jth* paper. Moreover, a frame of discernment with N hypotheses has 2^N subsets, which compose the power set $2^\Theta = \{\emptyset, v_1, \ldots, v_N, \{v_1, v_2\}, \ldots, \{v_1, v_N\}, \ldots, \{v_1, \ldots, v_{N-1}\}, \Theta\}$.

We normalize the fulfilled researcher-paper matrix $\check{\mathrm{IR}}_{M*N} = \{\widetilde{r_{ij}}\}$ by row, then the rows can be regarded as pieces of evidence, which can be formalized as

$$e_i = \left\{\big(v, p_{v,i}\big) \quad \forall v \in \Theta, \sum_{v\in\Theta} p_{v,i} = 1\right\} \quad (14)$$

where $(v, p_{v,i})$ is an element of evidence e_i indicating that the ith group member supports the hypothesis v with a probability of $p_{v,i}$, which is represented as that member's normalized predicted rating in the paper recommendation context.

The weight and reliability are redefined to make ER rule adaptive to the context of this paper. Concretely, weight indicates the importance of a piece of evidence. Here, we set the weight for each group member based on their corresponding reading quantities. The reason is that if a particular member has read substantial amount of papers, he/she could be more experienced and knowledgeable, thus more persuasive than other members when making group decisions. Therefore, we consider this member is more important and assign him/her a higher weight. Let q_i denote the number of papers researcher u_i has read, g_l one of the groups researcher u_i has joined, then the relative importance of researcher u_i in group g_l can be defined as

$$w_i = q_i \Big/ \sum_{u_h\in g_l} q_h. \quad (15)$$

It is far from enough to only consider the weight of evidence. Consider this problem, if a piece of evidence support a hypothesis with a certain probability, then how likely is the evidence true and to what extent can we believe the evidence? This is what the reliability measures, the quality of evidence. Here, we define the reliability as the precision of recommendation generated for each member. As mentioned above, a list of normalized predicted ratings on all papers is seen as a piece of evidence from a certain group member. If the recommendation precision for that member is high, then the list of predicted ratings is able to characterize that member's preferences on papers very well. Under this condition, the group rating obtained by aggregating the member ratings is possible to be accurate. If even the member ratings are not accurate enough, let alone the group rating obtained by aggregating these member ratings to be accurate enough to represent the preference of the whole group. Therefore, it is suitable to measure the quality of evidence by the individual recommendation precision. Let pr_i denote the recommendation precision for researcher u_i, then the reliability of u_i can be defined as

$$r_i = pr_i \times T \quad (16)$$

where T is the parameter to regulate the bound of reliability.

2) ER Rule With Redefined Weight and Reliability: In this section, we introduce the details of aggregation using ER rule. Providing there are only two members in the target group, then the combined evidence of the evidence from the two members can be profiled by

$$e_{(2)} = \left\{\big(v, p_{v,e(2)}\big) \quad \forall v \in \Theta, \sum_{v\in\Theta} p_{v,e(2)} = 1\right\} \quad (17)$$

where $p_{v,e(2)}$ denotes the joint support for hypothesis v from the two members and it can be generated by

$$p_{v,e(2)} = \begin{cases} 0, & v = \varnothing \\ \frac{\hat{m}_{v,e(2)}}{\sum_{A\subseteq\Theta}\hat{m}_{A,e(2)}}, & v \subseteq \Theta, v \neq \varnothing \end{cases} \quad (18)$$

$$\hat{m}_{v,e(2)} = \big[(1-r_2)\cdot m_{v,1} + (1-r_1)\cdot m_{v,2}\big] + \sum\nolimits_{B\cap C=v} m_{B,1} \times m_{C,2} \quad \forall v \subseteq \Theta \quad (19)$$

where $m_{v,i} = w_i \times p_{v,i}$, and B and C are any two sets in the power set 2^Θ whose intersection is v.

TABLE III
ALGORITHM OF THE INDIVIDUAL PAPER RECOMMENDATION METHOD

Input: the observed researcher-paper matrix $IR_{M*N} = \{r_{ij}\}$, the researcher-group matrix GU_{M*L}, number of iteration I, latent feature dimension D, regularization parameters $\lambda_U, \lambda_V, \lambda_{SU}, \lambda_{SV}$, and learning rate α
Output: the fulfilled researcher-paper matrix $\widetilde{IR_{M*N}}$

```
For i = 1,2,⋯,M do
    Calculate |G_i|
    For h = 1,2,⋯,M do
        If h! = i, Calculate |G_h|, and |CG_{i,h}|
        For l = 1,2,⋯,|CG_{i,h}|
            Calculate |cg_l|
        End for
        Calculate SU_{i,h} according to (3)
    End for
End for
For j = 1,2,⋯,N do
    For k = 1,2,⋯,N do
        If k! = j, Calculate SV_{j,k} according to (5)
    End for
End for
Initialize U and V randomly
For Iter = 1,2,⋯,I do
    For each ⟨i,j⟩ ∈ IR_{M*N} do
        Calculate ∂E/∂U_i and ∂E/∂V_j according to (12) and (13)
        Update U_i = U_i − α ∂E/∂U_i
        Update V_j = V_j − α ∂E/∂V_j
    End for
End for
Return IR~_{M*N} = {r~_ij | r~_ij = U_i^T V_j}
```

TABLE IV
ALGORITHM OF GENERATING GROUP RATING BY THE ER APPROACH

Input: the fulfilled researcher-paper matrix $\widetilde{IR_{M*N}} = \{\widetilde{r_{ij}}\}$, the researcher-group matrix GU_{M*L}
Output: the group-paper matrix GR_{L*N}

```
Normalize IR~_{M*N} = {r~_ij} by row
For g_l ∈ G, l = 1,2,⋯,L do
    For v_j ∈ V, j = 1,2,⋯,N do
        For u_i ∈ g_l, i = 1,2,⋯,|g_l| do
            Calculate member weight w_i according to (15)
            Calculate member reliability r_i according to (16)
        End for
        Calculate the aggregated rating of the first two
        members according to (17)-(19)
        if |g_l| > 2
            Calculate the aggregated rating of all members
            according to (20)-(23)
    End for
End for
Return GR_{L*N}
```

When there are more than two members in a group, the aggregation process is conducted recursively to yield the final results. Concretely, the combined result of the first i pieces of evidence can be represented as

$$e_{(i)} = \left\{ \left(v, p_{v,e(i)}\right) \quad \forall v \in \Theta, \sum_{v \in \Theta} p_{v,e(i)} = 1 \right\} \tag{20}$$

where $p_{v,e(i)}$ denotes the joint support for hypothesis v from the i members and it can be generated by

$$p_{v,e(i)} = \frac{\hat{m}_{v,e(i)}}{1 - \hat{m}_{2^\Theta,e(i)}} \quad \forall v \subseteq \Theta \tag{21}$$

$$\hat{m}_{v,e(i)} = \left[(1 - r_i) m_{v,e(i-1)} + m_{2^\Theta,e(i-1)} m_{v,i}\right] + \sum_{B \cap C = v} m_{B,e(i-1)} m_{C,i} \quad \forall v \subseteq \Theta \tag{22}$$

$$\hat{m}_{2^\Theta,e(i)} = (1 - r_i) m_{2^\Theta,e(i-1)}. \tag{23}$$

To sum up, $p_{v,e(i)}$ is the final rating of the target group with i members. The overall procedures of generating the group rating by the ER approach are shown in Table IV.

D. Group Recommendation

Through the above steps, predicted ratings on all unrated papers of the target group can be obtained. Then the papers are sorted in descending order, and top-K papers with the highest predicted ratings will be recommended to the target group.

IV. EXPERIMENTAL DESIGN

In this section, extensive experiments have been conducted to evaluate the performance of the GPMF_ER method. Description of the experimental dataset and evaluation metrics is presented in Sections IV-A and IV-B, respectively. Then the elaboration regarding compared methods and the experimental procedure is given in Section IV-C.

A. Experimental Dataset

The experimental data was collected from CiteULike (http://www.citeulike.org/), a leading SSN which has been widely used among researchers. In CiteULike, researchers are allowed to discover, store, organize, and share researcher papers [57]. Moreover, CiteULike also provides the group functionality through which the researchers are enabled to share academic resources, discuss academic frontiers and collaborate with others more conveniently. Therefore, the CiteULike dataset is fairly suitable for the experimental needs of this study. The pertinent information about researchers, papers, and groups was extracted from CiteULike via a crawler. More specifically, for each researcher, the researcher ID, the joining-group records, and the collecting-paper records were collected. For each paper, besides the paper ID, the content information was collected in the form of title and abstract. The group ID was also collected for each group, whereas the information about group size and group member can be inferred from researchers' joining-group records.

TABLE V
DESCRIPTION OF THE CITEULIKE DATASET

Number of researchers	1659
Number of papers	82376
Number of groups	718
Number of researcher-paper relations	198744
Sparsity of researcher-paper relations	99.85%
Number of researcher-group relations	3073
Sparsity of researcher-group relations	99.74%

A data cleaning task was performed to ensure the authenticity of the experiments. In particular, researchers who collected less than 15 papers, papers which were collected less than two times, and groups with less than two members were removed from the dataset. Finally, the experimental dataset consists of 1659 researchers, 82 376 papers, and 718 groups. Description of the dataset is summarized in Table V.

B. Evaluation Metrics

Four commonly used evaluation metrics in recommender systems, namely, Precision, Recall, mean average precision (MAP), and mean reciprocal rank (MRR), are adopted to measure the recommendation quality of all methods [15], [17], [22], [58]. Precision and Recall measure the recommendation accuracy whereas MAP and MRR measure the ranking of items as well. Detailed definition of these four metrics is presented as follows.

Precision: Precision indicates the percentage of items recommended correctly among all recommended items, where correctly recommended items mean items both in the recommendation list and the testing set at the same time. When the recommendation number equals K, the precision can be calculated according to

$$\text{Precision@}K = \frac{1}{|G|}\sum_{g=1}^{|G|}\frac{|\text{Rec}(g)@K \cap Te(g)|}{|\text{Rec}(g)@K|} \tag{24}$$

where G is the set of groups, $\text{Rec}(g)@K$ is the top K items in the recommendation list for group g, $Te(g)$ is the set of items corresponding to group g in the testing set, and $|\cdot|$ is the cardinality of set.

Recall: Recall indicates the percentage of items recommended correctly among all correct items where correct items mean items in the testing set. When the recommendation number equals K, the recall can be calculated as

$$\text{Recall@}K = \frac{1}{|G|}\sum_{g=1}^{|G|}\frac{|\text{Rec}(g)@K \cap Te(g)|}{|Te(g)|}. \tag{25}$$

Mean Average Precision: MAP is the mean of average precision of correctly recommended items, and it can be calculated according to

$$\text{MAP} = \frac{1}{|G|}\sum_{g=1}^{|G|}\frac{1}{|\text{Rel}_g|}\sum_{k=1}^{|\text{Rel}_g|}\frac{k}{\text{Rank}_k(g)} \tag{26}$$

where Rel_g is the set of items correctly recommended for group g, and $\text{Rank}_k(g)$ is the position of the kth correctly recommended item for group g in the recommendation list.

Mean Reciprocal Rank: MRR is derived by averaging the reciprocal of the first correctly recommended item's ranking, and it can be calculated as

$$\text{MRR} = \frac{1}{|G|}\sum_{g=1}^{|G|}\frac{1}{\text{Rank}_1(g)}. \tag{27}$$

C. Experimental Procedure

To validate the effectiveness of the proposed GPMF_ER method, we compare it with several representative baselines in group recommendation. The first three methods MB, MR, and CP are three kinds of memory-based CF methods employing certain aggregation strategies to produce group recommendation. In these three methods, users with similar preferences are clustered into the same group according to a given granularity, to meet constrains of the number of recommendation lists. Since the focus of this study is not on the limit of the number of recommendation lists, we left the clustering step out and use the original groups in CiteULike instead. The following two methods AF and BF are two kinds of variants of MF when extending it to group recommendation scenario. Details regarding these baselines are as follows.

Model Based (MB) [19]: The MB method first merges member preferences into a group preference by the additive strategy, then uses the item-based CF method to generate group recommendation.

Merge Recommendations (MR) [19]: The MR method first generates recommendation list for each group member by the user-based CF method, then utilizes the average strategy to merge these recommendation lists into the final group recommendation.

Cluster and Predict (CP) [19]: The MR method first generates predicted rating for each group member by the user-based CF method, then utilizes the additive strategy to merge these ratings to get the group rating.

After Factorization [6]: As the name implies, the AF method first conducts factorization on the user-item matrix. Afterward, the feature vectors of group members are merged to get the group feature vector.

Before Factorization [6]: The BF method first models the group preference by aggregating individual preferences in a group, then obtains the group feature vector by factorizing on the group-item matrix.

GPMF_ER: It is the proposed method. It combines the improved PMF model and ER rule to produce recommendations. Concretely, it employs the improved PMF model to generate predicted rating for each group member, then combines those predicted ratings into a group rating by ER rule.

The experimental dataset was used to construct a researcher-paper matrix where rows represent researchers and columns represent papers. If researcher i has collected paper j, then the corresponding element in the matrix was set to 1, 0 otherwise. After the construction of the researcher-paper matrix, it was divided into training data and testing data in the ratio of 8 : 2. More specifically, for each researcher, we randomly selected

80% of his/her collected papers and put them into the training set, whereas the remaining 20% were put into the testing set. In addition, we ran the experiments for 10 times with a different split of the dataset each time, to prevent the experimental results from being affected by the randomness of the spilt of the dataset. And we took the average of the 10 results as our final reported results. We conducted a grid-search in the first experiment to find the optimal value of the hyperparameters for our method, and those parameters were kept constant in the remaining nine experiments. The parameter settings of our method are as follows: the regulation parameters $\lambda_U = \lambda_V = 0.05$, $\lambda_{SU} = \lambda_{SV} = 0.1$, the learning rate $\alpha = 0.6$, the number of iteration Iter $= 1000$, the latent factor dimension $D = 15$, and the number of recommendation $K = 10$. The parameters of the baseline methods are set as in the corresponding papers.

V. Results and Discussion

In this section, we compare the proposed GPMF_ER method with several state-of-the-art methods to demonstrate its effectiveness. We also conduct ablation studies to investigate the contribution of the group information and ER rule. In addition, the impact of several relevant parameters is also explored.

A. Experimental Results

Table VI reports the Precision, Recall, MAP, and MRR values of the GPMF_ER method and the baselines under different settings of recommendation number K. Among the three kinds of memory-based CF methods, the MR method achieves the best performance followed by the CP and MB method. The difference between our results and those of Boratto *et al.* [19] may be attribute to the clustering step, by which the preferences of group members become harmonious and less conflicting. It can also be observed that the AF method achieves a better performance against the BF method, which is consistent with the results of Ortega *et al.* [6] when group size is small. Overall, the proposed GPMF_ER method consistently exhibits the best performance for all recommendation numbers, which demonstrates the superiority of the proposed method. More specifically, the proposed GPMF_ER method achieves the highest Precision of 5.571% at $K = 10$, the highest Recall of 3.31% at $K = 50$, the highest MAP of 14.082% at $K = 10$, and the highest MRR of 16.502% at $K = 50$.

B. Discussion

1) Impact of Group Information for Individual Prediction: Incorporating similarity regularization, especially the group information into the PMF model is one of the main contributions of the proposed method. Therefore, ablation study is conducted to test the effectiveness of group information. We compare the proposed GPMF_ER method with methods that using other information to calculate the researcher similarity. More specifically, the RPMF_ER method employs the ratings of researchers on papers to measure the similarity between researchers. The CPMF_ER method builds a profile for each researcher in the same way as the CBF method, and calculates the researcher similarity based on these researcher profiles, whereas the PMF_ER method exerts no constraints on the feature vectors of researchers when performing MF. Note that these compared methods are the same as the proposed GPMF_ER method, except for the way of calculating researcher similarity. Fig. 4 shows the performance of the GPMF_ER method and the compared methods. It can be seen that the GPMF_ER method that employs group information gives the best performance followed by the

TABLE VI
Results of the GPMF_ER Method and Baselines

Results (%)		MB	MR	CP	AF	BF	GPMF_ER
Precision	@10	2.939	3.507	3.126	5.209	5.097	5.571
	@20	2.061	2.774	2.382	3.851	3.691	4.004
	@30	1.657	2.319	1.875	3.115	2.883	3.375
	@40	1.476	1.985	1.613	2.782	2.556	2.89
	@50	1.304	1.763	1.509	2.535	2.334	2.618
Recall	@10	0.899	0.954	0.913	1.105	1.428	1.431
	@20	1.211	1.447	1.42	1.598	2.053	2.066
	@30	1.411	1.805	1.732	1.971	2.41	2.612
	@40	1.718	2.124	1.946	2.343	2.831	2.924
	@50	1.868	2.389	2.234	2.646	3.173	3.31
MAP	@10	7.315	10.778	10.569	13.32	12.039	14.082
	@20	7.272	10.236	10.042	12.183	11.839	13.487
	@30	7.097	10.015	9.967	11.824	11.719	13.149
	@40	6.96	9.854	9.733	11.107	11.243	12.604
	@50	6.879	9.679	9.518	10.627	10.8	12.256
MRR	@10	7.258	11.591	11.246	14.693	13.376	15.654
	@20	7.629	11.683	11.475	14.889	13.86	16.109
	@30	7.77	11.976	11.803	14.981	14.068	16.369
	@40	7.866	12.454	12.267	14.758	14.166	16.431
	@50	7.912	12.559	12.394	14.903	14.237	16.502

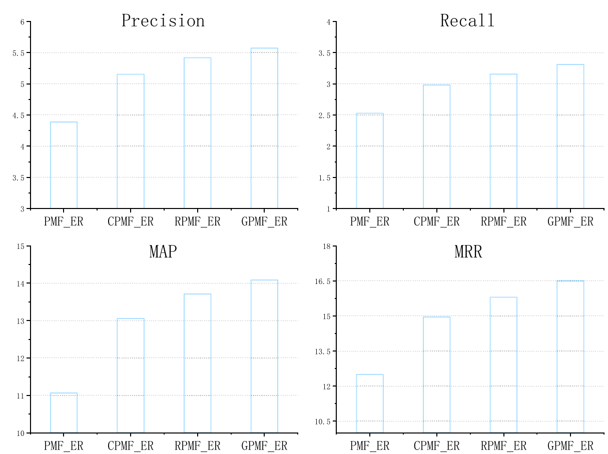

Fig. 4. Performance of the GPMF_ER method and the compared methods.

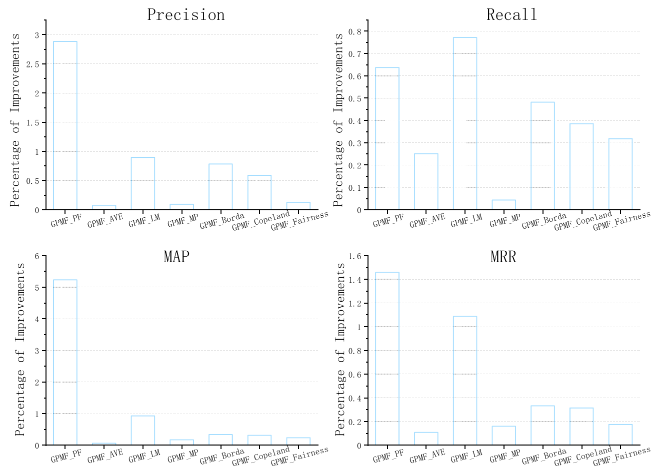

Fig. 5. Improvements of GPMF_ER against other GPMF-based methods.

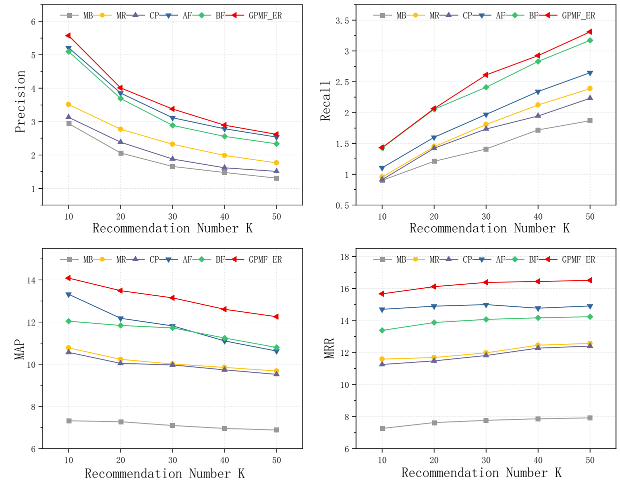

Fig. 6. Performance of GPMF_ER and baselines with different K.

RPMF_ER method. The CPMF_ER method has not achieved a satisfactory result, which may be attributed to the fusion of paper vectors to build a researcher profile. If the papers that a researcher interacted with are of various types, then the fusion of these paper vectors may lead to a loss of information, such that the built profile cannot represent the researcher properly. The PMF_ER method returns the worst performance, which is the same as we expected. The results evidence that incorporating group information has indeed improved the recommendation quality and it is reasonable to consider it when making recommendations.

2) Impact of ER Rule for Aggregation: To validate the effectiveness of ER rule, the performance improvements of the GPMF_ER method against GPMF-based methods that using other aggregation strategies are illustrated in Fig. 5. The aggregation strategies used here include one PA strategy (PF), AVErage (AVE), Least Misery (LM), Most Pleasure (MP), Borda Count (Borda), Copeland Rule (Copeland), and Fairness, and the corresponding methods are termed as GPMF_PF, GPMF_AVE, GPMF_LM, GPMF_MP, GPMF_Borda, GPMF_Copeland, and GPMF_Fairness. It can be observed that the GPMF_PF method returns the worst performance in most cases, which can be owing to the extreme sparsity of the data. Among the three RAL methods, the GPMF_Fairness method achieves the best performance followed by the GPMF_Copeland method and the GPMF_Borda method, whereas among the three RAR methods, the GPMF_AVE method achieves a better performance against the GPMF_MP method in terms of the Precision, MAP, and MRR. Generally speaking, the RAR methods gain a better performance than the RAL methods apart from one case that the GPMF_LM method gives a performance even worse than the GPMF_Borda method. Apparently, the GPMF_ER method consistently outperforms other GPMF-based methods in terms of all evaluation metrics, which demonstrates the indispensability of considering both the weights and the reliabilities of group members.

3) Parameter Analysis: The recommendation number K, the latent feature dimension D, the regulation parameter λ, and the threshold of reliability T are four influential factors for the recommendation results. Therefore, the recommendation performance under different settings of these four parameters is further explored.

Recommendation Number K: Fig. 6 shows the experimental results of the GPMF_ER method and the baselines, with the recommendation number K ranging from 10 to 50. It can be observed that with increased K, the Precision decreases significantly whereas the Recall is increasing. This is consistent with the previous studies, and the reason for this phenomenon is as follows. With the increase of the recommendation number K, the number of correct recommendations may also increase, but this increase is not as large as the increase of K, hence the Precision finally shows a downward trend. As for the Recall, the number of papers in the testing set is fixed. Therefore, with the increase of K, the number of correct recommendations also increase and the Recall finally shows an upward trend. Furthermore, with the increase of K, the MAP and MRR show a slight decrease and increase, respectively. It can also be observed that the GPMF_ER method consistently outperforms other baselines in spite of the recommendation number K, which also reveals the superiority of the proposed method.

Latent Feature Dimension D: The latent feature dimension D also has a considerable impact on the recommendation quality. Too small of D will result in an inadequate expression of the researcher and paper characteristics, while too large of D will lead to an over-fitting problem and the increase in computation complexity. Therefore, the sensitivity analysis on the latent feature dimension D is conducted to specify its optimal value. Fig. 7 illustrates the experimental results of the GPMF_ER method and the baselines under different latent feature dimension D ($D = 5, 10, 15, 20$). It depicts that with the increase of D, the Precision and Recall keep rising and finally reach the maximum when $D = 20$. As for the metrics MAP and MRR, they are initially increasing with the increase of D and reach the peak when $D = 10$. Subsequently, these two metrics begin to decline gradually as D increases further. Comprehensively, the results indicate that a good accuracy and a satisfactory order of the recommendations cannot be guaranteed simultaneously. Therefore, we finally choose

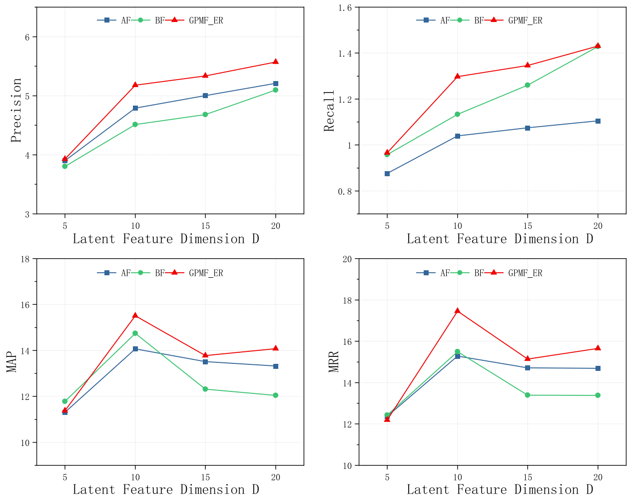

Fig. 7. Performance of GPMF_ER and baselines with different D.

$D = 15$ when performing experiments to make a compromise between the accuracy and the order.

Regulation Parameter λ: In the individual prediction step of the proposed GPMF_ER method, two kinds of auxiliary information are incorporated into the PMF model. And this comes with two corresponding regulation parameters $\ddot{e}_{SU}$ and λ_{SV} that play an important part in controlling how much the similarity information should be fused into the factorization process. Therefore, experiments should be carried out to study the impact of these two regulation parameters. For simplicity, we treat these two regulation parameters equally as λ. We vary the value of λ and gain the corresponding results of the GPMF_ER method, which are depicted in Fig. 8. It can be observed that when λ changes from 0.001 to 0.1, the Precision and Recall remains roughly stable with slight fluctuation, whereas the MAP and MRR are both increasing at a lower speed and reach the peak when λ equals 0.1. When λ continues to increase, all of the four metrics begin to decline sharply. Consequently, we can draw a conclusion that the optimal value for λ is 0.1.

Threshold of Reliability T: In the proposed method, weight and reliability are redefined for each group member. Herein weights $w_i (0 \le w_i \le 1)$ are a series of relative values and the total weights of all group members equal to 1. Meanwhile, reliabilities $r_i (0 \le r_i \le 1)$ are a series of absolute values that have no interaction effects with each other. Reliabilities indicate the trustable degree of each group member where $r_i = 0$ means "not reliable at all" and $r_i = 1$ means "fully reliable." However, in reality, there is not any member is fully reliable and can represent the whole group entirely. Hence, a threshold is needed to bound the range of the reliabilities. Fig. 9 shows the results of the GPMF_ER method and the PMF_ER method with the threshold of reliability T ranging from 0.75 to 0.9. From Fig. 9 we can observe a slight variation along with the rising of T. But the overall tendency is increasing and the two methods achieve their best performance when the threshold of reliability T is 0.9. Hence, we set $T = 0.9$ when performing experiments.

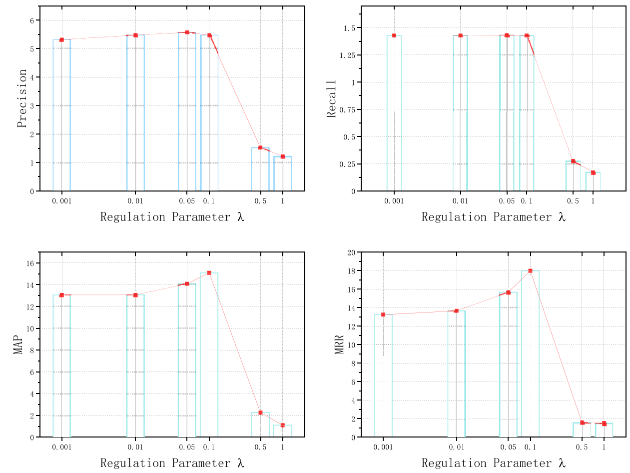

Fig. 8. Performance of GPMF_ER with different λ.

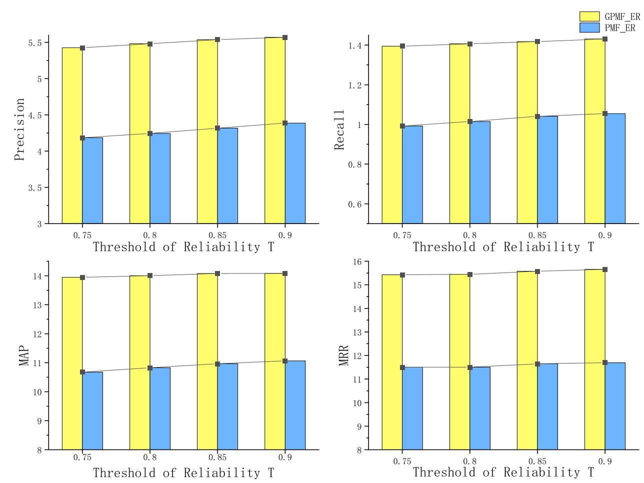

Fig. 9. Performance of GPMF_ER and PMF_ER with different T.

VI. Conclusion and Future Work

Recommending papers for academic groups on SSN is of great significance, which is beneficial for the collaboration among researchers and R&D project planning of the policymakers. Considering the shortcomings of current group recommendation methods, the GPMF_ER method is proposed in this article. The group and paper content information are incorporated into the PMF model to form a hybrid individual paper recommendation model, making the individual predicted results more adaptive to the group situation. ER rule is adopted to merge the predicted ratings of group members into a group rating. Compared with merely using heuristic strategies like average and least misery, ER rule considers the importance and reliability of group members at the same time, which makes the aggregation closer to the actual group decision-making process in reality, such that a more reasonable group rating can be obtained. Experiments on the real world CiteULike dataset indicate that the proposed method gets better recommendation results than the baselines, which demonstrates the effectiveness of the proposed method.

For the future work, one promising direction is to take the time factor into consideration to capture the dynamic changes with respect to the interests of the target group. Furthermore, in this study, only one kind of information is considered when computing researcher similarity and paper similarity. In the future research, the combination of various information, like the social relations among researchers and the citation relationships among papers, can be considered to get more accurate similarities.

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