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Group article recommendation based on ER rule in Scientific Social Networks

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ABSTRACT

Group Recommendation Systems (GRS) is an emerging area in both research and practice and has been successfully developed in many domains as a type of information filter to overcome the information overload problem. With the growth of Scientific Social Networks (SSNs), the need for article recommendation is emerging. Considering that researchers can be grouped according to their research interests, and article recommendation to a group of users has not been addressed in the literature, this paper aims to develop and test an inferential model to accurately recommend articles for group researchers in SSNs. In this paper, a novel approach for group article recommendation, referred to as GPRAH_ER, is proposed to improve the processes of both individual prediction and group aggregation. In the stage of individual prediction, the Probabilistic Matrix Factorization method is adopted and is further unified by using articles' contents and group information. In the stage of group aggregation, the ER rule is introduced in the aggregation process, since it possesses the advantages of identifying group members' impacts based on the group member's weight and reliability. To verify the performance of the proposed method, experiments are conducted on a real dataset CiteULike. The experimental results show that the proposed GPRAH_ER method outperforms other benchmark methods, and provides a more effective recommendation of articles to researchers in SSNs.

1. Introduction

Over the past years, Individual Recommendation Systems (IRS) have received a lot of attention [1]. They are used as a type of information filter to overcome the information overload problem in various areas such as the online community [2]. With the prevalence of the online community, most users in the community are intended to carry out a certain activity as a group, and users participate in many different groups can obtain more diverse information, thus another type of recommendation systems called Group Recommendation Systems (GRS) are gradually rising [1]. In many areas, the GRS have been successfully applied, such as music, movie, and travel fields. Recently, as the Scientific Social Networks (SSN) are growing up, there appears a growing number of researchers and articles, which lead to the information overload problem as well and makes researchers difficult to find their target articles. Some popular platforms like Google Scholar, ResearchGate, and CiteULike try to help researchers get their favorite articles conveniently. Google Scholar conducting article recommendations via the "related articles" and "create alerts" function, ResearchGate allows researchers to get recommendations on the home page, and CiteULike recommends articles to researchers according to researchers' behavior. To further facilitate the academic exchange in SSNs, various academic groups have been established by researchers who desire to keep informed with the current edge of their research fields. With such groups, certain research topics can be more easily and specifically focused, and academic exchanges can be more effectively conducted [2]. Since the groups that the researchers participated in can be a reflection of members' potential interests, and the researchers can obtain different types of articles from different groups, the group may play an important role in inferring the researchers' preferences. Therefore, it is reasonable to perform the article recommendation in group manners, i.e., applying group-oriented recommendation to the article in SSNs, and it would be a valuable problem that deserves our efforts [3–5].

For applying individual-oriented recommendation to the article, the main methods of it can be classified into three categories: Content-Based Filtering (CBF) method, Collaborative Filtering (CF) method, and Hybrid method [6–8]. At the early stage, the CBF

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method tries to recommend items based on the items' content and the users' historical preferences, which is based on the assumption that users who used to prefer certain types of items would still prefer them in the future [9]. For example, Hong et al. implemented the personalized article recommendation which exploited the user-profile-based method to extract keywords by keyword extraction and keyword inference [10]. Achakulvisut et al. introduced a new way to find relevant publications based on the content of articles, which aimed to adapt the new content and provided near-real-time recommendations [11]. Chandrasekaran et al. presented a recommendation system that used documents and the user profiles as trees of concepts and then computed similarities by the tree-edit distance algorithm [12]. Nascimento et al. introduced a source independent recommendation framework that generated potential queries by the single input article and then submitted to the existing web information sources which hold the research articles [13]. However, since the CBF method only emphasized the content of items, it makes the recommendation over specialized and ignores the opinions of other users. Moreover, the contents of items are always difficult to acquire automatically, which results in an inaccurate profile extraction problem. These problems significantly limit the performance of the recommendation [14–16].

Another effective method, the CF, has sprung up with the prevalence of recommendation and is known to be the most widely used method in present recommendation [17–19]. The main assumption of the CF method is that users who share similar preferences in the past would have similar preferences in the future. Given its wide application in e-commerce systems, such as Amazon and Netflix, there are a lot of explorations in article recommendation with the CF method as well. For example, Bogers et al. used a social reference manager as a test collection to recommend articles with multiple data and presented three user-based CF methods for recommendation [20]. Lee et al. considered self-defined social contacts and incorporated personal trust into traditional CF methods to improve recommendation quality [21]. McNee et al. built the citation graph between articles and then incorporated social citation networks into the CF method for recommending research articles [22]. Das et al. proposed novel methods to recommend Google News for users, which exploited the CF with MinHash clustering, and used a linear model to carry out recommendations [23]. However, the CF method also encounters several limitations such as data sparsity and cold start problems, which makes it unable to achieve the expected performance. Owing to the data sparsity, the similarity computation based on these sparse data may not be accurate and the performance of the recommendation would be affected. Meanwhile, for the cold start problem, the recommendation quality for a new user would be worse since the past preferences of it are absent.

To alleviate the problems of the CBF and the CF methods mentioned previously and meanwhile leverage the advantages of them, the hybrid method which combines the CBF method and the CF method is exploited [4,24]. Since the hybrid method is designed to overcome the disadvantages of either a single CF method or CBF method, it has gradually become a research hotspot to optimize the performance of recommendation [8]. For example, Wang et al. presented a recommendation method that combined the probabilistic topic model and an interpretable latent structure with CF to recommend both existing articles and newly published articles [25]. Pudhiyaveetil et al. proposed a method executed CBF based on the result trained through the decision tree, instead of incorporating the CBF approach into the CF approach [26]. Hwang et al. presented a hybrid method that switched between the co-authorship network-based method and the content-based method, which is= based on the content coherence of a task profile [27]. Ticha et al. used semantic data from items to build a user semantic model and then used the user semantic model with user ratings to recommend [28]. Chuanfei et al. built the TV program ontology to take the semantic relationship to estimate the concept similarity of contents, and then the CF method based on the ontology was presented on the personalized TV program application [29]. In these studies, many different hybrid strategies have been carried out to demonstrate the effectiveness of the hybrid method. They combined the different methods to make full use of each other's advantages and reduce their respective disadvantages.

For the GRS, it has previously been successfully developed in many domains, such as Music, Movies, Restaurant, and Travel fields, but has seldom applied for the article recommendation in SSNs [30–34]. As mentioned earlier, the group article recommendation in SSNs would be a valuable problem that deserves attention. The methods of the group recommendation can be classified into two types: Preference Aggregation (PA) method and Recommendation Aggregation (RA) method [2,5,35–37]. The PA method transforms individual members' preferences into a group preference, then takes the whole group as a pseudo-user to compute the prediction value by the individual prediction model. In other words, this method constructs a preference model for a whole group before predicting ratings for all items. For example, Kim et al. proposed a group recommendation method that used CBF to find neighbors and used CF to generate recommendation lists when group profiles had been generated and then removed irrelevant books from the recommendation list to improve the satisfaction of individual members [17]. McCarthy et al. introduced MusicFX to broadcast music stations for present exercising people in the fitness center via aggregating individual profiles before recommendation [32]. McCarthy et al. introduced CATS to recommend skiing vacation places for groups of friends by the preference aggregation as well [38]. Garcia et al. built group profiles by aggregating individual members' preferences and applying a mixed hybrid technique to elicit the preferences [39]. Ortega et al. proposed three group recommendation methods, one of which added weight to each rated item before folding in group factors by matrix factorization and then generated the final recommendation [2]. Quan et al. used Bayesian networks and analytic hierarchy process to infer groups' preferences and recommended appropriate TV program for users [40]. However, the PA method is poor in construct group profiles since there is a lot of original rating information absent. Therefore, it is not rigorous to simply merge the group preferences for that the opinions of some special group members may be ignored, and the preferences of the whole group cannot be effectively represented.

The latter method of GRS is the RA method, which has two main branches. One of them is the PRA method which merges individual predicted ratings, and the other is the RRA method which merges individual ranking lists on items. Both the predicted ratings and the ranking lists are the results generated from an individual prediction model, in which the ranking lists are sorted by the predicted ratings in descending order. The PRA method aggregates each group members' predicted ratings on all items in a group and takes it as the group's predicted ratings on the corresponding items. The RRA method aggregates each group members' ranking list into a final ranking list for a whole group. In sum, the RA method first generates predictions for each group member and then merges those predictions as final group recommendations [35,41–43]. For the studies of PRA, Ntoutsi et al. proposed a system gRecs that clustered the similar users into a group and used the collaborative methods to compute individual value scores in the first step and then aggregated the individuals' recommendations into group recommendation [33]. Sarik Ghazarian et al. focused on tackling the data sparsity problem in group recommendation systems by using SVM to evaluate similarities among items, and further to enhance the basic memory-based CF method [1]. Inma Garcia et al. proposed the group recommendation method Generalist Recommender System Kernel that computed individual members' recommendations by aggregating individual preferences, and then a group recommendation list was generated by individual members' recommendations [44]. For the studies of RRA, O'Connor et al. proposed PolyLens that recommended movies to group members who watched movies together via the RA method [31]. Likewise, Ardissono et al. proposed a RA method that recommended travel sites to group travelers and reduced the conflict among group members [34]. Ondrej et al. proposed a hybrid recommendation method that combined the CBF method and the CF method and finally used aggregation methods to recommend the most suitable results [8]. Generally, since the RRA method only uses the ranking information without knowing the details about the difference of two recommend items in the lists, it may lead to an imprecise group ranking list. Conversely, the PRA method which makes use of the prediction values for aggregation can be regarded as more concrete and accurate for group recommendation. Therefore, the main efforts of our study have been naturally focused on the PRA method.

To the best of our knowledge, the current researches have rarely concentrated on exploiting group recommendation for articles in the research field, and the present aggregation methods for the group recommendation is still imperfect. Therefore, to further improve the performance of the group article recommendation, a novel approach for group article recommendation based on evidential reasoning (ER) rule is proposed [45]. Firstly, for the individual prediction model, the Probabilistic Matrix Factorization (PMF) method is extended with side information. Specifically, the group information is incorporated as it can provide more information about researchers' potential preferences. To make full use of articles' contents, the similarities among articles are measured by the standard CBF method. Then, for the group aggregation methods, the ER rule is introduced since the traditional aggregation methods simply merge the individual members' results without considering the different impacts of group members. Specifically, the weights and the reliabilities are assigned to different members to make the group aggregation more reasonable in the group article recommendation. Having comprehensively considered the benefits of the hybrid method and the ER rule in the group article recommendation, a novel approach for group article recommendation based on ER rule, i.e., GPRAH_ER, is proposed.

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

(1) An enhanced framework for group article recommendation is proposed, which applies to the SSNs and significantly improves the recommendation performance. In the framework, the hybrid method with the side information is considered to make a tradeoff between the CF and the CBF method, and the ER rule is introduced to enhance the aggregation performance.

(2) An approach of the hybrid individual prediction model with the ER rule is proposed for group article recommendation. On the one hand, the PMF method is adopted with incorporating side information, since the side information from articles which is computed by the CBF method can leverage the articles' contents, and the group information incorporated into the PMF method can get more researchers' potential interest. On the other hand, the ER rule is introduced in the group aggregation, since it possesses the advantages of identifying group members' impacts based on the group member's weight and reliability.

(3) To evaluate the performance of the proposed GPRAH_ER method, the comparison experiments are conducted on the CiteULike dataset, and the experimental results show that the proposed method is effective.

The rest of this paper is organized as follows. The details of the proposed group article recommendation method are introduced in Section 2. Section 3 presents the experimental design that includes dataset, evaluation metrics, compared methods, and experimental procedure. The results analysis and the discussion of parameters are demonstrated in Section 4. In Section 5, the conclusions and the prospect are drawn.

2. A novel approach for group article recommendation based on ER rule

As the various academic groups are established by researchers in SSNs, researchers can focus on certain research topics easily and specifically, and the academic exchanges can be conducted more effectively. In general, such groups are formed based on different properties such as interest and specialty, and researchers can get diverse scholarly information from different types of groups they participated in [2]. Therefore, this study mainly focuses on the group article recommendation. As mentioned earlier, the group recommendation is a two-step process that one is prediction and another is aggregation [1,2,43]. In terms of prediction, the PMF method is combined with side information to improve the recommendation performance, in which the side information comprises the group information and the articles' similarities derived from the CBF method. In terms of aggregation, the traditional aggregation methods such as the least misery and the most pleasure, which only consider the maximum or the minimum rating of group members, may lose valuable information in the aggregation process. Moreover, group members should have different impacts on the aggregation process according to their different contributions. Therefore, the ER rule is introduced in the group aggregation, since it possesses the advantages of identifying group members' impacts based on the group member's weight and reliability.

The details of the proposed group article recommendation approach are presented as follows. First, the problem formalization is given: Suppose there are M researchers and N articles in the SSN, let $Re = \{u_1, u_2, \ldots, u_i, \ldots, u_M\}$ denote the set of researchers with u_i indicating the ith researcher, and let $Ar = \left\{v_1, v_2, \ldots, v_j, \ldots, v_N\right\}$ denote the set of articles with v_j indicating the jth article. Let the individual rating matrix $R_{M\times N} = \{\mathrm{r}_{ij}\}$ represent the preference of researchers on articles, where r_{ij} means the ith researcher's preference degree of the jth article. Then let $Gr = \{G_1, G_2, \ldots, G_k, \ldots, G_L\}$ indicates the set of groups, and $G_{M\times L} = \{\mathrm{p}_{ik}\}$ refers to the researcher–group matrix by p_{ik} indicating whether the ith researcher has participated in the kth group. Let $GR_{L\times N} = \left\{g_{kj}\right\}$ denote the final prediction results for the group of the article, where g_{kj} means the kth group's preference degree of the jth article. Let vector w_i $(0 \leq w_i \leq 1)$ and vector R_i $(0 \leq R_i \leq 1)$ denote the weight and the reliability of each group member respectively. The framework of the proposed approach consists of three components: data acquisition, individual prediction method, and group aggregation method. First, the original data are obtained, and the data analysis and the data pre-processing are conducted. Secondly, the individual prediction model is conducted based on the PMF method incorporating the side information from the articles' contents and the group information. Thirdly, the group aggregation method is constructed for each group to get the groups' final predicted ratings via ER rule. For each group, the final predicted ratings on articles are sorted by descending order, and then the top-ranked articles are recommended to groups. Fig. 1 shows an overview of the proposed GPRAH_ER method.

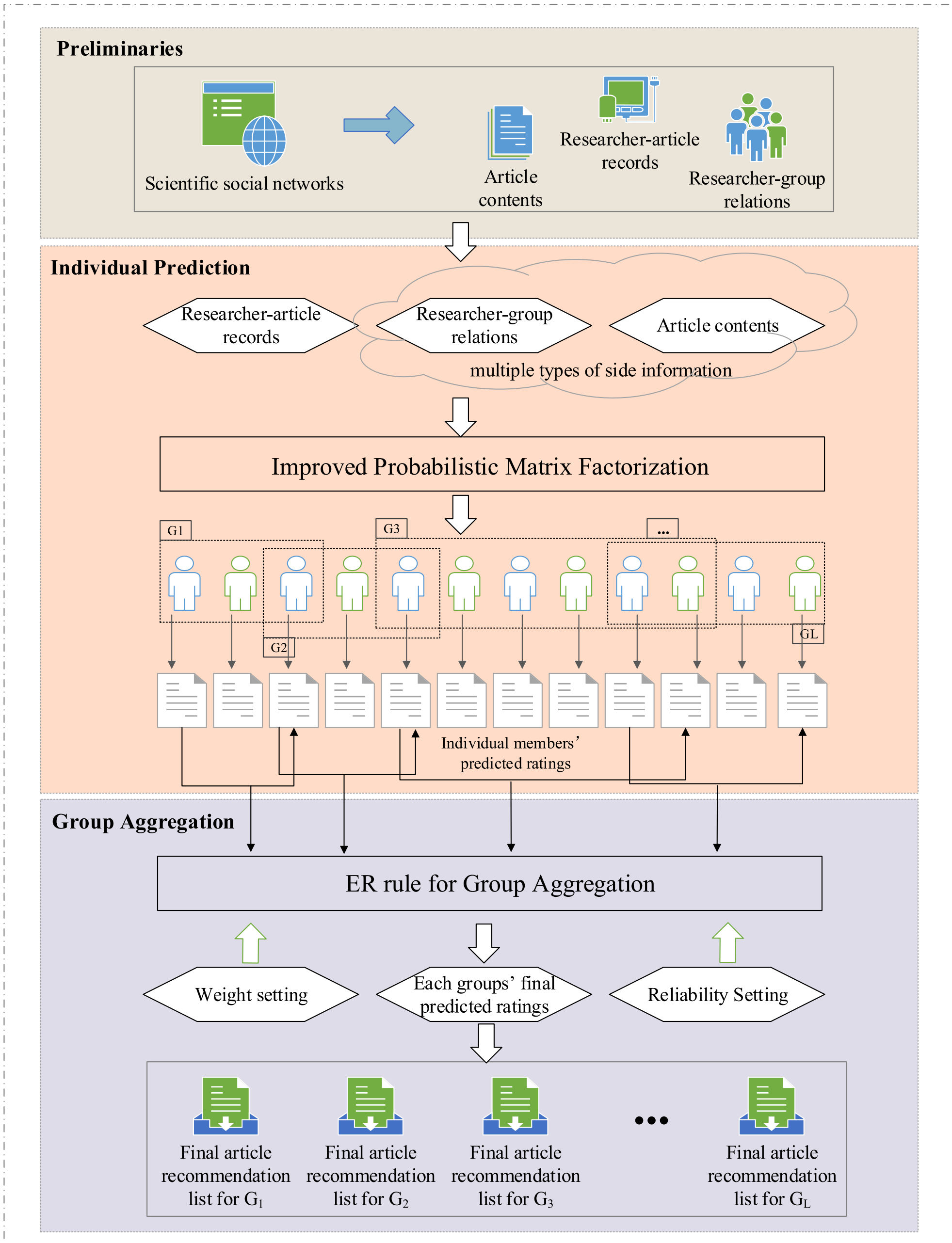

Fig. 1. Overview of the novel approach for group article recommendation based on ER rule.

2.1. Data acquisition

The original data is obtained by the web crawler which is used to retrieve all researchers, articles, and groups on the SSNs. The researchers' collecting records of articles, the researcher–group relations, the articles' contents, and other information are collected together. Since the collected original data might exist duplicated records and incomplete data to affect the recommendation, the data analysis and data pre-processing are needed to be conducted subsequently. The data pre-processing comprises three basic procedures: data denoising, word segmentation, and stop words removing [46,47]. Firstly, the researchers, groups and articles with insufficient information are abandoned. For instance, a group generated by one researcher is removed for it might lead to a bad performance. The same measures are also taken to the abandoned researchers and the abandoned articles. Subsequently, the main implement of English word segmentation is used to execute the term extraction process. It divides the articles into several segments and returns the word stem of third-person issue. Then, the non-informative word and the acting auxiliary word are stopped since they cannot effectively represent a specific article or a domain. For example, "an" or "the" such non-informative words would be removed to lead the rest of the words more accurately represented the article. The main purpose of the data preprocessing is to convert the original data into a structured data form and obtain more meaningful information to make better preparation for the recommendation.

2.2. Individual prediction model

For the individual recommendation, the CBF method concentrates on the item content, while the CF method focuses on the interaction among users. The CF method assumes that users who used to share similar preferences in the past would be regarded as a category of users with similar preferences in the future. Specifically, the CF method can be divided into the memory-based CF method and the model-based CF method [48]. For the memory-based CF method, the recommendation is based on the similarity of users, in which the similarity is computed by users' actual ratings on items. This method relies heavily on the simple similarity metrics, such as cosine similarity and Pearson correlation coefficients, to match similar users or items, and it ignores the sparsity problem of the rating matrix. For the model-based CF method, it tries to learn complex patterns based on training data and provide recommendations based on the trained models [49]. One of the popular model-based CF methods is the Probabilistic Matrix Factorization (PMF), which has been successfully applied in the recommendation systems [50]. The PMF method focuses on predicting unknown ratings by decomposing the rating matrix into two low dimensional latent factor matrices and making their product close to the rating matrix. It possesses an accurate and stable predictive performance in most cases and can leverage the side information to alleviate the data sparsity problems. Based on the assumption that articles with similar contents may attract the same kind of researchers and researchers participating in similar groups may have similar preferences, we use the side information derived from the CBF method to take full use of the articles' contents, and incorporate the group information to capture researchers' potential interests. To this end, the PMF method is utilized for the individual article prediction and is further improved by the articles' contents and the group information.

Generally, the decomposition process is conducted based on the researcher–article rating matrix $R_{M\times N}$ along with the researcher–group matrix $G_{M\times L}$, to get the researcher latent feature matrix $U \in R^{M\times K}$, the article latent feature matrix $V \in R^{K\times N}$, and the group latent feature matrix $C \in R^{K\times L}$. The probability graph model can be described in Fig. 2.

As shown in Fig. 2, the researcher–article rating matrix $R_{M\times N}$ has been decomposed into the researcher latent feature matrix U and the article latent feature matrix V. The U_i and V_j respectively refers to the ith researcher's latent feature vector and the jth article's latent feature vector. To ensure articles with similar contents can have similar feature vectors when performing matrix factorization, the content similarity between articles is computed based on the CBF method, and is then incorporated into the PMF method, as shown on the left of Fig. 1, where S_{jf} means the content similarity between articles υ_j and υ_f measured by the cosine similarity, and $t(j)$ refers to a set of similar articles of the article υ_j. Meanwhile, the group information is taken by the researcher–group matrix, which is decomposed together with the researcher–article rating matrix. As shown on the right of Fig. 2, a part of the researcher latent feature matrix U is obtained by the researcher–group matrix $G_{M\times L}$, which aims to constrain the original U that decomposed by the $R_{M\times N}$ with group information. In this process, the group latent feature matrix $C$is also generated. Specifically, according to the assumption of the traditional PMF method, the conditional distribution over the researcher–article rating matrix $R_{M\times N}$ and the researcher–group matrix $G_{M\times L}$ is defined as follows

$$P\left(R\left|U,V,\sigma_R^2\right.\right)=\prod_{i=1}^{M}\prod_{j=1}^{N}\left[N\left(R_{i,j}\left|g\left(U_i^TV_j\right),\sigma_R^2\right.\right)\right]^{I_{i,j}^R} \tag{1}$$

$$P\left(G\left|U,C,\sigma_G^2\right.\right)=\prod_{i=1}^{M}\prod_{k=1}^{L}\left[N\left(G_{\mathrm{i,k}}\left|g(U_i^TC_k),\sigma_G^2\right.\right)\right]^{I_{\mathrm{i,k}}^G} \tag{2}$$

where $N\left(x\left|\mu,\sigma^2\right.\right)$ refers to that x follows the Gaussian distribution with a mean of μ and a variance of σ^2. Function $g(x)$ means the function $g(x) = 1/(1+exp(-x))$, which is used to map the values of $x = U_i^TV_j$ etc. into [0,1]. The indicator function $I_{i,j}^R$ indicates whether the researcher u_i has collected the article υ_j. It means u_i has collected υ_j when $I_{i,j}^R$ is 1, and otherwise $I_{i,j}^R=0$. The $I_{\mathrm{i,k}}^G$ has the analogous meaning of the $I_{i,j}^R$.

Besides, the other assumption of the method is that U_i, V_j, and C_k are all following zero-mean Gaussian distributions. Meanwhile, an article feature vector is also affected by its similar articles' feature vectors. The distributions are shown as follows:

$$P\left(U\left|\sigma_U^2\right.\right)=\prod_{i=1}^{M}N\left(U_i\left|0,\sigma_U^2I\right.\right) \tag{3}$$

$$P\left(\mathrm{C}|\sigma_g^2\right)=\prod_{k=1}^{L}N\left(C_k|0,\sigma_g^2I\right) \tag{4}$$

$$P\left(V\left|S,\sigma_V^2,\sigma_s^2\right.\right)=\prod_{j=1}^{N}N\left(V_j\left|0,\sigma_V^2I\right.\right)\times\prod_{j=1}^{N}N\left(V_j\left|\sum_{f\in t(j)}S_{jf}V_f,\sigma_V^2I\right.\right) \tag{5}$$

Afterward, the posterior probability distribution can be obtained through the Bayesian inference.

$$\begin{aligned}&P\left(U,V,C\left|R,\mathrm{G},S,\sigma_U^2,\sigma_V^2,\sigma_g^2,\sigma_R^2,\sigma_G^2,\sigma_s^2\right.\right)\\&\quad\propto P\left(R\left|U,V,\sigma_R^2\right.\right)P\left(G\left|U,\mathrm{C},\sigma_G^2\right.\right)\\&\quad\times P\left(U\left|\sigma_U^2\right.\right)P\left(C\left|\sigma_g^2\right.\right)P\left(V|\,S,\sigma_V^2,\sigma_s^2\right)\\&=\prod_{i=1}^{M}\prod_{j=1}^{N}\left[N\left(R_{i,j}\left|g\left(U_i^TV_j\right),\sigma_R^2\right.\right)\right]^{I_{i,j}^R}\\&\quad\times\prod_{i=1}^{M}\prod_{k=1}^{L}\left[N\left(G_{\mathrm{i,k}}\left|g(U_i^TC_k),\sigma_G^2\right.\right)\right]^{I_{\mathrm{i,k}}^G}\times\\&\quad\prod_{j=1}^{N}N\left(V_j\left|0,\sigma_V^2I\right.\right)\times\prod_{j=1}^{N}N\left(V_j\left|\sum_{f\in t(j)}S_{jf}V_f,\sigma_s^2I\right.\right)\\&\quad\times\prod_{i=1}^{M}N\left(U_i\left|0,\sigma_U^2I\right.\right)\times\prod_{k=1}^{L}N\left(C_k|0,\sigma_g^2I\right)\end{aligned} \tag{6}$$

The above equation is then solved by the log of the posterior distribution, which is given as:

$$\begin{aligned}&\ln p\left(U,V,C\left|R,\mathrm{G},S,\sigma_U^2,\sigma_V^2,\sigma_g^2,\sigma_R^2,\sigma_G^2,\ \sigma_s^2\right.\right)\\&=-\frac{1}{2\sigma_R^2}\sum_{i=1}^{M}\sum_{j=1}^{N}I_{i,j}^R\left(R_{i,j}-g\left(U_i^TV_j\right)\right)^2\\&\quad-\frac{1}{2\sigma_G^2}\sum_{i=1}^{M}\sum_{k=1}^{L}I_{\mathrm{i,k}}^G\left(G_{\mathrm{i,k}}-g\left(U_i^TC_k\right)\right)^2-\\&\frac{1}{2\sigma_s^2}\sum_{j=1}^{M}\left(\left(V_j-\sum_{f\in t(j)}S_{\mathrm{jf}}V_f\right)^T\left(V_f-\sum_{z\in t(f)}S_{\mathrm{fz}}V_z\right)\right)\\&\quad-\frac{1}{2\sigma_V^2}\sum_{j=1}^{N}V_j^TV_j-\frac{1}{2\sigma_U^2}\sum_{i=1}^{M}U_i^TU_i-\frac{1}{2\sigma_g^2}\sum_{k=1}^{L}C_k^TC_k-\\&\frac{1}{2}\left(\sum_{i=1}^{N}\sum_{j=1}^{M}I_{i,j}^R\right)\ln\sigma_R^2-\frac{1}{2}\left(\sum_{i=1}^{N}\sum_{k=1}^{L}I_{\mathrm{i,k}}^G\right)\ln\sigma_G^2\\&\quad-\frac{1}{2}(M\times K)\ln\sigma_U^2-\frac{1}{2}(N\times K)\ln\sigma_V^2-\\&\frac{1}{2}(N\times K)\ln\sigma_s^2-\frac{1}{2}(M\times K)\ln\sigma_g^2+C\end{aligned} \tag{7}$$

where K means the latent feature dimension which the original rating matrix aims decomposing to and C means the constant term after computation. To maximize the log-posterior is

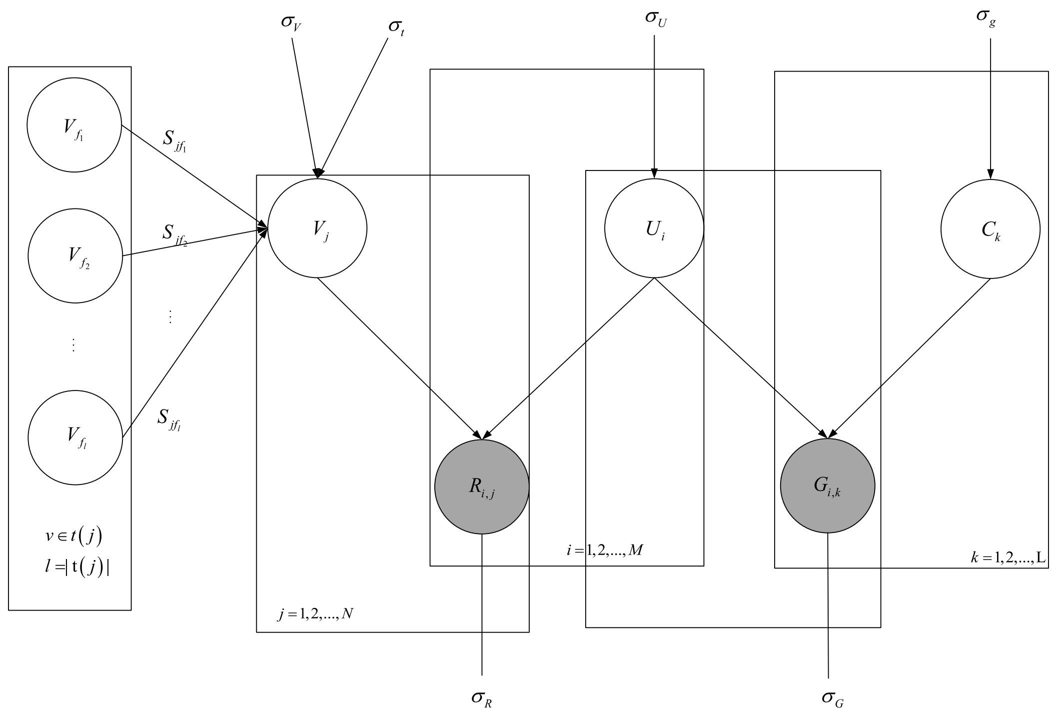

Fig. 2. The probability graph model of prediction with side information.

equivalent to minimize the following objective functions:

$$
\begin{aligned}
&E\left(U, V, C, R, G, S\right) \\
&= \frac{1}{2}\sum_{i=1}^{M}\sum_{j=1}^{N} I_{i,j}^{R}\left(R_{i,j} - g\left(U_i^T V_j\right)\right)^2 \\
&\quad + \frac{\lambda_G}{2}\sum_{i=1}^{M}\sum_{k=1}^{L} I_{i,k}^{G}\left(G_{i,k} - g\left(U_i^T C_k\right)\right)^2 + \frac{\lambda_u}{2}\sum_{i=1}^{M} U_i^T U_i + \\
&\frac{\lambda_s}{2}\sum_{j=1}^{N}(V_j - \sum_{f\in t(j)} S_{jf} V_j)^T (V_f - \sum_{z\in t(f)} S_{fz} V_f) \\
&\quad + \frac{\lambda_v}{2}\sum_{j=1}^{N} V_j^T V_j + \frac{\lambda_g}{2}\sum_{k=1}^{L} C_k^T C_k
\end{aligned}
\tag{8}
$$

where $\lambda_u = \frac{\sigma_R^2}{\sigma_U^2}$, $\lambda_v = \frac{\sigma_R^2}{\sigma_V^2}$, $\lambda_s = \frac{\sigma_R^2}{\sigma_S^2}$, $\lambda_g = \frac{\sigma_R^2}{\sigma_g^2}$, $\lambda_G = \frac{\sigma_R^2}{\sigma_G^2}$ reflect the influence of each matrix on the objective function.

Finally, to minimize the function (8), the gradient descent method is used to learn the researcher latent feature vector U_i, the article latent feature vector V_j, and the group latent feature vector C_k [51,52]. By differentiation the analytic expression, they are computed as follows:

$$
\begin{aligned}
\frac{\partial E}{\partial V_j} &= \sum_{i=1}^{M} I_{i,j}^{R}\left(g\left(U_i^T V_j\right) - R_{i,j}\right) g'\left(U_i^T V_j\right) V_j \\
&\quad + \lambda_s\left(V_j - \sum_{f\in t(j)} S_{jf} V_f\right) - \lambda_s \sum_{f\in t(j)} S_{jf}\left(V_f - \sum_{z\in t(f)} S_{fz} V_z\right) + \lambda_v V_j
\end{aligned}
\tag{9}
$$

$$
\frac{\partial E}{\partial C_k} = \lambda_G \sum_{k=1}^{L} I_{i,k}^{G}\left(g\left(U_i^T C_k\right) - G_{i,k}\right) g'\left(U_i^T C_k\right) C_k + \lambda_g C_k \tag{10}
$$

$$
\begin{aligned}
\frac{\partial E}{\partial U_i} &= \sum_{j=1}^{N} I_{i,j}^{R}\left(g\left(U_i^T V_j\right) - R_{i,j}\right) g'\left(U_i^T V_j\right) V_j \\
&\quad + \lambda_G \sum_{k=1}^{L} I_{i,k}^{G}\left(g\left(U_i^T C_k\right) - G_{i,k}\right) g'\left(U_i^T C_k\right) C_k + \lambda_u U_i
\end{aligned}
\tag{11}
$$

After computing the latent feature vectors, the value $\hat{r}_{ij} = U_i^T V_j$ is obtained, where $\hat{r}_{ij}$ symbolizes the predicted preference of the researcher i on the article j. Therefore, a fulfilled researcher–article matrix $\widetilde{R}_{M\times N}$ is formed and each member's prediction value list on all articles is obtained as well. The matrix $\widetilde{R}_{M\times N}$ obtained is to prepare for the group aggregation, and the member's prediction value list on all articles is used as a vital component to aggregate the group's results in the latter procedure. Fig. 3 shows the pseudo-code of the individual article prediction method.

2.3. Group aggregation method based on ER rule

Note that the group aggregation method plays an important role in the group article recommendation. To effectively aggregate each members' results into the group's results, many aggregation methods have been investigated in different aggregation situations. As mentioned earlier, there are two main kinds of aggregation methods, the PA and the RA methods, in which the RA method can be divided into the PRA and RRA methods. The PA method is not suitable for constructing group profiles when there is a lot of original rating information that is absent. The RRA method generates the final recommendation list only considering the rank but no precise difference among candidate items, which may lead to a rough result. For the PRA method, the traditional aggregation strategies comprise the least misery, the most pleasure, and the average. Specifically, the least misery and the most pleasure only consider the maximum or the minimum rating of the group members and the average only briefly takes the mean of the prediction values as the final aggregation results. On the one hand, all of them may lose the specific group information in the aggregation process. On the other hand, they assign the same weight to all individuals in the group, which does not reflect the real contributions of different group users in practice. In reality, all members of a group should have different impacts.

Input: initial observed researcher-article matrix $R_{M\times N}$, group-researcher matrix $G_{M\times L}$, latent feature dimension K, regularization parameter λ_u, λ_v, λ_s, λ_g, λ_G, and learning rate α

Output: the fulfilled researcher-article matrix $R_{M\times N}$ together with each member's prediction value list

```
For j=1, 2, 3, ⋯, N do
  For f=1, 2, 3, ⋯, N do
    If ( j != f)
      Calculate s_jf which refers to the cosine similarity between article v_j and v_f .
  End For
End For
Initialize U, V and C randomly
For iteration =1, 2, …, 1000 do
  For each <i, j> ∈ R_{M×N} do
    For each <i, j> ∈ R_{M×N} do
      Calculate ∂E/∂U_i , ∂E/∂V_j and ∂E/∂C_k using equation (9), (10), and (11) with current U, V and C
      Update U_i = U_i − α ∂E/∂U_i
      Update V_j = V_j − α ∂E/∂V_j
      Update C_k = C_k − α ∂E/∂C_k
    End for
  End for
End for
Return the fulfilled researcher-article matrix R_{M×N} ( R = {r̃_ij = U_i^T V_j}_{M×N} ) together with each member's prediction value list
```

Fig. 3. The algorithm of the individual article prediction method.

For one thing, the one who has an important position in the group or can make more contributions for the group, should have a higher weight when performing group recommendation. For another thing, considering that there will be some unreliable members in a group who always rate arbitrarily, which can result in inaccurate group recommendation, the reliability of members is also a necessary factor to be considered. Based on the above analyses, a novel aggregation method based on ER rule for the group article recommendation is introduced, which can identify group members' different important degrees by assigning different weights and reliabilities to each group member.

The Evidential Reasoning (ER) approach is a general approach for multiple criteria decision making analysis that using a unified belief structure to model various types of uncertainty, can be viewed as a probabilistic approach, and makes full use of all users' generated data [45,53–55]. The details of the novel aggregation method based on the ER approach are described as follows. After the individual prediction model is conducted in Section 2.2, a complete researcher–article matrix $\widetilde{R}_{M\times N} = \{r_{ij}\}$ is obtained by the hybrid method. Through the matrix $\widetilde{R}_{M\times N}$, each group members' prediction values on articles (i.e.,r_{ij}) can be shown. Then, the aggregation process that merging each group's final recommendation list by all members' prediction values is accomplished by the ER rule. For each member u_i in the group G_k, his prediction values on all articles can be taken as a piece of evidence to predict the "truth" that which article is compliant with the group's tastes. The aggregation method based on ER rule works as follows.

Definition 1 (*Discernment Frame*)**.** For a group, the set $\Theta = \{v_1, v_2, \ldots, v_N\}$ is supposed as a discernment frame [45], where Θ is a set of mutually exclusive and exhaustive hypotheses. Specifically, the hypotheses are defined as the candidate articles to be recommended, and v_j of the discernment frame represents the jth article. Moreover, all subsets of Θ comprise the power set P(Θ), which is described as $p(\Theta) = \{\varnothing, \{v_1\}, \ldots, \{v_N\}, \{v_1, v_2\}, \ldots, \{v_1, v_N\}, \ldots, \{v_1, \ldots, v_{N-1}\}, \Theta\}$.

Definition 2 (*Evidence*)**.** A piece of evidence e_i is denoted by a belief distribution, as:

$$e_i = \{(v, \mathrm{p}_{v,i}), \forall v \subseteq \Theta, \sum_{v\subseteq\Theta} p_{v,i} = 1\} \quad (12)$$

where $(v, \mathrm{p}_{v,i})$ indicates the evidence that supports the hypothesis v with a probability of $p_{v,i}$ formed by the ith member in the group. The probability $p_{v,i}$ is represented by the group member's prediction value for the article. Here v can be any subset of Θ or any element of P(Θ) except from the empty set.

Definition 3 (*Weight and Reliability*)**.** For each group member, suppose $w_i(0 \le w_i \le 1)$ and $R_i(0 \le R_i \le 1)$ is the weight and reliability of a member respectively. w_i indicates the important degree of each member with 0 represents "not important at all" and with 1 represents "the most important". R_i indicates the reliable degree of each member with 0 represents "not reliable at all" and with 1 represents "fully reliable" [45]. If a certain user has an important position in the group or can make more contributions for group recommendation, he should have a higher weight than others. The one who has a high weight but seldom collects articles or always collects the article irrelevant to the group, would have lower reliability than others.

For group member's weight, the recommendation *recall* of each member over the whole group can be considered as the weight. In which the recommendation *recall* represents the fraction of the member's actual preferred articles that are identified by the recommendation. Generally, all members of a group contribute to the same target which is to make the recommendation list satisfy with the group's preferences as much as possible. The higher *recall* of a member refers that this member can get more articles back from the group's actual preferences, which meanwhile demonstrates this member's higher contribution to the group. Therefore, the weight of the *i*th member in a group can be taken as the recommendation *recall*. To measure member's weight faithfully, the original data are divided into training set, validation set, and testing set randomly. The weight of the *i*th member in a group is described as

$$uw_i = \frac{\text{Number of the ith member's correctly recommended articles}}{\text{Total number of the articles in this group's validation set}} \tag{13}$$

Afterward, the group members' weights are normalized since the weight reflects the relative importance of the member versus others in a group.

$$w_i = \frac{uw_i}{\sum_{u_i \in G_k} uw_i} \tag{14}$$

For group member's reliability, it can be set based on the recommendation *precision* of each member, since it is reasonable to consider that if a group member has extremely low precision, he would not be reliable at all. Therefore, the more precise of a member, the more reliable of him. Let rp_i represents the *i*th member's recommendation *precision*, it can be presented as

$$rp_i = \frac{\text{Number of the ith member's correctly recommended articles}}{\text{Total number of the articles in the } i\text{th member's recommendation list}} \tag{15}$$

Furthermore, there almost nobody can represent a group entirely, which means nobody is fully reliable, a threshold of reliability is needed to bound the reliability of the highest reliable member in the group. Let S represents the threshold of reliability, the reliability of the ith member in a group can be described as

$$R_i = \frac{rp_i}{\underset{(u_i \in G_k)}{\text{Max}}\, rp_i} \bullet S \tag{16}$$

When both weight and reliability have been defined, the hybrid weight that combined weight and reliability is denoted as

$$\widetilde{w} = w_i/(1 + w_i - R_i) \tag{17}$$

Specifically, $1 - \widetilde{w}_i$ measures the residual support. It is regarded as a boundary to limit the effectiveness of other members which have also played a role in the combination [45].

Under the above condition, the group aggregation method based on ER rule with weight and reliability is presented as follows. The complete researcher–article matrix $\widetilde{R}_{M\times N} = \{\mathrm{r}_{ij}\}$ can be altered into the evidence profile $P_{N\times M} = \widetilde{R}^T_{M\times N} = \left\{p_{v,i}\right\}$. If there are only two users in a group, the aggregation is profiled by

$$E(2) = \{(v, \mathrm{p}_{v,\mathrm{E}(2)}), \forall v \subseteq \Theta, \sum_{v \subseteq \Theta} p_{v,\mathrm{E}(2)} = 1\} \tag{18}$$

where $\mathrm{p}_{V,\mathrm{E}(2)}$ means the aggregation results of the two users in the group, and

$$p_{v,E(2)} = \begin{cases} 0 v = \varnothing \\ \dfrac{\hat{m}_{v,E(2)}}{\sum_{D \subseteq \Theta} \hat{m}_{D,E(2)}} v \subseteq \Theta, v \neq \varnothing \end{cases} \tag{19}$$

$$\hat{m}_{v,E(2)} = [(1 - \widetilde{w}_2) \cdot \widetilde{w}_1 \mathrm{p}_{v,1} + (1 - \widetilde{w}_1) \cdot \widetilde{w}_2 \mathrm{p}_{v,2}] + \sum_{B \cap C = v} \widetilde{w}_1 p_{\mathrm{B},1} \cdot \widetilde{w}_2 p_{C,2} \forall v \subseteq \Theta \tag{20}$$

Whereas there are not only two users in a group, the aggregation process is conducted by using recursive methods to get the final results. The joint support of v can be generated as follows:

$$\hat{m}_{v,E(i)} = [(1 - \widetilde{w}_i) \cdot m_{v,E(\mathrm{i}-1)} + m_{p(\Theta),E(\mathrm{i}-1)} \cdot \widetilde{w}_i \mathrm{p}_{v,\mathrm{i}}] + \sum_{B \cap C = v} m_{B,E(\mathrm{i}-1)} \cdot \widetilde{w}_i p_{C,\mathrm{i}}, \forall v \subseteq \Theta \tag{21}$$

$$\hat{m}_{p(\Theta),\mathrm{E}(i)} = (1 - \widetilde{w}_i) \cdot m_{p(\Theta),\mathrm{E}(i-1)} \tag{22}$$

Finally, the combined results of the first i members in the group for the hypothesis v can be calculated by

$$p_{v,\mathrm{E(i)}} = \frac{\hat{m}_{v,\mathrm{E(i)}}}{1 - \hat{m}_{p(\Theta),\mathrm{E(i)}}}, \forall v \subseteq \Theta \tag{23}$$

After conducting the above processes, the aggregation results for a group are obtained. For each group, the group's results on articles are obtained by performing the aggregation method based on ER rule, and the articles with the highest aggregation values are recommended for each group subsequently. The higher result an article obtained, the more likely the group will be satisfied. Fig. 4 shows the algorithm of the group aggregation method based on the ER rule.

3. Experimental design

To evaluate the performance of the proposed method, some experiments have been conducted. In this section, the experimental dataset and evaluation metrics are introduced in the first two parts, and then, the compared methods and the experimental procedure is explained in the last two parts.

3.1. Experimental dataset

The experimental data were taken from CiteULike since it is a scientific social network platform and possesses the research groups. In the CiteULike platform, researchers can find, read, manage, and collect articles easily, and can establish the research groups to keep informed with the current edge of their research fields. The articles' contents can be accessed easily here, and researchers' preferences can be characterized by researchers' article-collecting records. Most importantly, it possesses the natural groups so that researchers' interaction with groups can be constructed from the natural groups. Above those considerations, we finally choose CiteULike as the dataset for the research problem.

To obtain the required data, the CiteULike was visited by a website crawler. The information that includes the users, the articles, and the groups were extracted from the CiteULike, and then the collected original data contain 12 379 users, 4748 groups, and 1343 257 articles. Subsequently, to ensure the validity of the experiment, the data cleaning work was conducted. The data such as the user who have collected more than 15 articles, the article which has been collected more than 2 times, and the group which obtains more than 2 members were chosen, and the other data were removed. Finally, the experimental dataset consists of 2065 users, 718 groups, and 85 542 articles.

3.2. Evaluation metrics

To measure the performance of the proposed method, several evaluation metrics were adopted. The Precision and the Recall were adopted to measure accuracy, and the mean average precision (MAP) was adopted to evaluate the satisfaction of rank [56–58]. The details of the evaluation metrics are as follow:

Input: the fulfilled researcher-article matrix $R_{M\times N}$, the set of groups G, the candidate result set $p(\Theta)$
Output: the matrix of groups' rating on articles $GR_{L\times N}$

1. Transform researcher-article matrix into an article-researcher matrix $P_{N\times M}=IR^{T}_{M\times N}=\{p_{V,i}\}$
2. For k=1, 2, ⋯, L and $G_k \subseteq G$ do
3. For j=1, 2, ⋯, N and $V \subseteq \Theta$ do
4. For i=1, 2, ⋯, z and $u_i \in G_k$ do
5. Set the weight W_i as equal in a group
   Set the reliability R_i based on the recommendation accuracy
6. Compute the hybrid weight $\tilde{W}_i$ by equation (17)
7. Normalization of each evidence of z members in G_k
8. Compute the aggregation result of the first two users E(2) by equation (18) ~ (20)
9. If(z>2)
10. Compute the aggregation results of the first i users E(i)=f(E(i-1)) by equation (21) ~ (23)
11. End For
12. End For
13. End For
14. Return the matrix of groups' rating on articles $GR_{L\times N}$

Fig. 4. The algorithm of group aggregation method based on ER rule.

Precision. This metric means the proportion of the number of articles that are truly meeting with the user's interest and the number of the recommended list.

$$Precision = \frac{Number\ of\ correctly\ recommended\ articles\ in\ the\ top-ranked\ \text{list}}{Total\ Number\ of\ recommended\ articles\ in\ the\ top-ranked\ \text{list}} \tag{24}$$

Recall. This metric refers to the proportion of all relevant items that are returned by the recommendation.

$$Recall = \frac{Number\ of\ correctly\ recommended\ articles\ in\ the\ top-ranked\ \text{list}}{Total\ Number\ of\ user\ collected\ articles\ in\ the\ testing\ data} \tag{25}$$

Mean Average Precision (MAP). The metric measures not only the recommendation accuracy but also the order of the ranking list. A group's MAP is the average of the group members' MAP.

$$MAP = \frac{1}{U}\sum_{i=1}^{|U|}\frac{1}{|m_i|}\sum_{k=1}^{|m_i|}P\left(R_{i,k}\right) \tag{26}$$

Where N is the number of articles in the recommendation list, $|U|$ indicates the total number of users, m_i denotes the number of relevant articles to the user u_i, and $P\left(R_{i,k}\right)$ is the precision of recommended results from the top result until reaching the article v_k.

3.3. Compared methods

For comparison, some existing methods were implemented in the experiments. On the one hand, the comparison for the prediction stage was chosen based on different individual article prediction methods: GPRAF_ER and GPRAH_ER. The GPRAF_ER refers to the method different from the GPRAH_ER in the individual article prediction method that GPRAF_ER utilized the PMF method, and the proposed GPRAH_ER method utilized the hybrid method. On the other hand, the comparison for the aggregation stage was chosen based on different aggregation phases and different aggregation strategies: GPAH, GPRAH_AVE, GPRAH_LM, GPRAH_MP, GRRAH_Borda, GRRAH_Copeland, GRRAH_Faieness, and GRRAH_ER. In these methods, the PA, PRA, and RRA, which included in the methods name, means the different aggregation phases of the group recommendation, and AVE, LM, MP, Borda, Copeland, Fairness, and ER represent the different aggregation strategies for the group aggregation [3,36,37,43,59]. The details of the aggregation strategies are listed as follows:

– *Average (AVE)* [3,37]. This strategy computes the average of all group members' preferences as the group's preference.

– *Least Misery (LM)* [16,37]. This strategy assumes that the least happy member can represent the group's happiness.

– *Most Pleasure (MP)* [16,59]. Diametrically opposite to Least Misery, this strategy assumes that the group's happiness depends on its happiest member.

– *Borda* [59]. Each item gets accumulate points from its order in an individual recommendation list, the more advanced position, the higher points of the article. This metric obtains the group preference by counting and comparing the accumulated points.

– *Copeland* [36]. This strategy is a voting mechanism in which the candidate articles are ordered by the number of pairwise victories, minus the number of pairwise defeat.

– *Fairness* [36]. Under this strategy, group members take turns to sort the recommended articles. The first recommended article to the group is the first member's favorite article, and the second recommended article to the group is the second member's favorite article. The rest of the recommendation list can be done in the same manner.

– *ER rule (ER)* [45]. This strategy utilized ER rule with different weights and reliabilities as mentioned earlier. For each group member, the weight and reliability were set to be adaptive to the group article recommendation in this paper.

In conclusion, all compared methods in the experiments are described as follows:

– *GPAH.* The individual article prediction method utilized the hybrid method that combined the PMF with the CBF method, and the group aggregation was conducted in the PA.

– *GPRAH_AVE.* This method used the hybrid method in the individual article prediction method, and the group aggregation was carried out in the PRA with the Average aggregation strategy.

– *GPRAH_LM*. This method used the hybrid method in the individual article prediction method, and the group aggregation was carried out in the PRA with the Least Misery aggregation strategy.

– *GPRAH_MP*. This method used the hybrid method in the individual article prediction method, and the group aggregation was carried out in the PRA with the Most Pleasure aggregation strategy.

– *GRRAH_Borda*. This method used the hybrid method in the individual article prediction method, and the group aggregation was carried out in the RRA with the Borda aggregation strategy.

– *GRRAH_Copeland*. This method used the hybrid method in the individual article prediction method, and the group aggregation was carried out in the RRA with the Copeland aggregation strategy.

– *GRRAH_Fairness*. This method used the hybrid method in the individual article prediction method, and the group aggregation was carried out in the RRA with the Fairness aggregation strategy.

– *GPRAF_ER*. This method used the PMF method in the individual article prediction method, and the group aggregation was carried out in the PRA with the aggregation strategy based on ER rule.

– *GPRAH_ER*. The proposed method.

3.4. Experimental procedure

The whole experiments were conducted after the data, the evaluation metrics, and the compared methods had been prepared. We implement the proposed approach and baselines based on a Java library named Mymedialite and deploy them on a workstation with Xeon-E5-2620@2.1 GHz CPU and 64G RAM. The experimental data were divided into training set, validation set, and testing set in the ratio of 6:2:2. To be specific, for each researcher, 60% of his/her collected articles were randomly selected as the training set, 20% were selected as the validation set to tune the hyper-parameters, and the remaining 20% were put into the testing set for the final performance comparison. Moreover, we ran the experiments 10 times with a different split of the dataset each time, to ensure the experimental results were not affected by the randomness. The final reported results were averaged over 10 times. The hyper-parameter settings are as follows: the recommendation number was searched in {10, 20, 30, 40, 50}, the feature dimension was tested in {5, 10, 15, 20}, and the threshold of reliability was tested in the value of {0.75, 0.80, 0.85, 0.90}. In the process of improved PMF method, we adopt the learning rate $\alpha = 0.01$, the number of iteration $iteration = 1000$, and the regularization parameters $\lambda_u = 0.01$, $\lambda_v = 0.01$, $\lambda_s = 0.05$, $\lambda_g = 0.01$, $\lambda_G = 0.05$.

4. Results and discussions

The values for different evaluation metrics were obtained and compared among the different methods and our proposed method applied to the CiteULike dataset. Section 4.1 analysis the detailed results of different evaluation metric performance for the proposed GPRAH_ER, and the compared methods at the top-ranked recommendation. Section 4.2 shows the discussion of a few parameters affecting the experimental results.

4.1. Experimental results

Generally, the experimental results were obtained across different group recommendation methods. The results of the GPRAF_ER and the proposed GPRAH_ER methods are listed in Table 1 to compare the individual recommendation method. The methods based on hybrid individual recommendation comprise the GPAH method, three kinds of the GPRAH methods, three kinds of the GRRAH methods, and the proposed GPRAH_ER method, of which results are listed in Table 1 to compare the different aggregation phase and the different aggregation strategy. Specifically, the rows in Table 1 are the values of evaluation metrics at the top-ranked list (*@the recommendation number* = 10, 20, 30, 40, 50), and the columns in them represent different group recommendation methods.

As shown in Table 1, the GPRAH_ER method tends to be superior to other methods since it achieved the highest Precision of 5.001% with the recommendation number 10, the highest Recall of 2.917% with the recommendation number 50, and the highest MAP of 14.054% with the recommendation number 10. The improvements of the GPRAH_ER method on Precision are more than 2.124% in contrast to GPRAH_AVE, on Recall are more than 10.744% in contrast to GRRAH_Fairness, and on MAP are more than 9.217% in contrast to GPRAH_MAP. Meanwhile, the methods conducted in the PRA stage seems to perform better than the one in the RRA and the PA stages. This observation is consistent with the aforementioned intuition. The PRA method which makes use of the prediction values for aggregation can be regarded as more concrete and accurate for group recommendation. There also exist some special observations such as the GPRAH_LM performed inferior to others. For the GPRAH_LM method performing the worst results in aggregation, a possible explanation of it is that the Least Misery strategy may miss the great majority of group members' actual "like". Since it assumes that the group's opinion is consistent with the unhappiest member's opinion to ensure that each group member is satisfied.

On the other hand, the GPRAF_ER method performed inferior to the GPRAH_ER method but superior to the other methods, which validates the effectiveness of the individual prediction method that combining the CBF method with the MF method for article recommendation. Comprehensively, the effectiveness of the proposed method GPRAH_ER, which uses the hybrid method in the stage of individual prediction and uses aggregation methods based on ER rule in the stage of group aggregation, is demonstrated by these results.

4.2. Discussion

For the proposed GPRH_ER method, the recommendation number, the latent feature dimension K, and the threshold of reliability are all important influence factors to affect the recommendation results. Therefore, the recommendation performance is further explored under different parameter settings. The following explorations were conducted on the CiteULike dataset, and under the condition that the others' methods took the optimal values.

4.2.1. Discussion of the recommendation number

For the group-oriented article recommendation, it is more necessary to recommend the most suitable article for groups rather than make the error between groups' real preference value and predicted preference value as small as possible. Therefore, the *recommendation number* is of great importance affecting the experiment results. Fig. 5 shows the Precision, Recall, and MAP of proposed GPRAH_ER and other compared methods when using different recommendation number.

As shown in Fig. 5, with the *recommendation number* increasing, the precision is falling while the recall is rising in contrast to the precision. The value of N increased, and the variation tendency has been gentle. Furthermore, the MAP decline with the increased *recommend number*. When the *recommend number* going up to a certain degree, the difference between methods is narrowing gradually whereas the value of the proposed still better than

Table 1
The experimental results.

Approach		GPAH	GPRAH _AVE	GPRAH _LM	GPRAH _MP	GRRAH_ Borda	GRRAH_ Copeland	GRRAH_ Fairness	GPRAF_ ER	GPRAH_ ER
Precision	@10	4.426	4.897	1.224	4.195	2.904	3.010	4.560	4.922	**5.001**
	@20	3.203	3.415	0.889	3.049	2.16	2.249	3.310	3.504	3.619
	@30	2.643	2.740	0.724	2.479	1.807	1.900	2.758	2.882	2.953
	@40	2.295	2.329	0.620	2.146	1.608	1.698	2.406	2.469	2.538
	@50	2.049	2.047	0.552	1.903	1.426	1.514	2.178	2.175	2.250
Recall	@10	1.049	1.197	0.512	1.170	0.833	0.846	1.117	1.222	1.267
	@20	1.511	1.675	0.740	1.672	1.204	1.221	1.618	1.679	1.824
	@30	1.821	2.046	0.896	2.023	1.500	1.526	2.015	2.130	2.275
	@40	2.063	2.350	1.019	2.325	1.774	1.805	2.333	2.368	2.593
	@50	2.280	2.608	1.129	2.565	1.937	1.973	2.634	2.672	**2.917**
MAP	@10	12.790	11.757	4.340	12.868	10.390	10.632	11.099	13.384	**14.054**
	@20	12.474	11.583	4.375	12.583	10.230	10.466	10.119	12.756	13.088
	@30	12.014	11.428	4.289	12.171	10.020	10.204	9.491	12.213	12.326
	@40	11.609	11.283	4.251	11.741	9.637	9.821	9.083	11.673	11.714
	@50	11.268	11.174	4.209	11.440	9.480	9.644	8.790	11.295	11.533

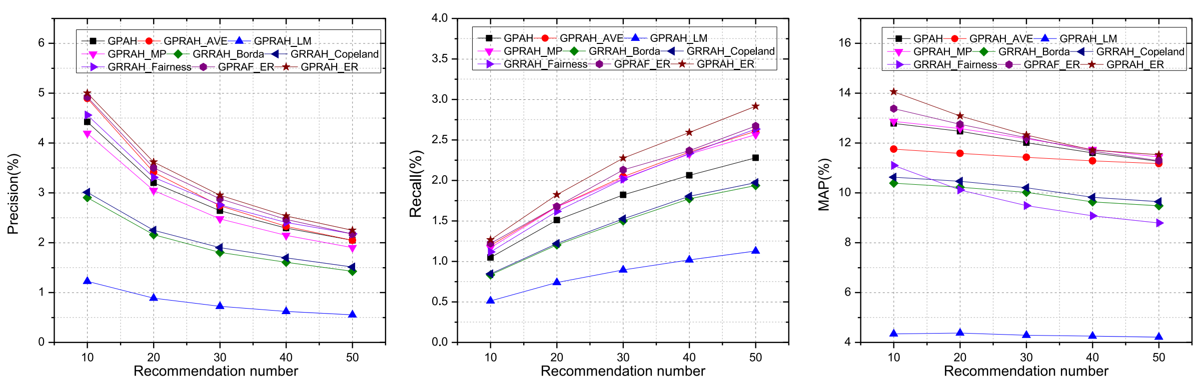

Fig. 5. The evaluation metrics of the proposed GPRAH_ER and other compared methods with different recommendation number.

that of other methods. The MAP achieved its best performance at recommendation number 10. There reveal other interesting observations that for the GRRH_Fairness method, the MAP at Top 10 is better than the GPRH_Borda method and GPRH_Copeland method while the MAP between Top 20 to 50 is poorer than that of two. A reasonable explanation may be that the aggregation strategy of Fairness has better accuracy than Borda and Copeland, but a worse recommend order than Borda and Copeland. This can be possible that a method cannot have both good accuracy and pretty order.

4.2.2. Discussion of the latent feature dimension

The *Latent feature dimension* of the researchers and the articles have a significant impact on the PMF related method. Too small of it may lead to the implicit characteristic of the researcher or the article unable to be expressed completely. In contrast, if the *Latent feature dimension* is set too large, the calculation complexity will increase meanwhile the overfitting problem will arise. Therefore, to determine the optimal value of the *Latent feature dimension* is of great significance. Fig. 6 shows the Precision, Recall, and MAP of proposed GPRAH_ER and other compared methods under different *Latent feature dimension*.

As shown in Fig. 6, the Precision, Recall, and MAP have kept the rising trends with the *Latent feature dimension* increasing. For the metrics of Precision and Recall, the performances of the methods are gradually enhanced by a growing K at the beginning and arrive at the highest with the K of 20. For the metrics of MAP, the methods' values increase rapidly when K varies from 5 to 10, and then begin to slow down and tend to be stable until the K increases at 20. Comprehensively, the results demonstrated that the best performances of the group article recommendation have been achieved on the *Latent feature dimension* D equaling 20.

4.2.3. Discussion of the threshold of reliability

For the group aggregation methods based on ER rule, the users' reliabilities are a series of absolute values which have no interaction effects from each other. It indicates the trust degree of each member, one seldom collects articles or always collect the article irrelevant to the group would be assigned with lower reliability than others. Although reliability equals 0 represents "not reliable at all" and reliability equals 1 represents "fully reliable", there almost nobody can be fully trusted to represent a group entirely. Therefore, the *threshold of reliability* was used to bound the reliability of the highest reliable member in the group. Here several empirical values were chosen to set the *threshold of reliability*. Fig. 7 shows the Precision, Recall, and MAP of the proposed GPRAH_ER and other compared methods under the different *threshold of reliability*.

As shown in Fig. 7, when the *threshold of reliability* equals 0.9, the Precision, Recall, and MAP of methods achieve their maximum value. Since the *reliability* have nothing to do with the methods except the GPRAH_ER and GPRAF_ER methods, the performance of them remain a straight line with the change of the *threshold of reliability*. For the GPRAH_ER and GPRAF_ER methods, they share the similar trends that the tendency is increasing along with the rising of the threshold, and both of them have achieved their best performances when the threshold of reliability was set to 0.9.

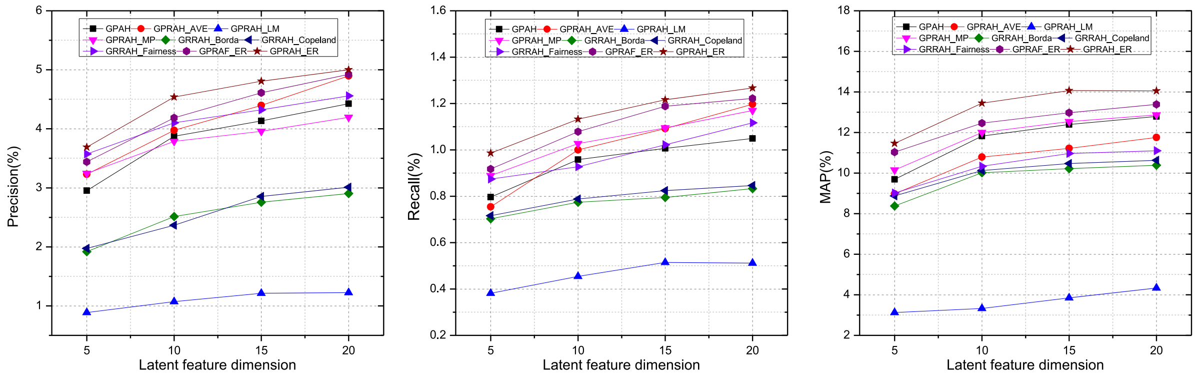

Fig. 6. The evaluation metrics of the proposed GPRAH_ER and other compared methods with different Latent feature dimension.

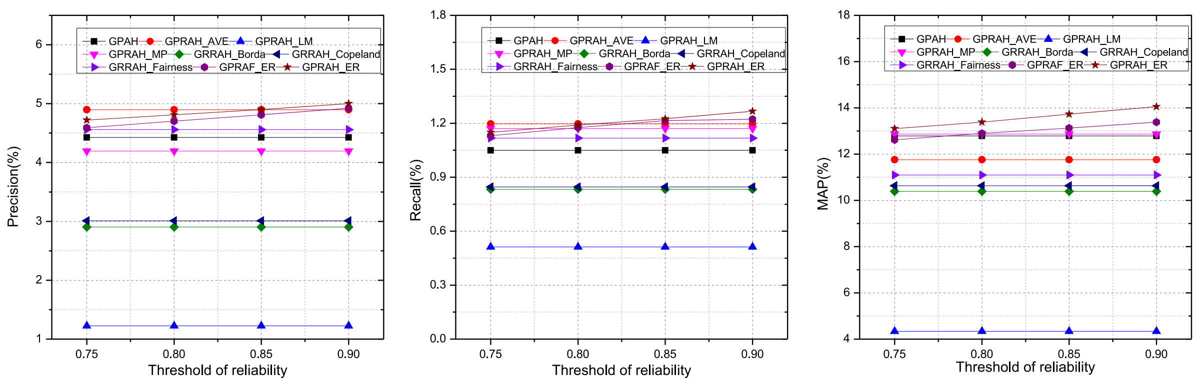

Fig. 7. The evaluation metrics of the proposed GPRAH_ER and other compared methods with the different thresholds of reliability.

5. Conclusions and future work

In this study, an improved group article recommendation method GPRAH_ER is proposed, which uses a hybrid method in the stage of individual prediction and an aggregation method based on the ER rule in the stage of group aggregation. For the individual prediction, the PMF method is adopted as it possesses an accurate and stable predictive performance in most cases and is further unified with group information and article content. For the group aggregation, the ER rule is introduced in the aggregation strategy, since it possesses the advantages of identifying the importance of individuals in a group based on individual weight and reliability. The experiments were conducted on the real dataset CiteULike to validate the effectiveness of the proposed GPRAH_ER method. The results show that the proposed GPRAH_ER method is superior to the other methods compared in this study. With the proposed group article recommendation method, the SSNs platforms can be effective in improving dissemination and communication.

There are several promising directions for future work. Firstly, it is worth exploring to design a better recommendation framework to reasonably integrate indirect indicators such as researchers' subjective preferences and direct indicators such as journal impact factor, number of citations, and relevance for the scientific community, hoping to improve researchers' satisfaction. Secondly, the individual prediction method can be improved by incorporating other useful additional information into the hybrid method, such as time dynamic series. Thirdly, many other effective aggregation methods remain to be discovered and improved for group article recommendation. Fourthly, we will further design a more general recommendation method, hoping to meet more scenarios. And thus various datasets and criteria can be used to make a more powerful verification of the method. In these ways, future research may achieve more superior recommendations.

CRediT authorship contribution statement

Gang Wang: Conceptualization, Methodology, Writing. **Han-Ru Wang:** Methodology, Software, Writing. **Ying Yang:** Conceptualization, Writing. **Dong-Ling Xu:** Conceptualization. **Jian-Bo Yang:** Conceptualization. **Feng Yue:** Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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