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An Enhanced Group Recommender System by Exploiting Preference Relation

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ABSTRACT With ties among people have been much more closer, making recommendations for groups of users became a more general demand, which facilitates the prevalence of group recommender system (GRS). Existing solutions for GRS are mostly established based on preference feedbacks of absolute form such as ratings, yet neglecting that preference assessment criteria are usually heterogeneous among different members. In this paper, we propose GRS-PR, an enhanced group recommender system by exploiting preference relation. First, a preference relation-based multi-variate extreme learning machine model is formulated to predict unknown preference relations in candidate items. Second, on the basis of predicted results, borda voting rule is employed to generate recommendation results from candidate items. In addition, efficiency, parameter sensitivity, and sparsity tolerance of the GRS-PR are evaluated through a set of experiments.

INDEX TERMS Group recommender system, preference assessment criteria, preference relation, extreme learning machine, borda voting rule.

I. INTRODUCTION

Along with increasing applications of the Internet, explosive growth of various information brings about severe information overload problem [1], [2]. As a consequence, users are usually sunk into ocean of information, and cannot acquire the contents they require [3], [4]. Recommender system (RS) [5], [6], viewed as a popular solution for this issue, suggests items for users through establishing their profiles according to preference feedbacks. Although the past decade has witnessed great progress of recommender system with respect to many fields like shopping, current RSs were mostly designed for individual users. Accompanied with more and more closer ties among people in contemporary world, suggesting items to groups of users has also been a general demand. For example, when friends gather to have dinner, it is expected to suggest a table of dishes for them with consideration of their different tastes. Thus Group Recommender System (GRS) was developed for this purpose [7], [67].

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Providing recommendations for multiple users, however, is never an easy task. Because users usually possess heterogeneous preferences, how to define the group profile remains challenging [15]. Existing Solutions for GRS can be classified into two categories [8], [9]: preference aggregation [10], [11] and score aggregation [12], [13]. For the former, as depicted in Figure 1(a), preferences of individual members are explicitly aggregated into group profile through various aggregation functions [16], [17]. Then, the group is viewed as a pseudo user, and recommendation results can be produced for the group through ordinary techniques [14]. For the latter, as described in Figure 1(b), recommendation results are firstly calculated for each member separately, and then aggregated into a recommendation list for the group through aggregation strategies [18], [19].

Nevertheless, prior works are mostly established upon preference feedbacks of absolute form such as ratings, yet ignoring the fact that preference assessment criteria are usually heterogeneous among different members. For example, persons who are kind usually give high rating values, while those who are critic used to give relatively low rating

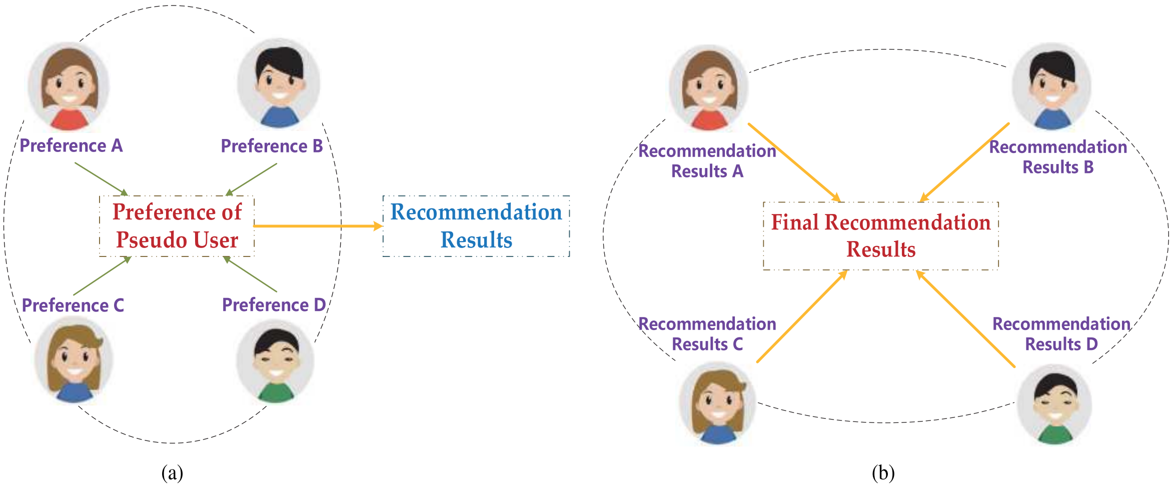


FIGURE 1. Illustration of two types of solutions for defining group profile: (a) Preference aggregation; (b) Score aggregation.

	Item A	Item B	Item C	Item D
User 1	5	4	2	4
User 2	4	3	2	3

	Rule 1	Rule 2	Rule 3	Rule 4	Rule 5	Rule 6
User 1	$A \succ B$	$A \succ C$	$A \succ D$	$B \succ C$	$B \cong D$	$C \prec D$
User 2	$A \succ B$	$A \succ C$	$A \succ D$	$B \succ C$	$B \cong D$	$C \prec D$

FIGURE 2. A typical example of transformation from absolute preference forms into relative ones.

scores. Thus as for a group, there lacks an uniform judgement standard for preference feedback of absolute form, which will bring about noise while modeling group profile. Intuitively, preference relation [20], preference feedback of relative form, is introduced to tackle this issue. As shown in Figure 2, it encodes absolute preference feedbacks in form of pairwise ordering between item pairs [21], and acts as an alternative to preference feedbacks of absolute form. Clearly, such a transformation reduces noise a lot while modeling group profile.

In view of above analysis, this paper proposes an enhanced Group Recommender System by exploiting Preference Relation (GRS-PR). First, definition of preference relation is announced. Then, based upon preference relations of item pairs in training set, a preference relation-based multi-variate extreme learning machine model is formulated to predict unknown preference relations in candidate items. Finally, in accordance with predicted results, borda voting rule is employed to generate recommendation results from candidate items. As far as we are concerned, this work is the first to enhance group-based recommendations by exploiting heterogeneity among members' preference assessment criteria.

We summarize main contributions of this paper as following three aspects:

- In terms of modeling group profile, we consider limitation of preference feedback of absolute form, and introduce preference relation as an alternative.
- In order to predict unknown preference relations in candidate items, a preference relation-based multi-variate extreme learning machine model is formulated.
- Borda voting rule is employed to generate recommendation results under preference feedback of current form.

The remainder of this paper is arranged as follows. Related research works are summarized in Section II. In Section III, we briefly introduce overview and workflow of the GRS-PR. Section IV describes mathematical modeling of recommendation mechanism in GRS-PR. In Section V, we evaluate efficiency of the GRS-PR through a set of experiments. Finally, Section VI presents conclusions of this paper.

II. RELATED WORK

This work aims to develop an enhanced group recommender system by exploiting preference relation. The following subsections sum up state of the art associated with our research.

A. RECOMMENDER SYSTEM

Thousands of research findings concerning RSs have been put forward during recent years [22], which can be classified into two types: content-aware (CA) methods and feedback-aware (FA) methods [23]. The CA methods make recommendations by means of capturing content features of users or items. While FA methods rely on preference feedback history to capture preference features. The proposed GRS-PR in this paper is a hybrid of CA and FA methods, and combines above two thoughts to avoid their limits.

Among, FA methods can be further classified into two types: memory-driven approaches [24], [25] and model-driven approaches [26], [27]. The former predict missing records with the aid of records from similar users or items [28], and the latter train a mapping model utilizing training data to make predictions or classifications [29]. It is believed that the model-driven ones are able to obtain more ideal results [30]. And the GRS-PR is founded on model-driven manner.

B. GROUP RECOMMENDER SYSTEM

GRSs have been in practice for various domains, such as music, restaurants, tourism, and movies [31], [32]. Ardissono *et al.* [35] proposed Average (AVG) strategy. The AVG takes average of group members ́ preference feedbacks as the group's preference feedback, and then builds group profile. The Least Misery (LM) strategy takes the lowest value of group members' preference feedbacks as group profile [34]. McCarthy and Anagnost [33] presented a similar strategy named Average Without Misery (AWM). In [36], a group recommender system was developed further considering and assuming that each member is assigned a contribution score. In [37], the proposed GRS firstly aggregates preference feedbacks of members through the Average Strategy, and then performs recommendations with Matrix Factorization approach. In [38], a hybrid recommendation mechanism that combines contents and feedbacks jointly was proposed. Queiroz *et al.* [39] constructed a group recommender system employing the fuzzy majority theory. Lin *et al.* [40] proposed an implicit feedback-oriented GRS which merges feedback records of members as records of a group and then suggests recommendations through item rankings. Hu *et al.* [41] proposed a joint model based on restricted Boltzmann machines that integrates individual selections and group decisions, and modeled group profile with such a deep model. In [43], a group recommender system was presented with transitive precedence taken into consideration. Kim *et al.* [44] presented a graph-based approach which utilizes links to represent relationships between users and items. In [19], a group recommender system GLFM was proposed, which extends classical matrix factorization model into the practice of group recommendations.

In order to achieve more comprehensive features, some extra factors like social relations are also introduced as assistance. Ye *et al.* [45] proposed a model to extract social influence between linked friends and their preference features. In [46], probabilistic inference was employed to predict unknown preferences given observed social relations and partially observed members' preferences. Liu *et al.* [48] considered both preferences and personal impacts while modeling group profile. Ji *et al.* [49] introduced natural language processing and proposed a topic-based probabilistic model to model group profile. In [50], the scenario of group decision was considered, and a probabilistic model was set up to model the process of group decision. Then, preferences of members were able to be estimated through reverse probabilistic inference. In [51], a GRS was designed for tourism, in which members' preferences and social relations are both considered for recommendation.

In all, the above-mentioned studies exploit preference features in form of absolute preference feedback. We distinguish our research from others by utilization of relative preference feedback instead of absolute ones.

C. PREFERENCE RELATION

Preference relation was firstly proposed in [52] and defined as "a relative ordering relation of two or more items to represent preference degrees towards them". And form of preference relation is established as input of collaborative filtering method. Desarkar *et al.* [20] proposed a matrix factorization based collaborative recommendation algorithm that uses preference relations instead of absolute ratings. And Liu *et al.* [54] proposed an algorithm named PrefMRF to optimize the above two works. However, these works just consider single preference feedback as local features, neglecting deeper features like contextual characteristics of items. Meanwhile, they cannot learn the generation pattern of pairwise preference relations. Baskin and Krishnamurthi [42] ever studied GRS under preference feedback of relative form. They proposed an algorithm that aggregates known preference relations by searching for a Kemeny-optimal ordering of items. But this approach cannot predict unknown preference relations. In a word, our research exceeds these prior works concerning preference relation.

D. EXTREME LEARNING MACHINE

Extreme learning machines (ELM) model was firstly proposed by Huang *et al.* [55]. It is a type of feedforward neural network with a single layer of hidden nodes [56], [68]. Learning goal of ELM is to estimate the mapping from samples to label values, naming the connections between hidden layer and output layer. Thus ELM is also a type of regressor with parameters like support vector regression [57].

ELM is also extended into problems of multi-dimensional regression, and some ELMs with form of MIMO (multiple inputs-multiple outputs) have been proposed. In [62], aiming at the over-fitting problem, a two-stage locally regularized method was proposed to establish MIMO model. Wang *et al.* [63] proposed a model selection approach for MIMO-based ELM. And ELM satisfying requirement of

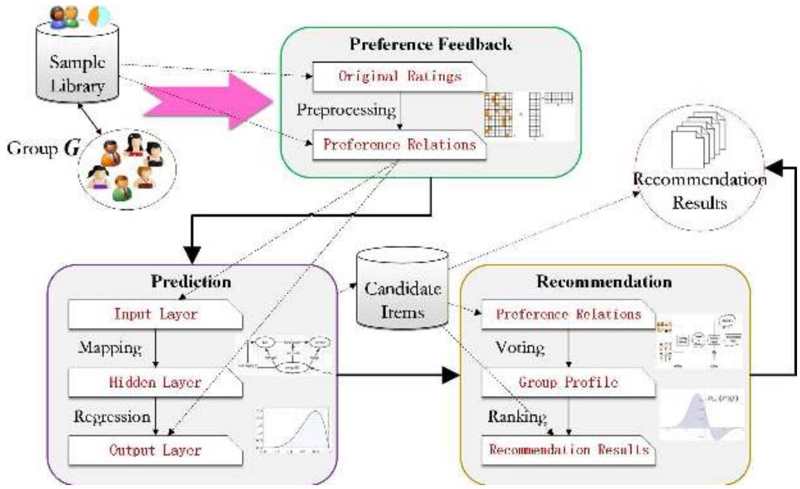


FIGURE 3. Framework of the group recommender system GRS-PR.

MIMO in this paper is called multi-variate extreme learning machine.

III. OVERVIEW OF THE GROUP RECOMMENDER SYSTEM

Framework of GRS-PR is demonstrated in Figure 3. In the beginning, we formulate the research problem in this paper. Let $u_k\ (k = 1, 2, \cdots, n)$ denote the set of n users who comprise a group G. It is assumed that sample library contains m items denoted as $x_i\ (i = 1, 2, \cdots, m)$, and that $I_l\ (l = 1, 2, \cdots, M)$ denotes a set of candidate items in who are the source of recommendation results. hence three main modules are designed: preference feedback module, prediction module and recommendation module.

Firstly, preference feedback module mainly transforms preference feedbacks of absolute form into preference relations. Then, in prediction module, a preference relation-based multi-variate extreme learning machine model is formulated to fit the generation of the group's preference relations. With the model parameters estimated after training, unknown preference relations of group G towards candidate items can be calculated accordingly. After that, recommendation module employs borda voting rule to aggregate predicted preference relations of members into group profile, and to produce recommendation results for the group.

IV. RECOMMENDATION MECHANISM

In this section, mathematical modeling of recommendation mechanism in GRS-PR is presented in detail. Definition of preference relation is announced in Section IV-A. In Section IV-B, a preference relation-based multi-variate extreme learning machine model is formulated to predict unknown preference feedbacks. And Section IV-C employs borda voting rule to generate recommendation results.

A. TRANSFORMATION OF PREFERENCE FEEDBACK

Let $x_i, x_j\ (i, j = 1, 2, \cdots, m)$ denote the set of item pairs in m items. Note that $i \neq j$ in this paper. Suppose that users express preference feedback through releasing their ratings towards items, and that a higher rating value means a higher preference level. Preference relation of user k between item x_i and x_j is represented as π_{kij} of which a higher value indicates user k prefers item i to item j. As for user k, interval range of preference relation is defined as follows [54]:

$$\Phi\left(\pi_{kij}\right) = \begin{cases} \left(\frac{2}{3}, 1\right] & if\, i \succ j \\ \left[\frac{1}{3}, \frac{2}{3}\right] & if\, i \cong j \\ \left[0, \frac{1}{3}\right) & if\, i \prec j \end{cases} \tag{1}$$

where $i \succ j$ denotes that user k prefers item i to item j, $i \prec j$ denotes taht user k prefers item j to item i, and $i \cong j$ denotes that item i and item j are equally preferable. And Φ is confined in the range of [0, 1]. In order to deduce expression of π_{kij}, the user-wise preference is defined as:

$$P_{ki} = \frac{\sum_{j=1}^{m}\left\langle \Phi\left(\pi_{kij} > \frac{2}{3}\right)\right\rangle - \sum_{j=1}^{m}\left\langle \Phi\left(\pi_{uij} < \frac{1}{3}\right)\right\rangle}{|\phi_{ki}|} \tag{2}$$

where $i \neq j$ and $\langle\cdot\rangle$ is a discriminative function defined as follows:

$$\langle\cdot\rangle = \begin{cases} 0 & if\ \ \cdot\ \ is\, false \\ 1 & if\ \ \cdot\ \ is\, true \end{cases} \tag{3}$$

ϕ_{ki} denotes set of user k's preference relations concerning item i, and operator $|\cdot|$ takes the numerical value. In training set, preference relation of user k towards item pair i and j is calculated as follows:

$$\pi_{kij} = \frac{1}{1 + \exp\left[-2\left(P_{ki} - P_{kj}\right)\right]} \tag{4}$$

Preference relations of the group G between item x_i and x_j is represented as the following vector:

$$\boldsymbol{t}_{Gij} = \left(\pi_{1ij}, \cdots, \pi_{nij}\right)^{\mathrm{T}} \tag{5}$$

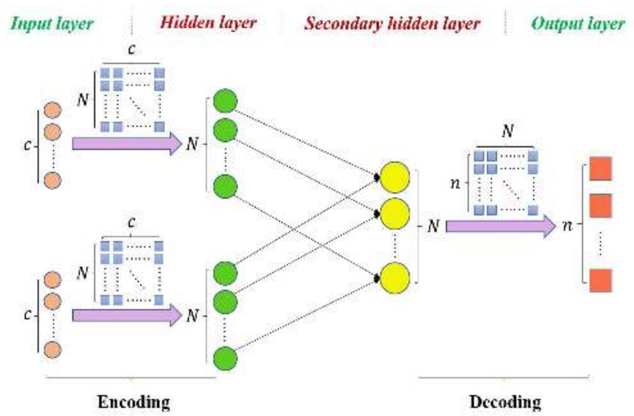


FIGURE 4. The architecture of the preference relation-based extreme learning machine model.

B. PREDICTION OF UNKNOWN PREFERENCE FEEDBACKS

1) PREFERENCE RELATION-BASED MULTI-VARIATE EXTREME LEARNING MACHINE

Input space of the model is obtained as:

$$\Omega_G = \{G, \boldsymbol{t}_{Gij}\} \tag{6}$$

and its goal is to learn a mapping from group G to preference relations towards item pairs. Thus architecture of the model is designed as shown in Figure 4. It contains four states: input layer, hidden layer, secondary hidden layer and output layer. Input layer contains $2c$ nodes, in which c-dimensional initial feature vectors of two items are input respectively. In hidden layer, each feature vector is transformed into an N-dimensional feature space through an $N \times c$ transition matrix, which is expressed as:

$$h'(\cdot) : \mathbb{R}^{N\times c} \times \mathbb{R}^{c} \rightarrow \mathbb{R}^{N} \tag{7}$$

In secondary hidden layer, two set of N hidden nodes are merged into one, representing N-dimensional feature space of the item pair. In output layer, preference relations of group G concerning the item pair are obtained.

Owing to $\pi_{kij} \in (0, 1)$, a sigmoid function is introduced to estimate preference relations of the group, which can be expressed as:

$$\boldsymbol{d}_{Gij} = \frac{1}{1 + \exp\left[\boldsymbol{W}h\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) - \boldsymbol{b}\right]} = \frac{1}{1 + \exp(-y)} \tag{8}$$

$$y = \boldsymbol{W}h\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) + \boldsymbol{b} \tag{9}$$

Among, $\boldsymbol{W} \in \mathbb{R}^{n\times N}$ and $\boldsymbol{b} \in \mathbb{R}^{n}$ are model parameters. $h\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right)$ is a mapping of item pair $\left(x_i, x_j\right)$ into higher-dimensional feature space, and is calculated as:

$$h\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) = h'(\boldsymbol{x}_i) - h'\left(\boldsymbol{x}_j\right) \tag{10}$$

where $h'(\boldsymbol{x}_i)$ and $h'\left(\boldsymbol{x}_j\right)$ are the mapping of x_i and x_j respectively into feature space.

Due to the fact that output is a multi-dimensional vector $\boldsymbol{t}_{Gij}$, it is supposed to formulate a multi-variant regression model and find a regressor $\boldsymbol{w}^k$ and b^k for each user of the group. With each user seen as a dimension of input, we generalize classical ELM model to preference relation-based multi-variant form, and formulate the following optimization problem:

$$\min\left[\frac{1}{2}\sum_{k=1}^{n}\left\|\boldsymbol{w}^k\right\|^2 + \lambda\sum_{i=1}^{m}\sum_{j=1}^{m}\beta\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right)\right] \tag{11}$$

where vector $\boldsymbol{w}^k$ is obtained by transposing the k-th row of $\boldsymbol{W}$, and $\beta\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right)$ is the loss function for the item pair $\left(x_i, x_j\right)$. For sake of simplicity, we employ Vapnik ε-insensitive loss function [59] to define it:

$$\beta\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) = \begin{cases} 0 & s_{ij} < \varepsilon \\ \left(s_{ij} - \varepsilon\right)^2 & s_{ij} \geq \varepsilon \end{cases} \tag{12}$$

$$s_{ij} = \left\|\boldsymbol{e}_{ij}\right\| \tag{13}$$

$$\boldsymbol{e}_{ij} = \boldsymbol{t}_{Gij} - \boldsymbol{d}_{Gij} \tag{14}$$

where $\boldsymbol{e}_{ij}$ is the empirical error, and s_{ij} is the norm of $\boldsymbol{e}_{ij}$. Note that $\beta\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right)$ is the Vapnik ε-insensitive loss function, meaning that loss can be ignored when its value is below the insensitive parameter [60].

2) MODEL FITTING

As directly solving the problem as standard ELM does via Karush-Kuhn-Tuker Theorem [58] is hard, we solve it through an appropriate method named Iterative Re-Weighted Least Square [61]. Firstly, objective function in Equation (10) is appropriated by its first order Taylor expansion over $\beta\left(x_i, x_j\right)$:

$$\Gamma'(\boldsymbol{W}, \boldsymbol{b}) = \frac{1}{2}\sum_{k=1}^{n}\left\|\boldsymbol{w}^k\right\|^2 + \lambda\sum_{i=1}^{m}\sum_{j=1}^{m}\beta\left(s_{ij}^{(g)}\right) + \lambda\sum_{i=1}^{m}\sum_{j=1}^{m}\left.\frac{d\beta(s)}{ds}\right|_{s_{ij}^{(g)}}\frac{\left(\boldsymbol{e}_{ij}^{(g)}\right)^{\mathrm{T}}\left(\boldsymbol{e}_{ij} - \boldsymbol{e}_{ij}^{(g)}\right)}{s_{ij}^{(g)}} \tag{15}$$

where g refers to the order number of iterations.

Substituting Equation (13) into Equation (14) leads to:

$$\begin{aligned}\Gamma''(\boldsymbol{W}, \boldsymbol{b}) &= \frac{1}{2}\sum_{k=1}^{n}\left\|\boldsymbol{w}^k\right\|^2 + \lambda\sum_{i=1}^{m}\sum_{j=1}^{m}\beta\left(s_{ij}^{(g)}\right) \\ &\quad + \lambda\sum_{i=1}^{m}\sum_{j=1}^{m}\left.\frac{d\beta(s)}{ds}\right|_{s_{ij}^{(g)}}\frac{\left[s_{ij}^2 - \left(s_{ij}^{(g)}\right)^2\right]}{s_{ij}^{(g)}} \\ &= \frac{1}{2}\sum_{k=1}^{n}\left\|\boldsymbol{w}^k\right\|^2 + \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m}a_{ij}s_{ij}^2 + \xi\end{aligned} \tag{16}$$

where

$$a_{ij} = \begin{cases} 0 & s_{ij}^{(g)} < \varepsilon \\ \dfrac{2\lambda\left(s_{ij}^{(g)} - \varepsilon\right)}{s_{ij}^{(g)}} & s_{ij}^{(g)} \geq \varepsilon \end{cases} \tag{17}$$

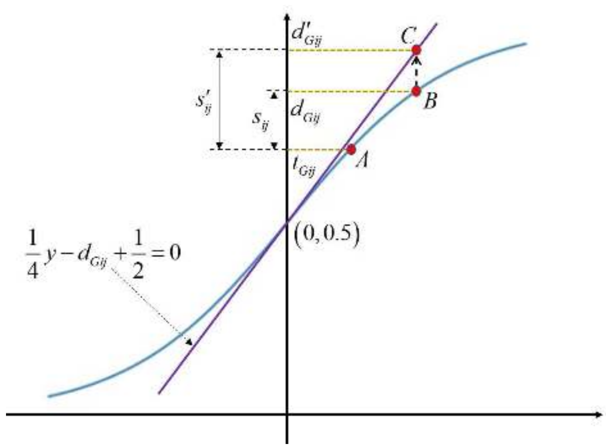


FIGURE 5. Illustration of loss transformation.

and ξ is sum of constant terms irrelevant to $\boldsymbol{W}$ and $\boldsymbol{b}$.

The problem still remains hard to be solved owing to the existence of exponential terms. We transform the loss function into an appropriate form. In Figure 5, point A denotes ground truth and point B denotes the estimated result, thus their ordinate values correspond to $\boldsymbol{t}_{Gij}$ and $\boldsymbol{d}_{Gij}$ respectively. As for the sigmoid function $\boldsymbol{d}_{Gij} = \left[1 + \exp(-y)\right]^{-1}$ in Equation (8), its tangent in point (0, 0.5) is represented as:

$$\frac{1}{4}y - \boldsymbol{d}_{Gij} + \frac{1}{2} = 0 \tag{18}$$

Move the point B upward to interact with the tangent in point C whose ordinate value is denoted as $\boldsymbol{d}'_{Gij}$. As it is hard to measure original empirical loss exploits s_{ij}, the Euclidean distance between $\boldsymbol{t}_{Gij}$ and $\boldsymbol{d}_{Gij}$. Here we solve it by measuring s'_{ij}, the Euclidean distance between $\boldsymbol{t}'_{Gij}$ and $\boldsymbol{d}'_{Gij}$, deducing the following formulas:

$$s'_{Gij} = \left\|\boldsymbol{e}'_{ij}\right\| \tag{19}$$

$$\boldsymbol{e}'_{ij} = \boldsymbol{d}'_{Gij} - \boldsymbol{t}'_{Gij} \tag{20}$$

Replacing s_{ij} with s'_{ij} in Equation (16-17) yields its approximate transformation as:

$$\Gamma'''(\boldsymbol{W}, \boldsymbol{b}) = \frac{1}{2}\sum_{k=1}^{n}\left\|\boldsymbol{w}^k\right\|^2 + \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{m} a'_{ij}\left(s'_{ij}\right)^2 + \xi' \tag{21}$$

where

$$a'_{ij} = \begin{cases} 0 & {s'_{ij}}^{(g)} < \varepsilon \\ \dfrac{2\lambda\left({s'_{ij}}^{(g)} - \varepsilon\right)}{{s'_{ij}}^{(g)}} & {s'_{ij}}^{(g)} \geq \varepsilon \end{cases} \tag{22}$$

and ξ' is current sum of constant terms.

The optimum can be found through letting the gradient equal to zero:

$$\frac{\partial \Gamma'''(\boldsymbol{W}, \boldsymbol{b})}{\partial w^k} = \boldsymbol{w}^k - \frac{1}{16}\sum_{i=1}^{m}\sum_{j=1}^{m}\{h\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right) \cdot a'_{ij} \cdot \left(4\boldsymbol{t}_{ij} - 2\right) - [h^{\mathrm{T}}\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right)\boldsymbol{w}^k + b^k]\} = 0 \tag{23}$$

$$\frac{\partial \Gamma'''(\boldsymbol{W}, \boldsymbol{b})}{\partial b^k} = -\frac{1}{16}\sum_{i=1}^{m}\sum_{j=1}^{m} a'_{ij}\{(4\boldsymbol{t}_{ij} - 2) - [h^{\mathrm{T}}\left(\boldsymbol{x}_i, \boldsymbol{x}_j\right)\boldsymbol{w}^k + b^k]\} = 0 \tag{24}$$

which can be expressed as a linear expression:

$$\begin{bmatrix} \boldsymbol{H}^{\mathrm{T}}\boldsymbol{D}_a\boldsymbol{H} + 16\boldsymbol{I} & \boldsymbol{H}^{\mathrm{T}}\boldsymbol{A} \\ \boldsymbol{A}^{\mathrm{T}}\boldsymbol{H} & \boldsymbol{1}^{\mathrm{T}}\boldsymbol{A} \end{bmatrix} \cdot \begin{bmatrix} \boldsymbol{w}^k \\ b^k \end{bmatrix} = \begin{bmatrix} -\left(4\boldsymbol{t}_{ij} - 2\right)\boldsymbol{H}^{\mathrm{T}}\boldsymbol{D}_a \\ -\left(4\boldsymbol{t}_{ij} - 2\right)\boldsymbol{A}^{\mathrm{T}} \end{bmatrix} \tag{25}$$

where

$$\boldsymbol{H} = [h(\boldsymbol{x}_1, \boldsymbol{x}_2), h(\boldsymbol{x}_1, \boldsymbol{x}_3), \cdots, h(\boldsymbol{x}_1, \boldsymbol{x}_m), h(\boldsymbol{x}_2, \boldsymbol{x}_3), \cdots, h(\boldsymbol{x}_{m-1}, \boldsymbol{x}_m)] \tag{26}$$

$$\boldsymbol{A} = \left[a'_{12}, a'_{13}, \cdots, a'_{1m}, a'_{23}, \cdots, a'_{m-1,m}\right]^{\mathrm{T}} \tag{27}$$

Let $\boldsymbol{H}_{(q)}$ $(q = 1, 2, \cdots, \alpha)$ denote the q-th element in vector $\boldsymbol{H}$, in which elements in $\boldsymbol{H}$ are ranked as the order in equation (25). q ranges from 1 to α, also representing that index ij has α combinations. The vector D_a is represented as:

$$\boldsymbol{D}_a = \left\{(\boldsymbol{D}_a)_{kq} \,|\, q = 1, 2, \cdots, \alpha; k = 1, 2, \cdots, n\right\} \tag{28}$$

$$(\boldsymbol{D}_a)_{kq} = a_q\delta(k, q) \tag{29}$$

The resolution of $\boldsymbol{w}^k$ and b^k can be obtained through Equation (25). Finally, Substituting the obtained optimal solutions $\boldsymbol{w}^k$ and b^k into Equation (8) leads to predicted preference relations towards all the item pairs I_l, I_r $(l, r = 1, 2, \cdots, M)$ in M candidate items.

C. GENERATING RECOMMENDATIONS

As preference relations among group members are usually heterogeneous, we employ average strategy-based borda counting rule to generate recommendations for the group.

Figure 6 illustrates the process of generating recommendations through a typical case. As for user k in group G, the predicted profile is preference relations between item pairs (I_l, I_r), which is denoted as π_{klr}. According to the definition in Equation (1-4), a ranking list of candidate items denoted as L_k can be suggested for user k. Then, we employ borda voting rule which selects tries to rank and select a set of preferable ones from candidate items. The rule is dominated by a non-negative vector f over M candidate items:

$$\boldsymbol{f} = (f_1, f_2, \cdots, f_M) \tag{30}$$

where elements in vector f are voting scores corresponding to M candidate items respectively. The voting score depends on the position in L_k. Thus, voting score of l-th candidate item is expressed as:

$$f_l = \sum_{k=1}^{n} f_{kl} \tag{31}$$

where

$$f_{kl} = M - v_k; (k = 1, 2, \cdots, n) \tag{32}$$

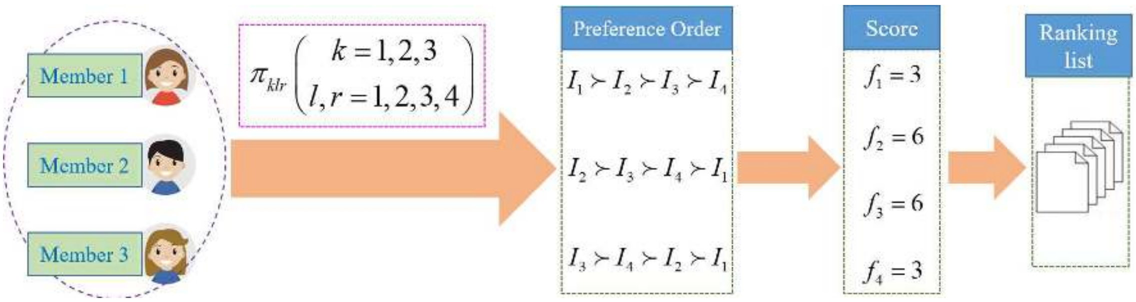


FIGURE 6. An Example for Process of generating recommendations.

and v_k denotes the ranking position that item I_l lies in list L_k. Finally, all the candidate items I_l are ranked by sorting the values f_l in descending order, resulting in the final ranking list as recommendation results.

V. EXPERIMENTS AND ANALYSIS

To evaluate performance of the proposed GRS-PR, we carried out a series of experiments on two real-world datasets.

A. EXPERIMENTAL SETUP

As no specialized datasets have been published for researches of GRS, we insteadly employ two popular datasets: "MovieLens 100K" dataset[1] (called MovieLens) and the "Netflix" dataset[2] (called Netflix). The above two datasets are usually used for evaluating performance of individual recommender system. It is assumed that items in sample library will not appear in candidate items. Also, we set the proportion of training set and testing set as 65% and 35% respectively. As the two datasets contain no group information, we randomly select users to construct groups.

We extract descriptive fields from IMDb[3] for training items and candidate items as their initial features. Features used in our experiments are selected as follows: Country, Language, Year, Running Time and Budget, Genre, Director, 1st Actor, 2nd Actor, Production Company. Data of the first five are structured and can be easily expressed as numerical values for calculation. While data of the last five are usually unstructured. For simplicity, elements are randomly assigned numerical values and are represented by them. Note that same elements are assigned one common numerical value. Besides, the parameter λ of Equation (10) is set to 1.0, and the tolerance parameter ε in Equation (11) is to 0.1.

As output of the GRS-PR is ranked recommendation results, we evaluate its performance by measuring utility of recommendation results. The following three metrics are introduced for evaluation: nDCG [36], MRR [64] and MAP [64]. The three metrics have been successfully utilized to evaluate efficiency of ranking list in other research works.

[1] http://www.grouplens.org/
[2] http://www.netflixprize.com/
[3] http://www.imdb.com/

Thus their detailed explanations are described in corresponding references.

Given above metrics, the GRS-PR will be compared with the following baseline methods:

- LM [66]–An aggregation strategy named least misery for group profile;
- AVG [66]–An aggregation strategy named average for group profile;
- AWM [33]–An aggregation strategy named average without misery for group profile;
- MCS [36] łAn aggregation strategy for setting up group profile with consideration of member contribution.

And detailed descriptions of the baselines are demonstrated in corresponding references.

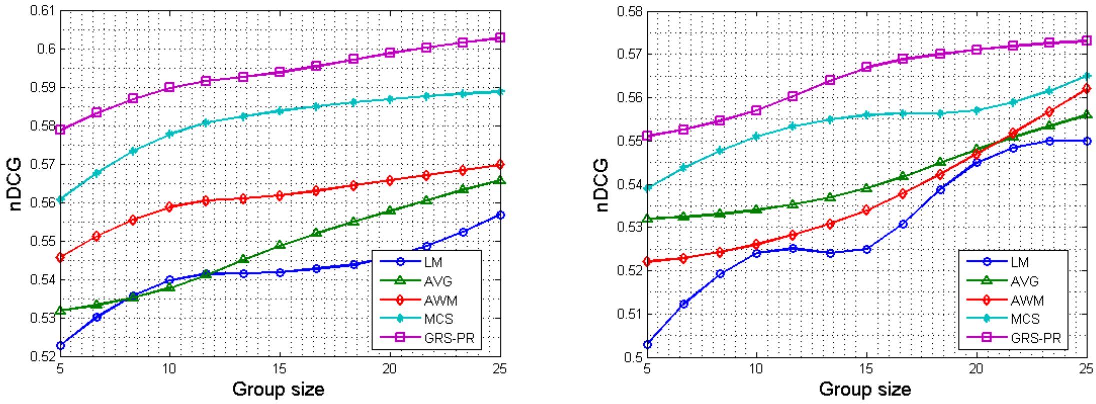
B. RESULTS AND ANALYSIS

In experiments, The GRS-PR and baseline approaches are implemented on two datasets. Performance of GRS-PR is compared with others through above three metrics. datasets Movielens and Netflix. The number of recommendation results is set to $z = 5$, and group sizes are set to $n = 5, 10, 15, 20, 25$ respectively.

Figure 7 shows the nDCG results obtained by GRS-PR and baselines on two datasets with different group sizes. It contains two subfigures: (a) corresponds to results on Movielens, (b) corresponds to results on Netflix. The X-axis and Y-axis respectively indicate the number of group sizes and values of nDCG. As shown in Figure 7, it is clear that GRS-PR consistently outperforms the baseline approaches, regardless of group sizes.

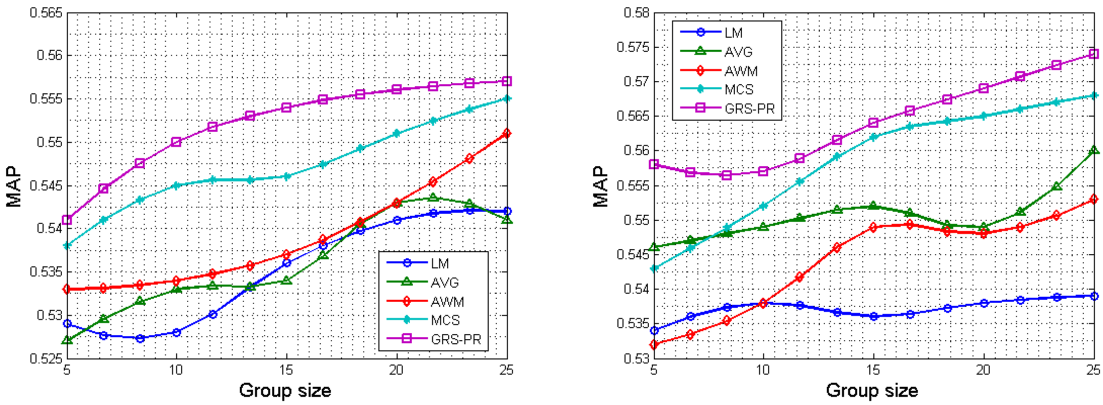
As for Movielens, results of LM, AVG and AWM are close, and AWM performs best when group size increases. When group size is 5, GRS-PR is about 10.7% better than LM and 6.0% better than AWM. When group size is 25, GRS-PR is about 8.3% better than LM and 5.8% better than AVG. MCS performs better than the above three methods but worse than GRS-PR. It is about 3.1% worse than GRS-PR under group size of 5, and about 2.3% worse than GRS-PR under group size of 25.

As for Netflix, results of LM, AVG and AWM are close, and AVG performs best when group size increases. When group size is 5, GRS-PR is about 9.5% better than LM



(a) (b)

FIGURE 7. nDCG results obtained by GRS-PR and baselines. (a) Results on movielens. (b) Results on netflix.



(a) (b)

FIGURE 8. MAP results obtained by GRS-PR and baselines. (a) Results on movielens. (b) Results on netflix.

and about 3.6% better than AVG. When group size is 25, GRS-PR is respectively 4.2% and 2.0% better than LM and AVG. Similarly, MCS and GRS-PR are two relatively good approaches, and performance of GRS-PR exceeds MCS a bit.

Figure 8 shows the MAP results obtained by GRS-PR and baselines on two datasets with the group sizes changing. Figure 8(a) corresponds to results on Movielens and Figure 8(b) corresponds to results on Netflix. The X-axis and Y-axis respectively indicate the number of group sizes and values of MAP. It can be intuitively observed that GRS-PR and MCS are also better than the other three approaches, and that GRS-PR performs better a little bit. AWM performs better than LM and AVG in this set of experiments.

Acquirement of above experimental results can be attributed to the fact that GRS-PR possesses two aspects of advantages. First, preference feedback of relative form is able to reduce noise caused by heterogeneity of members' assessment criteria, and thus can finely capture preference characteristics. Second, with the aid of borda voting rule, GRS-PR aggregates preference feedbacks of individuals into group profiles to generates recommendation results. In contrast, baseline approaches model group profiles utilizing single preference feedbacks of absolute form, yet neglecting heterogeneity of members' preference assessment standard.

Figure 9 shows the MRR results obtained by GRS-PR and baselines on two datasets with different group sizes. It contains two subfigures: Figure 9(a) corresponds to results on Movielens and Figure 9(b) corresponds to results on Netflix. The X-axis and Y-axis respectively indicate the number of group sizes and values of MRR. From Figure 9, experimental results of MCS and GRS-PR are also better than the other three approaches: LM, AVG and AWM. Results of these three approaches are close. LM performs better when group size is small, while AVG and AWM performs better when group size increases. GRS-PR exceeds MCS in most cases, but the superiority is not as obvious as above experiments'. On Movielens, GRS-PR is a little inferior to MCS when group size is 15, but superior to MCS under other group sizes. A reasonable explanation for this phenomenon is non-uniform distribution of data samples.

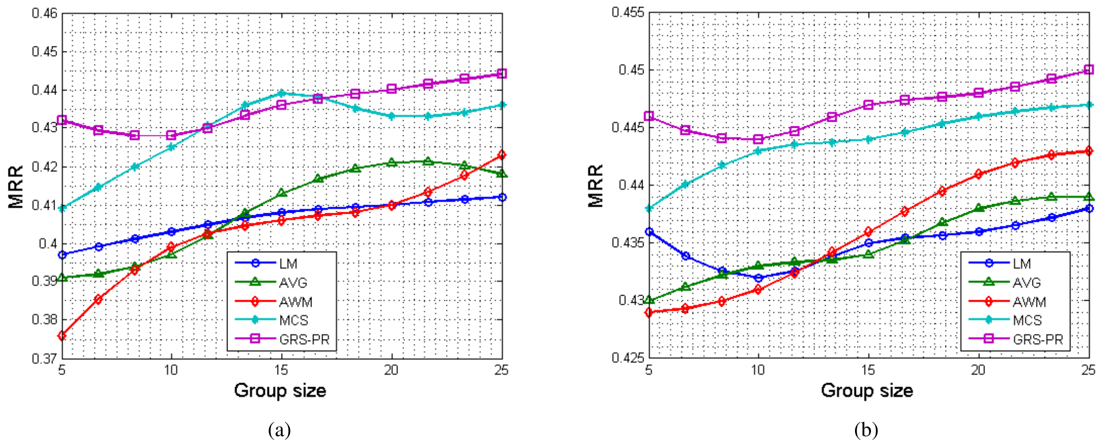


FIGURE 9. MRR results obtained by GRS-PR and baselines. (a) Results on movielens. (b) Results on netflix.

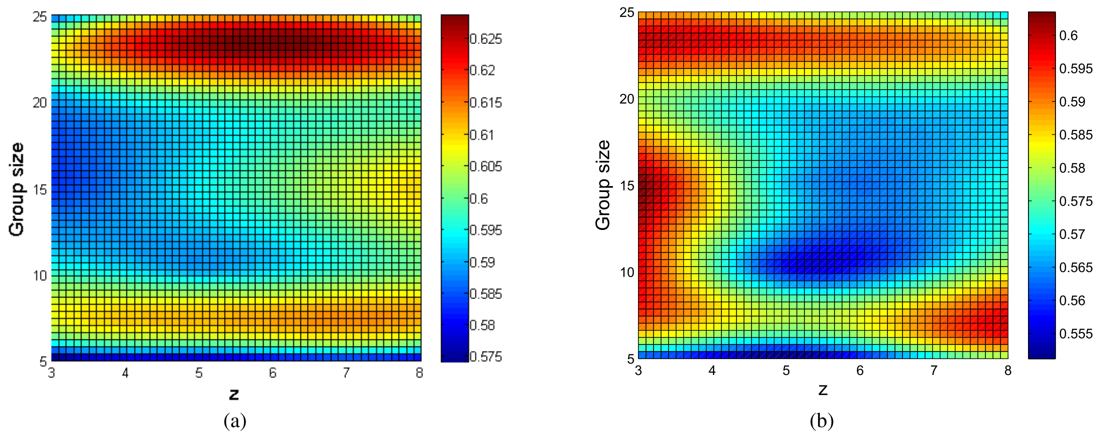


FIGURE 10. nDCG values obtained by GRS-PR with parameter z changing. (a) Results on movielens. (b) Results on netflix.

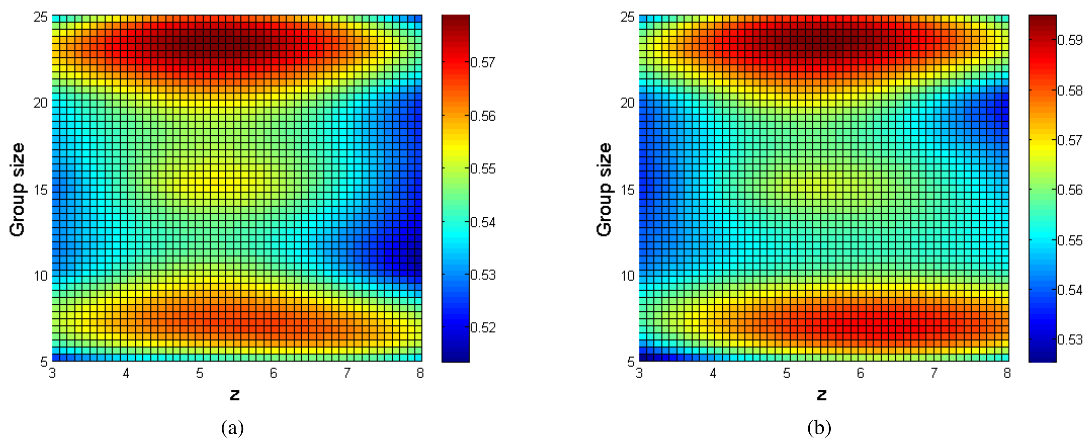
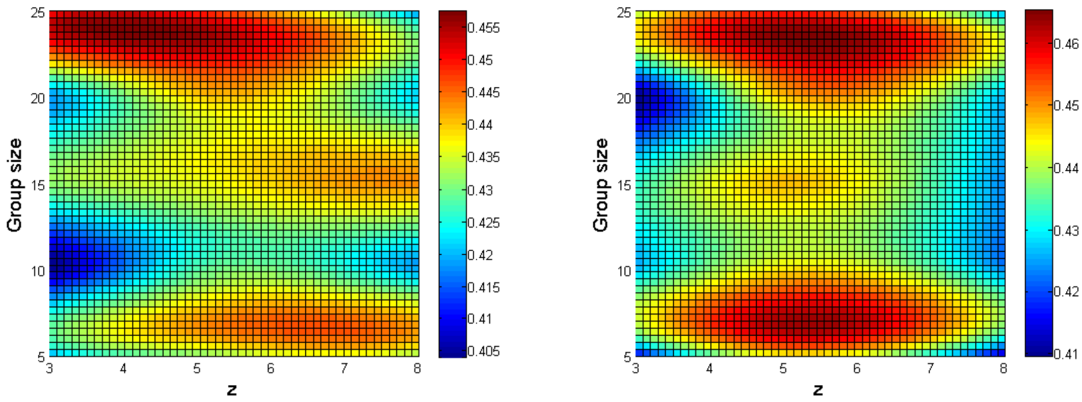


FIGURE 11. MAP values obtained by GRS-PR with parameter z changing. (a) Results on movielens. (b) Results on netflix.

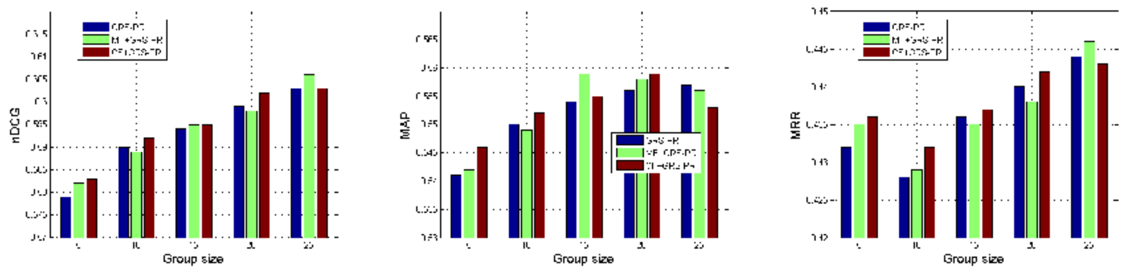
C. EXPLORATION OF PARAMETER SENSITIVITY

In previous experiments, number of recommendation results z in top-z recommendation is set to 5. This subsection will conduct a series of experiments to explore performance tendency of GRS-PR with the parameter z setting to different values. As this set of experiments just explore sensitivity of



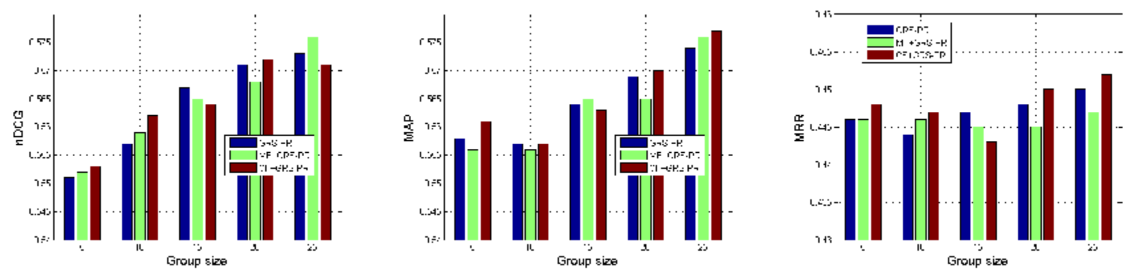
(a) (b)

FIGURE 12. MRR values obtained by GRS-PR with parameter z changing. (a) Results on movielens. (b) Results on netflix.



(a) (b) (c)

FIGURE 13. Experimental results on Movielens while introducing sparsity processing scheme. (a) nDCG results. (b) MAP results. (c) MRR results.



(a) (b) (c)

FIGURE 14. Experimental results on Netflix while introducing sparsity processing scheme. (a) nDCG results. (b) MAP results. (c) MRR results.

GRS-PR to parameter z, thus only GRS-PR is implemented on two datasets without making comparisons with baselines.

Figure 10, 11 and 12 respectively illustrate evolution trends of nDCG, MAP and MRR obtained by GRS-PR with parameter z changing. They all contain two subfigures: (a) corresponds to results on Movielens and (b) corresponds to results on Netflix. X-axis denotes change of group sizes, Y-axis denotes change of, and gradual change of color spectrum denotes variety of metric values. It can be observed from three set of figures that when z changes, values of metrics have small fluctuations but no dramatic variations. These results are able to well indicate good robustness of GRS-PR approach, and can be attributed to two main reasons. First, preference relation defined in Equation (1-4) can overcome missing of partial samples and remain robust to different sizes of samples. Second, preference feedback of relative form possesses strong stability, and is not susceptible to different scenario settings.

D. EXPLORATION OF SPARSITY TOLERANCE

This subsection aims to explore influence of data sparsity on GRS-PR. Two classical recommendation algorithm is introduced to complete some missing data: Collaborative Filtering (CF) and Matrix Factorization (MF). As for a group, ratings of members towards items are able to constitute a rating matrix. The two algorithms mine latent relations among members and ratings, and predict some missing data. Procedures of the two schemes are respectively described in [47] and [53]. Thus, GRS-PR is compared with "CF+GRS-PR" and "MF+GRS-PR". As for evaluation metrics, this subsection continues to utilize previous ones: nDCG, MAP and MRR. And parameter settings are same as Section V-B.

Figure 13 and 14 respectively demonstrate experimental results of sparsity tolerance on Movielens and Netflix. They all contain three subfigures: (a) corresponds to results of metric nDCG, (b) corresponds to results of metric MAP, and (c) corresponds to results of metric MRR. Two aspects of contents can be observed from the two sets of figures. First, results of the CF+GRS-PR and MF+GRS-PR cannot reflect obvious superiority to GRS-PR, and just exceed resuts GRS-PR in some cases. Second, introduction of sparsity processing schemes hardly brings distinct fluctuation to experimental results. Overall speaking, it can be concluded from this series of experiments that recovering some missing data is able to promote experimental results in some cases, and GRS-PR is not susceptible to data sparsity. A possible reason for this phenomenon is that preference feedback of relative form defined in Equation (1-4) is robust to data sparsity to some extent, and can eliminate some uncertainty brought by missing data.

VI. CONCLUSIONS

This paper manages to propose a recommender system for groups of users. When it comes to modeling group profile, current solutions are mostly based upon preference feedbacks of absolute form, bringing about some noise because preference assessment criteria are usually heterogeneous among different members. Therefore, a novel group recommender system is proposed. It firstly formulates a preference relation-based multi-variate extreme learning machine model to predict unknown preference relations. Then, on the basis of predicted results, it employs borda voting rule to generate recommendation results from candidate items. Finally, we conduct a series of experiments to verify performance of the proposed GRS.

There is no doubt that existing researches for GRS have obtained dramatic advances. And related proposals are displayed excellent performances in some cases. On this foundation, the enhanced group recommender system by exploiting preference relation optimizes process of modeling group profile, in order to improve efficiency of it. Results prove that the proposed GRS-PR is a highly effective approach.

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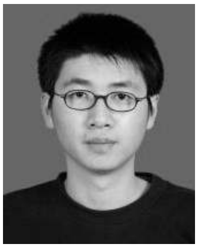

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