Alleviating New User Cold-Start in User-Based Collaborative Filtering via Bipartite Network

Alleviating New User Cold-start in User-based Collaborative Filtering via Bipartite Network

Zhipeng Zhang, Mianxiong Dong, *Member, IEEE,* Kaoru Ota, *Member, IEEE,* and Yasuo Kudo *Member, IEEE,*

***Abstract*—Recommender system (RS) can help us extract valuable data from huge amount of raw information. User-based collaborative filtering (UBCF) is widely employed in practical RSs owing to its outstanding performance. However, the traditional UBCF is subject to the new user cold-start issue because a new user is often extreme lack of available rating information. In this paper, we develop a novel approach that incorporates bipartite network into UBCF for enhancing the recommendation quality of new users. First, through the statistic and analysis of new users' rating characteristic, we collect niche items and map the corresponding rating matrix to a weighted bipartite network. Furthermore, a new weighted bipartite modularity index merging normalized rating information is present to conduct the community partition that realizes co-clustering of users and items. Finally, for each individual clustering that is much smaller than original rating matrix, a localized low-rank matrix factorization is executed to predict rating scores for un-rated items. And items with highest predicted rating scores are recommended to a new user. Experimental results from two real-world datasets suggest that, without requiring additional complex information, the proposed approach is superior in terms of both recommendation accuracy and diversity, and can alleviate the new user cold-start issue of UBCF effectively.**

***Index Terms*—Recommender systems, User-based collaborative filtering, Bipartite network, New user cold-start,**

I. Introduction

RECOMMENDER system (RS) assists customers to optimize the search results and recommends personalized products which they may prefer. Currently, RS gradually becomes a core application around our daily life in the era of big data, such as news feed, on-line shopping, and music/movie play. It has significant commercial values and research significances [1].

User-based collaborative filtering (UBCF) assumes that users who have similar interests in the past are inclined to own closer habits in the future. Because UBCF has high computation efficiency, and can only utilize users' historical ratings rather than any other special information to provide satisfactory recommendations, it achieves a remarkable success in modern RSs [2], [3]. However, the new user cold-start problem occurs in UBCF when new users have just entered RSs or not for long, because preferences of new users are difficult to be inferred by UBCF through their insufficient ratings [4], [5]. Note that, new user cold-start can be divided into complete new user cold-start where no rating record is available, and incomplete new user cold-start where only a tiny amount of ratings are usable [6]. In this paper, we focus on the problem of producing satisfying recommendations for new users with small number of ratings (i.e., incomplete new user cold-start).

To solve new user cold-start issue in UBCF, a number of researchers have done extensive studies, which can be classified into three lines [5]: (1) utilizing additional information (e.g., user profile, trust, opinions, and social tags) [3], [7], [8], [9], [10], [11], [12], [13]. However, some special additional information is difficult to obtain or incomplete; (2) determining the most prominent groups of analogous users without utilizing additional information [14], [15], [16], [17], [18], [19], [20]. However, it is difficult to choose the optimal number of groups and the splitting criteria. (3) calculating similarity or prediction of rating scores by hybrid approaches [21], [22], [23], [24], [25], [26], [27], [28]. However, they can improve recommendation accuracy or diversity, but not in both. Therefore, how to utilize accessible information merely (e.g., rating scores) to produce recommendations owning satisfying accuracy and diversity simultaneously for a new user is a big challenge that researchers are faced with.

Motivated by this, we proposed a novel approach by incorporating bipartite network into UBCF approach in this paper. The proposed approach first analyzed the rating characteristics of new users through two real datasets, and concluded that recommendations provided by UBCF for a new user have over-fitting phenomenon (i.e., recommendations concentrate on few types of items, even only popular items). Thus, the proposed approach focused on exploiting ratings on niche items that would better represent a new user's true preference, and mapped the rating matrix of niche items to a weighted bipartite network. In addition, a weighted bipartite modularity index was present to search the optimal number of co-clustering, so as to obtain a stronger bipartite network structure after community division. Further, a localized low-rank matrix factorization was subsequently applied to each individual rating matrix for predicting rating scores of un-rated items, and recommendations are generated from items owning highest predicted rating scores. Figure 1 demonstrates the flow chart of our proposed approach, and the main contributions of our proposed approach can be summarized as follows:

1) No additional information is required. Unlike some related approaches which need special additional information that is often incomplete or unavailable [3], [7],

This work was supported in part by JSPS KAKENHI under Grant JPJP16K00117 and Grant JP19K20250, in part by the Leading Initiative for Excellent Young Researchers (LEADER), in part by MEXT, Japan and KDDI Foundation. Mianxiong Dong is the corresponding author

Z. Zhang is with the School of Computer and Information Technology, Liaoning Normal University, Dalian 116081, China (zhipengzhang@lnnu.edu.cn).

M. Dong, K. Ota, and Y. Kudo are with the Department of Information and Electronic Engineering, Muroran Institute of Technology, Muroran 050-8585, Japan (mx.dong@csse.muroran-it.ac.jp; ota@csse.muroran-it.ac.jp; kudo@csse.muroran-it.ac.jp).

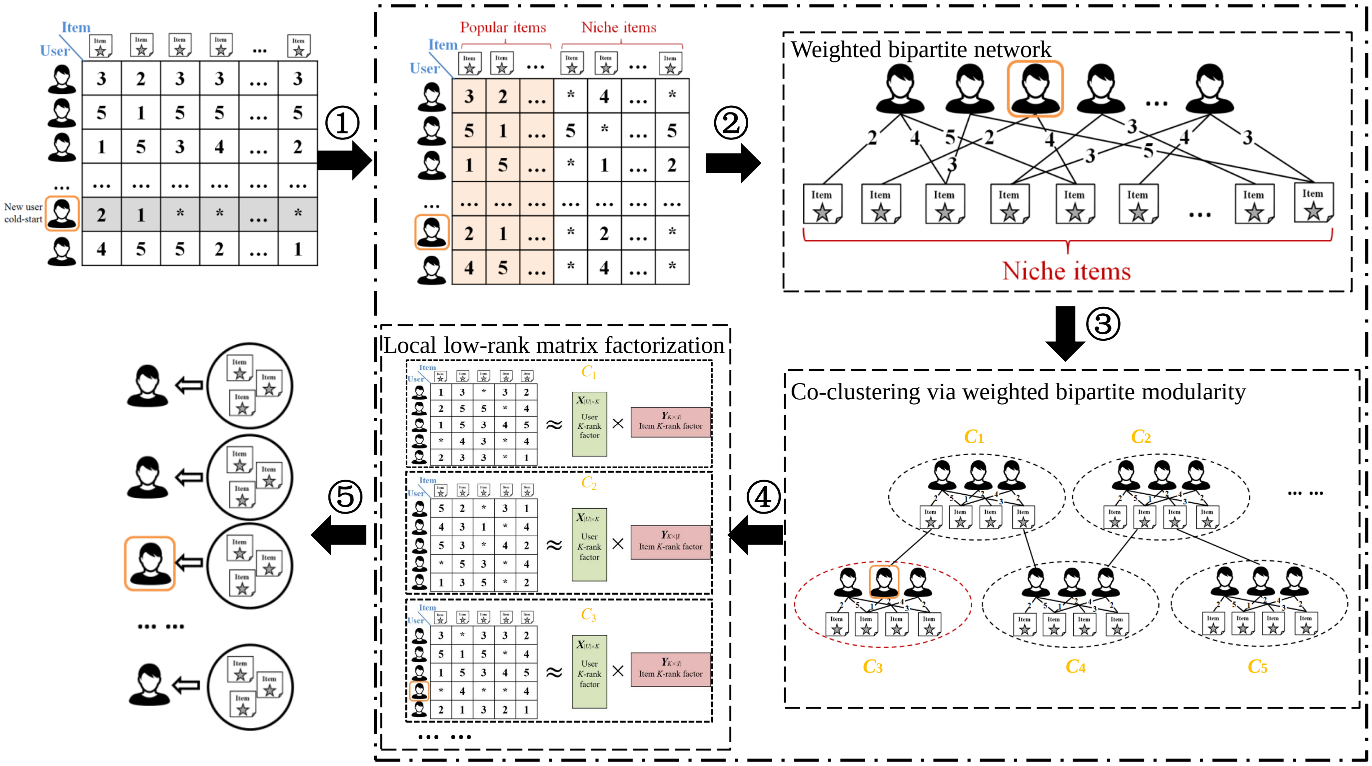


Fig. 1. The flow chart of our proposed approach. Our approach comprises the following main procedures: 1) divide item domain into popular and niche items; 2) map rating matrix of niche items to a weighted bipartite network; 3) conduct community division of the weighted bipartite network under the guidance of weighted bipartite modularity index; 4) utilize localized low-rank matrix factorization to predict rating scores in each individual clustering; and 5) recommend to a new user with items having highest predicted rating scores.

[8], [9], [10], [11], [12], [13], our proposed approach can only utilize accessible information (i.e., rating matrix) to address the new user cold-start issue.

2) A novel weighted bipartite modularity index is proposed to determine the optimum number of co-clustering which realizes clustering on both users and items. Most current methods only make clustering on the user or item one-sided without considering the relationship between them. In addition, the optimum number of groups is difficult to ascertain [14], [15], [16], [17], [18], [19], [20]. Our proposed approach maps the rating matrix to a weighted bipartite network, and engages community division to implement co-clustering on both users and items. Further, we present a novel weighted bipartite modularity index to conduct the clustering process, the highest value of weighted bipartite modularity corresponds the optimum number of clustering.
3) Both accuracy and diversity of recommendations are enhanced. Different from related methods which are able to enhance either recommendation accuracy or diversity, but not in both [21], [22], [23], [24], [25], [26], [27], [28], our proposed approach can produce recommendations for a new user with satisfying accuracy and diversity at the same time, and experimental results in Section V confirm this.

The rest of this paper is structured as follows. In Section II, we give contents of the traditional UBCF and related studies which are present to solve new user cold-start issue. In Section III, we summarize the rating characteristics of new users through an analysis of two real-world datasets and present problem setting. In Section IV, we explain the motivation, then present the detailed information about co-clustering and rating prediction as well as procedures of the proposed approach. In Section V, we execute experiments and make a comparison between our proposed approach with some related approaches. Finally, in Section VI, we present conclusions and offer suggestions for future work.

II. Related work

To introduce UBCF, we first present some RS-related notations. Suppose that in an RS, U means the set of users and I is the set of items, respectively. R and $\{\star\}$ indicate possible rating scores, and a missing rating value is demonstrated by $(\star)$. $r_{u,i} \in R \cup \{*\}$ denotes the rating score of user u on item i. θ is a rating threshold, items having rating scores no less than θ are identified as relevant items of a target user. $U(i) = \{u \in U | r_{u,i} \neq \star\}$ indicates the set of users who have rated item i. $I(u) = \{i \in I | r_{u,i} \neq \star\}$ means the set of items that were rated by the user u. $\widehat{I}(u)$ represents the set of items which user u has not rated yet.

In the era of big data, although huge information gives us facility on work and life [29], [30], [31], [32], [33], it still brings information overload problem. RSs come into being as the times require. The UBCF is one of the most significant approaches in RSs, which was first proposed by Herlocker et al. [34]. In the case of only utilizing the rating matrix information, UBCF can produce satisfying recommendations for a target user [3]. UBCF predicts rating scores for un-rated items according to the rating information of similar users, then selects items having higher predicted rating scores to recommend to a target user. The basic procedures of the traditional UBCF approach can be summarized as follow.

1) Neighbor selection. According to the rating information of co-rated items for each pair of users in the rating matrix, UBCF computes the similarity for each pair of users. Then, the top T users with highest similarity comprise the neighbor $N_{tu}(T)$ of a target user tu. Pearson correlation coefficient approach (Eq. 1) is often utilized to compute similarity:

$$sim(tu,u) = \frac{\sum\limits_{i\in I(tu)\cap I(u)} (r_{tu,i}-\bar{r}_{tu})(r_{u,i}-\bar{r}_u)}{\sqrt{\sum\limits_{i\in I(tu)\cap I(u)} (r_{tu,i}-\bar{r}_{tu})^2}\sqrt{\sum\limits_{i\in I(tu)\cap I(u)} (r_{u,i}-\bar{r}_u)^2}}, \tag{1}$$

here, $sim(tu,u)$ means the similarity between the target user tu and user u. $I_{tu}=\{i\in I|r_{tu,i}\neq\star\}$ indicates the set of items rated by the target user tu, $\bar{r}_{tu}$ means the average rating value of the target user tu:

$$\bar{r}_{tu} = \frac{\sum_{i\in I_{tu}} r_{nu,i}}{|I_{tu}|}.$$

2) Rating prediction. According to rating information of the neighbor of target user tu, UBCF predicts rating scores for each item that the target user has not rated yet. The weighted sum approach (Eq. 2) is successfully applied to predict rating scores:

$$p_{tu,i} = \gamma \sum_{u\in N_{tu}(T)\cap U(i)} sim(tu,u) * r_{u,i}, \tag{2}$$

here $p_{tu,i}$ indicates the predicted rating score of item i from target user tu, and multiplier γ represents a normalizing factor:

$$\gamma = \frac{1}{\sum_{u\in N_{tu}(T)\cap U(i)} sim(tu,u)}. \tag{3}$$

3) Make recommendation. After obtaining the predicted rating scores for all un-rated items of a target user, UBCF recommends the top N items with highest predicted rating scores to the target user.

However, in practical RSs, when a new user just enters an RS, available ratings are much less. In this case, UBCF cannot infer the true preference of a new user according to the insufficient information. Furthermore, neighbor selection is computed on the basis of rating scores of co-rated items, but a new user often has rated few items, thus co-rated items between the new user and other users will be rarer, resulting in neighbors selected for the new user may be unreliable [4], [5]. Therefore, the traditional UBCF cannot provide satisfactory recommendations for a new user, it suffers from new user cold-start problem.

Currently, a number of studies focus on resolving the new user cold-start problem in UBCF. Generally, they can be classified into three categories. In the first category, they take advantage of some additional information of new users, such as user profile, opinions, social tags, trust network and so on, for selecting reliable neighbor or obtaining accurate prediction. Zhang et al. [3] proposed a covering based collaborative filtering to remove redundant users from neighborhood based on relevant attributes. Chen et al. [7] constructed a user model by utilizing a new user's trust and distrust networks, so that useful recommendations for a new user can be provided by aggregating the user model. Rosli et al. [8] computed user similarity according to the rating cast, then combined a new user's genre interests to present a novel similarity measure. Son et al. [9], [10], [11] utilized demographic attributes and missing ratings to make fuzzy geographical clustering for a new user, and selected neighbors from each new user's corresponding clustering. Yang et al. [12] present a novel method that works to improve the performance of CF recommendations by integrating sparse rating data given by users and sparse social trust network among these same users. Yang et al. [13] developed a set of matrix factorization that explores user social network and group affiliation information for social voting recommendations. Although neighbor selection and rating prediction can become more reliable through utilizing the additional information, some complex information is often unavailable or incomplete in modern RSs. e.g., in most of on-line shopping websites, in order to protect personal information, users often give up providing their individual details such as profiles and demographic.

In the second category, studies aim to select the analogous users for a new user without utilizing additional information. Bobadilla et al. [14] treated the current evaluation metrics as the computing guide, utilized neural learning to propose a novel measure for computing the similarity between a new user and other users. Formoso et al. [15] combined the query expansion methods and user/item profile information to propose three types of profile-expansion approaches. Liu et al. [16] took advantage of both global preference of user behaviors and local context information of user ratings to present a novel user similarity model, this approach can alleviate the new user cold-start problem effectively. Liu et al. [17] utilized representative-based matrix factorization to extract representative users and items, then selected the most useful ratings to compute similarity and make recommendations. Qiu et al. [18] incorporated an item-oriented function with a heat and probability spreading process to propose a hybrid algorithm which can improve recommendation quality without requiring any additional information. Wu et al. [19] constructed a ratio-based method to calculate the similarity by comparing the attribute values directly, and they predicted the unknown value by comparing the values of a similar service and the current service that are invoked by common users. Lee et al. [20] developed a novel framework by injecting low values to a selected set of unrated user-item pairs in the UIRM. However, existing methods only cluster analogous users from the user or item one-sided, the internal relationships between users and items are not considered. In addition, the optimal number of clustering and the splitting criteria are difficult to determine.

In the third category, hybrid approaches are utilized to compute similarity and predict rating scores for a new user after determining the most analogous users. Aharon et al. [21] present a one-pass factorization of feature sets named OFF-Set through using latent factor analysis, OFF-Set can build non-linear interactions for each pair of features. Carrer-Neto et al. [22] proposed a hybrid RS approach according to knowledge and social networks, and added semantically empowered techniques to improve the quality of recommendations. Kim et al. [23] constructed an error-reflected model to predict the un-rated items of a new user on the basis of predicting actual ratings and identifying prediction errors. Nilashi et al. [24] incorporated adaptive neuron-fuzzy inference systems and self-organizing map clustering to improve the recommendation accuracy for a new user. Son [25] present a novel hybrid user-based fuzzy collaborative filtering approach to improve recommendations of a new user with higher recommendation accuracy, it utilized demographic data to integrate fuzzy similarity degree and hard degree for computing the similarity. Lian et al. [26] proposed a scalable implicit-feedback-based content-aware CF framework to incorporate semantic content and to steer clear of negative sampling. Li et al. [27] proposed a multi-stream stochastic gradient descent approach to remove the dependence on the user and item pair, for which the update process is theoretically convergent. Liu et al. [28] present a location-aware personalized CF method that leverages both locations of users and web services when selecting neighborhood for a target user. However, experimental results of this category suggest that they can improve either accuracy or diversity of recommendations, but they often cannot enhance them both.

III. Preliminaries

In this section, we make an analysis of two real-world datasets (i.e., MovieLens10M and Netflix) to extract the rating characteristics of a new user, and conclude that recommendations provided by UBCF for a new user have the over-fitting problem.

First, we make statistics on MovieLens10M and Netflix datasets which are popularly utilized to evaluate the performance of RSs [34]. Detailed information about two datasets is demonstrated in table I. Next, we analyze the proportion of items and ratings on two datasets. Tables II and III show the percentage of items and their corresponding ratings based on the different amounts of ratings. As can be found in the tables, in the MovieLens10M, although items owning more than 5K ratings play only a small fraction (i.e., 4.40%) of the whole item set I, ratings corresponding to them account for 48.69% of the total ratings. In the Netflix dataset, items having more than 50K ratings comprise only a 2.82% percentage of total items; however, their corresponding ratings make up a 45.63% portion of total ratings. According to statistical results from tables II and III, it can be concluded that in practical RSs, after sorting the total items by descending order based on the number of ratings, the top fewer items often hold a large percentage of total ratings. Therefore, we define them as popular items in this paper. And the remaining items that are

TABLE I
Description of MovieLens10M and Netflix datasets

Dataset	#Users	#Items	#Ratings	Rating scale
MovieLens10M	71,567	10,681	10,002,054	{0.5,1,1.5,...,5}
Netflix	480,189	17,770	100,480,507	{1,2,3,4,5}

TABLE II
Percentage of items and ratings in the MovieLens10M

$\lvert U(i)\rvert$ for each item i	Statistical information of eligible items			
	#Items	Item rate	#Ratings	Rating rate
$\lvert U(i)\rvert \leq$ 1K	8,647	80.96%	1,569,491	15.69%
1K $\leq \lvert U(i)\rvert <$ 5K	1,564	14.64%	3,562,589	35.62%
5K $\leq \lvert U(i)\rvert <$ 10K	**296**	**2.77%**	**2,112,854**	**21.12%**
$\lvert U(i)\rvert \geq$ 10K	**174**	**1.63%**	**2,757,120**	**27.57%**

TABLE III
Percentage of items and ratings in the Netflix

$\lvert U(i)\rvert$ for each item i	Statistical information of eligible items			
	#Items	Item rate	#Ratings	Rating rate
$\lvert U(i)\rvert \geq$ 50K	**501**	**2.82%**	**45,020,066**	**45.63%**
10K $\leq \lvert U(i)\rvert <$ 50K	1,541	8.67%	34,889,199	35.36%
1K $\leq \lvert U(i)\rvert <$ 10K	5,084	28.61%	17,193,080	17.42%
$\lvert U(i)\rvert \leq$ 1K	10,644	59.90%	1,569,491	1.59%

Algorithm 1 Niche item extraction algorithm (NIEA)

Input: Rating matrix RM and ratio threshold H
Output: The set of niche items I^{NIC}

for each item $i \in I$ **do**
  $|U(i)| \leftarrow$ Calculate the number of users $u \in U$ who have $r_{u,i} \neq \star$
end for
$I^{NIC} = I$
while $\frac{|I|^{NIC}}{|I|} \geq 1 - H$ **do**
  $i \leftarrow$ Extract an item $i \in I^{NIC}$ having minimum value $|U(i)|$
  $I^{NIC} \leftarrow I^{NIC} \setminus \{i\}$
end while
return I^{NIC}

not popular are called niche items. Algorithm 1 extracts the set of niche items through the rating matrix RM and the ratio threshold H $(0 < H < 1)$. In the algorithm 1, niche items are considered as the top $H \times 100\%$ items that own the minimum number of ratings from the set of all items I and the set of popular items is constructed by remaining $(1 - H) \times 100\%$ items.

Further, we conduct statistical analysis about the percentage of ratings on popular items. Table IV demonstrates the statistical result about users with ratings no more than {20, 30, 40, 50, 60, 70, 80, 90, 100, 150, 200} in two datasets, respectively. As can be found in the table, with increasing the number of ratings, the percentage of ratings on popular items is gradually reduced. It is worth noting that users having no more than 20 ratings have the largest proportion (i.e., 74.72% in the MovieLens10M and 72.74% in the Netflix). Generally speaking, new users usually rated fewer number of items (e.g., no more than 20 ratings) [14], [35], [36]. Therefore, we can conclude that most ratings of new users are focused on popular items.

Finally, we analyze the proportion of rating scores on popular items. Statistical results are shown in Table V. As shown in the table, although the rating scores of MovieLens10M are on a scale from 0.5 to 5 with 0.5 increments, most of the values are focused on $\{3, 4, 5\}$. For the Netflix, movies were rated on a scale of 1 to 5, however, most of the rating values are also concentrated on $\{3, 4, 5\}$. Statistical results demonstrate that rating scores on popular items are relatively concentrated, because UBCF computes similarity according to the rating scores of co-rated items, if most of the co-rated items of a pair of users are included in popular items, their rating scores will be approximate, thus similarity between them will be higher.

From the statistical results from tables IV and V, we can conclude that rating scores of a new user are focused on popular items and their values have no significant differences. It results in UBCF cannot capture the true preference of a new user effectively according to her/his rating scores. And further a new user's neighbor selected by UBCF will comprise users whose ratings concentrate on popular items. Therefore, recommendations provided by UBCF for a new user often comprise fewer types of items, even only popular items, we define this as over-fitting problem on the new user recommendation.

IV. Proposed approach

In this section, we first explain the motivation of the proposed approach. Then, we present a novel weighted bipartite modularity index to conduct co-clustering of weighted network bipartite. Afterward, a localized low-rank matrix factorization is executed to predict rating scores in each individual clustering. Finally, the detailed procedures of the proposed approach are introduced and discussed.

A. Motivation

The proposed approach aims to produce personalized recommendations for a new user with satisfying accuracy and diversity simultaneously without utilizing additional information (e.g., user demographic or tags).

To achieve this, firstly, the proposed approach should focus on an analysis of rating information on niche items, because as discussed in Section III, ratings on popular items cannot reflect a new user's true preference reliably. Further, an index that merges dependencies between users and items should be present to conduct the clustering process, so that an optimal clustering number can be obtained before making prediction. In addition, in order to enhance the recommendation efficiency and improve prediction quality, users and items in each clustering should be handled individually. To introduce our proposed approach, we first list the symbols in Table VI.

B. Co-clustering based on weighted bipartite modularity

Bipartite network is a significant expression in complex networks. It comprises two different types of nodes, and links only appear between nodes with different types. Community division is a core concept in bipartite network, which divides two types of nodes having a higher degree of correlation into a same community [37], [38], [39]. To achieve efficient community division, Barber et al. [40] proposed a bipartite modularity index. Supposing that there are m number of the red nodes and n number of blue nodes, the bipartite network can be represented by an $m \times n$ adjacent matrix $A = \{a_{i,j}\}$, where $a_{i,j} = 1$ if there is a link between red node i and blue node j, and $a_{i,j} = 0$ otherwise. The adjacent matrix A could be summarized as

$$A = \begin{pmatrix} 0_{m\times m} & \widetilde{A}_{m\times n} \\ \widetilde{A}^T_{m\times n} & 0_{n\times n} \end{pmatrix} \tag{4}$$

Here, $\widetilde{A}$ means the incidence matrix that demonstrates the interactions between red and blue nodes.

Further, we define the same block structure B which indicates the expected probability of links between the different types of nodes:

$$B = \begin{pmatrix} 0_{m\times m} & \widetilde{B}_{m\times n} \\ \widetilde{B}^T_{m\times n} & 0_{n\times n} \end{pmatrix} \tag{5}$$

Where $\widetilde{B}_{i,j}$ denotes the probabilities in the null model that a link exists between red node i and blue node j. Based on the adjacency matrix A and B, the bipartite modularity could be computed as

$$\begin{aligned} Q &= \frac{1}{M}\sum_{i=1}^{m}\sum_{j=1}^{n}(\widetilde{A}_{i,j} - \widetilde{B}_{i,j})\delta(g_i, h_j) \\ &= \frac{1}{M}\sum_{i=1}^{m}\sum_{j=1}^{n}(\widetilde{A}_{i,j} - \frac{D(i)D(j)}{M})\delta(g_i, h_j), \end{aligned} \tag{6}$$

here, M denotes the number of links in $\widetilde{A}$. $D(i)$ and $D(j)$ indicate the node degree for nodes i and j. In other words, $D(i)$ denotes the number of blue nodes which interacts with red node i; $D(j)$ indicates the number of red nodes which interacts with blue node j. Red node groups are indicated by g, and blue node groups are denoted by h. The Kronecker delta function $\delta(g_i, h_j)$ is equal to one when nodes i and j are divided into the same community or zero otherwise.

For RSs, if we treat U as the set of user nodes, and I as the set of item nodes, then, an RS can be converted to a bipartite network which contains $|U|$ number of user nodes and $|I|$ number of item nodes. Furthermore, the user-item bipartite network can be represented by an $|U| \times |I|$ adjacent matrix A. However, adjacent matrix A in a classical bipartite network cannot reflect the correlation degree between user and item nodes. In this paper, we propose a weighted bipartite network which treats adjacent matrix $A^W = \{a_{u,i} | a_{u,i} = r_{u,i} \in R \cup \{\star\}\}$, so that the edge has a weight $r_{u,i}$ to reflect the preference degree of user u on item i.

However, in practical RSs, each user has a different rating style. Some users tend to give low rating scores, but some prefer to give higher marks. Thus, ratings cannot be grouped together in the straightforward way. To deal with this phenomenon, we make rating unification to characterize the rating scores of user u through utilizing the mean μ_u and the standard deviation σ_u of rating scores given by user u, and compare

TABLE IV
PROPORTION OF RATINGS ON POPULAR ITEMS IN THE (A) MOVIELENS10M AND (B) NETFLIX DATASETS

Dataset	Proportion of ratings on popular items by users with no more than n ratings (%)										
	$n=20$	$n=30$	$n=40$	$n=50$	$n=60$	$n=70$	$n=80$	$n=90$	$n=100$	$n=150$	$n=200$
MovieLens10M	**74.72**	73.61	72.96	72.25	71.44	70.67	69.87	69.19	68.63	66.04	64.26
Netflix	**72.74**	72.69	72.45	72.24	72.01	71.82	71.67	71.58	71.50	71.34	71.02

TABLE V
PROPORTION OF RATING SCORES ON POPULAR ITEMS

Dataset	The number of ratings on different rating score									
	0.5	1	1.5	2	2.5	3	3.5	4	4.5	5
MovieLens10M	31,813	128,140	42,395	294,295	139,502	**1,106,837**	381,130	**1,480,631**	303,812	**961,419**
Netflix	-	1,625,172	-	3,912,019	-	**11,884,478**	-	**15,834,002**	-	**11,764,395**

TABLE VI
SUMMARY OF NOTATIONS

Symbols	Description
L	The number of clustering
C_l	The l-th clustering
$C(u)$	The clustering which user u belongs to
$C(i)$	The clustering which item i belongs to
$C(r_{u,i})$	The clustering which rating score $r_{u,i}$ belongs to
$U(C_l)$	The set of users which the l-th clustering contains
$I(C_l)$	The set of items which the l-th clustering contains
$P(C_l\|u)$	The probability that user u belongs to the l-th clustering
$P(C_l\|i)$	The probability that item i belongs to the l-th clustering
$P(C_l\|r_{u,i})$	The probability that rating score $r_{u,i}$ belongs to the l-th clustering
$\bar{r}_{C(u)}$	The average rating value of the clustering which user u belongs to
$\bar{r}_{C(i)}$	The average rating value of the clustering which item i belongs to
$\bar{r}_{C(r_{u,i})}$	The average rating value of the clustering which rating score $r_{u,i}$ belongs to

these values with the mean $\widehat{\mu}_U$ and the standard deviation $\widehat{\sigma}_U$ of ratings given by all users through the linear transformation:

$$\widehat{r}_{u,i} = \mu_U + (r_{u,i} - \mu_u)\frac{\sigma_U}{\sigma_u}, \tag{7}$$

where $\widehat{r}_{u,i}$ means rating score $r_{u,i}$ after making rating unification. Thus, in the user-item weighted bipartite network, the adjacent matrix $A^W = \{a_{u,i}|a_{u,i} = \widehat{r}_{u,i}\}$. Because different rating scores indicate different preference degrees, we define a weighted bipartite modularity Q^W as

$$\begin{aligned} Q^W &= \frac{1}{M}\sum_{u=1}^{|U|}\sum_{i=1}^{|I|}(\widetilde{A}^W_{u,i} - \widetilde{B}^W_{u,i})\delta[C(u), C(i)] \\ &= \frac{1}{M}\sum_{u=1}^{|U|}\sum_{i=1}^{|I|}(\widetilde{A}^W_{u,i} - \frac{RT(u)CT(i)}{M})\delta[C(u), C(i)], \end{aligned} \tag{8}$$

here, $\widetilde{B}^W$ indicates a matrix describing expectations of weighted interaction between user nodes and item nodes. $RT(u)$ and $CT(i)$ represent the totals of u-th row marginal and i-th column marginal of $\widetilde{A}^W_{u,i}$, respectively. The value of $\delta[C(u), C(i)]$ is 1 when user node u and item node i are classified into the same clustering or zero otherwise. A larger value of Q^W indicates a stronger community structure of user-item weighted bipartite network.

Further, based on the proposed weighted bipartite modularity, we present and execute a novel co-clustering algorithm to realize community division of user-item weighted bipartite network. First, for each $r_{u,i}$, we randomly initialize $P(C_l|r_{u,i})$, so that $\sum_{l=1}^{L} P(C_l|r_{u,i}) = 1$.

$$P(C_l|r_{u,i}) = \frac{[P(C_l|u) + \alpha] \times [P(C_l|i) + \beta]}{\sum\limits_{l'=1}^{L}[P(C_{l'}|u) + \alpha] \times \sum\limits_{l'=1}^{L}[P(C_{l'}|i) + \beta]}, \tag{9}$$

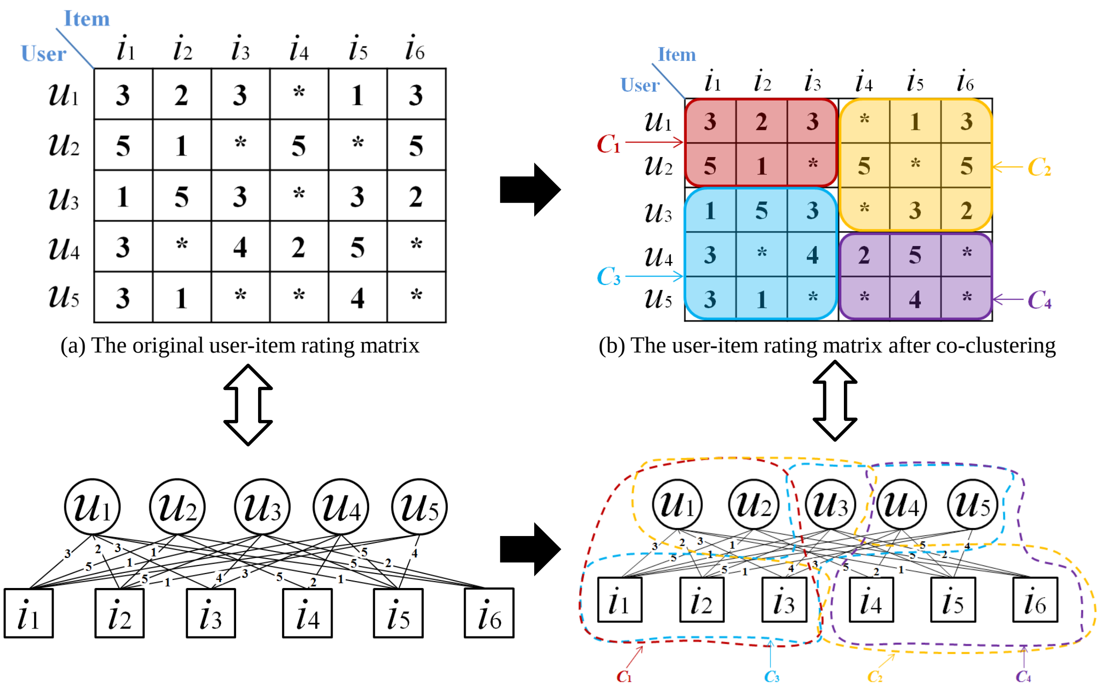
here, α and β are hyper-parameters that prevent the value of denominator from being 0. Then, according to the value of $P(C_l|r_{u,i})$ obtained by Eq. 9, we calculate $P(C_l|u)$ and $P(C_l|i)$:

$$P(C_l|u) = \frac{\sum_{i\in I(u)} P(C_l|r_{u,i})}{\sum_{l'=1}^{L}\sum_{i\in I(u)} P(C_{l'}|r_{u,i})}. \tag{10}$$

$$P(C_l|i) = \frac{\sum_{u\in U(i)} P(C_l|r_{u,i})}{\sum_{l'=1}^{L}\sum_{u\in U(i)} P(C_{l'}|r_{u,i})}. \tag{11}$$

Finally, we utilize Eq. 9 to recalculate $P(C_l|r_{u,i})$ according to the values of $P(C_l|u)$ and $P(C_l|i)$. Repeating the calculation above until $P(C_l|r_{u,i})$ converges, and we select the clustering with largest $P(C_l|r_{u,i})$ as the final clustering that rating $r_{u,i}$ belongs to. Note that, from minimum clustering number L_{min} to maximum number L_{max}, we compute weighted bipartite modularity Q^W during each iteration. It is easy to find the maximum value of Q^W as well as the corresponding optimal number L of co-clustering. Generally, $L_{min} = 2$, and L_{max} is unknown. In this paper, according to the research [41], we set $L_{max} = \sqrt{|U| \times |I|}$.

Figure 2 presents an example to show the corresponding relationship between rating matrix and weighted bipartite network during co-clustering process. As can be found in the figure, the original rating matrix includes five users and six items, which corresponds a weighted bipartite network having five user nodes and six item nodes. After executing the co-clustering process, the weighted bipartite network is divided into four communities. Accordingly, the original rating matrix also forms four clusterings. Each rating score can only belong to a unique clustering; however, the user/item may belong to



(a) The original user-item rating matrix

(b) The user-item rating matrix after co-clustering

(c) The original weighted user-item bipartite network

(d) The weighted bipartite network after co-clustering

Fig. 2. The corresponding relationship between rating matrix and weighted bipartite network during co-clustering

different clusterings. For example, $r_{1,1}$ only belongs to C_1, but u_1 is included in both C_1 and C_2, and i_1 belongs to both C_1 and C_3.

C. Rating prediction via localized low-rank matrix factorization

After finishing co-clustering with the optimal clustering number, to reduce the size of processing data and eliminate the interference of non-related rating information, we utilize localized low-rank matrix factorization to predict rating scores for un-rated items in each individual clustering.

The low-rank matrix factorization can approximate a rating matrix RM by a multiplication of K-rank factor:

$$\begin{aligned} & RM_{|U|\times|I|} \approx X_{|U|\times K} \times Y_{K\times|I|} = \widehat{RM}_{|U|\times|I|}; \\ s.t.\quad & X_{|U|\times K} \geq 0, Y_{|I|\times K} \geq 0, K \ll min(|U|,|I|), \end{aligned} \tag{12}$$

where $\widehat{RM}_{|U|\times|I|}$ indicates the matrix of predicted rating scores. Traditionally, the low-rank matrix factorization can be summarized by minimizing:

$$\begin{aligned} & \underset{X,Y}{min}\, \mathcal{F}(RM, X, Y) = ||RM_{|U|\times|I|} - X_{|U|\times K} Y_{K\times|I|}||_F^2; \\ s.t.\quad & X_{|U|\times K} \geq 0, Y_{|I|\times K} \geq 0, K \ll min(|U|,|I|), \end{aligned} \tag{13}$$

where $||*||_F^2$ indicates the Frobenius norm. However, a practical RM often contains a large number of missing values, we only need to factorize the observed ratings. Here, for each individual clustering C_l, we insert an incidence matrix $\widetilde{A}$ (Eq. 4) into classical low-rank matrix factorization:

$$\begin{aligned} & \underset{X,Y}{min}\, \mathcal{F}\left(RM^{C_l}, X, Y\right) = \\ & \frac{1}{2}\sum_{u=1}^{|U(C_l)|}\sum_{i=1}^{|I(C_l)|}\widetilde{A}_{u,i}^{C_l}\left[RM_{u,i}^{C_l} - \left(\sum_{k=1}^{K} X_{u,k}Y_{k,i}\right)\right]^2; \\ & s.t.\quad X_{|U(C_l)|\times K} \geq 0, Y_{|I(C_l)|\times K} \geq 0, \\ & \qquad K \ll min(|U(C_l)|, |I(C_l)|). \end{aligned} \tag{14}$$

According to the research [42], the performance of low-rank matrix factorization has a crucial relation with initialization of X and Y, because random initialization often leads to higher predicted rating scores for users who actually have lower rating scores. In the proposed approach, we initialize X and Y through the rating values of $\bar{r}_{C(r_{u,i})}$, $\bar{r}_{C(u)}$, $\bar{r}_{C(i)}$, $\bar{r}_u$, and $\bar{r}_i$:

$$\begin{aligned} \sum_{k=1}^{K} X_{u,k} &= \bar{r}_{C(r_{u,i})} + \left(\bar{r}_u - \bar{r}_{C(u)}\right), \\ \sum_{k=1}^{K} Y_{k,i} &= \bar{r}_{C(r_{u,i})} + \left(\bar{r}_i - \bar{r}_{C(i)}\right). \end{aligned} \tag{15}$$

A locally optimal solution of Eq. 14 can be found by performing gradient descent in feature vectors $X_{u,k}$ and $Y_{k,i}$:

$$\begin{aligned} & \frac{\partial \mathcal{F}}{\partial X_{u,k}} = \\ & = \sum_{u=1}^{|U(C_l)|}\sum_{i=1}^{|I(C_l)|}\widetilde{A}_{u,i}^{C_l}\left[\left(-RM_{u,i}^{C_l}Y_{k,i}\right) + \sum_{k=1}^{K} X_{u,k}Y_{k,i}^2\right] \\ & = -\widetilde{A}_{u,i}^{C_l}\left[\left(RM^{C_l}Y^T\right)_{u,k} - \left(XYY^T\right)_{u,k}\right] \end{aligned} \tag{16}$$

$$
\begin{aligned}
&\frac{\partial \mathcal{F}}{\partial Y_{k,i}} = \\
&= \sum_{u=1}^{|U(C_l)|} \sum_{i=1}^{|I(C_l)|} \widetilde{A}_{u,i}^{C_l} \left[\left(-RM_{u,i}^{C_l} X_{u,k} \right) + \sum_{k=1}^{K} X_{u,k}^2 Y_{k,i} \right] \\
&= -\widetilde{A}_{u,i}^{C_l} \left[\left(X^T RM^{C_l} \right)_{k,i} - \left(X^T XY \right)_{k,i} \right]
\end{aligned} \tag{17}
$$

According to the gradient descent, we give

$$
\begin{aligned}
X_{u,k}^{(t+1)} &= X_{u,k}^{(t)} - \lambda_{u,k} \frac{\partial \mathcal{F}}{\partial X_{u,k}^{(t)}}, \\
Y_{k,i}^{(t+1)} &= Y_{k,i}^{(t)} - \eta_{k,i} \frac{\partial \mathcal{F}}{\partial Y_{k,i}^{(t)}}.
\end{aligned} \tag{18}
$$

In this paper, we set

$$
\lambda_{u,k} = \frac{X_{u,k}^{(t)}}{\widetilde{A}_{u,i}^{C_l} \left(XYY^T \right)_{u,k}}, \qquad \eta_{k,i} = \frac{Y_{k,i}^{(t)}}{\widetilde{A}_{u,i}^{C_l} (X^T XY)_{k,i}}. \tag{19}
$$

Then, we can obtain the update rules for $X_{u,k}$ and $Y_{k,i}$, respectively:

$$
\begin{aligned}
X_{u,k}^{(t+1)} &= X_{u,k}^{(t)} - \frac{X_{u,k}^{(t)}}{\widetilde{A}_{u,i}^{C_l} \left(XYY^T \right)_{u,k}} \frac{\partial \mathcal{F}}{\partial X_{u,k}^{(t)}} \\
&= X_{u,k}^{(t)} + \frac{X_{u,k}^{(t)} \widetilde{A}_{u,i}^{C_l} \left[\left(RM^{C_l} Y^T \right)_{u,k} - \left(XYY^T \right)_{u,k} \right]}{\widetilde{A}_{u,i}^{C_l} \left(XYY^T \right)_{u,k}} \\
&= X_{u,k}^{(t)} + \frac{X_{u,k}^{(t)}}{\left(XYY^T \right)_{u,k}} \left(RM^{C_l} Y^T \right)_{u,k} - X_{u,k}^{(t)} \\
&= X_{u,k}^{(t)} \frac{\left(RM^{C_l} Y^T \right)_{u,k}}{\left(XYY^T \right)_{u,k}}
\end{aligned} \tag{20}
$$

$$
\begin{aligned}
Y_{k,i}^{(t+1)} &= Y_{k,i}^{(t)} - \frac{Y_{k,i}^{(t)}}{\widetilde{A}_{u,i}^{C_l} \left(X^T XY \right)_{k,i}} \frac{\partial \mathcal{F}}{\partial Y_{k,i}^{(t)}} \\
&= Y_{k,i}^{(t)} + \frac{Y_{k,i}^{(t)} \widetilde{A}_{u,i}^{C_l} \left[\left(X^T RM^{C_l} \right)_{k,i} - \left(X^T XY \right)_{k,i} \right]}{\widetilde{A}_{u,i}^{C_l} \left(X^T XY \right)_{k,i}} \\
&= Y_{k,i}^{(t)} + \frac{Y_{k,i}^{(t)} \widetilde{A}_{u,i}^{C_l}}{(X^T XY)_{k,i}} \left[(X^T RM^{C_l})_{k,i} \right] - Y_{k,i}^{(t)} \\
&= Y_{k,i}^{(t)} \frac{\left(X^T RM^{C_l} \right)_{k,i}}{\left(X^T XY \right)_{k,i}}
\end{aligned} \tag{21}
$$

Finally, we adjust and update $X_{u,k}$ and $Y_{k,i}$ along the gradient descent direction until convergence. Then, according to equation 22, we make prediction for the rating score $p_{u,i}$ of user u on item i:

$$
p_{u,i} = \sum_{k=1}^{K} X_{u,k} Y_{k,i} \tag{22}
$$

D. Procedures of the proposed approach

In order to provide satisfying recommendations for a new user without utilizing additional information, our proposed approach mainly adopts the following three aspects: (1) mapping rating matrix of niche items to a user-item weighted bipartite network; (2) presenting a novel weighted bipartite modularity to conduct the co-clustering of weighted bipartite network; (3) executing localized low-rank matrix factorization to predict rating scores of un-rated items in each individual clustering. The detailed procedures of the proposed approach can be summarized in Algorithm 2.

V. Experiments

In this section, we first give the introduction about the experimental datasets and metrics. Then, we present how to select the optimal number of co-clustering. Beside that, we make comparative experiments to examine the performance of our proposed approach on two real-world datasets.

A. Experimental setting and evaluation metrics

In our experiments, two real datasets MovieLens10M and Netflix were utilized to evaluate the proposed approach, the detailed information about two datasets can be found in table I. For each dataset, we utilized user-based 5-fold cross validation methodology to conduct evaluation. First, we split users into five equally sized groups. In each cross-validation stage, we kept users from four of the groups (80% users) in the training users, and the remaining 20% users in the fifth group as testing users. Further, the ratings of each testing user were randomly split into two subsets: training ratings and testing ratings. Similarly with other related methods [14], [35], [36], we defined users who have no more than 20 ratings as new users, to ensure each test user as a new user, we randomly removed ratings thus making each test user own at most 20 ratings in training ratings and at least 1 rating in test ratings.

To evaluate the performance of our proposed approach, precision and recall metrics were utilized to measure the recommendation accuracy. Furthermore, we employed mean novelty (MN) and mean personality (MP) [43] to measure the diversity of recommendations.

Precision metric indicates the percentage of a target user's relevant recommended items in all recommended items. And recall metric denotes the proportion of a target user's relevant recommended items in her/his total number of relevant items. It is worth noting that the higher values of two metrics, the better accuracy of recommendations. Supposing that N_s represents the number of recommended items for a new user, N_r means the number of items preferred by the new user, N_{rs} indicates the amount of the new user's relevant items that appear in the recommendation list. The precision and recall metrics are defined as follows:

$$
Precision = \frac{N_{rs}}{N_s}, \qquad Recall = \frac{N_{rs}}{N_r}. \tag{23}
$$

MN denotes the recommendation novelty [43], which computes the fraction of users who rated each item in the recommendation list, and then calculates the sum over all items in the set of recommendation $Rec_u(N)$ to obtain the novelty of

Algorithm 2 Proposed approach

Input: Rating matrix RM and a new user nu
Output: N number of recommendations for a new user nu
N : Number of items recommended to the new user nu
I^{NIC} : The set of niche items
$\widehat{I}(nu)$: The set of items which the new user nu has not rated yet
$C_l(\widehat{I}(nu))$: The set of items that have not been rated by the new user nu in clustering C_l
$p_{nu,i}$: Predicted rating score of the new user nu on item i

$I^{NIC} = NIEA(RM)$
Construct the rating matrix RM^{NIC} based on the ratings of I^{NIC} in RM
Map RM^{NIC} to a user-item weighted bipartite network
$Q = 0$; $L = 0$
for $L^{'}$ = L_{min} to L_{max} **do**
  for each rating score $r_{u,i} \in RM^{NIC}$ **do**
    Randomly initialize probability $P(C_l|r_{u,i})$, so that $\sum_{l=1}^{L^{'}} P(C_l|r_{u,i}) = 1$
  end for
  for each rating score $r_{u,i} \in RM^{NIC}$ **do**
    repeat
      Compute $P(C_l|u)$ and $P(C_l|i)$ according to equations 10 and 11, respectively
      Utilize values of $P(C_l|u)$, $P(C_l|i)$ to recalculate $P(C_l|r_{u,i})$ according to equation 9
    until $P(C_l|r_{u,i})$ is convergence
    Select a clustering having largest $P(C_l|r_{u,i})$ as the final clustering that $r_{u,i}$ belongs to
  end for
  Compute the value of weighted bipartite modularity Q^W according to equation 8
  if $Q \leq Q^W$ **then**
    Q = Q^W; $L = L^{'}$
  end if
end for
Obtain the user-item weighted bipartite network that has the optimal clustering number L
Reconstruct the rating matrix according to obtained user-item weighted bipartite network
for l = 1 to L **do**
  Initialize the low-rank matrix X and Y of RM^{C_l} according to equation 15
  Train the low-rank matrix X and Y according to equations 20 and 21 until convergence
  for each item $i \in C_l(\widehat{I}(nu))$ **do**
    Predict the rating score $p_{nu,i}$ for the new user nu on item i based on equation 22
  end for
end for
The top N items with the highest $p_{nu,i}$ are recommended to the new user nu

user $u \in U$. Finally, we count the average novelty value of all users U.

$$MN(N) = -\frac{1}{|U|} \sum_{1 \leq u \leq |U|} \sum_{i \in Rec_u(N)} log_2 f_i, \tag{24}$$

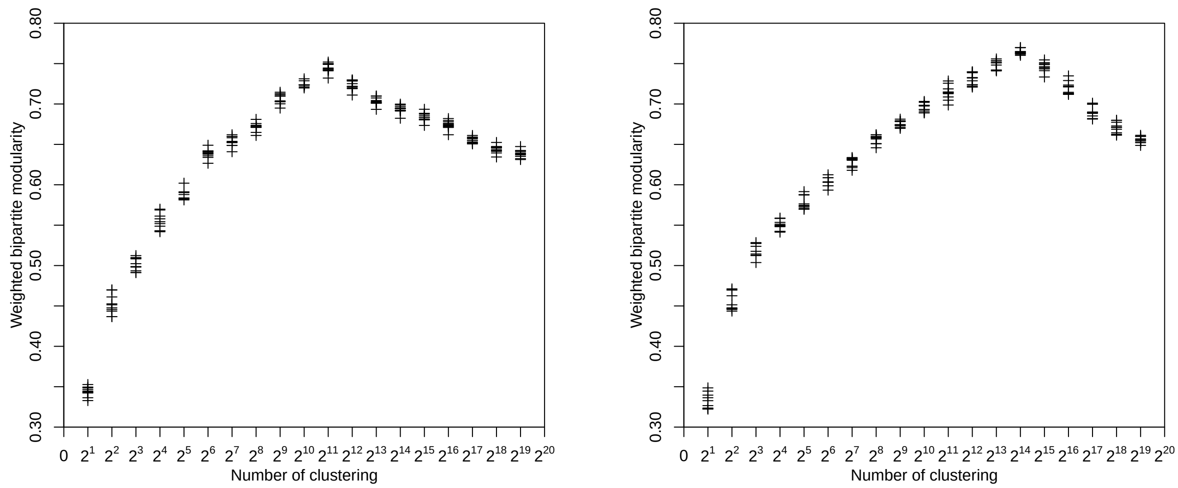
where f_i means the fraction of users who have ever rated the i^{th} item.

The MP metric denotes the average value of overlap degree between each pair of users' recommended items [43]. Assuming there are two users i and j, we extract top N number of recommendations $Rec_i(N)$ and $Rec_j(N)$, and further normalize it to obtain the overlap degree between two users' recommendation list. It is obvious that an approach owning higher recommendation diversity will have a larger value of MP, vice versa.

$$MP(N) = 1 - \frac{1}{N} \frac{2}{|U|(|U|-1)} \sum_{1 \leq i < j \leq |U|} |Rec_i(N) \cap Rec_j(N)|. \tag{25}$$

B. Selection of the optimal co-clustering number

The selection of optimal clustering number will directly affect the efficiency of co-clustering. Our proposed approach utilizes the weighted bipartite modularity (Eq. 8) to conduct the co-clustering process. In order to clarify the relationship between weighted bipartite modularity and the number of clustering, we execute the co-clustering algorithm by directly assigning the clustering number L to be doubling from 2 until 2^{19}, with each value running for 10 times. Figure 3 describes the relationship between weighted bipartite modularity and the number of clustering L in the MovieLens10M and Netflix,



(a) MovieLens10M (b) Netflix

Fig. 3. Weighted bipartite modularity versus the number of co-clustering on the (a) MovieLens10M and (b) Netflix datasets

TABLE VII
STATISTICS CORRESPOND TO THE MAXIMUM Q_B^W ON MOVIELENS10M AND NETFLIX DATASETS

	MovieLens10M	Netflix
Number of clustering	2,048	16,384
Average rating number of each clustering	373,245	520,810
Average user number of each clustering	1,237	1,429
Average item number of each clustering	325	364
Weighted bipartite modularity Q_B^W	0.746	0.769

respectively. As can be found in the figure, different values of L correspond to different weighted bipartite modularity. In MovieLens10M dataset, the largest value of weighted bipartite modularity appears when L is 2^{11}. On the other hand, Netflix dataset contains larger amount of users and items, the weighted bipartite modularity Q^W reaches the maximum value when the number of clustering $L = 2^{14}$. Because the larger value of Q^W, the better structure of bipartite network, we can obtain the optimal number of clustering on the MovieLens10M and Netflix datasets, respectively. Table VII demonstrates the statistics correspond to the largest value of Q^W on MovieLens10M and Netflix. As shown in the table, for the MovieLens10M dataset, the largest Q^W is almost equal to 0.746, and each clustering includes average number of 373,245 ratings of 1,237 users on 325 items. On the Netflix dataset, the largest Q^W reaches almost 0.769, and each clustering contains average number of 520,810 ratings of 1,429 users on 364 items.

C. Experimental results and comparative analysis

To evaluate the performance of the proposed approach, we make comparisons with a number of related approaches as well as the traditional UBCF. It is worth noting that in order to ensure the fairness, all of the comparative approaches do not require additional information, they only utilize rating matrix RM to provide recommendations for new users.

- **UBCF** [34]. The traditional UBCF predicts rating scores based on the rating information of the neighbor of a new user. More detailed information can be found in Section II.
- **ICBCF** (Improved covering-based CF) [44]. Our previous work which utilized covering reduction to remove the redundant users from the neighbor of a new user, and used the remaining reduct-users to make predictions and recommendations. According to [44], the decision class comprised the top 95% of items that have the fewest ratings in our experiment.
- **LRMF** (Low-rank matrix factorization) [45]. LRMF decomposes approximately high-dimensional rating matrix into low-dimensional user factor matrix and item factor matrix. Because genres of items in MovieLens10M are divided into 18, in LRMF and our proposed approach, the low-rank K was set to 18 in the course of the experiments.
- **IGCF** (Item-global CF) [15]. A profile expansion approach that can alleviate the new user cold-start by utilizing item-global rating expansion. Rating information of selected similar items is used to expend a target user's rating profile. According to [15], the best performances are obtained with the number of selected items no more than 10. Thus, in our experiment, the number of items added to the rating profile was set as 10.
- **ULCF** (User-local CF) [15]. Another expansion approach that performs very well and significantly improves the precision of recommendations. This approach expands the profile according to the selected rated items of a new user's neighbor. Same as IGCF, to gain the best experimental values, we set the number of selected items as 10 in our experiment.
- **PFCF** (Positive-only feedback CF) [46]. A memory-based CF approach that aims to alleviate new user cold-start by only utilizing reliable neighbors (warm users) to provide satisfactory recommendations for new users.

TABLE VIII
RESULT OF ACCURACY METRICS (PRECISION AND RECALL) ON THE MOVIELENS10M DATASET

#Recommendations	precision values						
	UBCF	ICBCF	LRMF	IGCF	ULCF	PFCF	Ours
$N=2$	0.872±0.002	0.902±0.004	0.834±0.002	0.894±0.003	0.879±0.003	0.897±0.003	**0.934±0.004**
$N=4$	0.875±0.003	0.913±0.002	0.825±0.003	0.897±0.004	0.883±0.004	0.891±0.004	**0.939±0.002**
$N=6$	0.879±0.002	0.904±0.003	0.829±0.002	0.891±0.002	0.885±0.002	0.886±0.002	**0.931±0.003**
$N=8$	0.883±0.004	0.895±0.002	0.834±0.005	0.885±0.004	0.881±0.002	0.882±0.005	**0.924±0.002**
$N=10$	0.878±0.002	0.887±0.004	0.827±0.002	0.879±0.002	0.872±0.005	0.875±0.002	**0.916±0.005**
$N=12$	0.862±0.002	0.881±0.003	0.831±0.003	0.872±0.003	0.861±0.004	0.868±0.004	**0.904±0.002**
$N=14$	0.856±0.005	0.878±0.002	0.823±0.003	0.867±0.003	0.854±0.002	0.859±0.005	**0.893±0.004**
$N=16$	0.851±0.002	0.864±0.004	0.814±0.004	0.861±0.002	0.846±0.005	0.852±0.003	**0.886±0.002**
$N=18$	0.845±0.003	0.859±0.002	0.805±0.002	0.855±0.004	0.835±0.004	0.847±0.002	**0.876±0.003**
#Recommendations	recall values						
	UBCF	ICBCF	LRMF	IGCF	ULCF	PFCF	Ours
$N=2$	0.144±0.012	0.156±0.014	0.117±0.021	0.161±0.012	0.142±0.012	0.158±0.011	**0.203±0.018**
$N=4$	0.181±0.016	0.204±0.016	0.149±0.017	0.217±0.015	0.184±0.015	0.193±0.013	**0.264±0.011**
$N=6$	0.223±0.011	0.256±0.011	0.175±0.015	0.259±0.016	0.239±0.018	0.236±0.015	**0.327±0.015**
$N=8$	0.264±0.013	0.305±0.017	0.217±0.013	0.308±0.019	0.271±0.014	0.278±0.017	**0.368±0.012**
$N=10$	0.308±0.009	0.349±0.014	0.247±0.018	0.347±0.021	0.312±0.012	0.331±0.013	**0.397±0.017**
$N=12$	0.341±0.017	0.387±0.018	0.285±0.012	0.381±0.009	0.358±0.019	0.371±0.014	**0.431±0.013**
$N=14$	0.388±0.012	0.431±0.012	0.318±0.014	0.445±0.015	0.381±0.014	0.419±0.011	**0.465±0.012**
$N=16$	0.426±0.014	0.463±0.017	0.352±0.016	0.476±0.012	0.422±0.012	0.451±0.018	**0.492±0.017**
$N=18$	0.449±0.017	0.502±0.011	0.393±0.018	0.509±0.017	0.459±0.017	0.495±0.015	**0.533±0.014**

TABLE IX
RESULT OF ACCURACY METRICS (PRECISION AND RECALL) ON THE NETFLIX DATASET

#Recommendations	precision values						
	UBCF	ICBCF	LRMF	IGCF	ULCF	PFCF	Ours
$N=2$	0.761±0.002	0.781±0.003	0.682±0.003	0.783±0.003	0.768±0.003	0.776±0.002	**0.822±0.003**
$N=4$	0.773±0.003	0.787±0.002	0.705±0.004	0.791±0.002	0.773±0.004	0.781±0.003	**0.835±0.002**
$N=6$	0.779±0.002	0.780±0.004	0.692±0.002	0.804±0.002	0.762±0.005	0.789±0.004	**0.846±0.005**
$N=8$	0.768±0.004	0.772±0.005	0.672±0.005	0.811±0.004	0.771±0.002	0.796±0.002	**0.857±0.004**
$N=10$	0.757±0.002	0.766±0.003	0.655±0.004	0.805±0.003	0.783±0.004	0.787±0.005	**0.848±0.004**
$N=12$	0.751±0.003	0.760±0.004	0.647±0.002	0.792±0.002	0.776±0.003	0.781±0.004	**0.832±0.003**
$N=14$	0.745±0.004	0.757±0.002	0.656±0.004	0.784±0.004	0.763±0.002	0.773±0.003	**0.827±0.004**
$N=16$	0.737±0.002	0.751±0.002	0.648±0.003	0.772±0.002	0.756±0.004	0.765±0.002	**0.819±0.002**
$N=18$	0.731±0.004	0.743±0.004	0.636±0.004	0.768±0.003	0.743±0.005	0.754±0.004	**0.803±0.005**
#Recommendations	recall values						
	UBCF	ICBCF	LRMF	IGCF	ULCF	PFCF	Ours
$N=2$	0.089±0.011	0.108±0.016	0.062±0.016	0.114±0.014	0.098±0.015	0.103±0.013	**0.136±0.018**
$N=4$	0.131±0.017	0.143±0.018	0.088±0.017	0.146±0.016	0.135±0.012	0.154±0.015	**0.184±0.014**
$N=6$	0.159±0.019	0.197±0.019	0.113±0.014	0.184±0.017	0.168±0.019	0.198±0.018	**0.235±0.015**
$N=8$	0.187±0.012	0.243±0.013	0.139±0.012	0.213±0.012	0.204±0.013	0.236±0.014	**0.278±0.012**
$N=10$	0.215±0.014	0.275±0.015	0.161±0.019	0.253±0.015	0.245±0.011	0.274±0.012	**0.334±0.016**
$N=12$	0.258±0.018	0.321±0.012	0.206±0.017	0.289±0.012	0.287±0.016	0.302±0.011	**0.378±0.019**
$N=14$	0.294±0.012	0.374±0.018	0.243±0.015	0.324±0.018	0.328±0.008	0.345±0.016	**0.421±0.012**
$N=16$	0.337±0.018	0.418±0.010	0.283±0.012	0.364±0.015	0.369±0.014	0.371±0.014	**0.468±0.016**
$N=18$	0.386±0.013	0.455±0.014	0.305±0.016	0.417±0.009	0.401±0.012	0.418±0.019	**0.492±0.013**

According to [46], the size of warm neighbors was set as 10 in our experiment.

It is worth noting that in all of our experiments, we utilized Pearson correlation coefficient (Eq. 1) to calculate similarity, and the weighted sum (Eq. 2) to predict rating scores. The top N items having highest predicted rating scores are recommended to new users. According to [34], we set the size of neighbors $T = 20$. Furthermore, to compute the precision and recall metrics, we set rating threshold $\theta = 3$, it means items that were rated no less than 3 will be considered as relevant items. The number of recommendations N was treated as $\{2, 4, 6, ..., 18\}$. We treat hyper-parameters α and β in co-clustering as 0.00,000,001. Note that, the ratio threshold H has a significant effect on our proposed approach. Based on statistical results obtained from MovieLens10M and Netflix in tables II and III, we have concluded that after sorting all items by descending order based on the number of ratings, the top 5% items correspond to about 50% of the ratings. So in our experiment, we treat the ratio threshold $H = 0.95$, it indicates the top 95% of items which have the minimum ratings are treated as niche items, and the remaining 5% items are considered as popular items.

Tables VIII and IX show the results of precision and recall metrics on the MovieLens10M and Netflix datasets, respectively. As can be found in the tables, with increasing the number of recommendations, the values of precision metric have different variation trend; however, recall values of all approaches increase as the number of recommendations increases. Values of precision and recall for the LRMF are lower than the traditional UBCF, indicating that LRMF cannot improve recommendation accuracy of UBCF. On the other hand, results of ICBCF, IGCF, ULCF, PFCF, and our proposed approach outperform UBCF with $N = 2$ to 18. It is worth noting that our proposed approach performs best

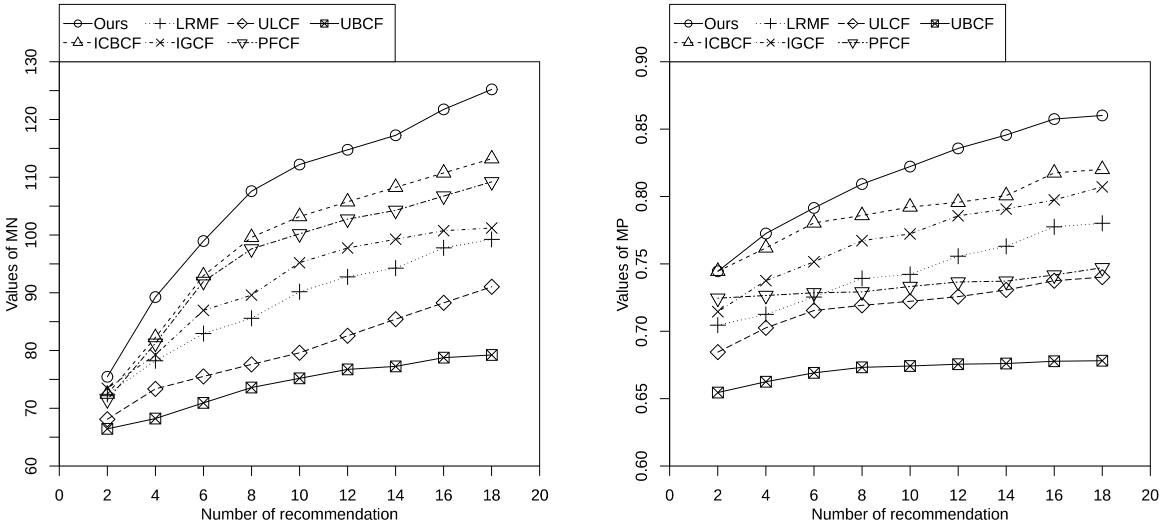


Fig. 4. Result of diversity metrics (MN and MP) on the MovieLens10M dataset

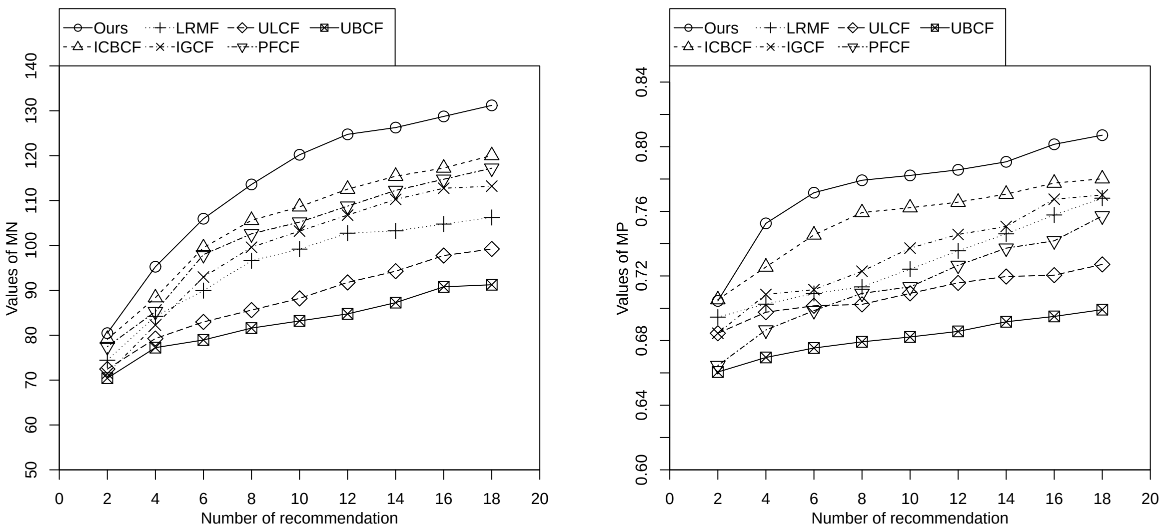


Fig. 5. Result of diversity metrics (MN and MP) on the Netflix dataset

on both precision and recall metrics, it attains highest values (precision is approximately equal to 0.939, recall is almost 0.533) when $N = 4$ and 18, respectively. Because higher values of precision and recall indicate better recommendation accuracy, indicating that our proposed approach outperforms other related approaches in terms of recommendation accuracy.

Figure 4 demonstrates the average values of MN and MP metrics on the MovieLens10M dataset. As shown in the figure, experimental values of both MN and MP for all approaches increase with the number of recommendation increases. The traditional UBCF has lowest values of MN and MP, indicating that other related approaches can improve recommendation diversity of UBCF effectively. Furthermore, both MN and MP of our proposed approach are greatly higher than other related approaches, indicating that our proposed approach outperforms the other approaches in terms of MN and MP on the MovieLens10M dataset. Figure 5 shows the values of MN and MP metrics on the Netflix dataset. From the figure we can find that both MN and MP metrics for all approaches increase with increasing the number of recommendations. Although the experimental values of MN and MP are almost the same when $N = 2$, our proposed approach increases faster than other related approaches. For the MN metric, ULCF approach outperforms the traditional UBCF slightly; on the other hand, our proposed approach and ICBCF increase the value of UBCF clearly, and our proposed approach is higher than ICBCF greatly. For the MP metric, the IGCF, LRMF, PFCF, and ULCF have nearly the same values, and our proposed approach and ICBCF obviously have higher MP values than other approaches, showing that our proposed approach and ICBCF can enhance MP of recommendations significantly. It is noticeable, however, that MP values of our proposed approach are higher than ICBCF as the number of recommendation increases. Therefore, we can draw a conclusion from figures 4 and 5 that the recommendation diversity of the proposed approach outperforms that of the other approaches, and can provide a wider variety of recommendations for a new user.

Experimental results demonstrate that, by utilizing only rating matrix, the proposed approach can produce recommendations for a new user with satisfying accuracy and diversity at the same time. In order to reflect a new user's true preference and prevent over-fitting recommendation problem effectively, our proposed approach employs rating information of niche items to construct a weighted bipartite network. Further, a novel weighted bipartite modularity is present to acquire the optimum number of co-clustering. Users in a same clustering can not only have same rating characteristics but also own interests on more types of items (i.e., not only popular items). It leads recommendations generated from each clustering can have a wider variety, so the recommendation diversity has been improved. Moreover, after obtaining each individual clustering, a localized low-rank matrix factorization is executed to eliminate the influence of irrelevant users and items, thus predicted rating scores can represent a new user's true ratings more accurately. Therefore, the recommendation accuracy is also enhanced in both MovieLens10M and Netflix datasets.

VI. Conclusions and Future Work

In this paper, we present a novel recommendation approach via bipartite network to solve the new user cold-start problem in UBCF. This approach constructs a novel weighted bipartite modularity to conduct the co-clustering between users and items, and utilizes the localized low-rank matrix factorization to predict rating scores of un-rated items. We have demonstrated the superior performance of our proposed approach over the state-of-the-art approaches by experiments on two real-world datasets and summarized the enhancement of our proposed approach in not only the accuracy but also the diversity of recommendations. Because of obtaining the optimal number of co-clustering by weighted bipartite modularity and implementing rating prediction through the localized low-rank matrix factorization, the proposed approach achieves significant improvements in both the accuracy and diversity of recommendations while only utilizing the rating matrix rather than any other special additional information.

Future work should concentrate on further improving the co-clustering algorithm and matrix factorization. Because co-clustering algorithm in this paper only implements hard clustering, resulting in a rating only belongs to one clustering; however, in practical RSs, the boundaries between users or items are not particularly clear. Moreover, matrix factorization is easy to fall into local optimum. Thus these issues will be the focus of our future work.

References

[1] J. Protasiewicz *et al.*, "A recommender system of reviewers and experts in reviewing problems," *Knowl.-Based Syst.*, vol. 106, pp. 164-178, Aug. 2016.

[2] M. Kunaver and T. Pozrl, "Diversity in recommender systems - A survey," *Knowl.-Based Syst.*, vol. 123, pp. 154-162, May 2017.

[3] Z.P. Zhang, Y. Kudo and T. Murai, "Neighbor selection for user-based collaborative filtering using covering-based rough sets," *Ann. Oper. Res.*, vol. 256, pp. 359-374, 2017.

[4] B. Lika, K. Kolomvatsos and S. Hadjiefthymiades, "Facing the cold start problem in recommender systems," *Expert Syst. Appl.*, vol. 41, no. 4, pp. 2065-2073, Mar. 2014.

[5] L.H. Son, "Dealing with the new user cold-start problem in recommender systems: A comparative review," *Inform. Syst.*, vol. 58, pp. 87-104, Jun. 2016.

[6] J. Wei, J.H. He, K. Chen, Y. Zhou and Z.Y. Tang, "Collaborative filtering and deep learning based recommendation system for cold start items," *Expert Syst. Appl.*, vol. 69, pp. 29-39, Mar. 2017.

[7] C.C. Chen, Y.H. Wan, M.C. Chung and Y.C. Sun, "An effective recommendation method for cold start new users using trust and distrust networks," *Inform. Syst.*, vol. 224, pp. 19-36, Mar. 2013.

[8] A.N. Rosli, T. You, I. Ha, K.Y. Chung and G.S. Jo, "Alleviating the cold-start problem by incorporating movies facebook pages," *Cluster Comput.*, vol. 18, pp. 187-197, 2015.

[9] L.H. Son, "DPFCM: a novel distributed picture fuzzy clustering method on picture fuzzy sets," *Expert Syst. Appl.*, vol. 42, no. 1, pp. 51-66, Jan. 2014.

[10] L.H. Son, "Optimizing municipal solid waste collection using chaotic particle swarm optimization in GIS based environments: a case study at Danang city," *Expert Syst. Appl.*, vol. 41, no. 18, pp. 8062-8074, Dec. 2014.

[11] L.H. Son, B.C. Cuong and H.V. Long, "Spatial interaction-modification model and applications to geo-demographic analysis," *Knowl.-Based Syst.*, vol. 49, pp. 152-170, May 2013.

[12] B. Yang, Y. Lei, J.M. Liu and W.J. Li, "Social Collaborative Filtering by Trust," *IEEE Trans. Pattern Anal.*, vol. 39, no. 8, pp. 1633-1647, Aug. 2017.

[13] X.W. Yang, C. Liang, M. Zhao, H.W. Wang, H. Ding, Y. Liu, Y. Li and J.L. Zhang, "Collaborative Filtering-Based Recommendation of Online Social Voting," *IEEE Trans. Comput. Soc. Syst.*, vol. 4, no. 1, pp. 1-13, Mar. 2017.

[14] J. Bobadilla, F. Ortega, A. Hernando and J. Bernal, "A collaborative filtering approach to mitigate the new user cold start problem," *Knowl.-Based Syst.*, vol. 26, pp. 225-238, Feb. 2012.

[15] V. Formoso, D. Fernandez, F. Cacheda and V. Carneiro, "Using profile expansion techniques to alleviate the new user problem," *Inform. Process. Manag.*, vol. 49, no. 3, pp. 659-672, May 2013.

[16] H. Liu, Z. Hu, A. Mian, H. Tian and X. Zhu, "A new user similarity model to improve the accuracy of collaborative filtering," *Knowl.-Based Syst.*, vol. 56, pp. 156-166, Jan. 2014.

[17] N.N. Liu, X. Meng, C. Liu and Q. Yang, "Wisdom of the better few: cold start recommendation via representative based rating elicitation," in *Proc. ACM RecSys*, 2011, pp. 37-44.

[18] T. Qiu, G. Chen, Z.K. Zhang and T. Zhou, "An item-oriented recommendation algorithm on cold-start problem," *Europhys. Lett.*, vol. 95, no. 5, 58003, Aug. 2011.

[19] X.K. Wu, B. Cheng and J.L. Chen, "Collaborative Filtering Service Recommendation Based on a Novel Similarity Computation Method," *IEEE Trans. Serv. Comput.*, vol. 10, no. 3, pp. 352-365, May 2017.

[20] J. Lee, W. Hwang, J. Parc, Y. Lee, S. Kim and D. Lee, "*l*-Injection: Toward Effective Collaborative Filtering Using Uninteresting Items," *IEEE Trans. Knowl. Data Eng.*, vol. 31, no. 1, pp. 3-16, Jan. 2019.

[21] M. Aharon *et al.*, "OFF-set: one-pass factorization of feature sets for online recommendation in persistent cold start settings," in *Proc. ACM RecSys*, 2013, pp. 375-378.

[22] W. Carrer-Neto, M.L. Hernandez-Alcaraz, R. Valencia-Garcia and F. Garcia-Sanchez, "Social knowledge-based recommender system. Application to the movies domain," *Expert Syst. Appl.*, vol. 39, pp. 10990-11000, 2012.

[23] H.N. Kim, A. El-Saddik and G.S. Jo, "Collaborative error-reflected models for cold-start recommender systems," *Decis. Support Syst.*, vol. 51, pp. 519-531, 2011.

[24] M. Nilashi, O.B. Ibrahim and N. Ithnin, "Hybrid recommendation approaches for multi-criteria collaborative filtering," *Expert Syst. Appl.*, vol. 41, pp. 3879-3900, 2014.

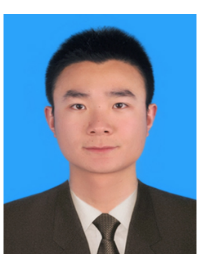
[25] L.H. Son, "HU-FCF: a hybrid user-based fuzzy collaborative filtering method in recommender systems," *Expert Syst. Appl.*, vol. 41, pp. 6861-6870, 2014.

[26] D.F. Lian, Y. Ge, F.Z. Zhang, N.J. Yuan, X. Xie, T. Zhou and Y Rui, "Scalable Content-Aware Collaborative Filtering for Location Recommendation," *IEEE Trans. Knowl. Data Eng.*, vol. 30, no. 6, pp. 1122-1135, Jun. 2018.

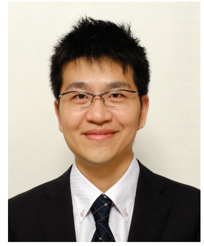
[27] H. Li, K. Li, J.Y. An and K.Q. Li, "MSGD: A Novel Matrix Factorization Approach for Large-scale Collaborative Filtering Recommender Systems on GPUs," *IEEE Trans. Parall. Distr.*, vol. 29, no. 7, pp. 1530-1544, Jul. 2018.

[28] J.X. Liu, M.D. Tang, Z.B. Zheng, X.Q. Liu and S.X. Lyu, "Location-Aware and Personalized Collaborative Filtering for Web Service Recom-

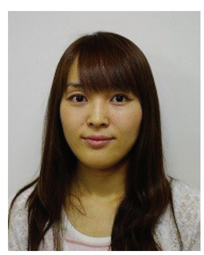
mendation," *IEEE Trans. Serv. Comput.*, vol. 9, no. 5, pp. 686-699, Sep. 2016.
[29] J. Wu, M.X. Dong, K. Ota, J.H. Li and Z.T. Guan, "FCSS: Fog-Computing-based Content-Aware Filtering for Security Services in Information-Centric Social Networks," *IEEE Trans. Emerging Topics Comput.*, vol. 7, no. 4, pp. 553-564, 2019.
[30] J.W. Xu, K. Ota and M.X. Dong, "Real-Time Awareness Scheduling for Multimedia Big Data Oriented In-Memory Computing," *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 3464-3473, 2018.
[31] H. Li, K. Ota and M.X. Dong, "Learning IoT in Edge: Deep Learning for the Internet of Things with Edge Computing," *IEEE Network*, vol. 32, no. 1, pp. 96-101, 2018.
[32] M. Tao, K. Ota and M.X. Dong, "Locating Compromised Data Sources in IoT-Enabled Smart Cities: A Great-Alternative-Region-Based Approach," *IEEE Trans. Industrial Informatics*, vol. 14, no. 6, pp. 2579-2587, 2018.
[33] J. Wu, K. Ota, M.X. Dong, J.H. Li and H.K. Wang, "Big Data Analysis-Based Security Situational Awareness for Smart Grid," *IEEE Trans. Big Data*, vol. 4, no. 3, pp. 408-417, 2018.
[34] J.L. Herlocker, J.A. Konstan, A. Borchers and J. Riedl, "An algorithmic framework for performing collaborative filtering," in *Proc. ACM SIGIR*, 1999, pp. 230-237.
[35] H.J. Ahn, "A new similarity measure for collaborative filtering to alleviate the new user cold-starting problem," *Inform. Syst.*, vol. 178, no. 1, pp. 37-51, Jan. 2008.
[36] B.K. Patra, R. Launonen, V. Ollikainen and S. Nandi, "A new similarity measure using Bhattacharyya coefficient for collaborative filtering in sparse data," *Knowl.-Based Syst.*, vol. 82, pp. 163-177, Jul. 2015.
[37] Z.P. Li, R.S. Wang, S.H. Zhang and X.S. Zhang, "Quantitative function and algorithm for community detection in bipartite networks," *Inform. Syst.*, vol. 367, pp. 874-889, Nov. 2016.
[38] X.D. Wang and J. Liu, "A comparative study of the measures for evaluating community structure in bipartite networks," *Inform. Syst.*, vol. 448, pp. 249-262, Jun. 2018.
[39] C.Q. Zhou, L. Feng and Q.C. Zhao, "A novel community detection method in bipartite networks," *Physica A*, vol. 492, pp. 1679-1693, 2018.
[40] M. Barber, "Modularity and Community Detection in Bipartite Network," *Phys. Rev.,* vol. 76, pp. 1-9, 2007.
[41] D.W. Zhang, M. Ji, J. Yang, Y. Zhang and F. Xie, "A novel cluster validity index for fuzzy clustering based on bipartite modularity," *Fuzzy Set. Syst.*, vol. 253, pp. 122-137, Oct. 2014.
[42] H. Wu, Y.J. Wang, Z. Wang, X.L. Wang and S.Z. Du, "Two-Phase collaborative filtering algorithm based on co-clustering," *Journal of Software*, vol. 21, no. 5, pp. 1042-1054, 2010.
[43] M.X. Gan and R. Jiang, "Constructing a user similarity network to remove adverse influence of popular objects for personalized recommendations," *Expert Syst. Appl.*, vol. 40, no. 10, pp. 4044-4053, Aug. 2013.
[44] Z.P. Zhang, Y. Kudo, T. Murai and Y.G. Ren, "Improved covering-based collaborative filtering for new users' personalized recommendations," *Knowl. Inf. Syst.*, 2020, to be published.
[45] Y. Koren, R. Bell and C. Volinsky, "Matrix factorization techniques for recommender systems," *Computer*, vol. 42, no. 8, pp. 30-37, Jan. 2009.
[46] A. Bellogin, I. Fernandez-Tobias, I. Cantador and P. Tomeo, "Neighbor selection for cold users in collaborative filtering with positive-only feedback," in *Proc. CAEPIA*, 2018, pp. 3-12.



Zhipeng Zhang received his Ph.D. in the Department of Information and Electronic Engineering from Muroran Institute of Technology, Japan in 2017. He is currently a Lecture in the School of Computer and Information Technology at the Liaoning Normal University, China. From April 2013 to March 2014, he was an exchange student sponsored by the government at Muroran Institute of Technology, Japan. His research interests include recommender systems, data mining, and artificial intelligence. Dr. Zhang serves as a PC member for ISKE2019, as well as a reviewer for Knowledge-based Systems, Knowledge and Information Systems, and Information Retrieval Journal. His research interests include database, data mining, and artificial intelligence.



Mianxiong Dong received B.S., M.S. and Ph.D. in Computer Science and Engineering from The University of Aizu, Japan. He became the youngest ever Professor of Muroran Institute of Technology, Japan where he currently serves as the Vice President. He was a JSPS Research Fellow with School of Computer Science and Engineering, The University of Aizu, Japan and was a visiting scholar with BBCR group at University of Waterloo, Canada supported by JSPS Excellent Young Researcher Overseas Visit Program from April 2010 to August 2011. Dr. Dong was selected as a Foreigner Research Fellow (a total of 3 recipients all over Japan) by NEC C&C Foundation in 2011. His research interests include Wireless Networks, Cloud Computing, and Cyber-physical Systems. He has received best paper awards from IEEE HPCC 2008, IEEE ICESS 2008, ICA3PP 2014, GPC 2015, IEEE DASC 2015, IEEE VTC 2016-Fall, FCST 2017, 2017 IET Communications Premium Award and IEEE ComSoc CSIM Best Conference Paper Award 2018. Dr. Dong serves as an Editor for IEEE Transactions on Green Communications and Networking (TGCN), IEEE Communications Surveys and Tutorials, IEEE Network, IEEE Wireless Communications Letters, IEEE Cloud Computing, IEEE Access, as well as a leading guest editor for ACM Transactions on Multimedia Computing, Communications and Applications (TOMM), IEEE Transactions on Emerging Topics in Computing (TETC), IEEE Transactions on Computational Social Systems (TCSS). He has been serving as the Vice Chair of IEEE Communications Society Asia/Pacific Region Information Services Committee and Meetings and Conference Committee, Leading Symposium Chair of IEEE ICC 2019, Student Travel Grants Chair of IEEE GLOBECOM 2019, and Symposium Chair of IEEE GLOBECOM 2016, 2017. He is the recipient of IEEE TCSC Early Career Award 2016, IEEE SCSTC Outstanding Young Researcher Award 2017, The 12th IEEE ComSoc Asia-Pacific Young Researcher Award 2017, Funai Research Award 2018 and NISTEP Researcher 2018 (one of only 11 people in Japan) in recognition of significant contributions in science and technology. He is currently the Member of Board of Governors and Chair of Student Fellowship Committee of IEEE Vehicular Technology Society, and Treasurer of IEEE ComSoc Japan Joint Sections Chapter. He is Clarivate Analytics 2019 Highly Cited Researcher (Web of Science).



Kaoru Ota was born in Aizu-Wakamatsu, Japan. She received M.S. degree in Computer Science from Oklahoma State University, USA in 2008, B.S. and Ph.D. degrees in Computer Science and Engineering from The University of Aizu, Japan in 2006, 2012, respectively. She is currently an Associate Professor with Department of Sciences and Informatics, Muroran Institute of Technology, Japan. From March 2010 to March 2011, she was a visiting scholar at University of Waterloo, Canada. Also she was a Japan Society of the Promotion of Science (JSPS) research fellow with Kato-Nishiyama Lab at Graduate School of Information Sciences at Tohoku University, Japan from April 2012 to April 2013. Her research interests include Wireless Networks, Cloud Computing, and Cyber-physical Systems. Dr. Ota has received best paper awards from ICA3PP 2014, GPC 2015, IEEE DASC 2015, IEEE VTC 2016-Fall, FCST 2017, 2017 IET Communications Premium Award and IEEE ComSoc CSIM Best Conference Paper Award 2018. She is an editor of IEEE Transactions on Vehicular Technology (TVT), IEEE Internet of Things Journal, IEEE Communications Letters, Peer-to-Peer Networking and Applications (Springer), Ad Hoc & Sensor Wireless Networks, International Journal of Embedded Systems (Inderscience) and Smart Technologies for Emergency Response & Disaster Management (IGI Global), as well as a guest editor of ACM Transactions on Multimedia Computing, Communications and Applications (leading), IEEE Internet of Things Journal, IEEE Communications Magazine, IEEE Network, IEEE Wireless Communications, IEEE Access, IEICE Transactions on Information and Systems, and Ad Hoc & Sensor Wireless Networks (Old City Publishing). She is the recipient of IEEE TCSC Early Career Award 2017, and The 13th IEEE ComSoc Asia-Pacific Young Researcher Award 2018.She is Clarivate Analytics 2019 Highly Cited Researcher (Web of Science).

Yasuo Kudo received the Ph.D. degree in systems and information engineering from Hokkaido University, Sapporo, Hokkaido, Japan, in 2000. He is currently a Professor with the College of Information and Systems, Muroran Institute of Technology, Japan. His research interests include rough set theory, non-classical logic, data mining, and recommender systems.