Weighted Bipartite Network Projection for Personalized Recommendations

Jing Wang, Fengjing Shao, Shunyao Wu, Rencheng Sun, and Ran Li

***Abstract*—To reduce the difficulty of personalized recommendations, the traditional network-based method constructed bipartite networks with stronger links (higher ratings). However, weaker links and link weights were almost ignored. Although the existing method effectively mined users' preferences, it was impossible to catch users' disgusts. Therefore, this paper proposed a novel method to effectively discover users' preferences and disgusts. Experimental results on the MovieLens dataset demonstrated that the proposed method was much more superior to the baseline method under the diversity index.**

***Index Terms*—Personalized recommendations, weighted bipartite network, users' preferences, users' disgusts, diversity.**

I. Introduction

With the rapid development of the Internet, the growing amounts of data had gone beyond our processing capacities, and we had entered into the era of data explosion. The overwhelming information brought the information overload problem, which had also become an urgent problem to mine valuable information from the huge data. As an important way to filter information, personalized recommendations had attracted more and more attention. Personalized recommendations aimed to discover users' preferences for recommending objects by utilizing the historical activities and personal profiles.

Currently, the recommendation methods were mainly divided into three classes, collaborative filtering methods, content-based methods and network-based methods [1], [2]. Collaborative filtering methods [3]-[6] aimed to identify some users whose preferences were similar to a given user, and then recommended objects they chosen to the target user.

Nevertheless, some limitations existed in collaborative filtering method, such as cold-start, data sparse and scalability [1]. Content-based methods [7], [8] tried to recommend the objects similar with those chose by a target user. Content-based methods overcame the cold-start and data sparse problems. However, it was difficult to predict new interests because this method was completely dependent on features of objects selected in the past. Meanwhile, Content-based methods could not recommend objects to new users without historical data.

Recently, to avoid false attribute information of the user or the object, network-based methods had been widespread concerned by researchers. Network-based methods abstracted users and objects into nodes and abstracted user-object relationships into edges. During the recommended process, the useful information was hidden in the relationships between users and objects. Aggarwal *et al*. [9] firstly proposed a network-based method based on collaborative filtering mechanics, and the simulation results validated the effectiveness and efficient of the method. To highlight a possible way for the better solution of personalized recommendation, Zhou *et al*. [10] proposed an effective projection method on the bipartite network, and designed a network-based inference algorithm for recommendations. To further improve the algorithm accuracy and made recommendation more diversified, Zhou *et al*. [11] introduced a free parameter to regulate the initial configuration of resource, so as to decrease the initial resource of popular objects.

However, network-based method only constructed bipartite networks with strong links (high user-object ratings) specified by a given threshold, but neglected low user-object ratings. To solve the above problems, some work had carried on the preliminary attempt but there were still some drawbacks. For instance, some work just used the user-object rating as the edge weight to construct weighted network. During the resource diffusion process, the resources were unequally allocated according to a proportion which was the edge's weight accounted for the total edges' weight of a given node, so as to ensure that the high-rating objects were recommended preferentially. However, ignoring weak links would lost opportunities to discover users' disgusts.

To effectively mine users' preferences and disgusts, this paper considered to differentiate the rating levels. Firstly, this paper normalized ratings by half cumulative distribution method for each user. Secondly, different impacts between weak links (i.e., lower ratings) and stronger links (i.e., higher ratings) were considered for personalized recommendations. Experimental results on MovieLens dataset demonstrated the diversity of the proposed method was much more superior to competitive methods.

II. Weighted Network-Based Inference

Bipartite networks had brought a new opportunity for personalized recommendations. A bipartite network consisted of two kinds of heterogeneous nodes, and edges just existed in heterogeneous nodes. Bipartite networks described the relationships between users and objects, such as purchase behaviors. This paper aimed to propose a novel weighted bipartite network projection method for personalized recommendations by effectively utilizing user-object ratings.

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A. Rating Normalization by Half Cumulative Distribution

The rating criteria varied from people to people. Some people were rather harshly, while some people were rather loosely. Generally, we assumed that users would choose those objects that were not only liked by many users but rated high scores. However, the original ratings could not exactly reflect users' preferences since different users had different rating criteria.

TABLE I: RATINGS FOR DIFFERENT OBJECTS BETWEEN U1 AND U2

Object	O_1	O_2	O_3	O_4	O_5	O_6	O_7	O_8	O_9	O_{10}
U1	1	2	3	3	3	4	4	4	4	5
U2	1	1	2	2	2	3	3	4	4	5

Table I provided an example of two users who gave scores to 10 objects. As shown in Table I, the objects were numbered in the ascending order of preference. User U1 rated loosely compared to user U2. For example, '4' indicated a stronger preference for U2 than U1 because user U2 only assigned '4' to 2 objects while U1 to 4 objects. In this case, the distribution of users' ratings could effectively recognize users' preferences. More specifically, it was important to convert the original rating into users' underlying preference likelihood. Therefore, this paper normalized users' ratings by making full use of the half cumulative distribution method [12]. The formula of normalizing ratings was as follows.

$$w_{ij}^{'} = \begin{cases} P(R \le R_{u_i}(o_j) \mid u_i) - P(R = R_{u_i}(o_j) \mid u_i)/2 & R > 0 \\ 0 & R = 0 \end{cases} \quad (1)$$

Here, R denoted the original ratings that the user u_i gave a score to the object o_j ; $R_{u_i}(o_j)$ denoted the rating set and ranged from 1 to 5; $P(R \le R_{u_i}(o_j) \mid u_i)$ denoted the rating possibility for user u_i to rate any objects was less than or equal to $R_{u_i}(o_j)$; $P(R = R_{u_i}(o_j) \mid u_i)$ denoted the rating possibility for user u_i to rate any object was equal to $R_{u_i}(o_j)$.

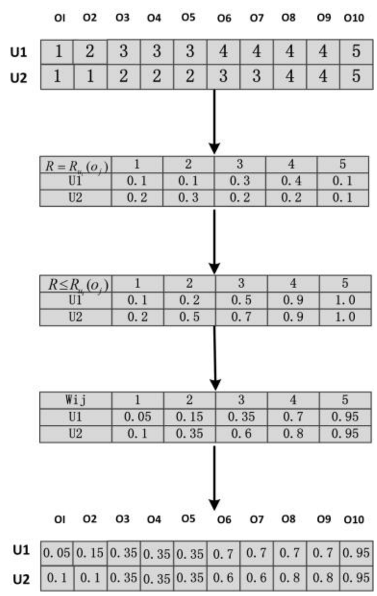

Fig. 1. The detailed steps of normalization for ratings.

To intuitively show the effect of rating normalization, Fig. 1 provided an example of normalizing users' ratings according to the half cumulative distribution method. As shown in Fig. 1, normalized score of '4' for two users (U1 and U2) were different. This example exactly showed how to mine users' tastes.

The rating normalization mapped the original ratings into the user's underlying preference likelihood. In general, a high rating indicated that a user has positive attitude on an object, while a low rating indicated that a user was likely to reject an object. Thus, we regarded the low rating as users' disgust attitude, and took both positive attitude and disgust attitude into account. It was helpful to mine the user's taste by considering the positive and the negative rating.

After normalizing ratings, the averaged preference likelihood for any user on all of the rated objects was exactly 0.5 according to the above Equation (1). Here, we proposed the following hypothesis [13]. If user u_i had not selected a given object o_j , it could not reflect the user's preference for lacking the rating.

Based on the above hypothesis, when user u_i had not select object o_j , we set $w_{ij}^{'} = 0$, which indicated that user's attitude was uncertain. And when user u_i had selected object o_j , we set $w_{ij}^{'} > 0.5$, which indicated that the user held the positive attitude; $w_{ij}^{'} < 0.5$ indicated user u_i held the disgusting attitude; $w_{ij}^{'} = 0.5$ indicated that the user's attitude was uncertain but there was a certain recommended capability, and this paper set up a relatively small tunable parameter to regulate the impact of this case.

Further, the new edge weight considering the positive and negative rating was computed by the following Equation (2).

$$w_{ij}^{''} = \begin{cases} w_{ij}^{'} - 0.5 + \varepsilon & 0 < w_{ij}^{'} < 1 \\ 0 & w_{ij}^{'} = 0 \end{cases} \quad (2)$$

Here, ε was a tunable parameter. It was used to distinguish $w_{ij}^{'} = 0$ and $w_{ij}^{'} = 0.5$.

B. Weighted Bipartite Network Projection.

Suppose there were n users and m objects in a recommended system, which could utilize bipartite network model to describe. Node sets in the bipartite network consisted of the object set and the user set. Denote the object set with $O = \{o_1, o_2, o_3 \ldots, o_n\}$, the user set with $U = \{u_1, u_2, u_3, \ldots, u_m\}$, the edge set with $E = \{e_1, e_2, e_3, \ldots, e_l\} = \{(u_i, o_j) \mid u_i \in U, o_j \in O\}$ and the edge weight set with $W = \{w_{ij} \mid (u_i, o_j) \in E, u_i \in U, o_j \in O\}$. The adjacent matrix of the network was denoted by $A = (a_{ij})_{n*m}$.

$$a_{ij} = \begin{cases} 0 & (u_i, o_j) \notin E \\ w_{ij} & (u_i, o_j) \in E \end{cases} \quad (3)$$

where $d(u_i)$ was the sum of the i^{th} column of A , which stood for the sum of weights of user u_i. And $d(o_j)$ was the sum of the j^{th} row of A, which stood for the sum of weights of object o_j.

Based on the resource-allocation dynamics, Zhou *et al.* [10] firstly designed Network-based Inference (NBI) in bipartite networks. NBI took full advantage of the user-object relationship and respectively regarded the degree of objects and the degree of users as the edge weight to equally allocate resources. And this paper was inspired by NBI. The mainly improvement was how to determine the edge weight according to the original ratings and used the edge weight to unequally allocate resources. For user u_i, the weighted network-based method started by assigning the initial resource for objects. If object o_j had been chosen by user u_i, it would be assign one unit resource as its initial resource, otherwise zero. The initial vector of user u_2, as shown in Fig. 2, was $(f(o_1), f(o_2), f(o_3), f(o_4)) = (0,1,1,0)$. Then the resource was redistributed between the object and the user in the weighted bipartite network. The resource-allocation process consisted of two steps.

1) The resource flowed from the object side to the user side.

The resource of object o_j was assigned to its neighbor users according to the ratio of the edge weights. The total resources of user u_l were as follows:

$$g(u_l) = \sum_{j=1}^{n} a_{lj} f(o_j) / d(o_j) \tag{4}$$

Here, $g(u_l)$ was the resource that user u_l would obtain from its neighbor objects; $f(o_j)$ was the initial resource for object o_j.

2) The resource flowed from the user side to the object side. In a similar way, the finally resources that object o_j obtained from its neighbor users across the whole process of allocation were as follows:

$$f'(o_j) = \sum_{l=1}^{m} a_{lj} g(u_l) / d(u_l) \tag{5}$$

By plugging Equation (4) into Equation (5), the resource-allocation process was simplified as:

$$f'(o_j) = \sum_{j=1}^{n} s_{ij} f(o_j) \tag{6}$$

Here, s_{ij} denoted the object o_i and object o_j similarity coefficient. The formula was defined as follows:

$$s_{ij} = (1/d(o_j)) \sum_{l=1}^{m} (a_{il} a_{jl}) / d(u_l) \tag{7}$$

Fig. 2 provided an example of the resource-allocation process for user u_2 in the weighted bipartite network:

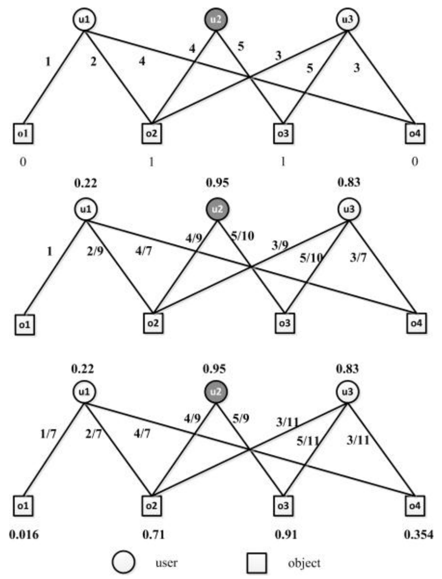

Fig. 2. Resource-allocation process in weighted bipartite network.

From the Fig. 2, the target user u_2 was filled with gray, for example. Objects that were chosen by user u_2 were distributed to one unit resource. Firstly, the resource flows from object to user, user u_2 obtained 0.95 unit resources from its neighbor object o_2 and o_3. User u_2 was more similar to user u_3 than user u_1 from Fig. 2. Then users' resources were returned to its neighbor objects again. Finally, object o_4 was priority to recommend user u_2. It was because user u_2 was similar to user u_3 and user u_3 gave a highly evaluation to object o_4.

The above method only regarded the original rating as the edge weight. Since different users had different rating criteria, the original ratings were normalized according to Equation (1) and the new edge w'_{ij} was calculated. The new edge weight set was $W' = \{w'_{ij} \mid (u_i, o_j) \in E, u_i \in U, o_j \in O\}$ and the new adjacent matrix of the network was denoted by $A' = (a'_{ij})_{n*m}$. Here, $a'_{ij} = w'_{ij}$. Meanwhile, the new similarity coefficient between any two objects was derived as follows:

$$s'_{ij} = (1/d(o_j)) \sum_{l=1}^{m} (a'_{il} a'_{jl}) / d(u_l) \tag{8}$$

Here, a'_{il} was the normalized rating instead of the corresponding original rating.

Based on the description, we also considered the positive and negative impacts after rating normalization, and then redefined the edge weight w''_{ij} by Equation (2). The latest edge weight set was $W'' = \{w''_{ij} \mid (u_i, o_j) \in E, u_i \in U, o_j \in O\}$ and the final adjacent matrix of the network was denoted by $A'' = (a''_{ij})_{n*m}$. Here, $a''_{ij} = w''_{ij}$. And the final resources' allocation was defined as follows:

$$f''(o_j) = \sum_{j=1}^{n} s''_{ij} f(o_j) \tag{9}$$

Here, s''_{ij} was computed by Equation (10), which denoted the similarity between any two objects

$$s''_{ij} = (1/d(o_j))\sum_{l=1}^{m}(a''_{il}a''_{jl})/d(u_l) \quad (10)$$

C. Algorithm Description

Algorithm1: Weighted Bipartite Network Projection Algorithms (WPNBI)

Input：the adjacent matrix of user-object *A*, user *i*, the object set chose by user *i*.

Output：recommendation list *L* for user *i*

1) Input the adjacent matrix *A*
2) Normalize the originally ratings by Equation (1) and obtain the normalized edge weight $w'_{ij} \in [0,1)$ for each user-object rating.
3) Obtain the final edge weight $w''_{ij} \in (-0.5, 0.5)$ by Equation (2)
4) Construct weighted bipartite network and the edge weight was w''_{ij}
5) Compute the similarity coefficient s''_{ij} by Equation (10) and get the final resource-allocate vector for user *i* by Equation (9).
6) Get the recommendation list *L*.

Algorithm 1 provided the basic description of WPNBI algorithm. It considered not only ratings' difference for different users, but also the negative impact caused by the lower ratings. It made recommendation lists became more diverse.

According to the above description, the basic assumption that the greater the recommended value was, the higher the possibility that user liked object. For a given user, his recommendations list that included his entire unselected objects was generated by the recommended value in descending order.

III. Result

A. Experiments Setup

In this paper, the MovieLens dataset was downloaded from the website of GroupLens Research (http://www.grouplens.org). Table II listed the detailed properties of the MovieLens data.

TABLE II: Dataset Properties

Properties	Value
number of users	943
number of movies	1682
rating Grade	1-5
rating>2	82520
all Ratings	100000
users' average degree	106.1
movies' average degree	59.4

To evaluate the performance of proposed algorithms, this paper set up three comparative experiments. There were NBI algorithm, WNBI algorithm and SWNBI algorithm. NBI, which was proposed by Zhou *et al*. [10] based on a resource-allocation process, extracted the ratings greater than 2 to construct weighted bipartite network and used the user-object relationships to equally allocate resources. Based on NBI, two improved algorithm respectively named WNBI and SWNBI were derived. Different with NBI, WNBI treated user-object original ratings as edge weights to unequally allocate resources. Furthermore, SWNBI utilized the normalized ratings computed by Equation (1) as the edge weight. Thus, WNBI, SWNBI and WPNBI used all the ratings to construct weighted bipartite network. Fig. 3 demonstrated the distribution of original ratings.

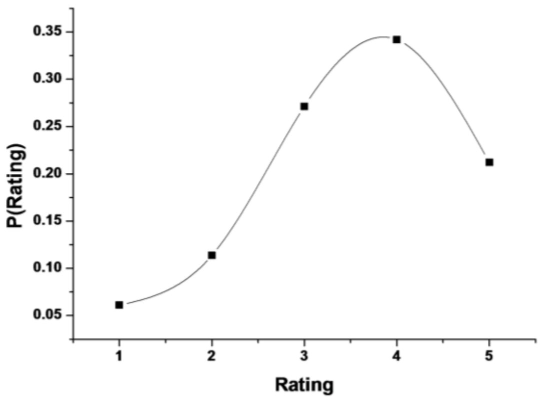

Fig. 3. The distribution of ratings before normalization.

To evaluate the performance of personalized recommendations, 10-fold cross-validation was adopted to randomly divide the dataset into the two parts, training set and test set. For each fold, 90% of the dataset were selected as training set, while the remaining 10% as test set. In addition, the tunable parameter set to $\varepsilon = 0.01$.

B. Evaluation Metrics

1) Precision and recall

Precision and Recall was typically employed to evaluate the algorithm performance, which was defined as follows:

$$P = \frac{1}{n}\sum_{i=1}^{n} N_r^i / L \quad (11)$$

Here, N_r^i represented the number of objects collected by user u_i appeared in both the testing set and recommendation list set; *L* was the length of recommendation list.

To give a definition of Recall was as follows:

$$R = \frac{1}{n}\sum_{i=1}^{n} N_r^i / N_p^i \quad (12)$$

Here, N_p^i represented the number of collected objects of user u_i in the testing set.

2) F index

Cleverdon C. W. [14] found that there was a negative correlation between Precision and Recall with increasing the length of recommendation list. In order to comprehensively verify the performance, Pazzani M. [15] proposed F index by simultaneously utilizing Precision and Recall. F index was defined as follows.

$$F = (2 \times R \times P)/(R + P) \tag{13}$$

3) Diversity

Personalized recommendation algorithms should present different of recommendation lists for different users according to their interests and habits. The average Hanming distance [11] was used to quantify the recommended diversity, $S = < H_{ij} >$, where H_{ij} was defined as follows.

$$H_{ij} = 1 - Q_{ij}(L)/L \tag{14}$$

Here, $Q_{ij}(L)$ represented the number of overlapped objects among the recommendation lists of u_i and u_j. S ranged from 0 to 1. $S = 1$ denoted that all of recommendation lists were entirely different, and $S = 0$ showed that all of recommendation lists were exactingly same.

4) Significant test

Significant test was used to check whether there were significantly difference between the proposed method and other comparison methods. Suppose H0 hypothesis was that there was no significant difference.

For conveniently judging whether there was the difference, the *p* value was used to quantify. Generally the *p* was 0.05. When $p < 0.05$ represented that it rejected H0 hypothesis and accepted H1 hypothesis and it had significant difference, otherwise.

C. Numerical Results

1) The comparison between WNBI and SWNBI

In order to validate the effectiveness of the rating normalization, we conducted a comparative experiment between WNBI and SWNBI. In this experiment, the length of recommendation list *L* was set to 20.

TABLE III: COMPARISON OF DIFFERENT METHODS

	Recall	Precision	F	Diversity
NBI	0.2461	0.107	0.149	0.704
WNBI	0.2383	0.1263	0.165	0.7183
SWNBI	0.2464	0.1306	0.1707	0.729

As shown in Table III, F and diversity of WNBI respectively outperformed NBI by 1.6% and 1.43%. This indicated that the accuracy and diversity was improved by considering the ratings information. Compared to WNBI, SWNBI respectively enhanced 3.45% and 1.53% in terms of F and diversity. Thus, it was helpful to improve the performance by reducing the rating differences among different users.

To verify the different performance of these algorithms on accuracy and diversity was not caused by sample error. We also conducted a significant test experiment on recall, precision, F value and diversity between SWNBI and the others. The experiment results showed that there was statistical significance between SWNBI and WNBI. Results were shows in Table IV.

TABLE IV: COMPARISON OF SIGNIFICANT-TEST RESULTS

SWNBI	Recall	Precision	F	Diversity
NBI	0.0047	0.2008	0.1369	0.024
WNBI	0.0354	0.0131	0.0046	0.0087

2) The comparison between WPNBI and SWNBI

In order to mine users' disgusts from lower ratings, the comparative experiment was conducted between SWNBI and WPNBI. In this experiment, the length of recommendation list *L* was set to 20.

TABLE V: COMPARISON BETWEEN SWNBI AND WPNBI

	Recall	Precision	F	Diversity
SWNBI	0.2464	0.1306	0.1707	0.729
WPNBI	0.250	0.1326	0.1733	0.826

As illustrated in Table V, the diversity of WPNBI improved significantly compared to SWNBI. This was because that users' disgust was easily found from lower ratings. It more accurately determined users' taste and provided personalized recommendations for users.

Meanwhile, the *p* values of the significant test on recall, precision, F index and diversity were 0.0134, 0.01539, 0.00218 and 0.0048 between SWNBI and WPNBI. There was statistical significance between SWNBI and WPNBI.

3) The scalability of comparison algorithms

To verify that the performance of WPNBI were superior to other comparison methods in different recommendation list length, especially under the diversity index. The comparison experiment was used to show the scalability of different algorithms. In this experiment, the recommendation list length *L* ranged from 10 to 100.

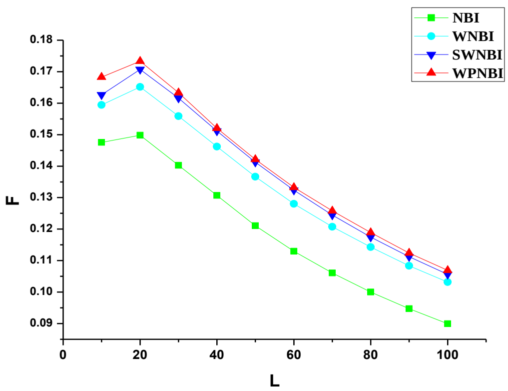

Fig. 4. The comparisons of the different methods under F index.

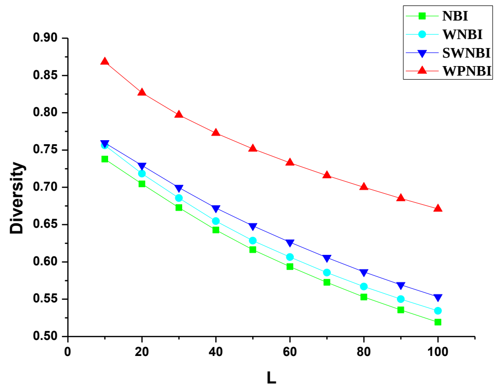

Fig. 5. The comparisons of diversity between different methods.

There was a negative correlation between precision and recall. The F value was used to measure the precision of the recommendation system. As shown in Fig. 4, WPNBI performed the best in all of comparison methods under F index.

Fig. 5 demonstrated the performance of different algorithms under the diversity index. Obviously, diversity decreased with increasing *L*. However, WPNBI was always superior to other algorithms. It clarified that mining users' disgusts from low ratings could effectively improve the diversity of personalized recommendations.

IV. Conclusion

This paper proposed a novel recommendation algorithm to improve the diversity of the recommendation lists. We introduced the half cumulative distribution method to normalize edge weights. More specifically, this method mapped the original ratings to users' preference possibility by a normalization process. And above all, this paper took into account the negative impact caused by low ratings, which could thoroughly mine users' tastes. Experimental results showed that the diversity of the proposed algorithm was obviously superior to competitive methods.

Acknowledgment

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