Graph-Theoretic One-Class Collaborative Filtering using Signed Random Walk with Restart

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***Abstract*—Graph-theoretic one-class collaborative filtering (gOCCF) has been successful in dealing with sparse datasets in one-class setting (*e.g.*, clicked or bookmarked). In this paper, we point out the problem that gOCCF requires long processing time compared to existing OCCF methods. To overcome the limitation of the original gOCCF, we propose a new gOCCF method based on *signed random walk with restart* (SRWR). Using SRWR, the proposed method accurately and efficiently captures users' preferences by analyzing not only positive preferences from rated items but also the negative preferences from uninteresting items. Through extensive experiments using real-life datasets, we verify that the proposed method improves the accuracy of the original gOCCF and requires processing time less than the original gOCCF.**

***Index Terms*—One-class collaborative filtering, graph theory, random walk with restart**

I. Introduction

The *collaborative filtering* (CF) [1] is one of the most popular techniques in recommender systems. CF exploits the past behavior of a user such as explicit feedback represented by his/her ratings (*i.e.*, multi-class setting) and implicit feedback represented by his/her clicks (*i.e.*, one-class setting) to recommend the most appealing top-N items to him/her [1]. Compared to the multi-class setting, the one-class setting has greater availability, thus facing wider applications. To serve such one-class setting, many one-class collaborative filtering (OCCF) methods have been proposed [2], [3].

In our recent work [4], we pointed out the problem that existing OCCF methods tend to become less effective in dealing with *sparse* datasets in one-class setting. To address this challenge, we proposed a graph-theoretic OCCF method, named as gOCCF, that exploits not only the rated items but also the *uninteresting items* [5] chosen from unrated items. To determine a right number of uninteresting items, it jointly considers the degree of interestingness on unrated items, the *graph shattering* theory [6], and the property of information propagation. gOCCF models the relationships between users and the rated/uninteresting items in a single signed graph or two separate (*i.e.*, positive and negative) graphs, and comes up with top-N recommendation based on two well-known graph analysis techniques, *random walk with restart* (RWR) [7] and *belief propagation* (BP) [8].

Despite the success of the original gOCCF in the sparse one-class setting, we observe that the following two challenges in gOCCF. First, the original gOCCF should find uninteresting items of all users and also analyze the relationships between users and uninteresting items along with those between users and rated items. This requires processing time longer than other OCCF methods [2], [3] that exploit only rated items. Second, SignedBP, the best performer among three variants of the original gOCCF, employs an extension of BP to analyze a signed graph. We note that BP has model complexity higher than RWR.

To have a better graph-theoretic OCCF method, we have two goals: (1) to improve the accuracy of the original gOCCF and (2) to provide processing time less than the original gOCCF. Towards the goals, we employ *signed random walk with restart* (SRWR) [9], a technique recently proposed to solve a node ranking problem in a signed graph. Specifically, SRWR extends the original RWR [7] to account for edge signs (*i.e.*, positive and negative), thereby employing the signed surfer to provide more accurate node rankings in a signed graph [9]. In this sense, SRWR is suitable to analyze positive preferences from rated items and negative preferences from uninteresting items together. In addition, RWR-based models are known to have model complexity lower than BP-based models.

In this paper, we propose an *efficient* and *effective* graph-theoretic OCCF method based on SRWR. Through extensive experiments using real-life datasets, we verify the effectiveness of the proposed method. The experimental results show that the proposed method successfully achieves the above goals to improve the original gOCCF. Specifically, in the MovieLens 100K dataset, the proposed method improves the accuracy (in terms of *normalized discounted cumulative gain* [10]) of the original gOCCF up to 26.87% and reduces the processing time of the original gOCCF up to 8.5 times.

The rest of this paper is organized as follows: Section 2 presents the proposed method in detail. Section 3 validates the effectiveness of the proposed method through extensive

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experiments. Finally, Section 4 summarizes and concludes the paper.

II. The Proposed Method

In this section, we propose a new graph-theoretic OCCF method based on SRWR. The proposed method includes the following four steps: (1) predicting the degree of interestingness on unrated items; (2) determining the number of uninteresting items; (3) modeling the relationships between users and rated/uninteresting items; (4) performing top-N recommendation by employing SRWR.

A. Predicting the degree of interestingness

We first predict the *degree of interestingness on every unrated item of a user* by referring to his/her rated items only. To do this, we can exploit any existing OCCF methods [2], [3]; in this paper, we employ a popular OCCF method, *weighted regularized matrix factorization* (WRMF) [2], following [4], [5]. WRMF represents rated and unrated items as positive (*i.e.*, 1) and negative (*i.e.*, 0) preferences, respectively, in a rating matrix and assigns different weights to those preferences for matrix factorization by quantifying their relative confidence. Then, it factorizes the rating matrix into two low-rank matrices (each representing the features of users or items as latent factors) by employing the *weight alternating least square* (wALS) technique [11] that reflects the weights assigned to preferences as their relative contributions. Finally, it predicts a user's preference on an unrated item of hers by taking the inner product of two latent factors of the user and the item.

B. Determining the number of uninteresting items

We should determine *a right number of uninteresting items* among unrated items. Based on the degree of interestingness computed by WRMF, we can consider some of unrated items having *low* degree of interestingness as uninteresting items. However, it is a very time-consuming task to find a right number of uninteresting items that provide the best accuracy in recommendation. For example, in the MovieLens 100K, we need to determine uninteresting items among 1.5M unrated items (*i.e.*, user-item pairs).

Following [4], we decide a right number of uninteresting items by employing the following two graph-theoretic tools: (1) *graph shattering* theory [6] that introduces a shattering point at which the connectivity of a graph becomes seriously collapsed when edges are continuously removed in a random way; (2) PageRank [12] that is known to best characterize the aspect of information propagation. By analyzing datasets using the above methods in [4], we demonstrated that setting the number of uninteresting items as *equal to* that of rated items helps to get topological properties most similar to those of a given dataset. Furthermore, we showed that this setting provide the highest accuracy in terms of recommendation. Therefore, we determine uninteresting items as many as rated items in a rating matrix.

C. Modeling the relationships between users and items

Now, we can convert the original dataset in one-class setting to one in binary-class setting with both positive preferences from rated items and negative preferences from uninteresting items. In order to model such binary-class information as in undirected graphs, we can consider the following two candidates [4]: (1) two *separate graphs* modeled by independent consideration of positive and negative edges; (2) a *single signed graph* modeled by taking both positive and negative edges together into account.

We can capture more-accurate users' preferences by combining two kinds of relationships: one with users and his/her rated items (*i.e.*, positive edges) and the other with users and his/her uninteresting items (*i.e.*, negative edges). The first candidate above with two separate graphs only exploits independently the information provided by each single sign. In this work, we model the binary-class information in a single signed graph. In the signed graph, the nodes represent users and items, the positive edges represent the relationships between users and their rated items, and the negative edges represent those between users and their uninteresting items.

D. Performing top-N recommendation

In order to provide efficient and effective recommendation, we employ the technique of *signed random walk with restart* (SRWR) [9]. To do this, we first define the following two probabilities: (1) $\mathbf{r}^+_{\mathbf{u}} = Pr_t(u, +)$ is the probability that the positive surfer arrives at node (*i.e.*, user or item) u after SRWR from the target user t; (2) $\mathbf{r}^-_{\mathbf{u}} = Pr_t(u, -)$ is the probability that the negative surfer arrives at node (*i.e.*, user or item) u after SRWR from the target user t. $\mathbf{r}^+$ indicates a positive SRWR score vector and $\mathbf{r}^-$ is a negative SRWR score vector for all nodes. Both vectors are used for predicting the preferences on all unrated items of a target user t.

To update two vectors $\mathbf{r}^+$ and $\mathbf{r}^-$, we formulate the following recursive equations [9]:

$$\begin{aligned}
\mathbf{r}^+ &= (1-c)(\tilde{\mathbf{A}}_+^\top \mathbf{r}^+ + \beta \tilde{\mathbf{A}}_-^\top \mathbf{r}^- + (1-\gamma)\tilde{\mathbf{A}}_+^\top \mathbf{r}^-) + c\mathbf{q}, \\
\mathbf{r}^- &= (1-c)(\tilde{\mathbf{A}}_-^\top \mathbf{r}^+ + \gamma \tilde{\mathbf{A}}_+^\top \mathbf{r}^- + (1-\beta)\tilde{\mathbf{A}}_-^\top \mathbf{r}^-),
\end{aligned} \tag{1}$$

where c is a restarting probability, β is a parameter for controlling the uncertainty of "the enemy of my enemy is my friend," and γ is a parameter for controlling the uncertainty of "the friend of my enemy is my enemy"; $\mathbf{q}$ is a vector whose t-th element (*i.e.*, target user) is set as 1 and all other elements are set as 0; $\tilde{\mathbf{A}}_+$ and $\tilde{\mathbf{A}}_-$ are the positive and negative semi-row normalized matrixes, respectively.

The iteration steps of SRWR are summarized as follows. First, we compute $\mathbf{r}^+$ and $\mathbf{r}^-$ via Eq. 1 and concatenate $\mathbf{r}^+$ and $\mathbf{r}^-$ into $\mathbf{r}$. Then, we compute the error between $\mathbf{r}$ and $\mathbf{r}'$ where $\mathbf{r}'$ is the result obtained in the previous iteration. We set $\mathbf{r}$ as $\mathbf{r}'$ for the next iteration. The iteration continues in the same way until the error becomes smaller than a threshold predefined. Finally, we recommend the top-N items that are most preferred by the target user based on the final SRWR scores computed by $\mathbf{r}^+ - \mathbf{r}^-$ (both are in $\mathbf{r}$).

TABLE I
DATASET STATISTICS

Datasets	# users	# items	# feedback	Sparsity
MovieLens 100K	943	1,682	100,000	93.69%
Watcha	1,391	1,927	100,000	96.98%

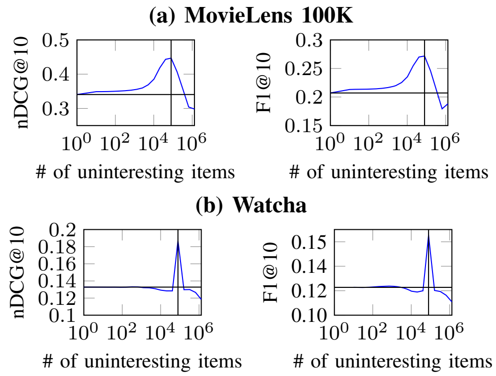

Fig. 1. Accuracy of the proposed method according to the number of uninteresting items.

TABLE II
ACCURACY OF THE ORIGIANL GOCCF AND THE PROPOSED METHOD

(a) MovieLens 100K

Methods	**gOCCF SeparateRWR**	**gOCCF SeparateBP**	**gOCCF SignedBP**	**Ours**
F1@10	0.216	0.212	0.263	**0.272**
F1@20	0.260	0.252	0.302	**0.314**
F1@50	0.261	0.259	0.292	**0.306**
nDCG@10	0.352	0.365	0.438	**0.447**
nDCG@20	0.354	0.356	0.426	**0.437**
nDCG@50	0.387	0.385	0.451	**0.466**

(b) Watcha

Methods	**gOCCF SeparateRWR**	**gOCCF SeparateBP**	**gOCCF SignedBP**	**Ours**
F1@10	0.109	0.117	**0.146**	**0.146**
F1@20	0.128	0.137	**0.164**	**0.164**
F1@50	0.126	0.128	0.147	**0.150**
nDCG@10	0.135	0.151	0.187	**0.188**
nDCG@20	0.158	0.173	**0.212**	**0.212**
nDCG@50	0.217	0.227	0.272	**0.275**

III. EVALUATION

A. Experimental Settings

For evaluation, we used two real-life datasets, MovieLens 100K and Watcha: they contain ratings ranged from 1 to 5 explicitly given by users (*i.e.*, multi-class setting). Since our goal is to address the OCCF problem, we convert their 1-5 ratings into 1 (*i.e.*, one-class setting), as popuarly done in other OCCF researches [2]–[4]. Table I shows the detailed statistics of the datasets.

We compared our proposed method with three variants (*i.e.*, SeparateRWR, SeparateBP, and SignedBP) of the original gOCCF. To evaluate the accuracy of recommendation, we performed top-N (=10, 20, 50) recommendation by each method and measured its accuracy in terms of F1 score and nDCG [10], which are popular in a recommendation research. The final accuracy was determined by averaging the five accuracies obtained from five-fold cross-validation for each metric. All experiments were conducted in Windows 10 running on Intel Core i7 processor (3.70 GHZ) with 64GB RAM.

B. Experimental Results

Effectiveness of uninteresting items. Note that we selected the number of uninteresting items having the lowest degree of interestingness exactly the same as that of rated items in the given dataset. We first conducted an experiment to verify whether our selection really helps improve the recommendation accuracy. Fig. 1-(a) and 1-(b) show top-10 recommendation accuracies of our proposed method according to different numbers of uninteresting items in MovieLens 100K and Watcha, respectively.[1] The x-axis represents the number of uninteresting items and the y-axis represents the accuracy measured. The vertical line shows the number of rated items in each dataset and the horizontal line shows the accuracy of the original RWR without using the concept of uninteresting items.

The results show that the proposed method always provides the highest accuracy when having the number of uninteresting items same as that of rated items. This trend coincides with those reported in [4]. Also, we found that exploiting uninteresting items is quite effective in improving the accuracy of the original RWR. Fig. 1 shows that our proposed method having the same number of uninteresting items as rated items *consistently and significantly* outperforms the original RWR. More specifically, our proposed method improves nDCG@10 of the original RWR by 31.17% and 40.86% for MovieLens 100K and Watcha, respectively. As a result, in subsequent experiments, we set the number of uninteresting items equal to the number of rated items.

Accuracy of the proposed method. We performed an experiment to compare the recommendation accuracies of the original gOCCF with those of our proposed method. Table II shows the accuracies for three variants of the original gOCCF (*i.e.*, SeparateRWR, SeparateBP, SignedBP) and our proposed method. The value in boldface indicates the best accuracy in each row.

The results show that our proposed method not only achieves significantly higher accuracy than those of SeparateRWR and SeparateBP but also provides the accuracy higher than or comparable to that of SignedBP. More specifically, our proposed method improves F1@10/nDCG@10 of the original gOCCF (*i.e.*, SeparateBP) up to 28.16%/26.87% and 34.57%/39.60% for MovieLens 100K and Watcha, respectively.

Processing time of the proposed method. We evaluated the performance of our proposed method by comparing it

[1]We omit the results for other top-Ns (=20, 50), because they showed tendency very similar to that in Fig. 1.

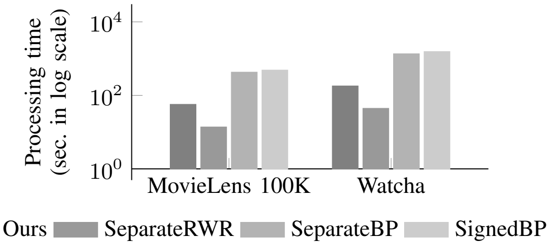

Fig. 2. Processing time of the original gOCCF and the proposed method.

with the original gOCCF. Fig. 2 shows the processing time of SeparateRWR, SeparateBP, SignedBP, and our proposed method. The x-axis represents methods in each dataset, and the y-axis does the processing time.

We summarize the results shown in Fig. 2 as follows. First, both the proposed method and SeparateRWR require low processing time in all datasets. However, we note that our proposed method significantly outperforms SeparateRWR in terms of recommendation accuracy (see Table II). Second, the proposed method always provides higher performance than SeparateBP and SignedBP. Specifically, for MovieLens 100K, the proposed method reduces the processing time of SeparateBP and SignedBP by 7.5 times and 8.5 times, respectively.

Parameter analysis of the proposed method. To understand the effect of parameters used in the proposed method, we carefully analyzed the changes of accuracy in recommendation according to different values for parameters: (1) β is a parameter for controlling the uncertainty of "the enemy of my enemy is my friend"; (2) γ is a parameter for controlling the uncertainty of "the friend of my enemy is my enemy."

Fig. 3-(a) and 3-(b) show the changes of accuracy in terms of nDCG@10 by our proposed method with different values of β and γ in MovieLens 100K and Watcha, respectively.[2] The x-axis represents the value of β, the y-axis does the value of γ, and the z-axis does the accuracy. Fig. 3 shows that larger values of β and γ help achieve high accuracy in all datasets. In particular, the results show that the accuracy is always the highest when β and γ are set as 0.9. These results coincide with those reported in [9], indicating that considering the uncertainty of the friendship of an enemy is beneficial to improving the accuracy of our method.

IV. Conclusions

In this paper, we proposed a new graph-theoretic OCCF method based on SRWR. Our proposed method is composed of the following four steps: (1) predicting the degree of interestingness on unrated items; (2) determining the number of uninteresting items based on the degree of interestingness, the graph shattering theory, and the property of information propagation; (3) modeling the relationships between users and rated/uninteresting items in a signed graph; (4) performing top-N recommendation by employing SRWR on the signed graph. Our experimental results demonstrated that

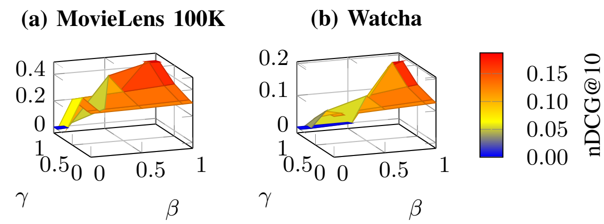

Fig. 3. Accuracy changes according to $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$.

our proposed method significantly improves the accuracy of the original gOCCF and requires less processing time than the original gOCCF. Specifically, for MovieLens 100K, the proposed method improves nDCG of the original gOCCF up to 26.87% and reduces the processing time of the original gOCCF up to 8.5 times.

[2] We omit the results for other top-Ns (=20, 50) and another metric (*i.e.*, F1 score), because they showed tendency similar to that in Fig. 3.

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