Published in "Physics Procedia 3(5): 1877-1885 , 2010"
which should be cited to refer to this work.

Enhancing personalized recommendations on weighted social tagging networks

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Abstract

Recently, *social tagging systems* have been widely applied in web systems and some physical properties have been found applications in efficiently and effectively personalized recommendation. Social tags can provide highly abstract information about not only item contents but also personalized preferences, hence they might help generate better personalized recommendations. However, how to find out the relevant yet diverse items that are not associated with any tag remains an open question for us. In this paper, we assume a basic attraction may exist for each item. Moreover, considering both personal and global vocabulary, as well as such attractor, we apply diffusion-based recommendation algorithm in weighted social tagging networks. We then evaluate it in a real-world data set *Del.icio.us*. Experimental results demonstrate that the usage of both tag information and attractor can significantly improve diversity of personalized recommendations, and thus it can be regarded as an alternative recommendation method.

Keywords: social tagging networks, personalized recommendation, diversity

1. Introduction

The exponential growth of web information has led people into an information overload era: they face too much information to be able to find out those most relevant and interesting for them. It is almost impossible to evaluate all these alternatives by themselves. Consequently, an urgent problem of how to automatically get the relevant information for us emerges.

Personalized recommender systems, using the personal information for recommendation, are considered to be the most promising way to efficiently find out useful information. Thus far, *personalized recommender systems* have successfully found applications in e-commerce [1], such as book recommendations in *Amazon.com* [2], movie recommendations in *Netflix.com* [3], video

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recommendations in *TiVo.com* [4], and so on. The design of an efficient recommendation algorithm has become a joint focus from various research communities. A considerable amount of algorithms have been proposed, of which *Collaborative Filtering (CF)* is one of the most prominent techniques. However, The performances of many algorithms (e.g. *CF*) are strongly limited by data sparsity. Additional information, such as user profiles [5], item contents [6] and attributes [7], is used to filter out irrelevant information. Nevertheless, these applications are usually strongly restricted to respect personal privacy, or limited due to the lack of available content information. On the other hand, *social tagging systems*, allowing users to freely assign words, so-called tags, to their collections, provide helpful information of item content and individual preference to better address the above issues. Tags are given by users themselves and therefore represent the personal vocabulary and preference to some extent.

Recently, a considerable number of algorithms are designed to make use of tagging information. Schenkel *et al.* [8] proposed an incremental threshold algorithm taking into account both the social ties among users and semantic relations of different tags, which performs remarkably better than the algorithm without tag expansion. Nakamoto *et al.* [9] created a tag-based contextual collaborative filtering model, where the tag information is treated as the users' profiles. Tso-Sutter *et al.* [10] proposed a generic method that allows tags to be incorporated to the standard collaborative filtering, via reducing the ternary correlations to three binary correlations and then applying a fusion method to re-associate these correlations. Zhang *et al.* [11] and Shang *et al.* [12] integrated tags into two bipartite networks to make better recommendation based on diffusion method [13]. In addition, Shang *et al.* [14] discussed a degree-based weighting method on social tagging networks.

In this paper, we introduce tag information of user-item pairs, as well as the attractor, to improve the diversity of the recommendation [15, 16]. Recently, the significance of diversity has attracted more and more attention in information filtering [17]. We consider the network with tags as a *social tagging system*, which make the network contain more semantic relations among items. These tags are words assigned freely by users to their collections in their own vocabularies, so they might provide more helpful preference information for better recommendation under the condition of respecting personal privacy. We use one benchmark data set, *Del.icio.us*, to evaluate our algorithm. Experimental results demonstrate that the usage of tag information can significantly improve both inter-diversity and intra-similarity of recommendations , and thus it can be regarded as an alternative recommendation algorithm to provide user a wider vision.

2. Method

In this paper, we adopt a tag-based weighted variant of the diffusion-based method proposed in [13] and here the weights are generated according to both personal and global vocabulary and combined with an interest attractor of each user-item pair ϵ. A *social tagging system* consists of three distinct sets, a user set $U = \{u_1, u_2, \ldots, u_n\}$, an item set $I = \{i_1, i_2, \ldots, i_m\}$, and a tag set $T = \{t_1, t_2, \ldots, t_l\}$, respectively. Generally speaking, there are three kinds of user behaviors in tagging systems. For a single user, s/he might 1) save an item (e.g. webpage) by serendipitous browsing and not assign any tag to it in any case (e.g. lack of suitable words to describe it); 2) save an item and assign some relevant tags to it definitely; 3) look into the baskets of other users' items via his favorite tags, select favorite items and collect them. Accordingly, the first way indicates that items are basically attractive to users to some extent, while the others reveal that tags play an important role in efficiently retrieving relevant and interesting items.

2.1. Tag-based weighted networks

A weighted bipartite network can be generated according to users' tagging behaviors. In the weighted process, both the personal vocabulary space and global vocabulary are taken into account. Moreover, the basic attraction of items is also considered as an important factor for recommendation. As shown in Fig 1, three users and four items constitute a bipartite network, while each edge represents a connection between a user and a specific item. The weight of each edge is generated according to his/her tagging behavior:

1. For a certain user $u_k (k = 1, 2, \ldots, n)$, all the tags s/he has employed can be regarded as his personal tag space $\Gamma(u_k)$. Thus the tag-based weight for one of his specific item, i_j, is defined as:
$$w_{k,j}^{(T)} = \sum_{t \in \Gamma(k,j)} (freq_{kt} * log \frac{|U|}{|\{u : t \in \Gamma(u)\}|}), \tag{1}$$
where $\Gamma(k, j)$ is the set of tags which are assigned to item i_j by u_k, $freq_{kt}$ is the frequency of tag t used by u_k in all his/her tagging history, $|U|$ is the total number of users in the whole data set. $\Gamma(u)$ is the set of tags used by user k, and thus the denominator in the logarithm term of Eq.1 is counted as the number of users who have used the tag t. Hence, the most frequently used words by the whole community would not contribute much to be considered as personalized information. This weighting method is firstly introduced as TF-IDF [18] in *Information Retrieval*.
2. An attractor ϵ is integrated with $w_{k,j}^{(T)}$ as the total weight of the edge between u_k and i_j, due to the fact that an essential preference exists between users and items, whatever u_k assigned tags to i_j or not by any chance. This assumption ensures that the information of users' preferences to items without tags can be reserved and that zero-tag items would have a more possible chance to be recommended by the proposed algorithm.

Then the final weight for any user-item pair would be the sum of these two factors:

$$w_{k,j} = w_{k,j}^{(T)} + \epsilon. \tag{2}$$

So each item collected by user u_k can be assigned with a final weight in the way as mentioned above, and the user-item bipartite network is also weighted according to users' tagging behaviors. The parameter ϵ can be tuned in order to reach the best performance for recommendation. Therefore, the final weight can indicate how the user likes to collect the item.

For the sake of easier understanding of the generation process of tag-based weights mentioned above, we give an example to make it clearer. In Fig. 1, u_1 has collected three items: i_1, i_2, i_3 and i_4, and s/he assigns tags: t_1, t_2, t_3 for i_1; t_4 for i_2; t_1, t_2, t_3 for i_3, and nothing for i_4. Therefore the frequency of each tag (t_1, t_2, t_3, t_4) used by u_1 is respectively 2/7, 2/7, 2/7 and 1/7 . Meanwhile, the number of users who have collected those tags are 3, 2, 2, 1 respectively. As a consequence, the final weight for $u_1 - i_1$ can be generated according to Eq. 1 and Eq. 2:

$$w_{1,1} = \sum_{t \in \Gamma(11)} (freq_{1t} * log \frac{3}{|\{u : t \in \Gamma(u)\}|}) + \epsilon = 0.232 + \epsilon. \tag{3}$$

Analogously, the other weights are generated as: $w_{1,2} = 0.157 + \epsilon$, $w_{1,3} = 0.232 + \epsilon$, and ϵ for $w_{1,4}$.

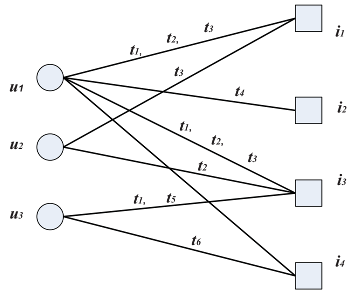

Figure 1: Illustration of a social tagging system.

2.2. *Recommendation via diffusion process*

In order to provide better recommendations, we will use the weights generated by tag information as mentioned above to make personalized recommendations via diffusion process. The diffusion process allows the values transferred between users and items. For any certain user u_k, it includes two steps shown as follows:

Step 1: Distribute averagely the value of each item i_j to the users who has collected it, and then the value that a user u_l will receive is:

$$p_l = \sum_{j \in \Gamma(u_k)} \frac{w_{k,j}}{d(i_j)}, \tag{4}$$

where $\Gamma(u_k)$ is the set of items that have been collected by u_k, and $d(i_j)$ is the degree of item i_j in the user-item bipartite network.

Step 2: Redistribute the value of each user u_l to his/her collections according to the weight defined in Eq (2). Finally, the final value $r_{k,j}$ corresponding to item i_j will be summarized as:

$$r_{k,j} = \sum_{l \in \Gamma(i_j)} (p_l * w_{l,j}), \tag{5}$$

where $\Gamma(i_j)$ is the set of users who collected item i_j.

Therefore, each user u_k has a final value vector $\vec{r_k}$ which is composed of $r_{k,j}$. In the diffusion procedure, the values are firstly distributed from items to users, and then in *Step 2*, the tagging behaviors are taken into account again and the values are distributed to items based on the derived weights. The final values can be considered as the scores for each item, making up u_k's value

Table 1: Basic Information of the data set.

Value	Description
9,998	number of users
287,531	number of items
136,311	number of tags
1,611,190	number of user-item relations
71,260	number of no-tag user-item relations
5,327,901	accumulative number of tags

vector $\vec{r}_k$. Finally, these scores in the same vector are sorted in a descending order, and the items with the top scores which have not been collected by u_k will be recommended to him/her.

3. Experimental Results

We use a benchmark data set, *Del.icio.us*, to evaluate the proposed algorithm. *Del.icio.us* is one of the most popular social bookmarking systems, which allows users not only to store, organize and share personal bookmarks (URLs), but also to look into other users' collections and find what they might be interested in by simply keeping track of other users' collections with the same tags or items. The data used in this paper is crawled from the website http://del.icio.us/ in May 2008. And we purified the meta data to guarantee that each user has collected at least one item. Table 1 summarizes the basic statistical properties of the data set. To test the algorithmic performance, we use all the data with tags and 23% of the data without tags as the training set, and the residual data without tags as the probe set.

In order to evaluate comprehensively the performance of our proposed method, we adopt three metrics: *inter-diversity*, *intra-similarity* and *ranking score* [13].

1. *Inter-diversity*. Inter-diversity [15] can be used to measure how diverse and personalized a recommendation algorithm is. Hamming distance, which is adopted to quantify the inter-diversity, is defined as
$$H_{pq} = 1 - \frac{O_{pq}}{L}, \tag{6}$$
where O_{pq} denotes the number of items overlapped in u_p's and u_q's recommendation lists, and L denotes the length of the recommendation list. Then we average the Hamming distance over all the user-user pairs to measure the diversity of recommendations. Therefore, the larger the average value of Hamming distance is, the more personalized recommendations are.
2. *Intra-similarity*. Intra-similarity [16] takes into account the diverse recommendations to a single user. For any user u_k, the intra-similarity of u_k's recommendation list can be defined as
$$Q_k = \frac{1}{L(L-1)} \sum_{p \neq q} s_{pq}, \tag{7}$$

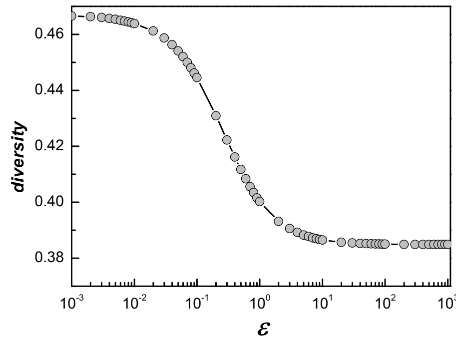

Figure 2: *Inter-diversity* vs. ϵ. The results reported here are averaged over four independent runs, and in each running the probe is obtained randomly from the data set without tags and both the residual data without tags and all the data with tags are used as the training set.

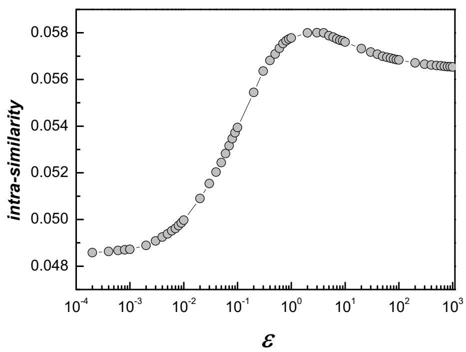

Figure 3: *Intra-similarity* versus ϵ. The results reported here are averaged over four independent runs, and in each running the probe is obtained randomly from the data set without tags and both the residual data without tags and all the data with tags are used as the training set.

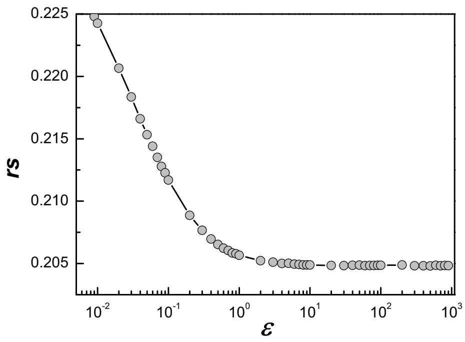

Figure 4: *ranking score* versus ϵ. The results reported here are averaged over four independent runs, and in each running the probe is obtained randomly from the data set without tags and both the residual data without tags and all the data with tags are used as the training set.

where s_{pq} is the similarity between item i_p and i_q, denoted as:

$$s_{pq} = \frac{|\Gamma(i_p) \bigcap \Gamma(i_q)|}{\sqrt{d(i_p)d(i_q)}}. \tag{8}$$

Then we average the intra-similarities of all the users to obtain the intra-similarity of the system. Therefore, the smaller the mean value of the intra-similarities is, the more diverse the recommendation is to users.

3. *Ranking score*. Ranking score can be used as a measurement to evaluate the accuracy of the recommendation method. For each user, an ordered queue (e.g.$\vec{r_k}$ for user u_k) of all its uncollected items can be provided by learning the training set. If the relation u_k-i_j is in the probe set, the position value is the ratio of the position of i_j to the length of the descending ordered queue. Then we average the position values over all the data in the probe set. Thus the average value is called *ranking score*, *rs* for short. Therefore, the smaller the ranking score is, the higher the accuracy of the algorithm is.

The Experimental results of *inter-diversity*, *intra-similarity* and *ranking score* are shown respectively in Figure 2, Figure 3 and Figure 4. We choose the method described in [13] as the baseline method for comparison. The length of recommendation list is set to 10. These figures show the change of our algorithmic performance with the gradual changes of attractor ϵ. It can be seen that the curves trend to approach gradually the performance of the baseline method when ϵ is larger than 1. It is because the proposed method is just almost the baseline method when ϵ is big enough, e.g. $\epsilon = 1000$. Since the mean tagged weight, of the training set is $\langle w \rangle$=0.1935, we pay close attention to the parts of the curves in the interval $\epsilon \in [0.01, 0.1]$, in the range of which our proposed method gives higher inter-diversity and lower intra-similarity than the baseline method. However, the accuracy will decrease when we obtain high diversity, thus the proposed method

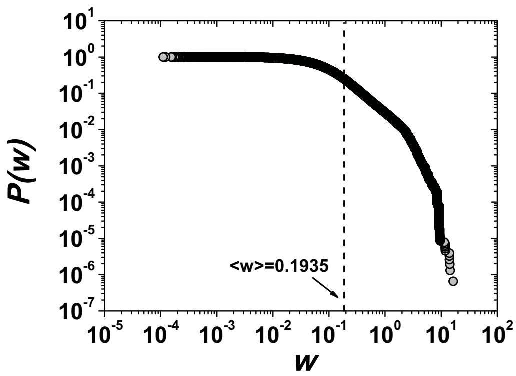

Figure 5: *Cumulative weight distribution of the dataset. The dash line shows the average weight.*

can be considered as an alternative method of previous researches [11, 12, 13, 14] For example, when $\epsilon = 0.06$, our method gives inter-diversity and intra-similarity furtherly improved by about 17% and about 6% respectively. It indicates that both the tag information and the attractor are useful to open a wider vision for users via recommendations. Additionally, in order to obtain in-depth understanding of the role of ϵ, we subsequently measure the the weight effects. Figure 5 shows the cumulative weight distribution of all the user-item pairs. , from which we can see that about 79.1% of data is smaller than $\langle w \rangle$. This might give a reasonable explanation that a small ϵ corresponds to high diversity.

4. Conclusion and Discussion

In this paper, we proposed a tag-based weighted variant of mass diffusion-based method, where the tag information and the item attractor are both introduced to enhance the diversity of recommendation. The proposed method has two features. First, the tag information, including personal and global vocabulary, makes the bipartite network more informative on semantics, which can help recommend more diversely. Second, the introduction of basic attractor can lead the recommendation more flexible according to the specific recommendation requirement.

How to give a better personalized recommendation is a challenge for information scientific communities. Meanwhile, when we recognize the effect of tag information to recommendation, we will further take into account some hybrid algorithms in the direction of combining tagging information and physical dynamics in order to improve the performance of recommendation in more aspects.

5. Acknowledgement

This work is partially supported by the Swiss National Science Foundation (Project 200020-121848). ZKZ acknowledges the National Natural Science Foundation of China under Grant Nos 60973069 and 90924011. WP and ZKZ acknowledge the Scholarship Program supported by China Scholarship Council (CSC Program).

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