Item Recommendation in Social Tagging Systems
Using Tag Network

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Abstract
How to profile users and items is a key problem for recommendation in tagging systems. In contrast to tag vector based methods which ignore the semantic relations between tags, we present a novel profiling method based on a weighted tag network model to fully exploit the rich tag relations. Furthermore, by considering the extent of other users’ usage of tags, we present a novel NTF-IUF-IIF method to calculate weights for tags, which can seize the user’s preference accurately. Instead of a single document of traditional methods, it is the first effort to regard each user as a document collection, which enables the statistics of all items. Then the extent of other users’ usage of tags can be counted via the global item information, and then used as a factor for accurate tag weighting. Finally, a Fusion Method (FM) is proposed for measuring similarities between tag networks of users and items to get the recommendation lists. Experimental results on MovieLens and CiteULike datasets validate the effectiveness of our methods.

Keywords: Social Tagging; Tag Network; Recommendation

1 Introduction
Social tagging systems are typical Web 2.0 applications, which have very strength of the interaction and user-centered design. The famous social tagging systems include Del.icio.us, MovieLens, and Flickr. For such system, the amount of resources of social tagging systems is increasing quickly because of daily increasing new users new resources uploaded by users. For example in Del.icio.us, approximately 120, 000 URLs are posted to Del.icio.us each day. Obviously, huge amount of information has gone beyond the users’ control, and users could not get useful resource quickly and accurately. Although most social tagging systems provide search function, they usually adopt keyword matching method, the quality of return result is not very high, and different user input same query will get same result, it can not satisfy user’s personal need.

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technology can help users get useful ones from massive resources, and how to profile users and items is a key problem for recommendation.

In Social tagging systems, there are three essential elements, i.e. users, tags and items. Since users assign tags to items, the tags can both capture user’s interests and show the topics of items. Therefore, it is feasible to exploit social tags to profile users and items. Most existing methods use tag vector to profile users or items [7, 11, 12, 10], where, however, semantic association between tags are ignored. Take “Kobe NBA” with respect to “Kobe Food” as an example, in case of considering semantic association, it is obvious that the tag “Kobe” appeared in conjunction with “NBA” means the name of a basketball player while the other with “Food” denotes the name of steak. In order to fully exploit the rich tag relations, the first contribution of this paper is to present a novel profiling method based on a tag network model. The tag network uses weighted nodes and edges to present the tags and their relations respectively. Since our model evolves only the most basic elements, i.e. users, tags and items, it can be generally applied to any social tagging system.

The second contribution of our work is to present a new NTF-IUF-IIF method to calculate weights for tags. Researchers in previous literature usually use TF [7] (tag frequency), NTF [11] (N is for normalized), TF-IUF [10] (IUF: inverse user frequency) and NTF-IUF [12] for tag weighting. However, the TF, NTF methods only focus on the user’s own usage and do not take other users into account. Though the TF-IUF, NTF-IUF methods extend the view to other users, they only care about whether the users have used the tag, without further considering how much they have used. In order to accurately measure the user’s preference, the proposed NTF-IUF-IIF (IIF: inverse item frequency) takes the first effort to treat each user as a document collection which enables the statistics of all items. Then the extent of other users using the tag can be counted via the global item statistics, and finally used as a factor to weight the tag.

After constructing profiles for users and items, the third contribution of us is to propose a Fusion Method (FM) for calculating similarity between networks, which is implemented by considering both the node and edge similarities. Since the structures of tag networks for users and items are the same, our method can be applied to either of them and as a result can be used in content-based recommendation [1] and collective-filtering recommendation [6]. Fig. 1 shows our

![Fig. 1: Recommendation framework](image-url)
recommendation framework. We use the tag network model to profile users and items, then calculate similarities between them to get the recommendation lists. Here we highlight that, this paper adopts Content-based recommendation to validate the effectiveness of our profiling methods, in fact, and our model is also applicable to Collaborative recommendations and so on.

The rest of this paper is organized as follows: Section 2 discusses related work; Section 3 introduces our methods; Section 4 presents experimental results that validate the effectiveness of our methodology; Finally, Section 5 concludes.

2 Related Work

With the development of social tagging systems, various recommendation technologies [1] are proposed to help users get useful item quickly and accurately. Recommendation methods are usually classified into the following categories: Content-based recommendations [3], Collaborative recommendations [8] and Hybrid approaches [4]. How to profile users and items is a key problem for recommendation. Most existing methods are based on tag vector, such as [7] uses the tag vector to profile users and items, in conjunction with the TF method for tag weighting. The authors in [11], [10] and [12] also use tag vector, and the methods they use for tag weighting are the NTF, TF-IUF and NTF-IUF respectively. Differently, our approach, based on a tag network model and using the NTF-IUF-IIF for tag weighting, can fully exploit the semantic relations between tags and accurately measure the user’s preference for tags.

Besides the tag vector model, there are also many other profiling methods. Tso-Sutter et al. in [9] extends the tag vector with items for user profiling while with users for item profiling, this method still can not overcome the shortage of tag vector. The authors in [6] use item-tag matrix to profile users for collaborative filtering. Though the item-tag matrix can capture the information of tagging behavior, it can not display the dynamic changes of users’ interest, this is caused by the fixed structure of item-tag matrix. In contrast, our approach can adapt to the variation of user’s interest by adjusting the structure of tag network continuously: adding new tags that the user begins to use and removing those the user haven’t used for a long time. In this paper, we mainly focus on static tag network, in the future work, we will introduce dynamic of tag network.

3 The Proposed Methods

In this section, we describe the proposed tag network model, the NTF-IUF-IIF method for weight calculation and the FM method for measuring similarity between networks in detail. Here, we illustrate these methods on users while applying them to items is in the same way.

3.1 Tag Network Model

A typical social tagging system includes three basic components: a set of users, \( U \); a set of items, \( I \); and a set of tags, \( T \). For a user \( u \in U \), it is usually profiled as a tag vector, \( u = (w_{t_1}, w_{t_2}, \ldots, w_{t_T}) \), in the tag space. Each weight \( w_{t_i} \) represents the interest degree of user \( u \) over tag \( t_i \). However, as we can see, no consideration of semantic relations between tags is taken in the tag vector.
To overcome this shortage and make full use of the rich tag relations, we present a novel profiling method based on a tag network model. The tag network of user $u$ can be formulated as an undirected graph $u = (V, E)$, where $V$ is the set of weighted nodes while $E$ is the set of weighted links. Each node represents a tag used by $u$, and its weight denotes the interest degree of the user over this tag, which is similar as in tag vector. Each link denotes the association relation between two tags, and its weight gives the strength of this relation. We use a vector $\vec{v}$ to record weights for nodes in $V$ and a matrix $M$ to record weights for links in $E$. Fig. 2 shows an example of the weighted tag network used to profile a user.

Fig. 2: An example of the weighted tag network. Larger node sizes indicate higher tag weights while rougher edges reflect stronger relations between tags

### 3.2 Node Weight

The weights of nodes indicate the interest degree of the user over tags, which is of significant importance in recommendation. In this part, we first analyze the general weighting mechanism which gives the antecedent of our improvement. Then we describe the proposed NTF-IUF-IIF method in detail, which is competent for accurately presenting the user’s preference. All the notations used are listed in Table 1.

<table>
<thead>
<tr>
<th>Label</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_t$</td>
<td>Set of items labeled with tag $t$</td>
</tr>
<tr>
<td>$I_u$</td>
<td>Set of items labeled by user $u$</td>
</tr>
<tr>
<td>$I_{u,t}$</td>
<td>Set of items labeled with tag $t$ by user $u$</td>
</tr>
<tr>
<td>$U_t$</td>
<td>Set of users using tag $t$</td>
</tr>
<tr>
<td>$U_i$</td>
<td>Set of users labeling item $i$</td>
</tr>
<tr>
<td>$U_{i,t}$</td>
<td>Set of users labeling item $i$ with tag $t$</td>
</tr>
</tbody>
</table>

### 3.2.1 Weighting Mechanism

All previous weighting methods treat each user as a single document, which contains all the tags a user labels to all items, see Fig. 3 (a). Traditional TF and NTF methods only focus on the use’s
own information and apply the frequency of the user used tag \( t \) to denote his interest degree in this tag \( t \):

\[
w_t^{(TF)} = |I_{u.t}|, \quad w_t^{(NTF)} = \frac{|I_{u.t}|}{|I_u|}
\]  

(1)

Obviously, this interest is in terms of his local field and do not take into account the global information of other users.

To overcome the shortage of TF and NTF, TF-IUF and NTF-IUF extend the consideration to other users, and NTF-IUF defines the weight by

\[
w_t^{(TF-IUF)} = (|I_u|) \times \log \left( \frac{|U|}{|U_t|} \right), \quad w_t^{(NTF-IUF)} = \left( \frac{|I_{u.t}|}{|I_u|} \right) \times \log \left( \frac{|U|}{|U_t|} \right)
\]  

(2)

it only simply counts the number of users who have used tag \( t \) (the second item), however, doesn’t consider the extents of they used.

### 3.2.2 The NTF-IUF-IIF Method

Since the structure of single document ignores the corresponding relationships between tags and items, traditional methods can not further compile the items labeled with a certain tag by other users, which indicate the extent of other users’ usage of this tag. To enable the statistics for all items, we view each user as a document collection, where each component document consists of tags labeled on the same item by the user, as shown in Fig. 3 (b). Based on this structure, we present a novel NTF-IUF-IIF method to calculate weights for tags, which measures the user’s preference by fusing the consideration of other users’ usage. Particularly, we not only consider whether other users have used this tag, but also specifically how much they have used, i.e. the number of items they have labeled with this tag. The proposed NTF-IUF-IIF method is formulated by:

\[
w_t^{(NTF-IUF-IIF)} = \left( \frac{|I_{u.t}|}{|I_u|} \right) \times \log \left( \frac{|U|}{|U_t|} \right) \times \log \left( \frac{|I_{u.t}| \times |I|}{|I| - |I_{u.t}| + 1} \right)
\]  

(3)

As we can see, the global item information is taken into account (the last item). For a user \( u \), the weight of tag \( t \) is proportional to the number of user \( u \) using tag \( t \) (\(|I_{u.t}|\)), is inversely proportional to the number of the other users except \( u \) using tag \( t \) (\(|I| - |I_{u.t}|\)), for solving the
problem of the denominator is zero ($|I_t| = |I_{u,t}|$, the other users did not use tag $t$), we set the denominator as $(|I_t| - |I_{u,t}| + 1)$. Under the same other conditions, the tag, which is used to label fewer items by other users, is more discriminative to user $u$ and can better present his preference.

Here, we take an example to illustrate the advantage of the proposed weighting method. Considering a dataset contains 100 users. User $u_1$ tags 100 items with $t_1$ “android” and 100 items with $t_2$ “iphone”. There are another 49 users, each of which also labels 100 items with “android” but only one item with “iphone”. The rest users do not use tag $t_1$ or $t_2$. We assume that there is no overlap between items labeled by different users. Then we calculate the weights of tag $t_1$ and $t_2$ for user $u_1$. Fig. 4 (a)(b) show the results of the traditional weighting methods. As we can see, the NTF and NTF-IUF methods assign equal weights for the two tags, since they do not consider the extent of other users’ usage of the tags. Actually, however, each of the 49 users uses the tag “iphone” for only one time, they are not very interested in it. Therefore, tag “android” can better reflect user $u_1$’s preference than “iphone” and should be largely weighted. The proposed NTF-IUF-IIF method, in contrast, by exploiting the item information labeled by other users, can measure user $u_1$’s preference accurately and assign more reasonable weights for tags, as shown in Fig. 4 (c).

For the tag network of item, the weight of tag $t$ can be calculated in the similarity method by:

$$w_t = \left( \frac{|U_{i,t}|}{|U_i|} \right) \times \log \left( \frac{|I|}{|I_t|} \right) \times \log \left( \frac{|U_{i,t}| \times |U|}{|U_i| - |U_{i,t}| + 1} \right)$$

(4)

### 3.3 Edge Weight

In our tag network model, if the user $u$ uses tag $t_m$ and $t_n$ to label a same item, a link $e_{mn}$ is then generated between the two tags. Its weight, representing the strength of this relation, can be counted as the number of items labeled with tag $t_m$ and $t_n$ by user $u$, i.e. $w_{mn} = |(I_{u,t_m}) \cap (I_{u,t_n})|$. 
Similarly in the tag network of item \(i\), if the item was labeled with tag \(t_m\) and \(t_n\) by the same user, then a link is generated between them. Its weight \(w_{mn}\) can be counted as the number of users who have labeled item \(i\) with tag \(t_m\) and \(t_n\), i.e. \(w_{mn} = |(U_{i,t_m}) \cap (U_{i,t_n})|\).

### 3.4 Similarity Measurement

Since we adopt content-based recommendation approach in this work, after constructing profiles for users and items as described above, we propose a Fusion Method (FM) to calculate the similarity between them. The FM firstly calculates the vector similarity \(S_{\vec{v}}\) and matrix similarity \(S_M\) by inner product, then use \(S_{\vec{v}} \ast (1 + S_M)\) to present the similarity of networks. The FM can measure the similarities not only between users and items, but also users and users. Therefore, it can be used in either user recommendation [13] or collaborative filtering.

### 4 Experimental Results

#### 4.1 Datasets and Metrics

In this section, we adopt two public datasets, MovieLens\(^1\) and CiteULike\(^2\), to test the proposed methods. Movielens dataset contains 3972 users, 14794 tags and 7540 items, while CiteULike dataset contains 119219 users, 767674 tags and 3863932 items. For each dataset, we removed non-English tags and those have been assigned to less than 10 items or used by less than 10 users.

From each dataset, we randomly pick 10% users as the test data and treat the remaining as training data. For each test user, we sort his items by time and choose the top 80% to construct the user profile while the rest are treated as ground truth for evaluation.

For evaluation metrics, we use Mean Average Precision (MAP) and Normalized Discount Cumulative Gain (NDCG) [2] to measure recommendation performance. Precision is defined as the number of correctly recommended documents (i.e. those which also appear in the user’s test bookmarks) divided by the number of all recommended documents. Average Precision (AP) is the average of precision scores after each correctly recommended item:

\[
AP = \frac{\sum_i Precision_{@i} \times corr_i}{No. of correctly recommended items}
\]

where \(Precision_{@i}\) is the precision at ranking position \(i\) and \(corr_i = 1\) if the document at position \(i\) is correctly recommended, otherwise \(corr_i = 0\). MAP is the mean of average precision scores over all test users. NDCG at position \(n\) is defined as:

\[
NDCG_{@n} = Z_n \sum_{i=1}^{n} (2^{r_i})/ \log_2(i + 1)
\]

where \(r_i\) is the relevance rating of item at rank \(i\). In our case, \(r_i\) is 1 if the corresponding item is in the users test items and 0 otherwise. \(Z_n\) is chosen so that the perfect ranking has a NDCG value of 1.

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\(^1\)http://www.grouplens.org/node/73

\(^2\)http://www.citeulike.org/faq/data.adp
4.2 Performance Evaluation

The evaluation in this section consists of three aspects corresponding to the three contributions of our work: 1) The tag network model; 2) The NTF-IUF-IIF method for weight calculation and; 3) The FM method for measuring similarity between networks. In order to show the improvements of these methods respectively, we compare them with the corresponding alternatives of tradition: 1) The widely used tag vector; 2) The NTF [11], NTF-IUF [12] methods for weight calculation; 3) The activation spreading (AS) method in [5] for measuring similarity between network and vector. Here, we employ it to calculate similarity between two networks by alternately regarding one of them as a vector. The compared methods are presented by Table 2.

The verification is carried out by implementing different combinations of the compared methods. Table 3 and Fig. 5 show the results of these combinations on MovieLens and CiteULike datasets. Then we analyse the performance of the proposed methods individually.

<table>
<thead>
<tr>
<th>The proposed methods</th>
<th>The baseline methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>tag network</td>
<td>tag vector</td>
</tr>
<tr>
<td>NTF-IUF-IIF</td>
<td>NTF/NTF-IUF</td>
</tr>
<tr>
<td>FM</td>
<td>AS</td>
</tr>
</tbody>
</table>

Table 3: MAP using different methods on MovieLens and CiteULike Datasets

<table>
<thead>
<tr>
<th>Dataset</th>
<th>MovieLens dataset</th>
<th>CiteULike dataset</th>
<th>Tag vector</th>
<th>Tag Network (AS)</th>
<th>Tag Network (FM)</th>
<th>Tag vector</th>
<th>Tag Network (AS)</th>
<th>Tag Network (FM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>NTF</td>
<td>0.0793</td>
<td>0.0850</td>
<td>0.0970</td>
<td>0.0291</td>
<td>0.0343</td>
<td>0.0425</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NTF-IUF</td>
<td>0.0867</td>
<td>0.0925</td>
<td>0.0978</td>
<td>0.0356</td>
<td>0.0358</td>
<td>0.0426</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NTF-IUF-IIF</td>
<td>0.0914</td>
<td>0.0968</td>
<td>0.1038</td>
<td>0.0488</td>
<td>0.0481</td>
<td>0.0563</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Tag network:** From Table 3 we can see that, under the same other conditions, using tag network can get larger MAP values than that using tag vector. Correspondingly, by comparing the lines same colored in Fig. 5 (a) (the same to Fig. 5 (c) for CiteULike dataset), we can easily notice the solid ones marked with circles are generally above the dotted ones marked with squares, demonstrating the superiority of the tag network model over the traditional tag vector.

**The NTF-IUF-IIF Method:** In Table 3, the MAP values using the proposed NTF-IUF-IIF method for weight calculation are obviously larger than that using traditional NTF and NTF-IUF. In Fig. 5 (a) (the same to Fig. 5 (b-d)), the red lines using NTF-IUF-IIF method lie higher than the corresponding same marked blue and green ones. All of these demonstrate the advantage of our proposed method, as well as the effectiveness of viewing the user as a document collection.

**The FM method:** As Table 3 shows, the MAP results using the proposed FM method to measure the similarity between networks, are more pleasant than those using traditional AS method. Moreover, for the same colored lines in Fig. 5 (b) (the same to Fig. 5 (d) for CiteULike dataset), the solid ones marked with circles are generally above the dotted ones marked with triangles, which indicates the superiority of the proposed FM method.
**Overall performance:** Best results are obtained by jointly using the proposed tag network, the NTF-IUF-IIF and the FM methods. As shown in Table 3, MAP of this combination increases 30.9% over that of traditional tag vector in conjunction with NTF [11] on MovieLens dataset and 93.4% on CiteULike dataset; increases 19.7% over that of tag vector in conjunction with NTF-IUF [12] on MovieLens dataset and 58% on CiteULike dataset.

**5 Conclusions**

We have presented a novel profiling method in this paper based on a weighted tag network model which can fully exploit the rich tag relations. Furthermore, in order to present the user’s preference accurately, we present a novel NTF-IUF-IIF method to calculate weights for tags. By regarding each user as a document collection, the statistics of all items is enabled to count the extent of other users’ usage of tags. Then the extent is taken into account by NTF-IUF-IIF as a factor for tag weighting. A Fusion Method (FM) is proposed for measuring similarities between tag networks of users and items to get the final recommendation lists. Experimental results have verified the reliability of our methods.
References


