Effective Personalized Recommendation in Collaborative
Tagging Systems

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ABSTRACT
Recently, collaborative tagging systems have attracted more
and more attention and have been widely applied in web
systems. Tags provide highly abstracted information about
personal preferences and item content, and are therefore po-
tential to help in improving better personalized recommenda-
tions. In this paper, we propose a tag-based recommenda-
tion algorithm considering the personal vocabulary and
evaluate it in a real-world dataset: Del.icio.us. Experimental
results demonstrate that the usage of tag information
can significantly improve the accuracy of personalized rec-
ommendations.

Categories and Subject Descriptors
H.2.8 [Database Management]: Database Applications-
Data mining; H.3.3 [Information Storage and Retrieval]:
Information Search and Retrieval-Information filtering

General Terms
Algorithms, Experimentation

Keywords
Personalized Recommendation, Diffusion, Collaborative Tag-
ging Systems, Folksonomy

1. INTRODUCTION
The exponential growth of web information has brought us
into an information overload era: We face too much data
and sources to be able to find out those most relevant and
interesting for us. Evaluating all these alternatives by our-
selves is not possible. As a consequence, an urgent problem
is how to automatically find out the relevant items for us.
Internet search engine \[3\] provides us a useful tool to find
out those information and it achieves great success over the
last decade. However, it does not take into account personal-
ized information and returns the same results for people
with far different habits. Comparatively, recommender sys-
tem \[15\], adopting knowledge discovery techniques to pro-
vide personalized recommendations, is now considered to be
the most promising way to efficiently gather the useful infor-
mation. Thus far, recommender systems have successfully
found applications in e-commerce \[16\], such as book recom-
mandations in Amazon.com \[11\], movie recommendations
in Netflix.com \[2\], video recommendations in TiVo.com \[1\],
and so on.

One of the most prominent techniques of recommender sys-
tems is Collaborative Filtering (CF), where a user is rec-
ommended items that people with similar tastes and pref-
erences liked in the past. Despite its success, the perfor-
mance of CF is strongly limited by the sparsity data. Thus,
a number of researches devoted to integrate additional in-
formation, such as user profiles \[10\], item content \[14\] and
attributes \[21\], to filter out possibly irrelevant recommenda-
dations. However, these applications are usually strongly
restricted to respect personal privacy, or limited due to the
lack of available content information.

Collaborative tagging systems (CTses), allowing users to
freely assign tags to their collections, provide promising pos-
sibility to better address the above issues. CTses require no
specific skills for user participating, thus can overcome the
limitation of vocabulary domains and size, widen the seman-
tic relations among items and eventually facilitate the emer-
gence of folksonomy \[9\]. In addition, tags can be treated as
abstracted content of items. Especially, tags are given by
users themselves and thus in somehow represent the per-
sonal vocabulary and preferences. In this paper, we propose
a tag-based recommendation algorithm to that takes into
account the personal vocabulary. We use one benchmark
data set, Del.icio.us, to evaluate our algorithm. Experimen-
tal results demonstrate that the usage of tag information
can significantly improve the accuracy of recommendations.

The rest of this paper is organized as follows. Section 2
reviews the related work. In Section 3 we introduce our
proposed algorithm and report the experimental results. Fi-
nally, we summarize this paper and outline some open issues
for future research in Section 4.

2. RELATED WORK
Recently, many efforts have been addressed in understanding
the structure, evolution \[4\] and usage patterns \[7\] of
CTses. A considerable number of algorithms are designed
to recommend tags to users, which may be helpful for bet-
ter organizing, discovering and retrieving items \[9\] \[12\] \[20\].
The current work focuses on a relevant yet different application of CTSes, that is, to provide personalized item recommendations with the help of tag information. Schenkel et al. [12] proposed an incremental threshold algorithm taking into account both the social ties among users and semantic relatedness of different tags, which performs remarkably better than the algorithm without tag expansion. Nakamoto et al. [13] created a tag-based contextual collaborative filtering model, where the tag information is treated as the users’ profiles. Tso-Sutter et al. [22] 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 reassociate these correlations. Chi et al. [3] presented a model considering probabilistic polyadic factorization for personalized recommendation. Shepitsen et al. [11] proposed a tag clustering-based method to improve the algorithmic accuracy. Zhang et al. [24] presented a diffusion-based hybrid algorithm for personalized recommendation in CTSes. Shang et al. [15] proposed a hybrid collaborative filtering algorithm on user-item-tag tripartite graphs.

### 3. ALGORITHM AND EXPERIMENTS

In this paper, we adopt a weighted variant of diffusion-based method proposed in [23], where the weights are given according to personal vocabulary in CTSes. A CTS consists of three sets, for users $U = \{U_1, U_2, \ldots, U_n\}$, items $I = \{I_1, I_2, \ldots, I_m\}$, and tags $T = \{T_1, T_2, \ldots, T_s\}$, respectively. Actually, it is easy to understand that different users may consider differently for the same item, and such difference can be characterized to some extent by looking into the different usage patterns of tags. Although those tags are freely given, people are supposed to give their most favorite words to describe their best collections. A latent assumption is that the more frequently a user uses a tag, the more likely the user likes this tag as well as the items labeled with it. On the other hand, users are not willing to give too many tags for a single item.

#### 3.1 Algorithm

In this subsection, we introduce a simple way that utilizes the tag information to provide better recommendations. As mentioned above, we will consider two factors: (i) the frequency of each tag used by each user; (ii) the number of tags assigned with a single item. Since our aim is to find the most relevant items for a particular user, so-called personalized recommendation, we will describe our algorithm for a target user $U_i$. The algorithm can be expressed in following steps:

**Step 1:** Define the initial value vector $\vec{f}$ for all the items, whose element reads:

$$f_j = \frac{1}{\sum_{j=1}^{m} \sum_{s'=1}^{s} K(t_{s'})} \sum_{s=1}^{s} K(t_s),$$

where $|T_{ij}|$ denotes the number of tags that $U_i$ has assigned to item $I_j$, and $K(t_s)$ is the number of times tag $t_s$ has been used by $U_i$.

**Step 2:** Distribute the value of each item evenly to the users who collect it, then the value a user $U_i$ will receive reads:

$$r_j = \sum_{j \in \Gamma(U_i)} \frac{f_j}{d(I_j)},$$

where $\Gamma(U_i)$ denotes the set of items collected by $U_i$, and $d(I_j)$ is the degree of $I_j$ in the user-item bipartite graph.

**Step 3:** Redistribute the value of each user $U_i$ to his/her collections according to the weight defined in Step 1. Then the final value vector $\vec{f}'$ of items will be summarized as:

$$f'_j = \frac{r_k}{\sum_{k=1}^{m} \sum_{s'=1}^{s} P(t_{s'})} \sum_{s=1}^{s} K(t_s),$$

where $|U_{I_j}|$ is the number of users collected item $I_j$.

The above procedure constitutes of a mutual reinforcement process that allows the values transferred between users and items. At the first step, we highlight the items selected by $U_i$ and assign each of them with an initial value according to $U_i$’s tagging activities. Step 2 transfers values from items to users. In Step 3, we consider the personal vocabulary again and distribute the values to items, which generates final score for each item. Finally, we sort these scores in a descending order, and the top items having not been collected by $U_i$ will be the recommended to $U_i$.

In CTSes, different individuals have different sizes of vocabulary, and each tag may take different significance. Some tags are frequently used while some others are seldom picked. Those frequently used tags should be of higher importance in the user’s viewpoint. If the user applies those frequently used tags to a specific item, it would indicate that this user prefers it to some other items assigned with infrequently used tags. Similar phenomenon also widely exists in our daily life, one can imagine that people are willing to illustrate a question using their familiar words. In addition, the number of tags assigned to an item represents how willing the user likes to describe it. By aggregating the fractions of all the tags labeling a specific item, one can estimate the importance of this item.

### 3.2 Data Set

We use a benchmark dataset, Del.icio.us, to evaluate the proposed algorithm. Del.icio.us is one of the most popular social bookmarking web sites, which allows users not only to store and organize personal bookmarks (URLs), but also to look into other users’ collections and find what they might be interested in by simply keeping track of the pools with same tags or items. The data used in this paper is crawled from the website [http://del.icio.us/](http://del.icio.us/) in May 2008. We guarantee that each user has collected at least one item, each item has

| Value     | Description          |
|-----------|----------------------|
| 9,991     | number of users      |
| 243,137   | number of items      |
| 102,752   | number of tags       |
| 1,257,908 | number of user-item  |
| 4,391,073 | accumulative number  |
been collected by at least two users, and assigned by at least one tag. Table 1 summarizes the basic information of the data set.

3.3 Experimental Results
To test the algorithmic performance, the data set is randomly divided into two parts: the training set, which is used as known information, contains 95% of entries, and the remaining 5% of entries constitute the testing set. We employ three metrics to characterize the algorithmic accuracy: Precision, Recall and F1, which are defined as follows:

\[
\text{Precision} = \frac{\sum_i N_i^r}{nL}, \quad (4)
\]

where \( n \) is the number of users, \( L \) is the length of recommendation list, and \( N_i^r \) is the number of recovered items in the recommendations for user \( U_i \).

\[
\text{Recall} = \frac{\sum_i N_i^r}{\sum_i N_p^r}, \quad (5)
\]

where \( N_i^p \) is the number of items collected by user \( U_i \) in the testing set.

\[
F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)
\]

Figure 1, Figure 2 and Figure 3 show the experimental results of Precision, Recall and F1 respectively. Since the typical length for recommendation list is tens, our experimental study focuses on the interval \( L \in [10, 100] \). For comparison, we choose the method described in [25] as the baseline algorithm. It can be seen that our proposed algorithm considering the personal vocabulary significantly outperforms the baseline method in all the three measurements.

4. CONCLUSION AND DISCUSSION

In this paper, we proposed an tag-based algorithm that takes into account the personal vocabulary. Our algorithm is based on the following hypotheses: (i) Tags assigned to a certain item by a particular user represent personal tastes of it. Even for the same item, different individuals may give different tags. (ii) Different tags play different roles for the same user. The frequency of tags might suggest the personal preferences: the higher the frequency, the more the user likes it. Experimental results demonstrate that the usage of tag information can significantly improve accuracy of personalized recommendations.

Recently, the collaborative tagging systems have attracted more and more attention both in the scientific and engineering worlds [1, 23]. A great number of publications and web applications have discussed/adopted tagging functions. Our experimental results show that tags can be used to not only assist personal resources organizing, but also help to filter out mass information. This paper only provides a simple way to consider the use of tags, and a couple of open issues remain for future study. From the perspective of human dynamics, the rank of tags within a single collection and the time the user chooses tags could also be taken into account. In addition, the hypergraph [6] description is a promising tool to exploit a comprehensive view of CTSes and bring us an in-depth understanding to the structure and evaluation of CTSes.

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