Personalized Service Recommendation for Collaborative Tagging Systems with Social Relations and Temporal Influences

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***Abstract*—Personalized service recommendation becomes increasingly essential because of the growing number of services. To enhance the performance of personalized service recommendation in collaborative tagging systems, not only tag information but also time and social relations information should be considered. In this paper, we propose a hybrid method aiming at taking advantage of tag, time and users' social relations information for a preferable service recommendation. We first improve a simple tag-based recommendation method by a time-decay function. Then we develop a temporal social-based recommendation method which analyzes user familiarity and user preference similarity between friends. Based on these two steps we integrate them as a temporal tag- and social-based (TTS) recommendation algorithm. Experiment results indicate that our method outperforms general tag-based and social-based recommendation methods.**

Keywords-service recommendation; collaborative tagging systems; user relations; temporal influences

I. INTRODUCTION

Nowadays, people have to make more effort to choose suitable services for some certain purposes when facing the increasing number of services. There are many methods for solving this problem. For example, predicting users' preference basing on quality of service (QoS) [1,2] or recommending services according to the similarity among users or services [3]. Moreover, collaborative tagging is also one of methods which are able to assist people to share and select services appropriately.

Collaborative tagging systems, also called folksonomy or social tagging systems, allow general users to label services with personalized tags. When labeling services, users can adopt a previously-used tag or create a new one. Moreover, they can use several tags for one service or the same tag for several services. Delicious, for instance, is a famous collaborative tagging website allowing users to bookmark any webpages with their own tags. Last.fm is another collaborative tagging website that presents music for users to tag in order to provide personalized service recommendation.

However, to achieve superior service recommendation, not only tag information should be considered but also other context information could be utilized. In real world, user's preference is not always fixed and may change with time. Furthermore, their preference can be affected by their friends, especially the friends with whom they are familiar or even have similar preferences in some areas. Therefore, time and users' social relations information are apparently important. Integrating tag information with these two types of information enhances the performance of recommendation in collaborative tagging systems. Based on this conclusion, the main contribution of our work is a new temporal tag- and social-based (TTS) recommendation algorithm.

The rest of this paper is organized as follows. We first review related works in Section Ⅱ and then describe the proposed method which integrates both temporal tag-based and temporal social-based recommendation algorithm in Section Ⅲ. In Section Ⅳ, we evaluate our method through the experiment results. Finally, we conclude this paper in Section Ⅴ.

II. RELATED WORK

Since tags can be regarded as users' personal opinion expression and even can be considered as implicit rating on services, tag information are certainly useful to enhance recommendation [4]. Service recommendation algorithms for tag-based recommender systems have been studied by several previous works. In tag-based recommender systems, user-service relation is extended to user-tag-service [5]. Tso-Sutter et al. [6] reduced this three-dimensional correlation to three two-dimensional contexts by extending standard user-service matrix with user tags as services and service tags as users. Ifada and Nayak [7] employed probabilistic ranking method based on tensor while Hotho et al. [8] employed tripartite graph with FolkRank which is inspired from the PageRank algorithm. On the other hand, Cohn and Hofmann [9] improved probabilistic latent semantic analysis (PLSA) in terms of document clustering while Wetzker et al. [10] improved PLSA in the aspect of topic model. However, these methods only focus on user-tag-service relations and do not take into account other elements such as time or social relations which can influence the prediction of users' preference.

In the aspect of time, the effectiveness of temporal modeling to enhance service recommendation has already been proved in [11] and [12]. Thus, considering that tags can reveal users' preference and users' preference drifts over time, time is certainly an important factor to achieve more accurate personalized service recommendation in collaborative tagging systems. Zheng and Li [13] built a resource-recommendation model that combines tag and time information in collaborating filtering (CF). In [14], Lacic et al. proposed a two-step collaborative service ranking using tag and time information approach that integrates user- and service- CF with Base-Level Learning (BLL) equation. Although these models are able to model the shift of users' preference over time, they do not consider the impact of friends.

As for social relations referring to users' friend relations, this information has already been adopted in many real-world service recommendation. The main reason for its application is that users are easily influenced by the friends they trust, especially those who have similarity preference. Thus, several previous works have studied on it. Konstas et al. [15] created a collaborative recommendation system with a Random Walk with Restarts (RWR) model by taking into account of both the social annotation and friendships inherent among users, services and tags. According to conventional similarity-based CF and trust-based service recommendation methods, Tang et al. [16] presented a hybrid service recommendation method which bases on the user-service relation and user-user social relation. Moreover, Chen et al. [17] extended the Bi-LDA model with social relations and temporal dynamic for normal service recommendation without tags. While these works prove the importance of social information, they study social network with tag, social trust and social relations with time separately. Therefore, in this work, we model users' preference change with tag, time and social relations information together for service recommendation.

III. PROPOSED METHOD (TTS)

In this section, we introduce a recommendation method that fuses temporal tag-based and temporal social-based service recommendation. This method has three major components. First, it improves a simple tag-based recommendation algorithm with temporal dynamic. Then it analyzes the social relations which can impact on service recommendation and models the similarity of users' preference over time. Finally, it integrates the former two components to generate a hybrid algorithm for achieving a more accurate service recommendation via tag, time and social relations information.

A. Temporal Tag-based Recommendation

In common collaborative tagging systems, users use different tags to tag different services. A tag can be used for many services while a service can be tagged by many tags. Therefore, for each candidate user u in the candidate user set to each candidate service i we calculate the preference value $p_{tag}(u,i)$ by a simple tag-based recommendation algorithm:

$$p_{tag}(u,i) = \sum_{g \in G(u) \cup G(i)} n_{ug} n_{gi} \tag{1}$$

where $G(u)$ is the set of tags the target user u has adopted, $G(i)$ is the set of tags the target service i has been labeled, n_{ug} is the number of times the tag g has been adopted by the user u and n_{gi} is the number of times the same tag g has been labeled for the service i.

However, this equation tends to recommend popular services corresponding to popular tags. To decrease the weight of popular tags and popular services, we develop the equation by introducing the thought of Term Frequency–inverse Document Frequency (TF-IDF):

$$p_{tag}(u,i) = \sum_{g \in G(u) \cup G(i)} \frac{n_{ug}}{\log(1+n_g^{(u)})} \frac{n_{gi}}{\log(1+n_i^{(u)})} \tag{2}$$

where $n_g^{(u)}$ is the number of users who use the tag g while $n_i^{(u)}$ is the number of users who label the service i.

As users' preference is not static and usually shifts over time, improving the original recommendation algorithm with temporal modeling is able to increase the precision of recommendation.

Assume that a user labeled the service i_1 one year ago and service i_2 one month ago. Obviously, the later behavior is more closed to the current preference of this user than the former one. Thus, it should give priority to recommend services based on recent behaviors of users. To achieve this purpose, we calculate the preference value $p_{tag}(u,i)$ by adding a time-decay factor α:

$$p_{tag+time}(u,i) = \sum_{g \in G(u) \cup G(i)} \frac{n_{ug}}{\log(1+n_g^{(u)})} \frac{n_{gi}}{\log(1+n_i^{(u)})} \frac{1}{1+\alpha\left|t_0 - t_g\right|} \tag{3}$$

where t_0 is the present time and t_g is the latest time the user u uses the tag g. In this equation, the parameter $\alpha \in [0,1]$ denotes the effectiveness of the time decay.

B. Temporal Social-based Recommendation

The simplest social-based recommendation method for a target user is recommending the services which the friends of this user prefer. Nevertheless, becoming friends does not mean that two people share a same preference totally. Hence, in order to take advantage of social relations information to gain better effectiveness of recommendation, we should not only take into account user familiarity but also pay attention to friend performance similarity when we calculate user importance of one user to the others.

Let us suppose for a candidate user u in the candidate user set, w_{uv} is the user importance of a candidate user v in the set of friends the target user u has. Then for the user u to each candidate service i we calculate the preference value $p_{social}(u,i)$ as follows:

$$p_{social}(u,i) = \sum_{v \in F(u)} w_{uv} r_{vi} \tag{4}$$

where $F(u)$ is the set of friends whom the target user u has, r_{vi} is the preference of the user v to the service i. As the rating information in tagging systems is usually implicit, here we set r_{vi} =1 if the user v has tagged the service i, otherwise r_{vi} =0.

Based on the discussion above, the user importance w_{uv} should contain two components including user familiarity and user preference similarity. Therefore, we should calculate these two elements first.

1) User familiarity Calculation

Generally, it can be considered that two users are familiar if they have many joint friends. Based on this view, we calculate the user familiarity $fam(u,v)$ by measuring the ratio of their joint friends:

$$fam(u,v) = \frac{|F(u) \cap F(v)|}{|F(u) \cup F(v)|}, v \in F(u) \quad (5)$$

where $F(u)$ is the set of friends whom the target user u has.

2) User preference similarity Calculation

The method to measure user preference similarity is similar to user-based CF. We calculate the user preference similarity $sim(u,v)$ by measuring the ratio of their joint favorite services:

$$sim(u,v) = \frac{|I(u) \cap I(v)|}{|I(u) \cup I(v)|}, v \in F(u) \quad (6)$$

where $I(u)$ is the set of services the target user u prefers.

3) *User Importance Calculation*

Simply, we can calculate the user importance w_{uv} directly as the product of the user familiarity $fam(u,v)$ and the user preference similarity $sim(u,v)$. In this case, supposing that user u and user v do not have any joint friends, their user familiarity $fam(u,v)=0$, which leads to the user importance $w_{uv}=0$. Then the final recommended services to the user u do not include any services that the user v prefers whether they have high user importance or not. It is obviously unreasonable in real world. Thus, we should adjust the equation of user importance w_{uv}:

$$w_{uv} = (1 + fam(u,v)) \times sim(u,v) \quad (7)$$

In this equation, when $fam(u,v)=0$, w_{uv} only relies on the user preference similarity $sim(u,v)$; when $0 \leqslant fam(u,v) \leqslant 1$, w_{uv} is determined by both $fam(u,v)$ and $sim(u,v)$.

4) Social-based Recommendation with Time-decay Factor

As the same reason to add temporal modeling into tag-based recommendation, here we also add a time-decay factor β when calculate the preference value $p_{social}(u,i)$:

$$p_{social+time}(u,i) = \sum_{v \in F(u)} w_{uv} r_{vi} \frac{1}{1 + \beta |t_{ui} - t_{vi}|} \quad (8)$$

where t_{ui} is the time the user u labels the service i and t_{vi} is the time the user v labels the service i. Here $\beta \in [0,1]$ presents the same function as α.

C. Hybrid Temporal Tag & Social based Recommendation

Finally, let us fuse the two recommendation algorithm described above. Considering that the temporal social-based recommendation only focuses on the services which the friends of a target user u prefer, it leads to $p_{social+time}(u,i)=0$ if the user preference similarity $sim(u,v)=0$. Therefore, we should avoid the situation that the final preference value $p(u,i)$ becomes zero once $p_{social+time}(u,i)$ equals to zero. As a result, we calculate the final preference value $p(u,i)$ as follows:

$$p(u,i) = p_{tag+time}(u,i) \times (1 + p_{social+time}(u,i)) \quad (9)$$

In this equation, when $p_{social+time}(u,i)=0$, $p(u,i)$ actually presents the temporal tag-based recommendation; when $0 \leqslant p_{social+time}(u,i) \leqslant 1$, $p(u,i)$ is influenced by both tag, time and social relations information.

After that, we are able to gain recommendation basing on the value of $p(u,i)$.

IV. PERFORMANCE EVALUATION

This section evaluates the performance of our service recommendation method by comparing the precision and several general tag-based and social-based recommendation methods.

A. Experimental Settings and Evaluation Measures

The dataset we used in our experiments is from the well-known social bookmarking website Delicious[1]. This dataset consists of two files. One file contains 437,593 tagging behaviors provided by 1,867 users, 38,581 bookmarks and 53,388 tags with timestamp over the period from November 2003 to November 2010. The other file contains 7,668 bi-directional user relations among the same users.

This dataset is divided into training data and testing data according to the order of timestamps. In detail, for each user, we first order the behavior of users to each service by the timestamps, and then select the latest behavior of each user as testing data so that the remainder is training data.

We employ the top-N recommendation and recommend N services for each user. The N services are those with the highest preference value but without being tagged by the user in training data.

To assess the performance of recommendation, we use Precision which is defined as follows:

$$Precision_N = \frac{\sum_u |R(u,N) \cap T(u)|}{\sum_u |R(u,N)|} \quad (10)$$

where $R(u,N)$ denotes the top-N recommendation list for a user u, $T(u)$ denotes the services that the user u prefers in the testing data.

B. Evaluation

To evaluate the performance of our temporal tag- and social-based recommendation (TTS) method, we compare it with four other recommendation methods:

- Tag-based method (Tag): This is a simple model that bases the using frequency of tags. No time and social relations information is employed.
- Social-based method (Social): This is a simple model that utilizes friends' information. No time and tag information is considered.
- Temporal tag-based method (Ttag): This is an improved method that integrates tag-based method with temporal influences. No social relations information is utilized.
- Temporal social-based method (Tsocial): This is an improved method that combines social-based method with temporal influences. It does not incorporate tag information.

Figure 1 indicates the precision curve for different value N in top-N recommendation. According to the experiment results, we can prove that single temporal modeling indeed enhance the performance of recommendation. Moreover, combining temporal and social relations modeling together achieves better performance.

[1] Delicious website, http://www.delicious.com

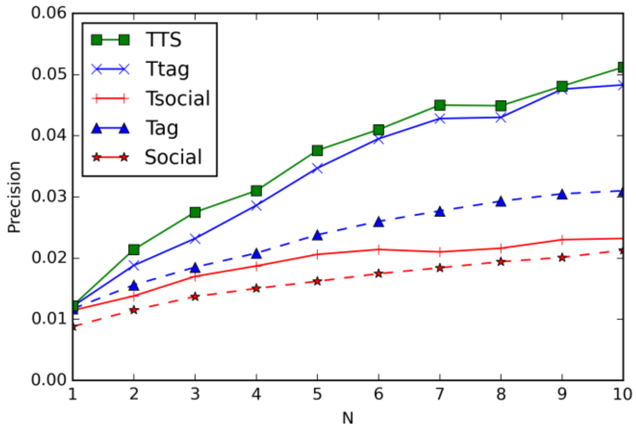

Figure 1. Precision curve for different valua of N

C. Parameter Estimation

There are two time-decay factors, α and β, in our hybrid service recommendation method. Figure 2 demonstrates the experiment results of precision for different values of α in temporal tag-based and β in temporal social-based Recommendation, respectively.

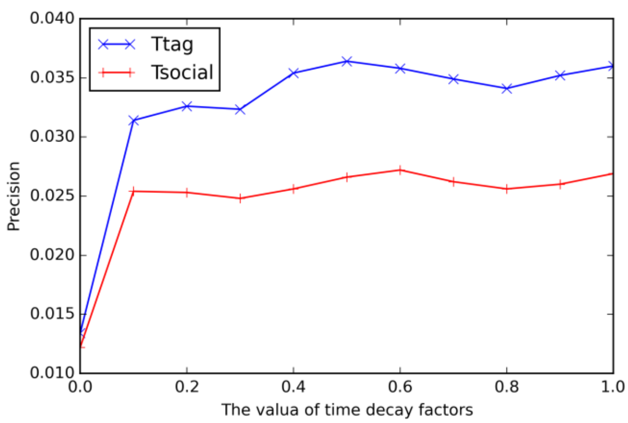

Figure 2. Precosion Curve for different value of α and β

In equation (3) and (8), the functions employing these factors are similar. The range of α and β we set here is from 0 to 1. Based on equation (3), when α = 0, the time-decay function equals to 1 and the preference value is simply relies on the tag-based recommendation algorithm. It has the same situation in equation (8), in which the preference value bases on the social-based recommendation when β = 0.

V. Conclusion and Future Work

In this paper, we have proposed a personalized service recommendation method for collaborative tagging systems with time and social relations information. This method considers the influence of both time and social relations for users' preference. Experiment results demonstrate that our method outperforms general tag-based and social-based recommendation methods.

Additionally, our future work will aim at conducting further improvement for our method by evaluating the performance of our method in diversified datasets and also with more different recommendation methods.

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