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TIME-AWARE SOCIAL RECOMMENDATION BASED ON USER FEEDBACK

XING XING, WEISHI ZHANG, XIUGUO ZHANG

School of Information Science and Technology, Dalian Maritime University, Dalian 116026, China

ABSTRACT

Context information such as time, social relationship and user feedback information can be exploited to improve the quality of recommendation. However, most collaborative filtering based methods ignore this kind of information in social recommendation. In this paper, we propose a time-aware social recommendation method based on user feedback for top-k item recommendation in social networks. Our method incorporates the temporal factors by introducing a time weight function, which models the decay of user interest. Moreover, our method considers the user positive feedback and negative feedback information, as well as the social relationship information for recommendation. Empirical analysis and experiments are conducted in Sina Weibo, one of the most popular social network sites in China. The experimental results demonstrate that our method outperforms the collaborative filtering method in terms of MAP for top-k item recommendation.

Keywords: *Collaborative Filtering, User Feedback, Time-aware Recommendation, Social Network*

1. INTRODUCTION

Recently social networks, such as Facebook, Twitter, Sina Weibo, and Google+, are becoming the major platforms of Internet, with millions of or even a billion users (Facebook) from all over the world. The amount of user-generated information in social networks is increasing far more quickly than user's ability to deal with it (called information overload), which has become so prevalent in today. The key to success is to provide accurate recommendation services for users to filter the information in social networks.

Collaborative filtering is one of the most successful solutions to the information overload issue , which has been widely used in real world recommendation systems such as GroupLens [1] and Amazon.com [2]. Collaborative filtering methods build on the user-item similarity measures [3], and the basic idea underlying collaborative filtering methods is that if two users have historically had similar interests on some items, they are likely to be interested in other items similarly. However, collaborative filtering methods ignore the context information such as time, social relationship and user feedback information, which can be exploited in order to produce more accurate recommendations.

In this paper, we present a time-aware social recommendation method based on the user feedback information. The intuition underlying our method is that the most recent preferences of the active user reflect in a better way of his actual preferences in a near future, moreover, both the positive feedback and negative feedback reflect the user interest preferences.

Motivated by this intuition, we introduce a time weight function to model the decay of user-item interest. Then we combine both positive feedback and negative feedback, together with the social relationship information to predict the interest of the active user. We evaluate the effectiveness of our method in a real scenario of top-k item recommendation on Sina Weibo, which is one of the most popular social network sites in China. The experimental results show that our method is able to improve the performance of recommendation in terms of MAP.

The rest of paper is organized as follows. In Section 2, we describe the formalization of time-ware social recommendation. In Section 3, we propose a time-aware social recommendation method based on user feedback. Section 4 presents experimental settings and reports the results. Section 5 gives an overview of related work. We make a conclusion in Section 5.

2. PROBLEM FORMALIZATION

In this section, we first give three definitions for representing the social networks and user feedback. And then we formalize the task of time-aware social recommendation.

The social network can be represented as a graph $G = (V, E)$, where V is a set of vertices

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corresponding to users or items, and *E* is a set of edges corresponding to the relations connecting two vertices. Figure 1 depicts a typical example of social network graph with timestamps, where user-item click network is high correlated with user-user follow relationship network.

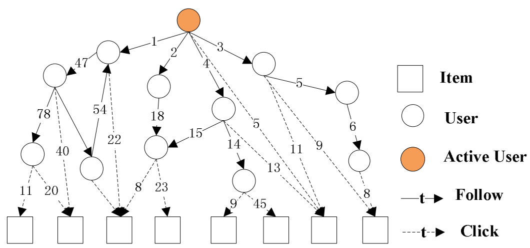

Figure 1: An Example Of Social Network Graph With Timestamps

In order to incorporate the temporal factors and user feedback information into recommendations, we define three representations as follows.

Social Graph Representation: Let a social graph $G_S = (V, follow, \mathcal{T}, u)$ such that *V* represents a set of users $U = \{u_1, u_2, ..., u_n\}$ in online social networks, *follow* represents the social relationship *followship* between a pair of users at a time *t*, $\mathcal{T}$ represents the following timestamps, and *u* is the active user.

The neighbors of the active user *u* given time *t* is defined by

$$Neighbor(u,t) = \{u' \mid (u,u') \in G_S, t_{u,u'} \le t, u, u' \in U\} \quad (1)$$

where $t_{u,u'}$ denotes the timestamp when *u* follows *u'*.

Positive Feedback Representation: Let a graph $G_+ = (V, click, \mathcal{T}, u)$ such that *V* represents a set of users $U = \{u_1, u_2, ..., u_n\}$ and a set of items $\mathcal{I} = \{i_1, i_2, ..., i_m\}$, and *click* represents the user-item *click* relationship from U to $\mathcal{I}$ at the time *t*, $\mathcal{T}$ represents the clicked times of U to $\mathcal{I}$ and *u* is the active user.

The items clicked by the active user *u* given time *t* are defined as

$$\mathcal{I}^+(u,t) = \{i \mid (u,i) \in G_+, t_{u,i} \le t, u \in U, i \in \mathcal{I}\} \quad (2)$$

where $t_{u,i}$ denotes the time when *u* clicks *i*.

The user-item click information can be viewed as the positive feedback of the active user. Meanwhile, there exists another kind of feedback such as the recommended items not clicked by the active user. This kind of feedback is considered as the negative feedback of the active user.

Negative Feedback Representation: Let a graph $G_- = (V, unclick, \mathcal{T}, u)$ such that *V* represents a set of users $U = \{u_1, u_2, ..., u_n\}$ and a set of items $\mathcal{I} = \{i_1, i_2, ..., i_m\}$, and *unclick* represents the user-item *unclick* relationship from U to $\mathcal{I}$ at the time *t*, $\mathcal{T}$ represents the unclick times of U to $\mathcal{I}$, and *u* is the active user.

Similarly, we use $\mathcal{I}^-(u,t)$ to denote the negative feedback of the active user, given time *t*.

$$\mathcal{I}^-(u,t) = \{i \mid (u,i) \in G_-, t_{u,i} \le t, u \in U, i \in \mathcal{I}\} \quad (3)$$

To consider the temporal effects in recommendations, we define the recommendation items for the active user *u* given time *t* as

$$\mathcal{I}^{rec}(u,t) = \mathcal{I} - \mathcal{I}^+(u,t) - \mathcal{I}^-(u,t) \quad (4)$$

Time-aware Social Recommendation: Given a time *t*, the time-aware social recommendation is to learn a target function $\mathcal{F}$, which satisfies

$$\mathcal{F}(i \mid u, t, G_S, G_+, G_-) \to \Re \quad (5)$$

where $i \in \mathcal{I}^{rec}(u,t), u \in U$.

Finally, the top-k item recommendation list in online social networks can be obtained in a descending order based on the predictions using Equation (5).

3. OUR METHOD

The user interest is dynamic, which implies that the recommendation quality is sensitive to time. To improve the quality of recommendation, the recommendation method should assign different weights based on the different intervals of time between two clicks of the same item. Moreover, user feedback provides additional information that can be exploited in determining user interest and building the recommendation method.

To incorporate the temporal factor and user feedback information into the recommendation method, we define a time-weighted user interest similarity measure based on user feedback as

$$sim^t(u,u') = \alpha \frac{\sum_{i=1}^{k} weight(t_{u,i} - t_{u',i})}{\left|\mathcal{I}^+(u,t) \cup \mathcal{I}^+(u',t)\right|} + (1-\alpha) \frac{\sum_{i=1}^{k'} weight(t'_{u,i} - t'_{u',i})}{\left|\mathcal{I}^-(u,t) \cup \mathcal{I}^-(u',t)\right|} \quad (6)$$

where

- α is a control parameter to be determined in the experiments,

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- $k = \left| \mathrm{I}^{+}(u,t) \bigcup \mathrm{I}^{+}(u',t) \right|$ denotes the common interest between *u* and *u'* by the positive feedback,
- $t_{u,i}$ is the time when *u* clicks *i*,
- $k' = \left| \mathrm{I}^{-}(u,t) \bigcup \mathrm{I}^{-}(u',t) \right|$ denotes the common interest between *u* and *u'* by the negative feedback,
- $t'_{u,i}$ is the time when *u* refuses to click *i*.

Note that if we set $\alpha = 1$ in Equation (6), then only positive feedback affects in the similarity computation.

Let $\Delta t = t_{u,i} - t_{u',i}$, the time weight function is defined as

$$weight(\Delta t) = \begin{cases} e^{-\lambda \cdot \Delta t}, & \Delta t \geq 0 \\ 0, & \Delta t < 0 \end{cases} \quad (7)$$

The time weight function is a monotonic decreasing function in the range from [0, 1], which reduces uniformly with the interval of time Δt at the decay rate λ. The idea underlying the defined time weight function for recommendation is that the more recent the user-item data, the more contributions to the similarity computation. The old data reflects users' previous preferences, thus it should be assigned a small weight. The decay rate of data is determined by the parameter λ, which means the higher the value of λ, the faster data decays, and as a result the less importance of the data.

To take the social relationship into consideration, we propose a time-aware social recommendation method based on similar neighbors in social networks to model the target function F as follows.

$$\mathrm{F} \equiv p(i \mid u,t,G_S,G_+,G_-) = \frac{\sum_{u' \in Neighbor(u,t)} sim^t(u,u') \times click^t(u',i)}{\sum_{u' \in Neighbor(u,t)} sim^t(u,u')} \quad (8)$$

where $i \in \mathrm{I}^{rec}(u,t), u \in \mathrm{U}$ and $click^t(u',i) = 1$, if $t_{u',i} \leq t$ otherwise 0.

Algorithm 1

Algorithm 1: Time-aware social recommendation method

Input: $u, t, t', G_S, G_+, G_-, \alpha, \lambda$

$List(u,t') \leftarrow \varnothing$
while $i \in \mathrm{I}^{rec}(u,t)$ do
  Compute $p(i \mid u,t,G_S,G_+,G_-)$ according to Equation (6), (7), (8)
  $List(u,t') \leftarrow (i, p(i \mid u,t,G_S,G_+,G_-))$
  $i = i + 1$
end
Sort $List(u,t')$ based on $p(i \mid u,t,G_S,G_+,G_-)$ in a descending order

Output: top-*k* item recommendation list $List(u,t')$

Algorithm 1 describes the recommendation process of our method for top-k item recommendation in online social networks. We need find an appropriate λ, which determines the decay rate of user interest, and α, which determines the combination of user positive and negative feedback for recommendation.

4. EXPERIMENTS

In this section, we have conducted several experiments on a real dataset collected from Sina Weibo. We present the experimental results of our method compared with the collaborative filtering method.

4.1 Data description

We collected the data from Sina Weibo, one of the most popular online social network sites in China, between October 12th, 2011 and November 12th, 2011.

We cleaned up the data by excluding the user who clicked less than 100 items or with less than 10 followees, in order to reduce effects of the data sparsity issue [4] for recommendations.

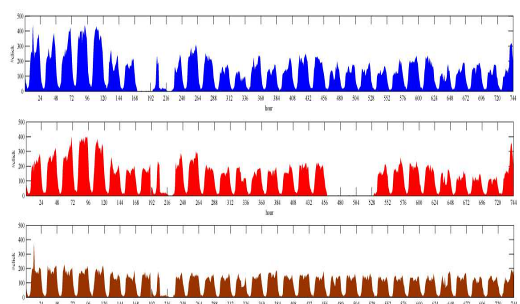

Figure 2: Top-3 Clicked Items Changing Over Time

The data has 6,101 users, 2,343 items, 954,015 clicked item logs (with clicked timestamps), 1,203,421 unclick item logs, and 132,747 followship connections. Figure 2 shows the number of top-3 clicked items changing over time.

4.2 Experimental setup

Our goal is to develop a time-aware social recommendation method, which can provide high quality recommendations for the task of top-k item recommendation in social networks. To investigate

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the quality of our method, we use mean average precision (MAP) and average precision at *k* (AP@*k*) as the evaluation metrics [5, 6]. MAP is the mean of AP@k over a set of queries and is widely used in rank-based systems.

We compare our method with the collaborative filtering method. Specially, we implement the item-based top-k item recommendation method proposed in [3] as the baseline method for comparisons. We divide the dataset into a training set with the item clicked time before November 2nd, 2011 and a test set from November 3rd, 2011 to November 12th, 2011 for evaluating the methods.

4.3 Experimental results

In the first experiment, we set the parameter *k* by given top5, top10, top15 and top20 respectively. We vary the value of λ from 0.5, 0.01 to 0.005, and α 0.2, 0.4, 0.6, 0.8, 1.0, to investigate the impact of λ and α for top-k item recommendation in social networks.

The performance of our method using different λ and α is shown in Figure 3 and Table 1 respectively. Different settings of the decay rates have different impacts on the performance of our method. The parameter λ controls the decay rate of user interest and affects the performance of our method. Furthermore, we combine positive feedbacks and negative feedbacks to model the user interest, using the parameter α to determine the weights of them. Note that if we set $\alpha = 1.0$, then negative feedback has no effect on the social recommendation.

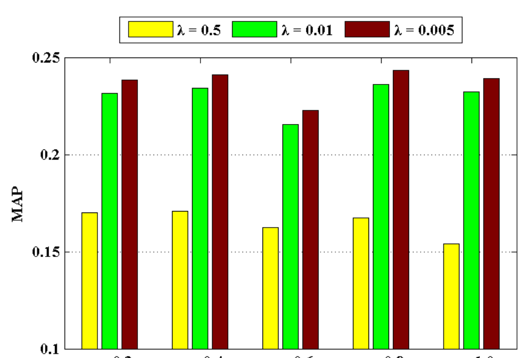

Figure 3: Performance In Terms Of MAP With Varying λ And α

Table 1: Performance Of Our Method In Terms Of AP@K And MAP With Varying λ And α

Metrics	α	$\lambda = 0.5$	$\lambda = 0.01$	$\lambda = 0.005$
AP@5	0.2	0.1128	0.1420	0.1500
AP@10		0.1671	0.2196	0.2265
AP@15		0.1974	0.2727	0.2796
AP@20		0.2040	0.2932	0.2993
MAP		0.1704	0.2319	0.2388
AP@5	0.4	0.1113	0.1358	0.1437
AP@10		0.1717	0.2248	0.2317
AP@15		0.1964	0.2778	0.2848
AP@20		0.2043	0.2995	0.3056
MAP		0.1709	0.2345	0.2414
AP@5	0.6	0.1091	0.1398	0.1477
AP@10		0.1596	0.2113	0.2182
AP@15		0.1873	0.2486	0.2555
AP@20		0.1939	0.2641	0.2702
MAP		0.1625	0.2159	0.2229
AP@5	0.8	0.1120	0.1419	0.1498
AP@10		0.1691	0.2307	0.2376
AP@15		0.1916	0.2766	0.2835
AP@20		0.1975	0.2969	0.3030
MAP		0.1676	0.2365	**0.2435**
AP@5	1.0	0.0964	0.1378	0.1457
AP@10		0.1493	0.2217	0.2287
AP@15		0.1821	0.2764	0.2833
AP@20		0.1887	0.2945	0.3006
MAP		0.1541	0.2326	0.2396

We find that the best performance in terms of MAP is 0.2435 when $\alpha = 0.8, \lambda = 0.005$. In this case, we fix α at 0.8 and compare our method with the baseline method with the same settings as described in Section 4.2. Table 2 and Figure 4 show the performance comparison in terms of AP@k and MAP respectively.

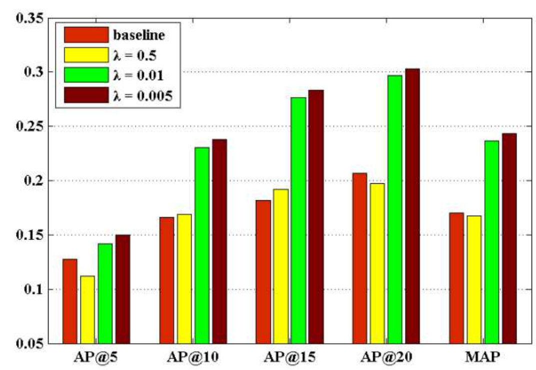

Figure 4: Performance Comparison In Terms Of AP@K And MAP With Varying λ

In Table 2, the score of MAP for the baseline method is 0.1705. By contrast, the best MAP score of our method is 0.2435, improving nearly 30% compared with the baseline method. One possible explanation for such substantial improvement is that our method incorporates the temporal factor and adopts an appropriate α combing the positive and negative feedback for recommendation.

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Table 2: Performance Comparison In Terms Of AP@K And MAP With Varying λ And $\alpha = 0.8$

Metrics	baseline	our method		
		λ = 0.5	λ = 0.01	λ = 0.005
AP@5	0.1275	0.1120	0.1419	0.1498
AP@10	0.1661	0.1691	0.2307	0.2376
AP@15	0.1819	0.1916	0.2766	0.2835
AP@20	0.2067	0.1975	0.2969	0.3030
MAP	0.1705	0.1676	0.2365	**0.2435**

5. RELATED WORK

Collaborative filtering (CF) is one of the most wildly used techniques for making recommendations [4, 6-9]. CF can be classified into two main categories: memory-based CF [3, 10] and model-based CF [9, 11, 12].

In memory-based CF systems, the recommendation for an item is computed as weighted average of ratings given by a group of people called neighbors, with similar interests of the active user.

User-item interest can also be modeled by the user-click models [13], which predict users clicking behaviors based on CF technique [14].

Model-based CF methods [15, 16] have been developed to cluster users based on their similar interest in items for improving the performance of recommendations. Once the model is generated, it produces high performance for predictions of recommendations. For example, Hofmann presented a probabilistic latent semantic model for collaborative filtering [17]. The observed user ratings are modeled as a mixture Gaussian distribution in a latent interest group, where users can have one or more groups of interest. And it reported that the performance outperforms memory-based CF methods.

Recently temporal factors in CF have attracted more attention [18-21]. Lee et al [22] proposed a CF algorithm based upon implicit feedback (purchase data) with a somewhat more general temporal model. Ding and Li incorporated a time based weight into a memory-based CF to give ratings different effect with respect to recency [23]. Sugiyama et al [24] explored a time-based CF with detailed analysis of users browsing history in one day. Although the results reported in these work are promising, the time weighting scheme seems limited for that the valuable ratings information are undervalued or underestimated.

6. CONCLUSIONS

In this paper, we study the temporal effects of user interest and user feedback information on social recommendations. We propose a time-aware social recommendation method based on user feedback information.

Unlike traditional CF-based recommendation methods that ignore the temporal effects and negative user feedback information during the recommendation computation, we utilize a predefined time weight function to model the temporal factor of user interest.

Furthermore, our method combines the positive and negative feedback for recommendation. We evaluate the performance of our method on a real dataset collected from Sina Weibo. Compared with the CF-based recommendation method, our method leads to substantial improvement in the task of top-k item recommendation.

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