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A recommender system based on tag and time information for social tagging systems

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ABSTRACT

Recently, social tagging has become increasingly prevalent on the Internet, which provides an effective way for users to organize, manage, share and search for various kinds of resources. These tagging systems offer lots of useful information, such as tag, an expression of user's preference towards a certain resource; time, a denotation of user's interests drift. As information explosion, it is necessary to recommend resources that a user might like. Since collaborative filtering (CF) is aimed to provide personalized services, how to integrate tag and time information in CF to provide better personalized recommendations for social tagging systems becomes a challenging task.

In this paper, we investigate the importance and usefulness of tag and time information when predicting users' preference and examine how to exploit such information to build an effective resource-recommendation model. We design a recommender system to realize our computational approach. Also, we show empirically using data from a real-world dataset that tag and time information can well express users' taste and we also show that better performances can be achieved if such information is integrated into CF.

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1. Introduction

With the dramatic development of the Internet, Web 2.0 has emerged and become popular, which transforms users from passive consumers to active producers of content (Zanardi & Capra, 2008). Social tagging systems, such as Del.icio.us (<http://delicious.com/>), CiteULike (<http://www.citeulike.org/>), Flickr (<http://www.flickr.com/>), etc., as typical representatives of Web 2.0, allow users to assign personal labels to resources based on their own background knowledge with a purpose to share, discover and recover resources (Xu, Fu, Mao, & Su, 2006). Along with tagging behaviors, a great deal of valuable information emerged, which strongly suggests the need to make use of such information to provide personalized services.

Among information in social tagging systems, tags and time are two main factors occurred in the process of tagging behaviors. Tags can reflect the interests of a user and as time goes by, users' lists of tags can be considered as descriptions of the interests they hold (Golder & Huberman, 2006). A tag performs as a bridge between a user and a resource through which user's preference for the resource is expressed, and the more frequently a tag has been used, the more interested a user is in the related resource. Assuming that

Alice often uses "baby health" and "education" as her bookmarks, which show her main interests in the area of baby health and education. Hence, resources tagged with these tags by Alice should be given higher weights than others. Additionally, tags are time sensitive and interest drifts exist in social tagging systems. For instance, Alice previously used plenty of "baby health" to bookmark related resources which denoted her main interest in baby health, probably because she just had a baby to take care of. While at present, she changes her focus to "education" as her child grew up. Thus she concentrates on resources relevant to education. In this case, it is inappropriate to set the same weight over all the resources for Alice. In contrast, a higher weight should be assigned to more recent resources (tagged by "education") than those appeared to be long time ago (tagged by "baby health"), because more recent bookmarked resources reflect a user's current interests and they may have strong impacts on future prediction. It becomes necessary to mine and utilize these information from social tagging systems to grasp a user's current main interests in order to provide better personalized services.

Traditional CF offers a way to provide personalized recommendations. As we discussed above, tag and time information are two important elements in social tagging systems. Therefore, it is necessary to integrate tag and time information in CF to provide effective personalized recommendations for social tagging systems. However, how to exploit tag and time information in a systematic manner in CF remains to be investigated. In this paper,

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we hypothesize that tag and time information could help improve the quality of personalized recommendations. More specifically, we have built a resource-recommendation model which provides personalized services in social tagging systems by following three phases: rating generation, user similarity calculation and resource recommendation. Under this model, we propose three strategies to generate modified ratings based upon tag and time information. Tag-weight strategy aims to weight each resource based on tag information. Time-weight strategy whose aim is to deal with interest drifts computes weight for each resource based on when a user bookmarked a resource. In tag and time strategy, we discover users' current main interests by generating rating values simultaneously using tag and time information.

This paper makes the following contributions to the study of personalized recommendations for social tagging systems: (1) it systematically demonstrates that tag information and time information are important when predicting users' preferences and we develop a computational approach to exploit such information to provide personalized recommendations for social tagging systems, and (2) our proposed recommender system using real data from a social tagging system shows better performances by adding such information in collaborative filtering.

The remainder of this paper is organized as follows: Section 2 contains the literature review. In Section 3, we present details about the computational approach adopted by resource-recommendation model. Section 4 introduces our recommender system. Experimental results and analysis are given in Section 5; and we conclude and discuss our future work in Section 6.

2. Literature review

The ever-growing social tagging behaviors on the Web have offered a rich data source to provide personalized recommendations. Many approaches on social tagging systems and personalized recommendations have been proposed. In this section, we will introduce the related work on social tagging systems and context-based recommendations.

2.1. Researches on social tagging systems

Researches on social tagging systems have experienced a dramatic change during the last five years. Early researchers mainly focused on the characteristics of user-created tags, such as ambiguity and synonym of tags and growth trend analysis of tags (Mathes, 2004; Golder & Huberman, 2006). Recently, there has been an increasing interest in knowledge discovery based on tags. Much work has been done on user model construction (Yeung, Gibbins, & Shadbolt, 2008b; Yun & Boqin, 2008; Michlmayr & Cayzer, 2007; Yeung, Gibbins, & Shadbolt, 2008a), tag prediction (Sigurbjörnsson & Van Zwol, 2008; Xu et al., 2006), semantic web search (Bao et al., 2007; Heymann, Koutrika, & Garcia-Molina, 2008), as well as social network discovery (Li, Guo, & Zhao, 2008). Additionally, tags have been used in recommendations in these two years (Marco Degemmis, Giovanni Semeraro, & Pierpaolo Basile, 2008; Shepitsen, Gemmell, Mobasher, & Burke, 2008).

2.2. Context-based recommendation

Both tag and time information can be viewed as contextual information in social tagging systems. Context has different definitions depending on different applications. According to Merriam-Webster, context is defined as "the interrelated conditions in which something exists or occurs". In this paper, context is defined as the intention and condition when a user bookmarked a resource in social tagging systems. According to this definition, both tags

and time are forms of contextual information, because tags reflect a user's special interests in a particular resource, which is the intention of user's tagging behaviors and time indicates when a user bookmarked a particular resource, which is the condition of user's tagging behaviors.

Contextual information has been proved to be efficient in recommender systems. Adomavicius, Sankaranarayanan, Sen, and Tuzhilin (2005) presented a reduction-based approach for multidimensional recommendation model that incorporates contextual information, such as place and time, into the process of recommendation. Chen (2005) presented a context-aware CF system that predicted a user's preference in different context situations so that what other like-minded users had done in similar context could be used to predict a user's preference towards an activity in the current context. In Palmisano, Tuzhilin, and Gorgoglione (2008), the authors empirically demonstrated that context matters when predicting customer behavior and granularity of the contextual information also has an influence. Recently, He, Pei, Kifer, Mitra, and Giles (2010) designed a novel probabilistic model to measure the context-based relevance between a citation context and a document. Their empirical results in the CiteSeerX digital library showed the effectiveness and the scalability of the approach. These researches show a bright prospect to integrate contextual information for better personalized services.

2.2.1. Tag-based CF

An active interest is observed in involving tags in CF in recent literature. Nakamoto, Nakajima, Miyazaki, and Uemura (2007) proposed a tag-based contextual CF by using the overlaps of tags. The authors constructed two models to integrate tags into user similarity calculation stage and score prediction stage, respectively. However, the system may have problems if there is not sufficient reuse of tags for users. In Ji, Yeon, Kim, and Jo (2007), the authors used tags to find similar users in order to form candidate tag set (CTS) for each user, and then they implemented recommendation approach with a Naïve Bayes classifier based on CTS. In Tso-Sutter, Marinho, and Schmidt-Thieme (2008) three matrices were built i.e. user-item matrix, user-tag matrix and tag-item matrix, to generate a generic mechanism that allowed tags to be integrated into standard CF. For user-based CF, user-item matrix was extended with user-tag matrix, while in the case of item-based recommendations, user-item matrix was extended with tag-item matrix. Bogers and Bosch (2008) applied traditional user-based and item-based CF in CiteULike for recommending scientific articles to users, and found that user-based CF performed better than item-based CF in CiteULike. A tag-based collaborative filtering (TBCF) was proposed in Zhao et al. (2008), calculating user similarity based on the semantic distance among tags. WordNet was introduced to calculate the semantic similarity between two tags.

Our approach takes a different stance: we use tags which belong to a single user's tag space instead of using tags in the whole users' space. Since tags are freely chosen according to one's background knowledge, tags among different users suffer from ambiguity and synonym problems, our approach treat tags in a single user's space where these problems are alleviated.

2.2.2. Time-based CF

Some work is carried out to investigate time information in recommendations. User purchase time and item launch time were considered in Lee, Park, and Park (2008) in order to improve recommendation accuracy. Two piecewise rating functions to compute the weights based on temporal information were proposed. They further analyzed a variety of temporal information including item launch time, user buying time, the time difference between the two, as well as several combinations of these three by conducting an empirical study (Lee, Park, & Park, 2009). Their

results showed that such temporal information could improve the recommendation accuracy of a CF-based recommender system for character images in a mobile e-commerce environment. The work which is most directly related to ours is Ding and Li (2005), the authors used exponential time decay function to compute time weights for different items according to each user and each cluster of items. Each rating was assigned a weight defined by the time function in the phase of preference prediction in item-based collaborative filtering.

In the above literature on tag-based and time-based recommendations, only one factor is taken into consideration, either tags or time. However, in this paper, we propose a resource-recommendation model, which is an integrated framework fusing these two kinds of information. Namely, we use tag and time information to generate ratings which could well express users' interests and their interests drift. Besides, as such information is exploited in the phase of rating generation, the influence of these factors will be covered during the whole recommender processes. Empirical evaluations with real dataset show that performance improvements can be achieved by our resource-recommendation model.

3. Proposed approach

3.1. Problem statements

Among various recommendation approaches, collaborative filtering which relies on users with similar preferences has been widely used in e-commerce applications. "Collaborative filtering approach helps users find the resources they would like to purchase at e-commerce sites by producing a predicted likeliness score or a list of top-N recommended resources for a given user by considering rating matrix only" (Sarwar, Karypis, Konstan, & Reidl, 2001). Therefore, rating matrix acts as a basic in CF, for user similarity are discovered from rating matrix and resource recommendation are also calculated based on rating matrix. Traditional log-based ratings are generated based on user's log behaviors with each element taken a binary value 1 or 0, indicating whether a user has transacted/viewed a resource (Lee, Jun, Lee, & Kim, 2005). In this case, each transacted/viewed resource plays an equal role for a user and ratings are static over time, which may be against the common sense that people tend to present different preferences towards different resources and their degree of interests may shift as time goes by. Thus, we take users' favorableness towards

different resource and their interests shift into account when constructing rating matrix to provide better personalized recommendations.

In this paper, we propose a computational approach that recommends resources for a particular user by following three steps. First, we generate modified rating matrix by designing three strategies using tag or time or both tag and time information. Second, user similarity is built based on the precomputed rating matrix that captures the relation between different users. Finally, resource recommendation is implemented to identify a list of resources to be recommended.

Two matrices are used throughout this article.

- **User-resource binary matrix B .** $B(m \times n)$ is the traditional log-based matrix associated with m users $U = \{u_1, u_2, \dots, u_m\}$ and n resources $R = \{r_1, r_2, \dots, r_n\}$. Each $B_{u,r}$ takes the value of 1 if a user u has bookmarked a resource r and 0 otherwise.
- **Modified user-resource rating matrix M .** $M(m \times n)$ is the modified rating matrix either involving tags, time, or both tag and time information that we use to generate user similarity and resource recommendation. In tag-weight strategy, each $M_{u,r}$ refers to tag weight value, which reflects tag frequency of a user u . Similarly, in time-weight strategy, each $M_{u,r}$ sets to be time weight value, denoting the time when a user u bookmarked a resource r . For tag and time strategy, each $M_{u,r}$ takes the value of the integration of tag weight value and time weight value.

3.2. Resource-recommendation model

Fig. 1 illustrates our proposed resource-recommendation model based on users' tagging behaviors. Typical social tagging behaviors are depicted on the left-hand side of Fig. 1. Three main elements in a social tagging system are users, tags and resources. A bookmark is a triple containing a user, a resource tagged by the user and all tags the user gave to the resource, for instance, $\{u_1, r_2, \text{tag1}|\text{tag2}\}$ is a bookmark from Fig. 1. Generally speaking, resources may have different meanings according to different domains. For example, resources in Del.icio.us, CiteULike, Flickr refer to web pages, academic papers and photos, respectively.

On the right-hand side of Fig. 1 is our resource-recommendation model. We first use tag and time information provided by users' tagging behaviors to generate rating matrix, and then calculate user similarity based on modified ratings to find neighbors for each user, and finally, resource recommendation is followed based

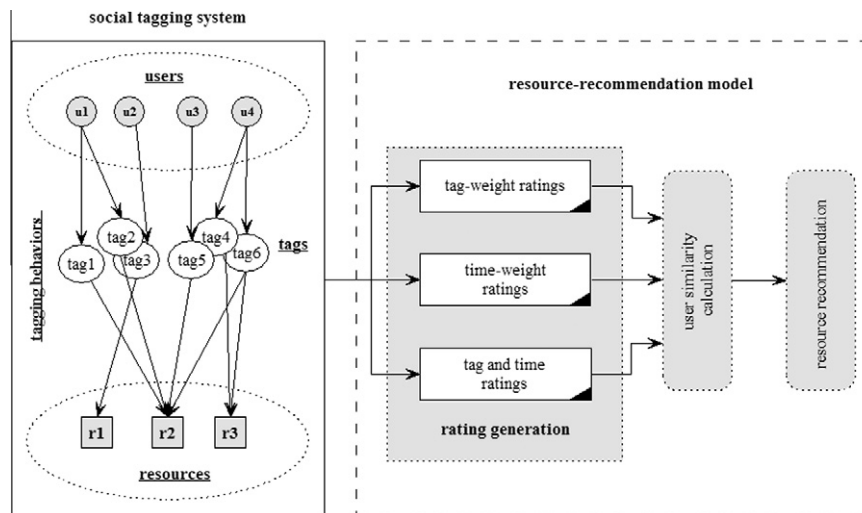


Fig. 1. The framework of resource-recommendation model.

on neighbors' modified ratings. The section below describes each phase of our resource-recommendation model in details.

3.3. Rating generation

In rating generation process, we investigate how to integrate tag and time information from social tagging systems into ratings. We propose three strategies to generate rating values in user-resource matrix. First, in tag-weight strategy, tag weight for each element in the rating matrix is generated according to tags a user chose to bookmark and tags' frequency of the user. Second, in time-weight strategy, we use an adaptive exponential forgetting function to track and measure interest drifts for each user automatically as well as construct time weight for each element in the user-resource matrix. Finally, a fusion scheme to integrate tag weight and time weight is proposed to form the modified ratings, which is called tag and time strategy.

3.3.1. Tag-weight strategy

Generally speaking, the more a tag has been used, the more interests the user has in the related resource. Thus, our tag-weight strategy starts from an assumption that a user is likely to prefer the resources bookmarked with the tags of high usage by him, that is, the tag frequency is high for the user. And we also assume that a single user will use the same tags when describing similar resources to express his interests. Therefore, tag weight is defined as:

$$w_{tag}(u, r) = \sum_{t_a \in tag(u, r)} w_{u, t_a} \quad (1)$$

where $tag(u, r)$ denotes the set of tags with which a user u has bookmarked to a resource r , w_{u, t_a} denotes tag score of each tag t_a in $tag(u, r)$. Tag weight, $w_{tag}(u, r)$, measures how a user u is interested in a bookmarked resource r , which implies a user's preference for a resource.

Tag score, w_{u, t_a} , of each tag bookmarked by a user is calculated as follows:

$$w_{u, t_a} = \frac{freq(u, t_a)}{\sum_{i=1}^k freq(u, t_i)} \quad (2)$$

where $freq(u, t_a)$ represents how many times a tag t_a has been tagged by a user u , k is the total number of tags a user u has bookmarked with any resources. Notice that $\sum_{i=1}^k w_{u, t_i} = 1$.

According to the definition of tag score, tag weight takes a real number between 0 and 1, and the higher the weight is, the more interests a user is in a resource. In this way, users' main interests could be grasped by tag-weight strategy.

In addition, our approach does not suffer from natural language issues, such as ambiguity and synonym, which are the main problems when dealing with tags (Marco Degemmis et al., 2008; Golder & Huberman, 2006; Shepitsen et al., 2008; Xu et al., 2006; Zanardi & Capra, 2008), since tag weight is generated within a single user's tag space.

3.3.2. Time-weight strategy

Generally speaking, the time when each user bookmarked each resource is different. The primary motivation behind this time-weight strategy is the fact that human interests drift as time goes by, which has been demonstrated in Lathia, Hailes, and Capra (2008). Most work on interest drifts uses either time window or forgetting functions to learn and track the changes of user's behavior as time passes, and most time window methods have completely forgotten the old information (Maloof & Michalski, 2000).

The exponential forgetting function is widely used in temporal applications to measure concept drifts to gradually discount the history of past behavior (Aggarwal, Han, Wang, & Yu, 2004).

Considering both the latest bookmarks and the old bookmarks are important in social tagging systems. Our adaptive exponential forgetting function, which is like the one in Cheng et al. (2008) is defined as follows:

$$w_{time}(u, r) = \exp\{-\ln 2 * time(u, r) / hl_u\} \quad (3)$$

where $w_{time}(u, r)$ is the time weight denoting the degree a user's interests have declined to; $time(u, r)$ is a non-negative integer. $time(-u, r)$ takes the value of 0 for the last tagging day of a user u and $time(u, r)$ sets to be 1 for the penultimate tagging day of the same user, and so on. $time(u, r)$ remains the same for the same tagging day. hl_u represents the half-life for each user, which adapts to each user's life circle. For users with a large hl_u , that is they have a long life span in tagging behaviors, their interests will fall slowly; while for users with a small hl_u , that is they have a short life span in tagging behaviors, their interests will fall quickly. When $time(u, r) = hl_u$, $w_{time}(u, r)$ falls to 1/2. For a given user, $time(u, r)$ is smaller when the bookmarked time is closer to the recent bookmarked time. Consequently, a higher time weight value will be given to a more recent bookmark, while an old bookmark will be assigned with a lower value. In this way, users' current interests could be detected by time-weight strategy.

3.3.3. Tag and time strategy

As our objective is to provide a resource-recommendation model with both tag and time information provided by social tagging systems, we combine the two weights into a single one in tag and time strategy, which is given in Eq. (4):

$$\mathbf{M}_{u, r} = \lambda w_{tag}(u, r) + (1 - \lambda) w_{time}(u, r) \quad (4)$$

where parameter λ is introduced to adjust the significance of the two weights. Note that, both tag and time information can be easily obtained within social tagging systems. In contrast to the traditional log-based ratings, our resource-recommendation model uses both tag and time information to construct modified ratings. On one hand, such ratings take tags into consideration which indicate user's degrees of preferences; on the other hand, bookmarked time is integrated into ratings which can reflect interest drifts of a user in order to denote user's preferences more accurately. Therefore, tag and time strategy could easily find out users' current main interests. The impact of λ will be examined experimentally in Section 5.

Based on the generated rating matrix, user similarity and resource recommendation are calculated to provide personalized recommendations for social tagging systems. Our rating generation approach represents an extension to existing recommender algorithms.

3.4. User similarity calculation

User similarity calculation aims to mine the relationship among users. There are a number of techniques to calculate the similarity between users, such as Pearson correlation coefficient, Spearman correlation coefficient, cosine similarity and Jaccard similarity. In this paper, we use cosine similarity to compute the similarity value between user u and user v which is defined as follows:

$$sim(u, v) = \frac{\vec{u} \cdot \vec{v}}{\|\vec{u}\| \cdot \|\vec{v}\|} = \frac{\sum_{x \in X(u, v)} \mathbf{M}_{u, x} \times \mathbf{M}_{v, x}}{\sqrt{\sum_{x \in X(u, v)} \mathbf{M}_{u, x}^2} \times \sqrt{\sum_{x \in X(u, v)} \mathbf{M}_{v, x}^2}} \quad (5)$$

where $X(u, v)$ is the set of resources that both user u and user v have tagged. In our approach, we use Eq. (5) to find k-nearest neighbors for an active user, and the higher score a user owns, the more similar he is with the active user.

3.5. Resource recommendation

Finally, the measure to predict resources user u may prefer is given by

$$\text{score}(u, r) = \frac{\sum_{v \in \text{Neighbor}(u)} \mathbf{M}_{v,r} \times \text{sim}(u, v)}{\left| \sum_{v \in \text{Neighbor}(u)} \text{sim}(u, v) \right|} \quad (6)$$

where $\text{Neighbor}(u)$ denotes the neighborhoods of a user u .

3.6. An example

In this section, we illustrate our computational approach by considering a small example with four users, five resources and ten tags with bookmarking information shown in Table 1. Here, the actual bookmarked time is given in bold characters which follows the pattern “month-day-year” and $\text{time}(u, i)$ is shown in square bracket. Based on the information of original tagging behaviors shown in Table 1, the corresponding log-based ratings are shown in Table 2. After applying tag-weight strategy tag-weight matrix is generated which presents in Table 3. Each non-empty element denotes tag weight on a particular resource for a given user. Table 4 shows the results of time-weight strategy. Tag and time rating matrix by taking tag and time strategy is shown in Table 5. To consider the equal importance of tag and time information, we set λ to be 0.5 in Eq. (4) when generating tag and time ratings.

Supposed we want to recommend a resource to U1, with log-based model (Table 2), it is obvious that U3 is the most similar user with U1 after computing cosine similarity because of most common resources they have tagged; therefore, the system will recommend R5 to U1. In tag-weight model (from Table 3), the nearest neighbor of U1 is U4 as they hold the same interest degree towards the same resources; it is more likely that they have the same taste, thus R2 will be recommended. Under this circumstance, users' different interesting degrees towards the same resource could be detected by our tag-weight model. By time-weight model (from Table 4), U1 is also recommended with R2 because both U1 and U4 like R4 nowadays, while U3 liked R4 a long time ago, and his interest has changed to R1 from R4 at present. Consequently, it is more accurate to put U1 and U4 in the same neighborhood. Our time-weight model can capture interest drifts and provide more accurate neighbors for users. Finally, with tag and time matrix (see Table 5), the system also recommends R2 to U1 as U1 and U4 hold strong agreements on the resources by considering both tag and time information. In fact, our empirical analysis has shown that all our three strategies provide promising results.

4. A recommender system

In this section, we describe the implementation of our recommender system. We firstly describe the architecture of the system and then introduce each functional module in the system respectively.

Table 1
User- resource bookmarking information.

	R1	R2	R3	R4	R5
U1	Tag1, Tag2 12-5-06 [2]		Tag1, Tag3, Tag4 1-10-07 [1]	Tag1, Tag4, Tag5 2-1-07 [0]	
U2		Tag4 5-5-06 [1]		Tag4, Tag6 1-10-07 [0]	
U3	Tag1, Tag7 12-5-06 [0]		Tag8 12-4-06 [1]	Tag4 5-5-06 [2]	Tag1, Tag7 12-4-06 [1]
U4	Tag9, Tag10 8-29-06 [1]	Tag1, Tag9 8-29-06 [1]		Tag9, Tag1 10-4-06 [0]	

Table 2
Log-based rating matrix.

	R1	R2	R3	R4	R5
U1	1		1	1	
U2		1		1	
U3	1		1	1	1
U4	1	1		1	

Table 3
Tag-weight rating matrix.

	R1	R2	R3	R4	R5
U1	0.5		0.75	0.75	
U2		0.67		1.0	
U3	0.67		0.17	0.17	0.67
U4	0.67	0.83		0.83	

Table 4
Time-weight rating matrix.

	R1	R2	R3	R4	R5
U1	0.25		0.5	1.0	
U2		0.5		1.0	
U3	1.0		0.5	0.25	0.5
U4	0.5	0.5		1.0	

Table 5
Tag and time rating matrix.

	R1	R2	R3	R4	R5
U1	0.375		0.625	0.875	
U2		0.585		1.0	
U3	0.835		0.335	0.21	0.585
U4	0.585	0.665		0.915	

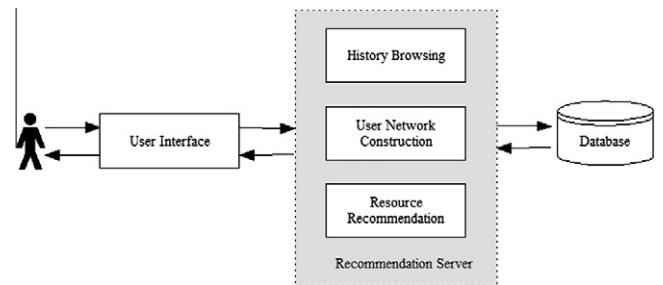


Fig. 2. The architecture of our recommender system.

4.1. System architecture

Fig. 2 illustrates the architecture of the system. It consists of three parts: (1) user interface; (2) database; (3) recommendation server. There are three main modules in recommendation server: (1) history browsing; (2) user network construction; (3) resource recommendation.

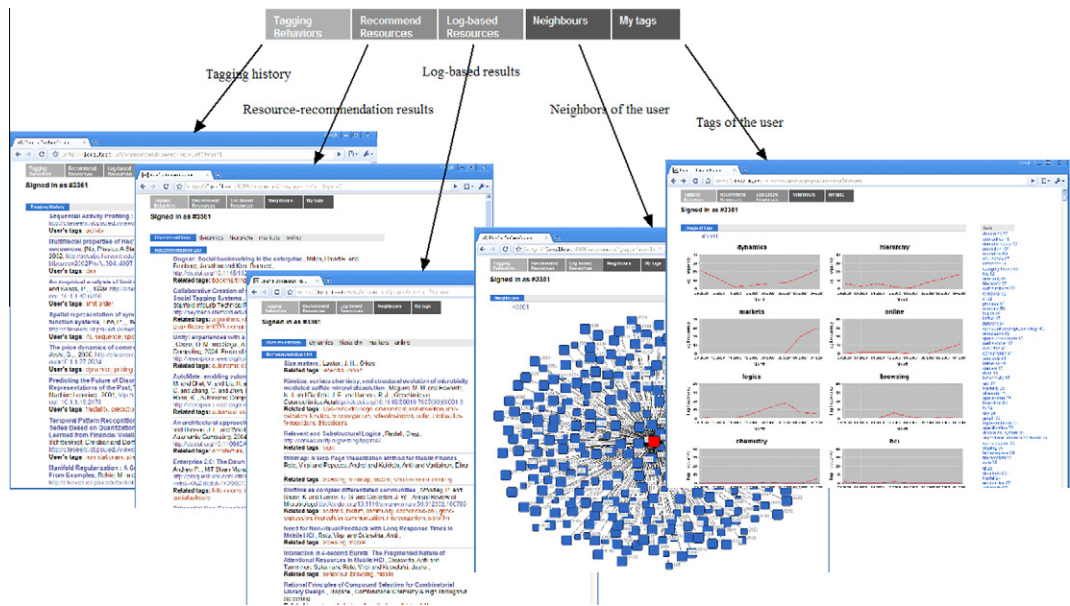


Fig. 3. User interface of the recommender system.

Recommendation server connects on one side to a user's Web browser and on the other side to database. When a user requests a visualization of a Web page, recommendation server processes it on database and returns the results to the Web browser. The system is implemented as JSP plus Servlet on a Windows OS running the Apache Web server.

4.2. User interface

Fig. 3 shows the user interface of the system. A user could browse his tagging history, acquire resource recommendation based on either our resource-recommendation model or log-based model, view his neighbors in the form of social network visualization and observe the changing trend of his tags as time passes, which are the five functional modules of the system. We choose a user #3361 from the CiteULike database to demonstrate our system in the following.

4.3. Database

Our database is constructed by using data from CiteULike, a well-known social bookmark service supporting collaborative tagging, which enables researchers to organize their libraries with personal tags. We downloaded the older datasets that are available on a daily basis (<http://www.citeulike.org/faq/data.adp>). A sample of 18,467 users with 166,504 distinct tags and 557,101 distinct bookmarked papers typed before 05/30/2007 was available, so that for each user the dataset contains the user's complete history. In our experiments, we reduced the raw data by filtering out the users whose bookmarks numbers are less than 20. The final experimental data involve 4384 users, 152,513 different tags, 489,797 different papers and 589,273 bookmarks. The dataset's sparsity is 0.027% and each user has bookmarked 134.4 papers on average. A statistic description of the dataset is shown in Fig. 4. The left plot of Fig. 4 shows that a large number of users tag only a few

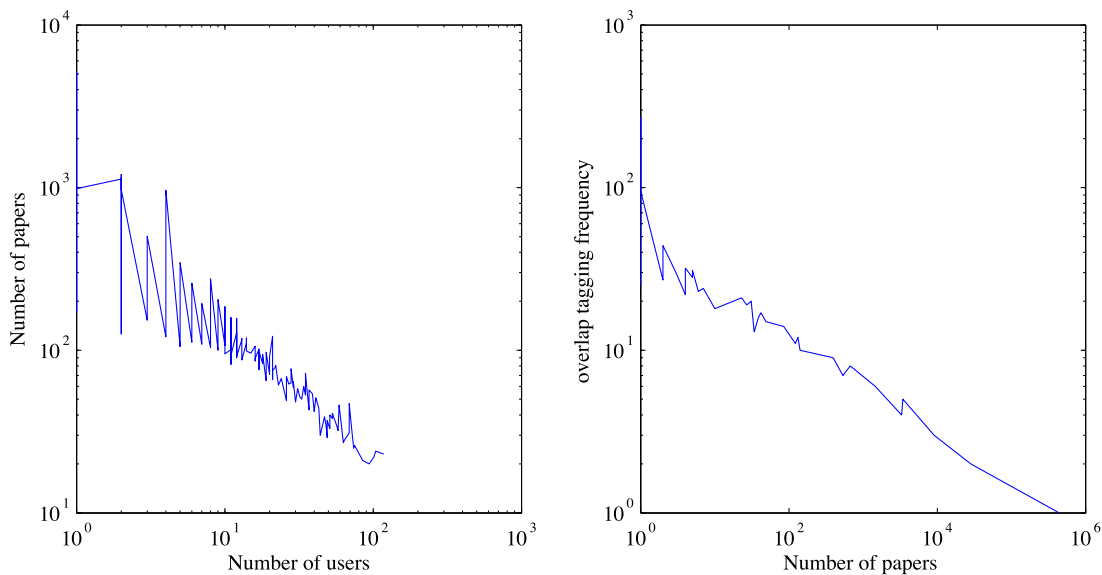


Fig. 4. Left: the log-log plot of the number of users to the number of papers. Right: the log-log plot of the number of papers to overlap tagging frequency.

papers, while a few users tag a large number of papers. The right plot of Fig. 2 indicates that a large number of papers have a small overlap tagging frequency, while a small number of papers get a high overlap tagging frequency. These observations are consistent with the dataset's sparsity.

4.4. Recommendation server

As we described above, recommendation server contains three modules: history browsing, user network construction and resource recommendation. In this section, we introduce these three modules respectively.

4.4.1. History browsing

Two functions are related to history browsing: one is tagging history browsing and the other is tag browsing.

4.4.1.1. Tagging history browsing. This function is similar with most common social tagging systems that a user could browse his tagging history including information about paper name, author, publisher, year and user's own tags which is ordered by descending time.

4.4.1.2. Tag browsing. We use JFreeChart (<http://sourceforge.net/projects/jfreechart/files/>) to draw the changing trends of user's tags as time passes. JFreeChart is an open-source framework and a free software written in Java, which allows the creation of complex charts in a simple way. Main body of Fig. 5 shows some typical changes of tags of user #3361. The side bar shows the statistical frequency of each tag used by #3361 ordered by decreasing order.

Comparing among these tag trend charts, when considering tag frequency only, we could find that the main interests of user #3361 are “dynamics”, “hierarchy”, “markets”, “online” and “logics”, because tag frequencies of these tags are much higher than the rest. Our resource-recommendation model integrates tag frequency which could grasp user's main interests like this. By observing

the changing trend of each tag only, we find that the user has a growing interest in “dynamics” since November 2006, in “hierarchy” since January 2007, in “markets” and “online” since February 2007, and in “chemistry” since March 2007, but has a decreasing interest in both “browsing” and “hci” since December 2006, in “logics” since February 2007. Therefore, user #3361's current interests are “dynamics”, “hierarchy”, “markets”, “online” and “chemistry”. Our resource-recommendation model could detect these interest drifts by considering time information of each bookmark. Considering both tag and time information, we may easily discover that “dynamics”, “hierarchy”, “markets” and “online” are the current main interests of user #3361. After knowing the current main interests of a user, we could find his neighbors with the similar taste more accurately and finally provide better personalized resource recommendation.

4.4.2. User network construction

In user network construction module, NetDraw (<http://www.analytictech.com/downloadnd.htm>) is used to draw relations among neighbors, which is a free program for visualizing social network data. The network is constructed according to user similarity. Each vertex denotes a user; the red one presents the active user and the blue ones illustrate his neighbors; the size of the vertex denotes the strength of similarity between two users. The bigger a vertex is, the more similar the neighbor is with the active user (see Fig. 6). By viewing the neighbors in a network style, an active user could have an intuitionistic sense of users who may have the similar interests with him. We believe this sense is crucial in user community; on one hand, user could find other users who have the similar taste with him easily; on the other hand, user could observe similarity degree with each neighbor intuitively.

4.4.3. Resource recommendation

The core of our recommender system is the resource recommendation module, in which two kinds of resource recommendations



Fig. 5. Usage of tags of user #3361.

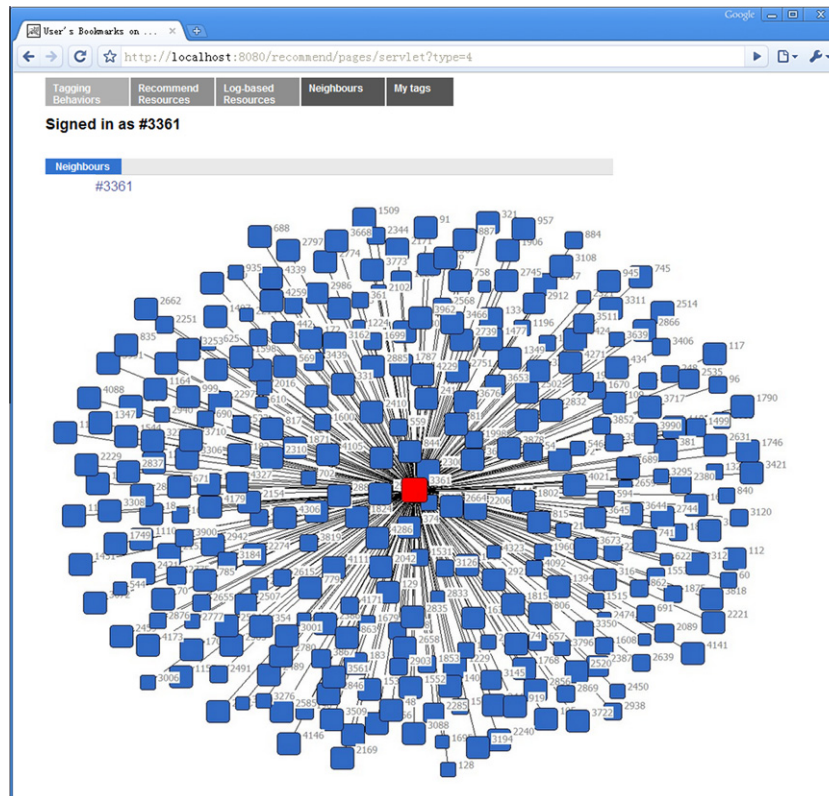


Fig. 6. Social network visualization of user #3361's neighbors.

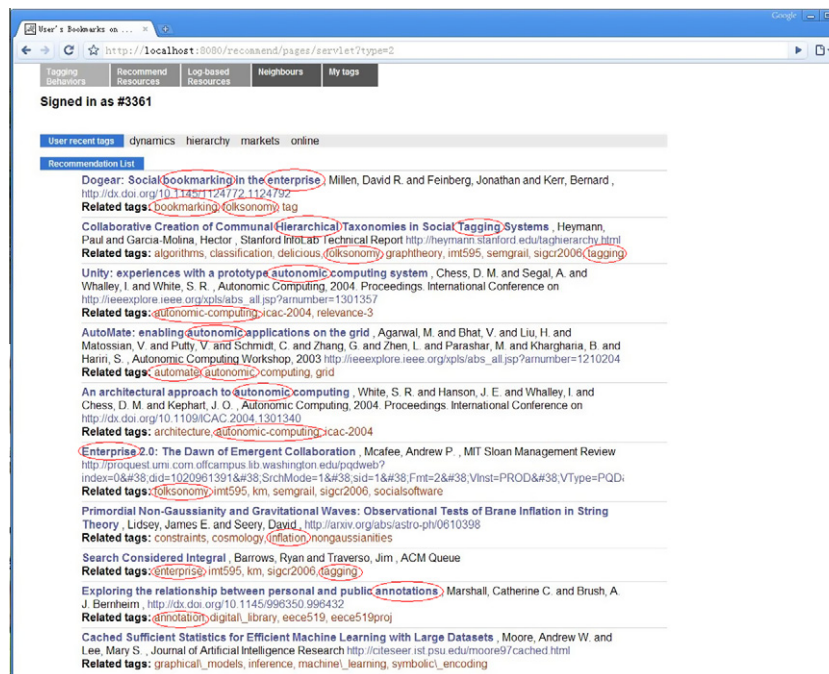


Fig. 7. Resource recommendation based on resource-recommendation model for user #3361.

are provided: recommendation based on proposed resource-recommendation model and recommendation based on log-based model.

4.4.3.1. *Resource recommendation based on our resource-recommendation model.* Fig. 7 shows the Top-10 recommendation results of

our resource-recommendation model. Most of the results are related to “dynamics”, “markets”, “hierarchy” and “online”, which are the current main interests of user #3361. As we have highlighted in Fig. 7, “automate”, “autonomic”, “autonomic-computing” and “inflating” are relevant to “dynamics”; “enterprise” is related to “markets”; “hierarchical” is relevant to “hierarchy” and

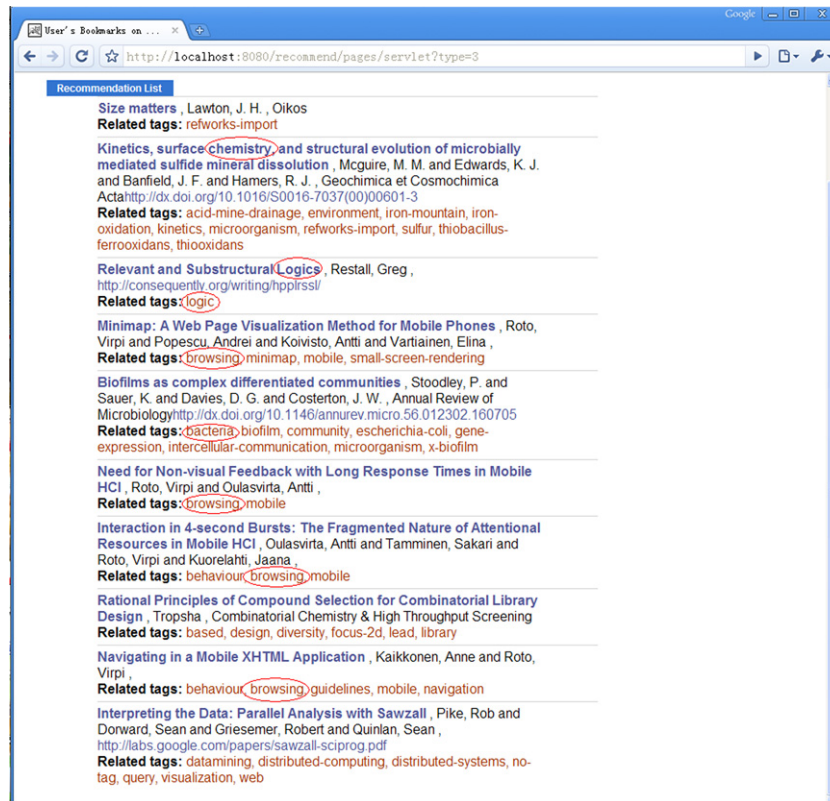


Fig. 8. Resource recommendation based on log-based model for user #3361.

“bookmarking”, “folksonomy”, “tagging” and “annotation” are related to “online”.

4.4.3.2. *Resource recommendation based on log-based model.* Fig. 8 shows the Top-10 recommendation results of log-based model. Some of the results are relevant to “chemistry”, which is not the main interests of user #3361, because tag frequency of “chemistry” is relatively low. Some of the results are related to “logics”, which is not the current interest of user #3361, because the trend of tag “logics” shows a decreasing interest since February 2007. There are also some results relevant to “browsing”, which is neither the main interest nor current interest of user #3361, because of both the low tag frequency of “browsing” and the declining trend of “browsing”.

Comparing the recommendation results between resource-recommendation model and log-based model, we may safely draw the conclusion that our model could grasp user’s current main interests efficiently and recommend the most relevant resources to a user. In fact, our empirical analysis has shown that our model could get a remarkable improvement.

5. Experimental evaluation

In this section, we report an experimental study aimed at finding whether tag and time information could predict users’ preference and if our computational approach exploiting such information could provide better personalized recommendation for social tagging systems.

5.1. Experimental procedure

We repeat our experiments on 10 randomly selected sampled subsets by using resampling technique. To form each subset, 1000 users were randomly selected from our dataset with all their

Table 6

Description of each subset from CiteULike.

Data sets	Users	Papers	Tags	Bookmarks
Subset1	1000	129,349	88,709	143,568
Subset2	1000	126,051	75,606	133,460
Subset3	1000	122,121	81,802	131,678
Subset4	1000	133,148	87,089	142,125
Subset5	1000	127,848	80,178	141,626
Subset6	1000	127,847	82,272	135,945
Subset7	1000	133,269	84,748	141,219
Subset8	1000	119,492	78,620	130,585
Subset9	1000	127,933	84,959	137,751
Subset10	1000	125,260	78,728	133,603

bookmarked history. Then each subset is divided into two parts: 20% most recent bookmarks of each user form the testing set and the remaining earlier 80% form the training set. The statistical description of each subset is provided in Table 6.

On each subset, we implement all of the experiments by generating a fixed number of Top-10 recommendation list for each user. We expect that the size of neighborhood could be a significant factor affecting recommendation quality, so we vary neighborhood sizes from 5 to 100 by an interval of 5. And the baseline is computed by using log-based matrix **B** as the rating matrix. Note that all algorithms use cosine correlation to compute the relations between different users.

5.2. Evaluation metrics

Hit-rate and Hit-rank (Deshpande & Karypis, 2004) are two popular evaluation metrics in measuring recommendation quality. Hit-rate metric evaluates the accuracy of a system by calculating hits, the intersection of recommended resources and the resources

in the testing set for each user. Hit-rate is defined as below (Deshpande & Karypis, 2004):

$$\text{Hit-rate} = \frac{\text{number of hits}}{m} \quad (7)$$

where m is the total number of users.

Hit-rate is permutation-insensitivity, that is, simply rearranging the order of resources in recommendation list does not affect the result of Hit-rate. However, the actual position for each resource in recommendation list is important because the earlier a resource occurred in the list, the more impacts it will have on a user. Therefore, we use Hit-rank to deal with the position of each resource in hits occurred in recommendation list (Deshpande & Karypis, 2004).

$$\text{Hit-rank} = \frac{1}{m} \sum_{i=1}^h \frac{1}{p_i} \quad (8)$$

where h is the number of hits which occurred at positions p_1, p_2, \dots, p_h within recommendation list. We adopt Hit-rate and Hit-rank as evaluation metrics in our experiments.

5.3. Experimental results and analysis

We demonstrate that our computational approach is effective empirically by conducting three sets of experiments. The first set of experiments we conduct aims to analyze the impact of tag weight alone on resource-recommendation model. In the second set of experiments, to evaluate the impact of time information, we compare the evaluations with time information and without time information. In the third part of the experiments, we analyze how the performance of resource-recommendation model with both tag and time information compared with traditional log-based model.

5.3.1. Tags' impact

An important issue for our study is to address whether tags have indeed captured users' interests. In this section, we mainly focus on the impact of tags. We compare our tag-weight model (using tag-weight ratings) with traditional log-based model (using user-resource binary matrix \mathbf{B}). Hit-rate and Hit-rank results

averaged on 10 subsets with neighborhood sizes from 5 to 100 are shown in Fig. 9.

We can clearly see that for all neighborhoods, average Hit-rate and average Hit-rank on 10 subsets of our tag-weight model are higher than log-based model, which indicates that by simply adding tag information into resource-recommendation model, the accuracy of recommendation can be improved significantly. Since the aim of our experiments is to check the impact of tags by comparing the performance of tag-weight model vs. log-based model, a test of statistical significance needs to be performed. Since the biggest variance of log-based model is 0.000616 and the maximum variance of tag-weight model is 0.000599, which are relatively small, we could safely draw the conclusion that tag-weight model outperforms log-based model. We believe that as tags hold the relationship between users and resources, tags can well express interests of users. Moreover, the more frequently a user uses a tag, the higher interests he/she holds on the corresponding resources.

5.3.2. Time's impact

To evaluate the effect of time, we conduct our second experiment on time-weight model (using time-weight ratings) and traditional log-based model. Fig. 10 illustrates the results.

Obviously, the results show that after introducing time weight, there is a significant increase in the performance, which indicates that interest drifts exist in our CiteULike dataset. Moreover, the improvement of performances is statistically significant over different neighborhood sizes, with the biggest variance is 0.001117. Since in real world, users' interests may change as time goes by, dynamically simulating interest drifts based on the assumption that future prediction is rely on more recent tagging behaviors may help to find more accurate neighbors for an active user in social tagging systems. As our time-weight model deals with volatility of user's neighborhoods, it gains higher recommendation accuracy.

5.3.3. Model with both tag and time information

Now that we have observed how tags and time influenced on the recommendation quality separately, we then build ratings based on both tag weight and time weight according to tag and

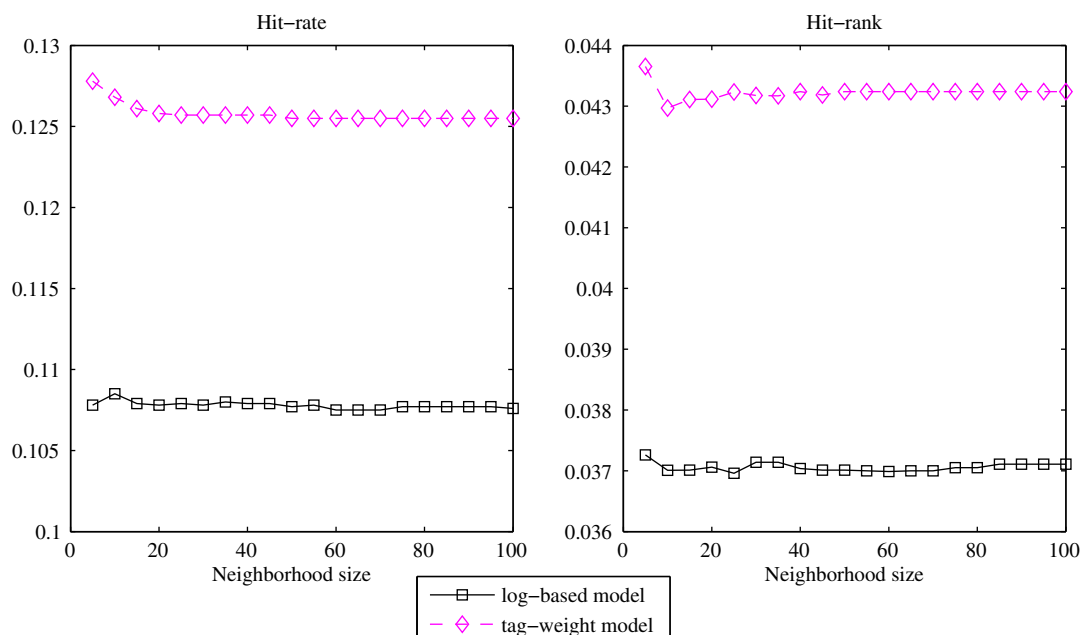


Fig. 9. Left: Hit-rate of tag-weight model vs. log-based model. Right: Hit-rank of tag-weight model vs. log-based model.

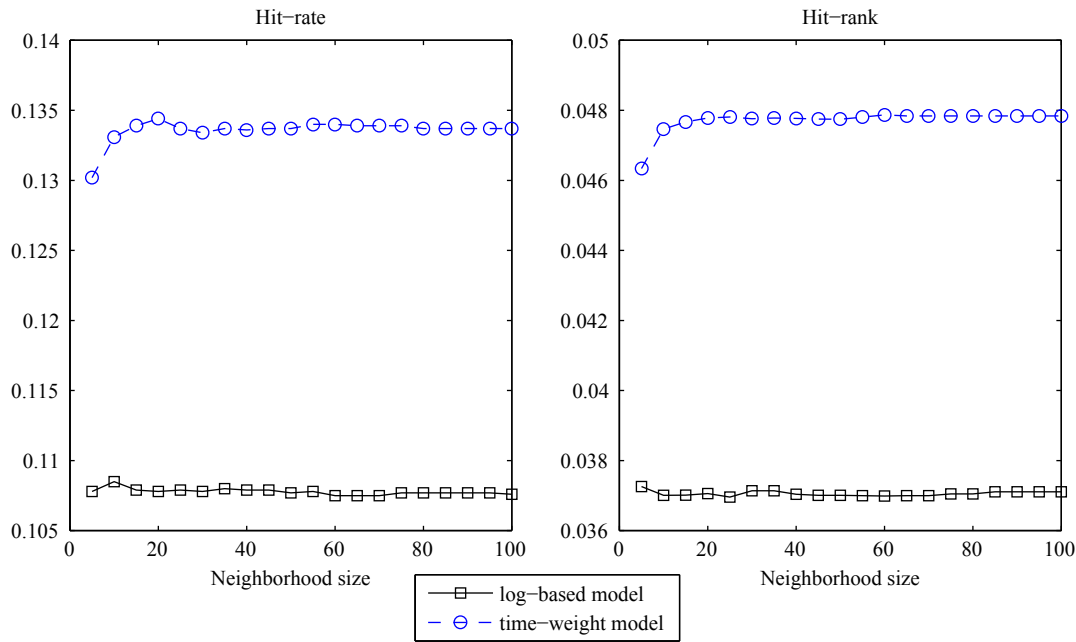


Fig. 10. Left: Hit-rate of time-weight model vs. log-based model. Right: Hit-rank of time-weight model vs. log-based model.

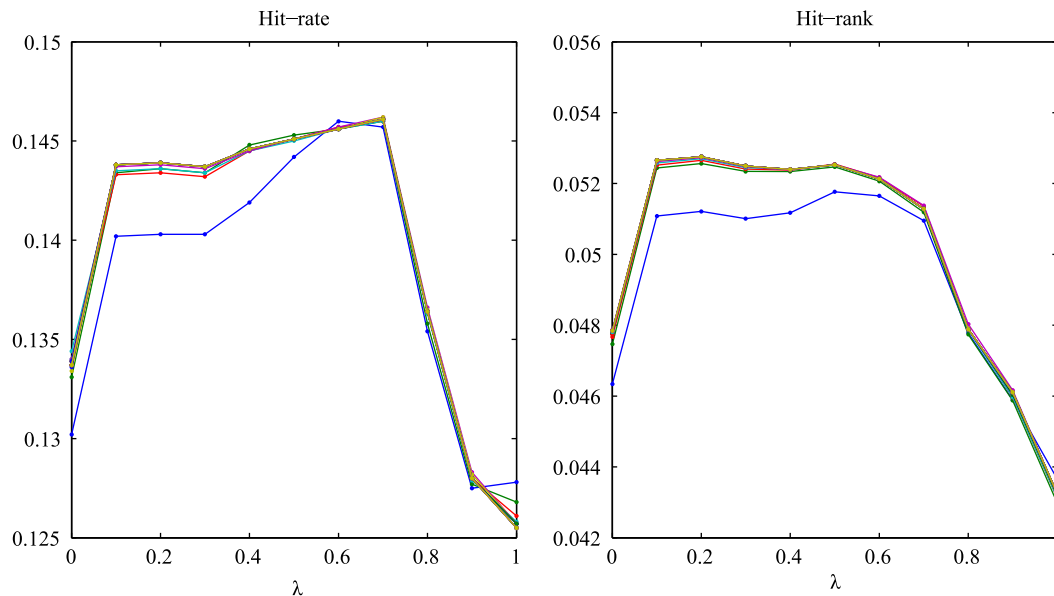


Fig. 11. Left: the variation of Hit-rate of different λ on each neighborhood size. Right: the variation of Hit-rank of different λ on each neighborhood size.

time strategy. We vary the parameter λ from 0 to 1 with an interval of 0.1. The average Hit-rate results and average Hit-rank results over 10 subsets, using different λ with distinct neighborhood size, are demonstrated in Fig. 11. Each curve represents the performance on a fixed neighborhood size, so there are 20 curves in each plot because of 20 neighborhood sizes.

It can be observed from the plots that the parameter λ actually influences the performance. However, for different neighborhood size, the trend of both performances appears to be consistent. Also, the performances of resource-recommendation model with both tag and time information are better than the models containing only one factor (when $\lambda = 0$ or $\lambda = 1$). Both tag and time information have influences on the results. Studying the trend of Hit-rate and Hit-rank for different λ , we notice that the best average Hit-rate is gained when λ is chosen to be 0.7, while the best average Hit-

rank is gained when λ is chosen to be 0.2. To further explain this observation, we assume that tags could reflect users' preferences, and time could express interest drifts. By using tag information, resources related to users' main interests are more likely to be recommended; by considering time information, resources which users prefer at present could be recommended first. Since Hit-rate is permutation-insensitive, tag information may take a strong impact on the result, while since Hit-rank is sensitive with recommendation order, time information may have a crucial impact on the result. In the following experiments, we set $\lambda = 0.7$ in calculating Hit-rate and set $\lambda = 0.2$ when computing Hit-rank. Fig. 12 presents comparison results of four models (log-based model, tag-weight model, time-weight model as well as tag and time model).

Not surprisingly, our computational approach with both tag and time information outperforms traditional log-based model. As

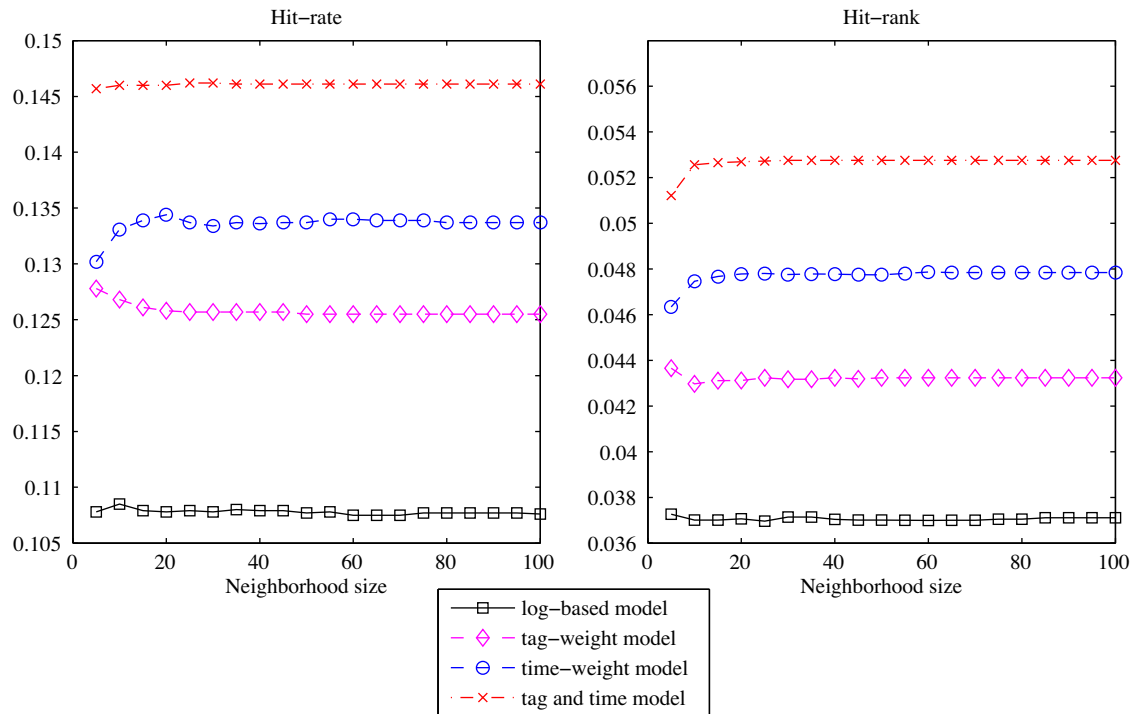


Fig. 12. Left: Hit-rate of four models. Right: Hit-rank of four models.

shown in Fig. 12, we can see quite significant accuracy improvement in Hit-rate (34.56–35.91%) and in Hit-rank (37.45–42.66%) by incorporating tag and time information compared with log-based model. The improvement of performances is statistically significant as the maximum variance for tag and time model is 0.001006. This confirms our assumptions that tags can express users' preferences and more recent bookmarks better reflect users' interests. Both tag and time information are crucial in providing personalized recommendations.

Another interesting finding in Fig. 12 is that fluctuation exists among all the four models when neighborhood is less than 30, which indicates that recommendation quality is sensitive to the number of neighborhood within this range on our dataset. When neighborhood size is larger than 30, four models get relatively smooth performances. We believe that it results from that with sufficient number of neighbors, the process of resource recommendation is strongly affected by a certain part of users who have high similarity scores with the active user.

Taking an overall review in Fig. 12, we find that time-weight model outperforms tag-weight model on all neighborhood sizes. We believe this result is due to the attribute of our dataset from CiteULike. Since researchers always focus on a certain topic in a time period and their research interests are likely to change according to the discovering of hot problems at different time. Thus, the dataset is more sensitive with time information.

6. Conclusion and future work

Social tagging systems contain numerous useful information, therefore, it is important to provide personalized services based on these valuable information. In this paper, we have built a resource-recommendation model to utilize tag and time information available from online social tagging systems to generate ratings. We build a recommender system to provide personalized resource recommendation. Experimental results show that all three strategies are effective means to personalize navigational recommenda-

tion that lead to better performances than traditional log-based model. Our approaches could be easily expansive to cross domain recommendations among tagging systems.

In this paper, there is a limitation that we used only CiteULike dataset for experiments. It is needed to evaluate our computational approach using other datasets. Therefore, for the future work, we want to evaluate our resource-recommendation model with other datasets, such as Del.icio.us, Flickr and MovieLens. Also, we plan to extend our work to social network analysis in social tagging systems.

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