

Dynamic User Modeling in Social Media Systems

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Social media provides valuable resources to analyze user behaviors and capture user preferences. This article focuses on analyzing user behaviors in social media systems and designing a latent class statistical mixture model, named *temporal context-aware mixture model* (TCAM), to account for the intentions and preferences behind user behaviors. Based on the observation that the behaviors of a user in social media systems are generally influenced by *intrinsic interest* as well as the *temporal context* (e.g., the public's attention at that time), TCAM simultaneously models the topics related to users' intrinsic interests and the topics related to temporal context and then combines the influences from the two factors to model user behaviors in a unified way. Considering that users' interests are not always stable and may change over time, we extend TCAM to a dynamic temporal context-aware mixture model (DTCAM) to capture users' changing interests. To alleviate the problem of data sparsity, we exploit the social and temporal correlation information by integrating a social-temporal regularization framework into the DTCAM model. To further improve the performance of our proposed models (TCAM and DTCAM), an item-weighting scheme is proposed to enable them to favor items that better represent topics related to user interests and topics related to temporal context, respectively. Based on our proposed models, we design a temporal context-aware recommender system (TCARS). To speed up the process of producing the top- k recommendations from large-scale social media data, we develop an efficient query-processing technique to support TCARS. Extensive experiments have been conducted to evaluate the performance of our models on four real-world datasets crawled from different social media sites. The experimental results demonstrate the superiority of our models, compared with the state-of-the-art competitor methods, by modeling user behaviors more precisely and making more effective and efficient recommendations.

Categories and Subject Descriptors: H.3.3 [Information Search and Retrieval]: Information Filtering; H.2.8 [Database Applications]: Data Mining; J.4 [Computer Applications]: Social and Behavior Sciences

General Terms: Algorithms, Design, Experimentation, Performance

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1. INTRODUCTION

With the rising popularity of social media, a better understanding of users' rating behaviors¹ is of great importance for the design of many applications, such as personalized recommendation, information filtering, behavioral targeting, and computational advertising. Research efforts [Michelson and Macskassy 2010; Stoyanovich et al. 2008] have been undertaken to model users' interests to help them find interesting items by analyzing their historical behaviors. However, existing works [Michelson and Macskassy 2010; Stoyanovich et al. 2008; Wen and Lin 2010] simply assume that users prefer items based on their intrinsic interests, which may not be accurate in many social application scenarios. For example, when choosing a book to read or a movie to watch, the users are likely to prefer books/movies that interest them. In contrast, when selecting news to read or users to follow in a social network (e.g., Twitter), users are most likely to be attracted, respectively, by breaking news or famous users who are followed by the general public [Xu et al. 2012; Liu et al. 2010a; Cha and Cho 2012]. Therefore, users' rating behaviors on items may not necessarily indicate users' intrinsic interests. New models are required to better account for user behaviors in social media to learn user preferences more precisely.

Inspired by the early works about user posting behaviors in microblogs [Xu et al. 2012; Diao et al. 2012; Yin et al. 2013], we investigated and analyzed user rating behaviors on multiple social media datasets including Digg,² Delicious,³ Movielens,⁴ and Douban Movie.⁵ The experimental section provides details of these four datasets. According to our observations on these social media datasets, intuitively, user rating behaviors are significantly influenced by two factors: *the intrinsic interest of the user* and *the attention of the general public*. While the user's intrinsic interest is relatively stable, the attention of the general public changes from time to time. For example, as shown in Figure 1, where the x-axis denotes the months in the year of 2009 and the y-axis represents the normalized topic popularity, the hot topics in Delicious vary over time. Hence, in our work, we refer to the attention of the public during a particular time period as *temporal context*.

The two factors have different degrees of influence on user rating behaviors for different types of social media platforms as a result of the different characteristics (e.g., life cycles and updating rates) of various types of social media items. For instance, we observe that news in Digg is very time sensitive with a short life cycle—few people want to read outdated news—while the life cycle of movies in Movielens and Douban Movie is relatively longer, with many classic old movies being highly ranked in the popularity list. For time-sensitive social media items such as news, users are more easily influenced by the temporal context, whereas they tend to make decisions based on their intrinsic interests when choosing items that are not so time sensitive (e.g., books and movies).

¹We use the term “rating behavior” to denote general user actions on items in social media systems, such as rating and viewing.

²<http://digg.com/>.

³<https://delicious.com/>.

⁴<http://www.movielens.org/>.

⁵<http://movie.douban.com/>.

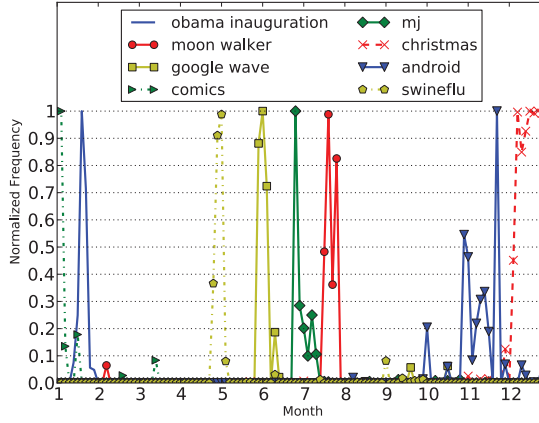


Fig. 1. Dynamic public's attentions observed from the Delicious dataset.

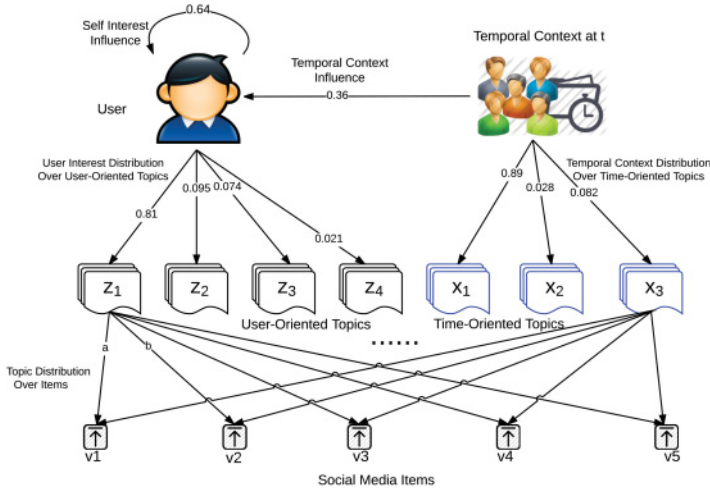


Fig. 2. An example of TCAM.

To model user rating behaviors in social media systems, therefore, it is critical to identify users' intrinsic interests as well as the temporal context. Moreover, it is essential to model the influence degrees of the two factors in different social media systems.

To this end, we proposed a temporal context-aware mixture model (TCAM) in our previous work [Yin et al. 2014a] to mimic user rating behaviors in a process of decision making. As shown in Figure 2, TCAM is a latent class statistical mixture model that simultaneously models the topics [Blei et al. 2003] related to users' intrinsic interests and the topics related to the temporal context and then combines the influences from the user interest and the temporal context to model user behaviors in a unified manner. Specifically, the model discovers (1) users' personal interest distribution over a set of latent topics, (2) the temporal context distribution over a set of latent topics, (3) an item generative distribution for each latent topic, and (4) the mixing weights that represent the influence probabilities of users' personal interest and the temporal context. It is worth mentioning that the set of latent topics used to model user interest is different from the set of topics used to model the temporal context. The former are called *user-oriented topics* and the latter are referred to as *time-oriented topics*.

The generative process of user rating behaviors in TCAM is briefly illustrated as follows. Suppose a user u selects an item v at time slice t . TCAM first tosses a coin, based on the influence probabilities of the two factors, to decide whether this behavior results from the influence of the user's personal interest or the influence of the temporal context. If it results from the influence of the user's personal interest, TCAM chooses a *user-oriented topic* for u based on the user's intrinsic interest (with a certain probability). The selected topic in turn generates an item v following the topic's item generative distribution. Otherwise, if the influence from the temporal context is sampled, TCAM chooses a *time-oriented topic* according to the general public's interest at t , which in turn generates an item v .

TCAM assumes that the temporal context is dynamic while the user interest distribution is stable; that is, the temporal context is time dependent, while the user interest distribution is time independent. However, users' interests are not always stable and may change over time in reality. For instance, users will naturally be interested in parenting issues after they have a baby and probably ignore their other interests. Accurately capturing this change has been proved to be commercially very valuable since it indicates purchase intents. Therefore, we extend TCAM [Yin et al. 2014a] by designing a dynamic TCAM (i.e., DTCAM) to model user dynamic interests in this article. DTCAM allows users to have different interests in different time periods. However, user rating data at a time slice is very sparse, so the dynamic user interest at a time slice is easily overestimated or underestimated. To alleviate the problem of data sparsity, we exploit the social and temporal correlation information to enhance the prior knowledge about users' dynamic interests in each time slice in this article.

Similar to traditional topic models where popular words in a document corpus are usually ranked high in each topic [Cha and Cho 2012; Cha et al. 2013], popular social media items tend to be estimated as having high generation probability by our proposed models (i.e., TCAM and DTCAM), which impairs the quality of the discovered user-oriented topics and time-oriented topics. User-oriented topics are supposed to capture user intrinsic interests, but a popular item favored by many users conveys less information about a user's intrinsic interest than an item favored by few users (i.e., a salient item) [Yin et al. 2012]. Similarly, a popular item constantly favored by users cannot well represent a time-oriented topic because the public's attention changes over time. Hence, to improve the performance of our proposed models, we devise an item-weighting scheme to promote the importance of salient and bursty items, which enhances the quality of the underlying topics detected by TCAM and DTCAM.

Based on our proposed models, we design a temporal context-aware recommender system (TCARS) that exploits both user interests and the temporal context. TCARS consists of two main parts: *modeling component* and *recommendation component*. The modeling component uses DTCAM to infer users' personal interest distribution and the general public's attention (i.e., the temporal context) at each time slice t , as well as the weights of each item on each topic. Given a querying user u at time t , the recommendation component computes a ranking score for each item v by automatically combining u 's interest and the public's attention at time t , which are inferred by the modeling component. The traditional approach to produce the top- k recommendations is to first compute a ranking score for each item and then rank all of them. However, when the number of available items becomes large (e.g., millions of), to produce a top- k ranked list using the traditional method is very time consuming. To speed up the process of producing recommendations for large social media data with millions of candidate items, we design an efficient query-processing technique by extending the Threshold Algorithm (TA) [Fagin et al. 2001]. Briefly, we precompute K sorted lists of items according to the K latent topics learned by DTCAM. In each list, items are sorted based on their generative probabilities with respect to the corresponding topic.

At query time, we access items from the K sorted lists and compute the top- k items by extending the TA. The algorithm has the nice property of terminating early without scanning all items. Specifically, it terminates when the ranking score of the k th item in the result list is higher than the threshold score. This TA-based scheme allows us to efficiently return the top- k recommendations by computing the ranking score for the minimum number of items instead of all.

To sum up, this article focuses on the problem of modeling users' dynamic behaviors on social media systems. We have presented our preliminary study of user behavior modeling in Yin et al. [2014a]. This article extends Yin et al. [2014a] with an in-depth investigation and performance analysis. Specifically, this article makes the following new contributions: first, we provide a more comprehensive analysis and review of related work; second, based on TCAM, we propose a new DTCAM to capture user dynamic interests; third, to alleviate the problem of data sparsity in DTCAM, we exploit the social-temporal correlation information by extending DTCAM with a social-temporal regularization framework; and fourth, we conduct more extensive experiments to evaluate the performance of DTCAM and the enhanced DTCAM with a social-temporal regularization framework (RDTCAM). We also test the performance of RDTCAM to overcome the cold-start problem in the temporal recommendation.

The main contributions of our work are summarized as follows:

- We make a comprehensive analysis and review of previous related works.
- We extend our TCAM proposed in DTCAM to more accurately capture user dynamic interests and model their dynamic behaviors more accurately. Moreover, to alleviate the problem of data sparsity, we integrate a social-temporal regularization framework into our DTCAM by effectively exploiting the social and temporal correlation information.
- Based on our models, we design a temporal context-aware recommender system. To speed up the recommendation process in TCARS, we develop an efficient query-processing technique.
- We conduct extensive experiments to evaluate the performance of the proposed models based on four sets of real-life data from different social media systems. The experimental results demonstrate the superiority of our models over existing approaches.

The remainder of the article is organized as follows. Section 2 reviews the existing work related to our research. Section 3 details the temporal context-aware mixture model, and Section 4 presents the dynamic temporal context-aware mixture model. We propose a social-temporal regularization technique to exploit the social and temporal correlation in Section 5. We present an item-weighting scheme to enhance our models in Section 6. We present a temporal context-aware recommender system in Section 7. We carry out extensive experiments and report the experimental results in Section 8 and conclude the article in Section 9.

2. RELATED WORK

In this section, we review related research from the following two areas: topic modeling and temporal recommendation techniques.

Topic Model. Topic models provide a useful means to discover topic structures from large document collections. While traditional topic models, such as LDA [Blei et al. 2003] and PLSA [Hofmann 1999], do not address the temporal information in a document corpus, a number of temporal topic models have been proposed to consider topic evolution over time. Mei and Zhai [Mei and Zhai 2005; Wang et al. 2007] studied mining evolutionary topics from texts by comparing topics modeled in consecutive time slices. Wang and McCallum [2006] designed the TOT model that treats timestamps

of documents as an observed continuous variable generated by topics. This model is designed to capture temporal features with beta distribution, confining each topic into a narrow time distribution. Other models, such as the Dynamic Topic Model (DTM) [Blei and Lafferty 2006], MAP-PLSA [Gohr et al. 2009], and Online LDA [AlSumait et al. 2008], are also proposed to study topic changes over time.

The TimeUserLDA model proposed by Diao et al. [2012] is designed for finding bursty topics from microblogs. Although this model assumes that user posting behaviors are influenced by both user interest and global topic trends, there is only one shared set of underlying topics in TimeUserLDA; that is, there is no distinction between underlying user-oriented topics and time-oriented topics. Thus, the topics detected by their models look confusing and noisy since they conflate both user interest and temporal context. To improve the topic discovery process, Yin et al. [2013] recently proposed a unified model to detect both stable and temporal topics simultaneously from social media data.

Recently, topic models have been applied to collaborative filtering. Jin et al. [2005] proposed an approach based on LDA to discover the hidden semantic relationships between items for recommendation. In Chen et al. [2009], a hard-constraint-based LDA method was used to deal with user-community data, in which each user is viewed as a document and the communities that this user joins are viewed as words in the document. In contrast, Kang and Yu [2010] proposed a soft-constraint-based LDA method for community recommendations. We refer to these topic-model-based CF methods as “traditional” recommendation techniques, which simply assume that items rated by users represent their intrinsic interests and ignore the influence from other factors. Recently, Yin et al. [2013, 2014] proposed a location-content-aware topic model to produce location-based recommendations. Besides, Yin et al. [2014b] proposed LA-LDA, a location-aware probabilistic generative model that exploits location-based ratings to model user profiles and produce recommendations. Xu et al. [2012] and Ye et al. [2012] assumed that user behaviors are influenced by both user interests and the behaviors of their social friends and proposed mixture latent topic models to capture these factors. Again, these models make use of one set of shared topics to model two factors. The estimated topics are confusing and difficult to interpret, which causes the recommendation results to degenerate. Moreover, these models do not exploit the temporal information.

Yin et al. [2014a] proposed a TCAM for user rating behaviors on social media systems, but TCAM assumes that users’ interests are stable. In reality, users’ interests are not always stable and may change over time. So, in this article, we extend the TCAM into a dynamic version (i.e., DTCAM) where users’ interests can change over time. Besides, the TCAM does not consider the effect of social networks. To further alleviate the problem of data sparsity and model users’ behaviors more accurately, we exploit the social network information to enhance the prior knowledge about users’ dynamic interests in this article.

Temporal Recommendation. The time factor has been widely used for the conventional recommendations (e.g., books, music, and movies) by considering the time gap between the occurring time of a previous rating and the recommendation time as a decaying factor to weigh the rating [Ding and Li 2005]. Ding and Li [2005] proposed a time weighting scheme for a neighborhood-based collaborative filtering approach. When making a recommendation, the similarities between users and previously rated items decay as the time difference increases. The decay rate is both user dependent and item dependent. Zimdars et al. [2001] treated collaborative filtering (CF) as a univariate time-series problem: given a user’s previous behaviors, predict the next behavior. They developed two families of methods for transforming data to encode time order in ways amenable to the off-the-shelf decision tree learning tool. At the stage of prediction, the learned decision tree model is used. Lathia et al. [2009] formalized CF as a time-dependent iterative prediction problem and found that certain prediction

methods that improve prediction accuracy in the Netflix dataset do not show similar improvement over a set of iterative train-test experiments with growing data. So they proposed a method to automatically assign and update peruser neighborhood sizes other than setting global parameters. Xiang et al. [2010] proposed a graph-based recommendation model named Session-based Temporal Graph (STG) to simultaneously model users' long-term and short-term preferences over time. Based on the STG model framework, they also provided an Injected Preference Fusion (IPF) recommendation algorithm and extended the personalized Random Walk for temporal recommendation. Yu et al. [2014] extended STG to a hybrid model called Topic-STG by introducing topic information. This model was used to learn user preference for tweet recommendations. Ahmed et al. [2011] designed a dynamic topic model to model users' dynamic interests. Their proposed dynamic model was then deployed to the scenario of behavior targeting and ad recommendation. The model is heavily dependent on the content information, which is not always available on social media systems.

Many successful temporal collaborative filtering methods are based on latent factor models. For example, the Netflix award-winning algorithm *timeSVD++* [Koren 2009] assumes that the latent features consist of components that evolve over time with a dedicated bias for each user at each specific time point. This model can effectively capture local changes to user preferences, which the authors claim to be vital for improving performance. Xiong et al. [2010] proposed a Bayesian probabilistic tensor factorization model (BPTF). BPTF represents users, items, and time in a shared low-dimensional space and predicts the rating score that a user u will assign to item v at time t using the inner product of their latent representations. Demonstrated by the experimental results on Netflix data, both BPTF and *timeSVD++* perform well on the rating prediction task because they incorporate time effects into models. One main disadvantage with these models is that the learned latent low-dimensional space is difficult to interpret. Recently, Liu et al. [2010b] addressed a new problem, online evolutionary collaborative filtering, which tracks user interests over time for the purpose of making timely recommendations. They extended the widely used neighborhood-based algorithms by incorporating temporal information and developed an incremental algorithm for updating neighborhood similarities with new data. However, most of the existing temporal recommendation models [Koren 2009; Xiong et al. 2010; Liu et al. 2010b] are designed for the task of rating prediction rather than the top- k recommendations.

Campos et al. [2014] provided a comprehensive survey about time-aware recommender systems and analyzed existing evaluation protocols. They also provided a comprehensive classification of evaluation protocols and proposed a methodological description framework to make the evaluation process reproducible.

3. USER RATING BEHAVIOR MODELING

In this section, we first introduce relevant definitions and notations used throughout this article. We then present the novel temporal context-aware mixture model for modeling user rating behaviors in social media systems.

3.1. Notations and Definitions

The notations used in this article are summarized in Table I.

Definition 3.1 (User Rating). A user rating is a triple (u, t, v) that denotes a rating behavior (e.g., purchasing, clicking, and tagging) made by user u on item v at time slice t .

Note that the time information available for each rating record in the collected raw datasets is in the form of timestamp (e.g., "2010-07-24, 13:45:06"), and we divide the timestamps into time slices at a predefined granularity (e.g., daily or weekly

Table I. Notations Used in This Article

SYMBOL	DESCRIPTION
u, t, v	user u , time slice t , item v
N, T, V	number of users, time slices, and items
M_u	number of items rated by user u
λ_u	the mixing weight specific to user u
K_1	number of user-oriented topics
θ_{uz}	probability that user-oriented topic z is chosen by user u
θ_u	intrinsic interest of user u , denoted by $\theta_u = \{\theta_{uz}\}_{z=1}^{K_1}$
θ_u^t	intrinsic interest of user u at time t , denoted by $\theta_u^t = \{\theta_{uz}^t\}_{z=1}^{K_1}$
ϕ_z	item proportions of user-oriented topic z , denoted by $\phi_z = \{\phi_{zv}\}_{v=1}^V$
ϕ_{zv}	probability that item v is generated by user-oriented topic z
K_2	number of time-oriented topics
θ'_t	the temporal context at time slice t , denoted by $\theta'_t = \{\theta'_{tx}\}_{x=1}^{K_2}$
θ'_{tx}	probability that time-oriented topic x is generated by time slice t
ϕ'_x	item proportions of time-oriented topic x , denoted by $\phi'_x = \{\phi'_{xv}\}_{v=1}^V$
ϕ'_{xv}	probability that item v is generated by time-oriented topic x

granularity) when preprocessing the datasets. t is an ordinal variable and we use t to index the t th time, slice which corresponds to a specific time period.

Definition 3.2 (User Document). Given a user u , the user document, D_u , is a collection of items rated by him or her.

Definition 3.3 (Rating Cuboid). A rating cuboid \mathbf{C} is an $N \times T \times V$ cuboid, where N is the number of users, T is the number of time slices, and V is the number of items. A cell indexed by (u, t, v) stores the rating score that user u assigned to item v at time slice t , which indicates user u 's preference on item v at time t .

User actions on items, such as tagging, downloading, purchasing, and clicking, can be represented as a user rating. Either explicit feedback or implicit feedback can be used to compute the value of the rating score $C[u, t, v]$. For the explicit feedback, we generally collect the star ratings⁶ (e.g., movie ratings and book ratings) provided by user u for item v at time t as the rating score $C[u, t, v]$. We assume that the star ratings are integers in this article. For the implicit feedback, we intuitively choose the interaction frequency between user u and item v at time t to represent the rating score $C[u, t, v]$. For example, given a user u who uses a tag v for n times at time slice t , the usage frequency n can be used as the rating score to reflect the user's preference on the tag during that time period. In our models, $C[u, t, v]$ is viewed as the frequency of item v 's appearance in the user document D_u at time t .

We adopt the concept of topic from the field of text mining [Mei et al. 2008; Blei et al. 2003], and it is defined as follows.

Definition 3.4 (Topic). Given a collection of items $\mathbf{I} = \{v_i\}_{i=1}^V$, a topic z is defined as a multinomial distribution over \mathbf{I} , that is, $\phi_z = \{\phi_{zv_i}\}_{i=1}^V$, where each component ϕ_{zv_i} denotes the weight of item v_i on topic z .

⁶[http://en.wikipedia.org/wiki/Star_\(classification\)](http://en.wikipedia.org/wiki/Star_(classification)).

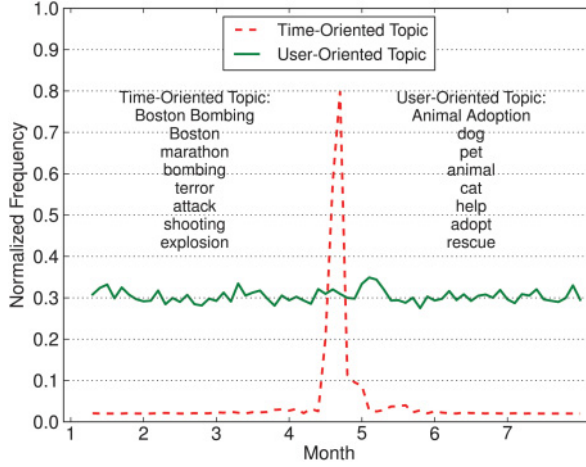


Fig. 3. An example of two types of topics in Delicious.

To illustrate the semantic meaning of a topic, we choose the top- k items that have the highest probability under the topic, as shown in Figure 3. Our work distinguishes between **user-oriented topics** ϕ_z and **time-oriented topics** ϕ'_x , although both are represented by a multinomial distribution over items. User-oriented topics are used to model user interest, which is assumed to be generally stable over time. In contrast, time-oriented topics are used to model the temporal context (i.e., the public's attention during a particular time), which has a clear temporal feature. For example, the popularity of the topics may increase or decrease over time and reach a peak during a certain period of time, as shown in Figure 3.

Definition 3.5 (User Interest). Given a user u , her or his intrinsic interest, denoted as θ_u , is a multinomial distribution over user-oriented topics. So, θ_u is also called u 's interest distribution.

Definition 3.6 (Temporal Context). Given a time slice t , the temporal context at t , denoted as θ'_t , is a multinomial distribution over time-oriented topics or items.

Definition 3.7 (Dynamic User Interest). Given a user u , her or his intrinsic interest at time t , denoted as θ_u^t , is a multinomial distribution over user-oriented topics. So, θ_u^t is also called u 's dynamic interest distribution at t .

3.2. Temporal Context-Aware Mixture Model

Given a rating cuboid \mathbf{C} that stores users' rating histories, we aim to model user rating behaviors by exploiting the information captured in \mathbf{C} . Before presenting the devised model, we first describe an example to illustrate the motivation of our design.

As mentioned before, users' rating behaviors in social media systems are influenced by not only intrinsic interest but also the temporal context. It is crucial to distinguish between user-oriented topics and time-oriented topics, because the two have very different characteristics. For example, Figure 3 shows an example of a user-oriented topic and a time-oriented topic detected by the TCAM from Delicious. As a demonstration, we present only the top eight tags that have the highest probability under each topic. We can easily tell the difference between the two topics from both their temporal distributions and the content descriptions. For the time-oriented topic, the items (i.e., tags) are related to a certain event (e.g., "Boston Marathon bombings"). The popularity of the topic experiences a sharp increase at a particular time slice (e.g., in April 2013).

For the user-oriented topic, the items are about the user's regular interest (e.g., "Pet Adoption"). The temporal distribution of the topic does not show any spike-like fluctuation. Hence, our TCAM models the user-oriented topics and the time-oriented topics simultaneously.

To consider the influence of the user intrinsic interest and the temporal context in a unified manner, TCAM computes the likelihood that a user u will rate an item v at a time slice t as follows:

$$P(v|u, t, \Psi) = \lambda_u P(v|\theta_u) + (1 - \lambda_u) P(v|\theta'_t), \quad (1)$$

where Ψ denotes the model parameter set; $P(v|\theta_u)$ is the probability that item v is generated from u 's intrinsic interest, denoted as θ_u ; and $P(v|\theta'_t)$ denotes the probability that item v is generated from the temporal context at time slice t , that is, θ'_t . The parameter λ_u is the mixing weight, which represents the influence probability of the user interest. That is, user u is influenced by personal interest θ_u with probability λ_u and is influenced by the temporal context θ'_t with probability $1 - \lambda_u$ when making decision. It is worth mentioning that TCAM holds personalized mixing weights for individual users, considering the differences between users in personalities (e.g., openness and agreeableness).

The user interest component θ_u is modeled by a multinomial distribution over a set of user-oriented topics, and each item is generated from a user-oriented topic z . $P(v|\theta_u)$ is then computed as follows:

$$P(v|\theta_u) = \sum_{z=1}^{K_1} P(v|\phi_z) P(z|\theta_u). \quad (2)$$

As for the temporal context component θ'_t , it is modeled as a multinomial distribution over a set of latent time-oriented topics, and each item is generated from a time-oriented topic x . Then, $P(v|\theta'_t)$ is formulated as follows:

$$P(v|\theta'_t) = \sum_{x=1}^{K_2} P(v|\phi'_x) P(x|\theta'_t). \quad (3)$$

As an illustrative example in Figure 2, the user is influenced by personal interest and the temporal context with probabilities 0.64 and 0.36, respectively. Four user-oriented topics and three time-oriented topics are also shown respectively, where the weights representing the user's interest distribution over the user-oriented topics as well as the temporal context distribution over the time-oriented topics are labeled in the corresponding edges. We can see that user-oriented topic U1 dominates the user's interest, and time-oriented topic T1 attracts the most attention from the general public at time t . The probabilities of topics' generating items are also labeled in the corresponding edges. For example, the weight b on the edge linking topic U1 and item v_2 represents the probability of U1 generating item v_2 .

Figure 4 illustrates the generative process of TCAM with a graphical model. The structure of TCAM is similar to the PLSA model, but TCAM has additional machinery to handle the mixing weight λ_u . In particular, a latent random variable s , associated with each item, is adopted as a switch to determine whether the item is generated according to the temporal context θ'_t or the user's interest θ_u . s is sampled from a user-specific Bernoulli distribution with the mean λ_u . N indicates the number of users, K_1 is the number of user-oriented topics, K_2 is the number of time-oriented topics, T is the number of time slices, and M_u is the number of items rated by u . The generative process of TCAM is summarized as follows.

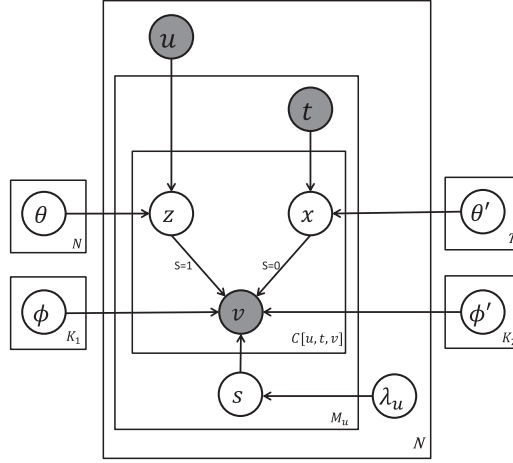


Fig. 4. The graphical representation of TCAM.

For each item v rated by u at time slice t :

- (1) Sample s from $Bernoulli(\lambda_u)$.
- (2) If $s = 1$:
 - (a) Sample user-oriented topic z from $Multinomial(\theta_u)$.
 - (b) Sample item v from $Multinomial(\phi_z)$.
 - (c) Repeat the previous two steps $C[u, t, v]$ times.
- (3) Otherwise:
 - (a) Sample time-oriented topic x from $Multinomial(\theta'_t)$.
 - (b) Sample item v from $Multinomial(\phi'_x)$.
 - (c) Repeat the previous two steps $C[u, t, v]$ times.

3.3. Model Inference

Given a rating cuboid C , the learning procedure of our model is to estimate the unknown model parameter set $\Psi = \{\theta, \phi, \theta', \phi', \lambda\}$. The log likelihood is derived as follows:

$$L(\Psi|C) = \sum_{u=1}^N \sum_{t=1}^T \sum_{v=1}^V C[u, t, v] \log P(v|u, t, \Psi), \quad (4)$$

where $P(v|u, t, \Psi)$ is defined in Equation (1).

The goal of parameter estimation is to maximize the log likelihood in Equation (4). As this equation cannot be solved directly by applying Maximum Likelihood Estimation (MLE), we apply an EM approach instead. In the expectation (E) step of the EM approach, we introduce $P(s|u, t, v; \hat{\Psi})$, which is the posterior probability of choosing personal interest θ_u (i.e., $s = 1$) or temporal context θ'_t (i.e., $s = 0$), respectively, given user rating behavior (u, t, v) and the current estimations of the parameters $\hat{\Psi}$. In the maximization (M) step, parameters are updated by maximizing the expected complete data log-likelihood $Q(\Psi)$ based on the posterior probability computed in the E-step.

In the **E-step**, $P(s|u, t, v; \hat{\Psi})$ is updated according to Bayes formulas as in Equation (5):

$$P(s|u, t, v; \hat{\Psi}) = \frac{s\lambda_u P(v|\theta_u) + (1-s)(1-\lambda_u)P(v|\theta'_t)}{\lambda_u P(v|\theta_u) + (1-\lambda_u)P(v|\theta'_t)}, \quad (5)$$

where $P(v|\theta_u)$ and $P(v|\theta'_t)$ are defined as in Equations (2) and (3), respectively. To obtain the updated parameters $P(z|\theta_u)$ and $P(v|\phi_z)$, the posterior probability $P(z|s = 1, u, t, v; \hat{\Psi})$ is computed as

$$P(z|s = 1, u, t, v; \hat{\Psi}) = \frac{P(v|\phi_z)P(z|\theta_u)}{\sum_{z'=1}^{K_1} P(v|\phi_{z'})P(z'|\theta_u)}. \quad (6)$$

Based on $P(z|s = 1, u, t, v; \hat{\Psi})$ and $P(s = 1|u, t, v; \hat{\Psi})$, we introduce the notation $P(z|u, t, v; \hat{\Psi})$ as follows:

$$P(z|u, t, v; \hat{\Psi}) = P(z|s = 1, u, t, v; \hat{\Psi})P(s = 1|u, t, v; \hat{\Psi}). \quad (7)$$

To obtain the updated parameters $P(x|\theta'_t)$ and $P(v|\phi'_x)$, we update the posterior probability $P(x|s = 0, u, t, v; \hat{\Psi})$ as follows:

$$P(x|s = 0, u, t, v; \hat{\Psi}) = \frac{P(v|\phi'_x)P(x|\theta'_t)}{\sum_{x'=1}^{K_2} P(v|\phi'_{x'})P(x'|\theta'_t)}. \quad (8)$$

Based on $P(x|s = 0, u, t, v; \hat{\Psi})$ and $P(s = 0|u, t, v; \hat{\Psi})$, we introduce the notation $P(x|u, t, v; \hat{\Psi})$ as follows:

$$P(x|u, t, v; \hat{\Psi}) = P(x|s = 0, u, t, v; \hat{\Psi})P(s = 0|u, t, v; \hat{\Psi}). \quad (9)$$

With simple derivations [Hofmann 1999], we obtain the expectation of complete data log-likelihood for TCAM:

$$\begin{aligned} Q(\Psi) &= \sum_{u=1}^N \sum_{v=1}^V \sum_{t=1}^T C[u, t, v] \{P(s = 1|u, t, v; \hat{\Psi}) \\ &\quad \times \sum_{z=1}^{K_1} P(z|s = 1, u, t, v; \hat{\Psi}) \log[\lambda_u P(v|\phi_z)P(z|\theta_u)] + P(s = 0|u, t, v; \hat{\Psi}) \\ &\quad \times \sum_{x=1}^{K_2} P(x|s = 0, u, t, v; \hat{\Psi}) \log[(1 - \lambda_u)P(v|\phi'_x)P(x|\theta'_t)]\}. \end{aligned} \quad (10)$$

In the **M-step**, we find the estimation Ψ that maximizes the expectation of the complete data log-likelihood $Q(\Psi)$ with the constraints $\sum_{v=1}^V P(v|\phi_z) = 1$, $\sum_{v=1}^V P(v|\phi'_x) = 1$, $\sum_{z=1}^{K_1} P(z|\theta_u) = 1$, and $\sum_{x=1}^{K_2} P(x|\theta'_t) = 1$, using the following updating formulas:

$$P(z|\theta_u) = \frac{\sum_{v=1}^V \sum_{t=1}^T C[u, t, v] P(z|u, t, v; \hat{\Psi})}{\sum_{z'=1}^{K_1} \sum_{v=1}^V \sum_{t=1}^T C[u, t, v] P(z'|u, t, v; \hat{\Psi})} \quad (11)$$

$$P(v|\phi_z) = \frac{\sum_{t=1}^T \sum_{u=1}^N C[u, t, v] P(z|u, t, v; \hat{\Psi})}{\sum_{v'=1}^V \sum_{t=1}^T \sum_{u=1}^N C[u, t, v'] P(z|u, t, v'; \hat{\Psi})} \quad (12)$$

$$P(x|\theta'_t) = \frac{\sum_{v=1}^V \sum_{u=1}^N C[u, t, v] P(x|u, t, v; \hat{\Psi})}{\sum_{x'=1}^{K_2} \sum_{v=1}^V \sum_{u=1}^N C[u, t, v] P(x'|u, t, v; \hat{\Psi})} \quad (13)$$

$$P(v|\phi'_x) = \frac{\sum_{t=1}^T \sum_{u=1}^N C[u, t, v] P(x|u, t, v; \hat{\Psi})}{\sum_{v'=1}^V \sum_{t=1}^T \sum_{u=1}^N C[u, t, v'] P(x|u, t, v'; \hat{\Psi})}. \quad (14)$$

With an initial random guess of Ψ , we alternately apply the E-step and M-step until a termination condition is met. To adapt to different users, we estimate the parameter λ_u in M-step, instead of picking a fixed λ value for all users. This personalized treatment can automatically adapt the model parameter estimation for various users. Specifically, λ_u is estimated as follows:

$$\lambda_u = \frac{\sum_{t=1}^T \sum_{v=1}^V C[u, t, v] P(s = 1|u, t, v; \hat{\Psi})}{\sum_{t=1}^T \sum_{v=1}^V \sum_{s=0}^1 C[u, t, v] P(s|u, t, v; \hat{\Psi})}. \quad (15)$$

3.4. Discussion About TCAM

A number of relevant issues of the proposed TCAMs are discussed in this subsection.

Hyperparameter Setting. In our model, we still have four hyperparameters to tune manually, including the number of user-oriented topics K_1 , the number of time-oriented topics K_2 , the number of time slices T , and the number of EM iterations. K_1 and K_2 are the desired numbers of user-oriented topics and time-oriented topics, respectively, which need to be tuned empirically. T is the number of time slices used in our model to generate time-oriented topics, which provides users with the flexibility to adjust the granularity/length of the time slice. The larger T is, the more fine-grained time slices are. Regarding the number of EM iterations, we observe that convergence can be achieved in a few iterations (e.g., 50) because the model inference procedure using the EM approach is fast. The time cost of each iteration is $\mathcal{O}(NK_1V + TK_2V)$, which is very similar to the time cost required for PLSA implementation [Hofmann 1999]. It is worth mentioning that EM algorithms can be easily expressed in MapReduce [Das et al. 2007; Wolfe et al. 2008], so the inference procedure of TCAM can be naturally decomposed for parallel processing, which is scalable to large-scale datasets.

Guidance with Dirichlet Priors. Prior knowledge can be integrated into TCAMs to guide the topic discovery process. For example, in the MovieLens dataset, we can introduce prior knowledge and guide the user-oriented topics so that they are related to the genres of movies, such as action and comedy. Another example is the Digg dataset, where we can integrate prior knowledge to guide the time-oriented topics so that they are aligned with breaking events. Specifically, we define a conjugate prior (i.e., Dirichlet prior) on each multinomial topic distribution. Let us denote the Dirichlet prior β_z for user-oriented topic z and β'_x for time-oriented topic x . $\beta_z(v)$ and $\beta'_x(v)$ can be interpreted as the corresponding pseudo counts for item v when we estimate the topic distributions $P(v|\phi_z)$ and $P(v|\phi'_x)$, respectively. With these conjugate priors, we can use the Maximum a Posteriori (MAP) estimator for parameter estimation, which can be computed using the same EM algorithm except that we should replace Equations (12) and (14) with the following formulas, respectively:

$$P(v|\phi_z) = \frac{\sum_t \sum_u C[u, t, v] P(z|u, t, v; \hat{\Psi}) + \beta_z(v)}{\sum_{v'} \sum_t \sum_u (C[u, t, v'] P(z|u, t, v'; \hat{\Psi}) + \beta_z(v'))},$$

$$P(v|\phi'_x) = \frac{\sum_t \sum_u C[u, t, v] P(x|u, t, v; \hat{\Psi}) + \beta'_x(v)}{\sum_{v'} \sum_t \sum_u (C[u, t, v'] P(x|u, t, v'; \hat{\Psi}) + \beta'_x(v'))}.$$

Advantages of TCAM. The advantages of TCAM are summarized as follows: (1) We unify the influences from the user interest and the temporal context to model user rating behaviors. (2) We distinguish between user-oriented topics and time-oriented topics. Two different types of latent topics are proposed to model user interest and the temporal context, respectively. By taking away the influence of the temporal context, *user-oriented topics* can capture user intrinsic interests more precisely. Likewise, without the influence of user interests, *time-oriented topics* can better reflect the temporal

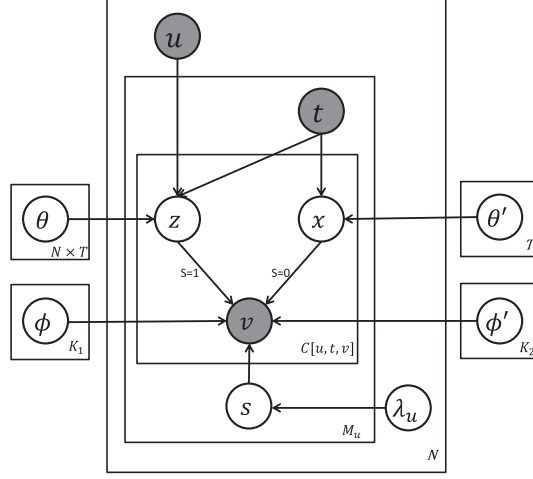


Fig. 5. The graphical representation of DTCAM.

context because the noise induced by a wide variety of user interests could contaminate the time-oriented topics. (3) TCAM can generate interpretable individual user profiles that can be presented alongside item recommendations to allow users to understand the rationale behind the recommendations. We will show sample user profiles in Section 8.6.

4. DYNAMIC USER INTEREST MODELING

In TCAM, we assume that user interest distribution θ_u is stable, that is, constant over time. However, this is not always true in reality. Users' interests may change over time and new interests may arise. The appearance of new topics of interest in the user's stream of actions can be predictive of his or her real-time interest.

4.1. Model Description of DTCAM

Now we turn to model the dynamics in the user-specific interests. We use the notation θ_u^t to denote interest distribution of user u at time t . Thus, the likelihood that a user u will rate an item v at time t can be recomputed as in Equation (16):

$$P(v|u, t, \Psi) = \lambda_u P(v|\theta_u^t) + (1 - \lambda_u) P(v|\theta'_t). \quad (16)$$

Similar to the static user interest component θ_u , the dynamic user interest component θ_u^t is modeled by a multinomial distribution over user-oriented topics, and each item is generated from a user-oriented topic z . Thus, $P(v|\theta_u^t)$ is computed as in Equation (17):

$$P(v|\theta_u^t) = \sum_{z=1}^{K_1} P(v|\phi_z) P(z|\theta_u^t). \quad (17)$$

The temporal context-aware mixture model with dynamic user interest is called dynamic TCAM. Figure 5 illustrates the generative process of DTCAM with a graphical model. The generative process of DTCAM is also summarized as follows. For each item v rated by u at time t :

- (1) Sample s from $Bernoulli(\lambda_u)$.
- (2) If $s = 1$:
 - (a) Sample topic z from $Multinomial(\theta_u^t)$.

- (b) Sample item v from $Multinomial(\phi_z)$.
- (c) Repeat the previous two steps $C[u, t, v]$ times.
- (3) Else:
 - (a) Sample topic x from $Multinomial(\theta'_t)$.
 - (b) Sample item v from $Multinomial(\phi'_x)$.
 - (c) Repeat the previous two steps $C[u, t, v]$ times.

4.2. Model Inference

To estimate model parameters in DTCAM, we similarly apply an EM approach. In the **E-step**, similar to the parameter estimation in TCAM, the probability $P(s|u, t, v; \hat{\Psi})$ is redefined as follows:

$$P(s|u, t, v; \hat{\Psi}) = \frac{s\lambda_u P(v|\theta_u^t) + (1-s)(1-\lambda_u)P(v|\theta'_t)}{\lambda_u P(v|\theta_u^t) + (1-\lambda_u)P(v|\theta'_t)}, \quad (18)$$

where $P(v|\theta_u^t)$ is defined as in Equation (17). To obtain the updated parameters $P(z|\theta_u^t)$ and $P(v|\phi_z)$, the posterior probability $P(z|s = 1, u, t, v; \hat{\Psi})$ is recomputed as follows:

$$P(z|s = 1, u, t, v; \hat{\Psi}) = \frac{P(v|\phi_z)P(z|\theta_u^t)}{\sum_{z'=1}^{K_1} P(v|\phi_{z'})P(z'|\theta_u^t)}. \quad (19)$$

For DTCAM, the expectation of complete data log-likelihood $Q(\Psi)$ is formulated as follows:

$$\begin{aligned} Q(\Psi) = & \sum_{u=1}^N \sum_{v=1}^V \sum_{t=1}^T C[u, t, v] \{P(s = 1|u, t, v; \hat{\Psi}) \\ & \times \sum_{z=1}^{K_1} P(z|s = 1, u, t, v; \hat{\Psi}) \log[\lambda_u P(v|\phi_z)P(z|\theta_u^t)] + P(s = 0|u, t, v; \hat{\Psi}) \\ & \times \sum_{x=1}^{K_2} P(x|s = 0, u, t, v; \hat{\Psi}) \log[(1-\lambda_u)P(v|\phi'_x)P(x|\theta'_t)]\}. \end{aligned} \quad (20)$$

In the **M-step**, we find the estimation Ψ that maximizes the expectation of the complete data log-likelihood $Q(\Psi)$. Specifically, the model parameters $P(x|\theta'_t)$, $P(v|\phi'_x)$, $P(v|\phi_z)$, and λ_u are estimated according to Equations (13), (14), (12), and (15), respectively. $P(z|\theta_u^t)$ is inferred using the following formula:

$$P(z|\theta_u^t) = \frac{\sum_{v=1}^V C[u, t, v] P(z|u, t, v; \hat{\Psi})}{\sum_{z'=1}^{K_1} \sum_{v=1}^V C[u, t, v] P(z'|u, t, v; \hat{\Psi})}, \quad (21)$$

where $P(z|u, t, v; \hat{\Psi}) = P(z|s = 1, u, t, v; \hat{\Psi})P(s = 1|u, t, v; \hat{\Psi})$.

4.3. Intuitive Interpretation and Analysis of Dynamic User Interest

We run our DTCAM on the Delicious dataset, and the description about the dataset is presented in Section 8.1. Based on the results achieved by DTCAM, we qualitatively analyze the dynamics of user interests. For demonstration, we choose two users living in China to study their dynamic interests. Figure 6 illustrates the dynamic interests of the two users. For each user, we plot the temporal dynamics of his or her interests in the four chosen salient user-oriented topics. For each chosen user-oriented topic, we present the top-ranked tags with the highest generation probabilities in Table II, where the words in the second rows summarize the themes of topics. The figures show the dynamic interest of two users as a function of time. From the figures, we observe that

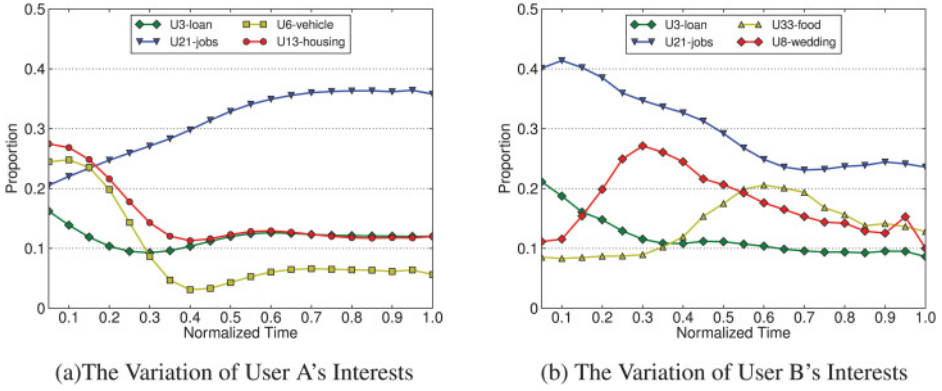


Fig. 6. Dynamic interests of two users learned by DTCAM.

Table II. User-Oriented Topics Preferred by User A and User B

U3	U21	U33	U6	U8	U13
loan	jobs	food	vehicle	wedding	housing
loan	job	food	car	wedding	home
lend	career	recipe	BMW	dress	department
bank	business	cooking	Bora	church	house
mortgage	hiring	dessert	Hoda	bride	rent
interest	salary	drink	Audi	groom	building
lender	hr	cake	Benz	maid	room

the interests of the two users are not stable but change over time, which verifies our intuitions behind DTCAM and also accounts for the potential superiority of DTCAM in user behavior modeling and temporal recommendation. Our DTCAM discovers that A has an increasing interest in jobs, and this may be because A has just bought a house and a car by loan. He needs a well-paid job to repay the loan in time. We find that B has a bursty interest in a wedding first and then focuses on cooking. Meanwhile, B has a decreasing interest in jobs. This may be because B is a female user and has just gotten married. In other words, her focus of attention changes from work to home after marriage, which is a typical phenomenon in China and Japan.

5. SOCIAL-TEMPORAL REGULARIZATION

User rating data at a time slice is very sparse, so the dynamic user interest θ_u^t is easily overestimated or underestimated. To alleviate the problem of data sparsity, we exploit the social and temporal information to enhance the prior knowledge about dynamic user interest distribution θ_u^t . Our enhancements make use of two intuitions. First, if two users u and u' are close in the social network G , their dynamic interest distributions θ_u^t and $\theta_{u'}^t$ are similar to each other. Second, if two time slices $t, t+1 \in T$ are adjacent in the time axis, the dynamic interest distributions θ_u^t and θ_u^{t+1} approximate to each other. In other words, the dynamic user interest distribution θ_u^t changes smoothly along the social and the temporal dimensions, respectively.

5.1. Social Smoothing

The phenomenon of homophily in social networks is attributed to the effects of selection and social influence [Wasserman 1994]. Selection means that people tend to form relationships with those sharing similar preferences and interests. Because of social influence, related people in a social network tend to influence each other and thus

become more similar. For example, the interests and posting behaviors of a user on a microblog platform, like retweeting and forwarding on Twitter, are often affected by his or her neighbors on the graph structure of interactions. The increasing availability of online social media data has provided a valuable source of social information, which, however, has not been fully utilized.

Motivated by this, we exploit the social information in a social network to improve user behavior modeling in social media systems. To integrate the information of social smoothness into our DTCAM, we propose a new social regularization framework to model user behaviors in the presence of a user network. Specifically, we make each user's dynamic interest dependent on the interests of her or his direct neighbors in the social network. The criterion of the regularizer in the framework is succinct and natural: users who are connected to each other tend to have similar interest distributions $P(z|\theta_u^t)$.

5.1.1. Framework. Formally, we define a regularized data likelihood as follows:

$$\mathcal{O}(\mathbf{C}, \mathbf{G}) = L(\Psi|\mathbf{C}) - \lambda R(\mathbf{C}, \mathbf{G}), \quad (22)$$

where $L(\Psi|\mathbf{C})$ is the user rating cuboid \mathbf{C} 's log likelihood (defined in Equation (4)), and $R(\mathbf{C}, \mathbf{G})$ is a harmonic regularizer defined on the social network graph \mathbf{G} . We adopt the network regularizer $R(\mathbf{C}, \mathbf{G})$ [Mei et al. 2008] as our social regularizer, which is defined as follows:

$$R(\mathbf{C}, \mathbf{G}) = \frac{1}{2} \sum_{(u, u') \in E} \pi(u, u') \sum_z \sum_t (P(z|\theta_u^t) - P(z|\theta_{u'}^t))^2, \quad (23)$$

where $\pi(u, u')$ denotes the similarity or affinity between user u and his or her friend u' . Our proposed social regularization framework can leverage the power of both DTCAM and the social network. Intuitively, $L(\Psi|\mathbf{C})$ in Equation (22) measures how likely is the data generated by DTCAM. By maximizing $L(\Psi|\mathbf{C})$, we make the model parameters Ψ fit the user rating data as much as possible. By minimizing $R(\mathbf{C}, \mathbf{G})$, we smooth the dynamic user interest distributions on the social network, where adjacent vertices have similar interest distributions. The parameter λ controls the balance between the data likelihood and the smoothness of dynamic user interest distributions over the network. It is easy to see that if $\lambda = 0$, the objective function degenerates to the log-likelihood of generating the user rating cuboid \mathbf{C} in Equation (4).

5.1.2. Model Parameter Estimation. In this section, we discuss parameter estimation of DTCAM enhanced with social regularization.

The enhanced DTCAM adopts the same generating schemes as that of the basic DTCAM. Thus, the enhanced model has exactly the same E-step as that of the basic model. The M-step can be derived from the relevant part of the expected complete data log-likelihood for the enhanced model, as follows:

$$\mathcal{Q}(\Psi) = \mathcal{Q}(\Psi) - \lambda R(\mathbf{C}, \mathbf{G}). \quad (24)$$

Since the social regularization part $R(\mathbf{C}, \mathbf{G})$ only involves the parameters $P(z|\theta_u^t)$, we can obtain the same M-step re-estimation equations for $P(x|\theta_t')$, $P(v|\phi_x')$, $P(v|\phi_z)$, and λ_u as in Equations (13), (14), (12), and (15). However, we do not have a closed-form re-estimation equation for $P(z|\theta_u^t)$. In this case, the traditional EM algorithm cannot be applied.

In the following, we discuss how to use the generalized EM algorithm (GEM) [Neal and Hinton 1998] to maximize the regularized log-likelihood of our enhanced DTCAM in Equation (22). The major difference between EM and GEM is in the M-step. Instead of finding the globally optimal solution Ψ , which maximizes the expected complete data

log-likelihood $Q(\Psi)$ in the M-step of the EM algorithm, GEM only needs to find a “better” Ψ in each new iteration. Let Ψ_n denote the parameter values of the previous iteration and Ψ_{n+1} denote the parameter values of the current iteration. The convergence of the GEM algorithm only requires $Q(\Psi_{n+1}) \geq Q(\Psi_n)$ [Neal and Hinton 1998].

In each M-step, we have parameter values Ψ_n and try to find Ψ_{n+1} that satisfy $Q(\Psi_{n+1}) \geq Q(\Psi_n)$. Obviously, $Q(\Psi_{n+1}) \geq Q(\Psi_n)$ holds if $\Psi_{n+1} = \Psi_n$. As $Q(\Psi) = Q(\Psi) - \lambda R(\mathbf{C}, \mathbf{G})$, we first find $\Psi_{n+1}^{(1)}$, which maximizes $Q(\Psi)$ instead of the whole $Q(\Psi)$. This can be done by simply applying Equations (13), (14), (12), (21), and (15). Clearly, $Q(\Psi_{n+1}^{(1)}) \geq Q(\Psi_n)$ does not necessarily hold. We then decrease $R(\mathbf{C}, \mathbf{G})$ by starting from $\Psi_{n+1}^{(1)}$, which can be done by the Newton-Raphson method [Neal and Hinton 1998]. Notice that $R(\mathbf{C}, \mathbf{G})$ only involves parameters $P(z|\theta_u^t)$, so we only need to update the $P(z|\theta_u^t)$ part in Ψ_{n+1} .

Given a function $f(x)$ and the initial value x_m , the Newton-Raphson updating formula to decrease (or increase) $f(x)$ is

$$x_{m+1} = x_m - \gamma \frac{f'(x_m)}{f''(x_m)}. \quad (25)$$

Since we have the following regularizer:

$$R(\mathbf{C}, \mathbf{G}) = \frac{1}{2} \sum_{(u,u') \in E} \pi(u, u') \sum_z \sum_t (P(z|\theta_u^t) - P(z|\theta_{u'}^t))^2 \geq 0,$$

the Newton-Raphson method decreases $R(\mathbf{C}, \mathbf{G})$ in each updating step. Integrating $R(\mathbf{C}, \mathbf{G})$ and $\Psi_{n+1}^{(1)}$ into Equation (25), we obtain the closed-form solution for $\Psi_{n+1}^{(2)}$, and then $\Psi_{n+1}^{(3)}, \dots, \Psi_{n+1}^{(m)}, \dots$, where

$$P(z|\theta_u^t)^{(m+1)} = (1 - \gamma)P(z|\theta_u^t)^{(m)} + \gamma \frac{\sum_{(u,u') \in E} \pi(u, u') P(z|\theta_{u'}^t)^{(m)}}{\sum_{(u,u') \in E} \pi(u, u')}. \quad (26)$$

Obviously, $\sum_z P(z|\theta_u^t)^{(m+1)} = 1$ and $P(z|\theta_u^t)^{(m+1)} \geq 0$ hold in the previous equation as long as $\sum_z P(z|\theta_u^t)^{(m)} = 1$ and $P(z|\theta_u^t)^{(m)} \geq 0$. Notice that the $P(x|\theta'_l)_{n+1}$, $P(v|\phi'_x)_{n+1}$, $P(v|\phi_z)_{n+1}$, and λ_u^{n+1} parts in Ψ_{n+1} will remain the same.

Every iteration of Equation (26) makes the dynamic user interest distribution θ_u^t smoother with respect to the nearest neighbors in the social network. The step parameter γ can be interpreted as a controlling factor to smooth the user interest distributions between neighbors. When it is set to 1, the new interest distribution of a user is the average of the old distributions from the neighbors. This parameter affects the convergence speed only but not the convergence result.

We continue the iteration of Equation (26) until $Q(\Psi_{n+1}^{(m+1)}) \leq Q(\Psi_{n+1}^{(m)})$. After that, we test whether $Q(\Psi_{n+1}^{(m)}) \geq Q(\Psi_n)$. If not, we reject the proposal of $\Psi_{n+1}^{(m)}$ and return the Ψ_n as the result of the M-step. This social regularization process is formalized in Algorithm 1.

5.1.3. Similarity Computation. The proposed social regularization term requires the knowledge of similarity between users. Since we have the rating information of all the users, the evaluation of similarities between two users can be calculated by measuring the rating history of these two users. There are many classic methods to compute the similarity, such as the Pearson Correlation Coefficient (PCC) [Breese et al. 1998],

ALGORITHM 1: Social Regularization**Input:** Parameters Ψ_{n+1} , Social Regularization parameters λ , Newton step parameter γ ;**Output:** $P(z|\theta_u^t)_{n+1}$;

```

1 Initialize  $m \leftarrow 1$ ;
2 Initialize  $P(z|\theta_{u'}^{(m)}) \leftarrow P(z|\theta_u^t)_{n+1}$ ;
3 Compute  $P(z|\theta_{u'}^{(m+1)})$  as in Equation (26);
4 while  $Q(\Psi_{n+1}^{(m+1)}) \geq Q(\Psi_{n+1}^{(m)})$  do
5    $m \leftarrow m + 1$ ;
6   Compute  $P(z|\theta_{u'}^{(m+1)})$  as in Equation (26);
7 end
8 if  $Q(\Psi_{n+1}^{(m)}) \geq Q(\Psi_n)$  then
9    $P(z|\theta_{u'}^t)_{n+1} \leftarrow P(z|\theta_{u'}^{(m)})$ ;
10 end
11 Return  $P(z|\theta_u^t)_{n+1}$ ;
```

Vector Space Similarity (VSS) [Ma et al. 2011], and the Jaccard Index,⁷ and all of them can be applied to our work.

The Jaccard Index defines the similarity between users u and u' based on the items they rated in common:

$$\pi(u, u') = \frac{|D_u \cap D_{u'}|}{|D_u \cup D_{u'}|}, \quad (27)$$

where D_u is the set of items rated by user u .

VSS computes the similarity between users u and u' , as follows:

$$\pi(u, u') = \frac{\sum_{v \in D_u \cap D_{u'}} \sum_t C[u, t, v] \cdot C[u', t, v]}{\sqrt{\sum_{v \in D_u \cap D_{u'}} \sum_t C^2[u, t, v]} \cdot \sqrt{\sum_{v \in D_u \cap D_{u'}} \sum_t C^2[u', t, v]}}, \quad (28)$$

where D_u is the set of items rated by user u , and v belongs to the subset of items that user u and user u' both rated. From this definition, we can see that the VSS in $\pi(u, u')$ is within the range $[0, 1]$, and a larger value means users u and u' are more similar.

Similarly, the computation of PCC is defined as follows:

$$\pi(u, u') = \frac{\sum_{v \in D_u \cap D_{u'}} \sum_t (C[u, t, v] - \bar{C}[u]) \cdot (C[u', t, v] - \bar{C}[u'])}{\sqrt{\sum_{v \in D_u \cap D_{u'}} \sum_t (C[u, t, v] - \bar{C}[u])^2} \cdot \sqrt{\sum_{v \in D_u \cap D_{u'}} \sum_t (C[u', t, v] - \bar{C}[u'])^2}}, \quad (29)$$

where $\bar{C}[u]$ represents the average rate of user u . From this definition, user similarity $\pi(u, u')$ is in the range $[-1, 1]$, and a larger value means users u and u' are more similar. For consistency with VSS and Jaccard similarities, we employ a mapping function $f(x) = (x + 1)/2$ to bound the range of PCC similarities into $[0, 1]$.

5.2. Temporal Smoothing

To encode the intuition that user interest distribution θ_u^t changes smoothly over time, we propose the following temporal regularizer:

$$R(\mathbf{C}, T) = \sum_{t=1}^{T-1} \sum_z (P(z|\theta_u^t) - P(z|\theta_u^{t+1}))^2. \quad (30)$$

⁷http://en.wikipedia.org/wiki/Jaccard_index.

Formally, we define the data likelihood with temporal regularization as follows:

$$\mathcal{O}(\mathbf{C}, T) = L(\Psi|\mathbf{C}) - \xi R(\mathbf{C}, T). \quad (31)$$

The parameter ξ plays a similar role to λ in Equation (22), controlling the balance between the data likelihood and the smoothness of user interest distributions over time. Similar to social regularization, DTCAM with temporal regularization adopts the same generative schemes as that of DTCAM. Thus, the enhanced model has exactly the same E-step as that of the basic model. The M-step can be derived from the expected complete data log-likelihood for the enhanced model, which is

$$\mathcal{Q}(\Psi) = \mathcal{Q}(\Psi) - \xi R(\mathbf{C}, T). \quad (32)$$

For the same reason as the social regularization, we cannot obtain a closed-form solution for $P(z|\theta_u^t)$ in the M-step. The generalized EM algorithm is also adopted to estimate all parameters and latent variables in the enhanced model with the temporal regularization since $R(\mathbf{C}, T)$ enjoys a similar form with the social regularizer $R(\mathbf{C}, G)$. Clearly, just as for the social regularizer $R(\mathbf{C}, G)$, the temporal regularizer $R(\mathbf{C}, T)$ is nonnegative, so the Newton-Raphson method decreases $R(\mathbf{C}, T)$ in each updating step. By integrating $\Psi_{n+1}^{(1)}$ and $R(\mathbf{C}, T)$ into Equation (25), we obtain the closed-form solution for $\Psi_{n+1}^{(2)}$, and then $\Psi_{n+1}^{(3)}, \dots, \Psi_{n+1}^{(m)}, \dots$, where

$$P(z|\theta_u^t)_{n+1}^{(m+1)} = (1 - \gamma)P(z|\theta_u^t)_{n+1}^{(m)} + \gamma \frac{P(z|\theta_u^{t-1})_{n+1}^{(m)} + P(z|\theta_u^{t+1})_{n+1}^{(m)}}{2}. \quad (33)$$

Notice that the $P(x|\theta'_t)_{n+1}$, $P(v|\phi'_x)_{n+1}$, $P(v|\phi_z)_{n+1}$, and λ_u^{n+1} remain the same in Ψ_{n+1} , and the temporal regularization process is formalized in Algorithm 2.

ALGORITHM 2: Temporal Regularization

Input: Parameters Ψ_{n+1} , Temporal Regularization parameters ξ , Newton step parameter γ ;

Output: $P(z|\theta_u^t)_{n+1}$;

```

1 Initialize  $m \leftarrow 1$ ;
2 Initialize  $P(z|\theta_u^t)_{n+1}^{(m)} \leftarrow P(z|\theta_u^t)_{n+1}$ ;
3 Compute  $P(z|\theta_u^t)_{n+1}^{(m+1)}$  as in Equation (33);
4 while  $\mathcal{Q}(\Psi_{n+1}^{(m+1)}) \geq \mathcal{Q}(\Psi_{n+1}^{(m)})$  do
5   |  $m \leftarrow m + 1$ ;
6   | Compute  $P(z|\theta_u^t)_{n+1}^{(m+1)}$  as in Equation (33);
7 end
8 if  $\mathcal{Q}(\Psi_{n+1}^{(m)}) \geq \mathcal{Q}(\Psi_n)$  then
9   |  $P(z|\theta_u^t)_{n+1} \leftarrow P(z|\theta_u^t)_{n+1}^{(m)}$ ;
10 end
11 Return  $P(z|\theta_u^t)_{n+1}$ ;
```

5.3. Social-Temporal Smoothing

Now we combine all the pieces and provide a full overview of our enhanced DTCAM with spatial-temporal regularization. We summarize the model fitting approach of our enhanced DTCAM by using the generalized EM algorithm in Algorithm 3. In the fully enhanced DTCAM, the regularized data log-likelihood is defined as follows:

$$\mathcal{O}(\mathbf{C}, G, T) = L(\Psi|\mathbf{C}) - \lambda R(\mathbf{C}, G) - \xi R(\mathbf{C}, T), \quad (34)$$

ALGORITHM 3: Generalized E-M estimation Iteration

Input: $\Psi_n = \{P(z|\theta_u^t)_n, P(x|\theta_t^t)_n, P(v|\phi'_x)_n, P(v|\phi_z)_n, \lambda_u^n\}$ of previous iteration, Regularization parameters λ and ξ , Newton step parameter γ ;
Output: $\Psi_{n+1} = \{P(z|\theta_u^t)_{n+1}, P(x|\theta_t^t)_{n+1}, P(v|\phi'_x)_{n+1}, P(v|\phi_z)_{n+1}, \lambda_u^{n+1}\}$ for next iteration;

- 1 E-Step:
- 2 Estimate $P(z|u, t, v; \hat{\Psi})_{n+1}$ as in Equation (7);
- 3 Estimate $P(x|u, t, v; \hat{\Psi})_{n+1}$ as in Equation (9);
- 4 M-Step:
- 5 Estimate $P(z|\theta_u^t)_{n+1}$ as in Equation (21);
- 6 Estimate $P(v|\phi_z)_{n+1}$ as in Equation (12);
- 7 Estimate $P(x|\theta_t^t)_{n+1}$ as in Equation (13);
- 8 Estimate $P(v|\phi'_x)_{n+1}$ as in Equation (14);
- 9 Estimate λ_u^{n+1} as in Equation (15);
- 10 $P(z|\theta_u^t)_{n+1} \leftarrow \text{Social Regularization}()$;
- 11 $P(z|\theta_u^t)_{n+1} \leftarrow \text{Temporal Regularization}()$;
- 12 **if** $Q(\Psi_{n+1}) < Q(\Psi_n)$ **then**
- 13 $\Psi_{n+1} \leftarrow \Psi_n$;
- 14 **end**

and the expected complete data log-likelihood in the enhanced M-step is

$$Q(\Psi) = Q(\Psi) - \lambda R(C, G) - \xi R(C, T). \quad (35)$$

6. ITEM WEIGHTING FOR TCAM

In this section, we first introduce the challenge, arising from popular items and encountered by our models (e.g., TCAM and DTCAM), and then propose an item-weighting scheme to improve our proposed models.

Similarly to traditional topic models, both TCAM and DTCAM assume that all items are equally important in computing generation probabilities. As a result, popular items with more ratings tend to be estimated with high generation probability and ranked in top positions in each topic, which impairs the quality of both the user-oriented topics and the time-oriented topics.

For user-oriented topics, popular items are not good indicators of user intrinsic interests. A popular item rated by many users conveys less information about a user's interest than an item rated by few users. For time-oriented topics, it is expected that items representing the public's attention at a given time should be highly ranked, such as items with bursty temporal distributions, since bursts of items are generally triggered by breaking news or events that attract the public's attention. Unfortunately, bursty items are most likely to be overwhelmed by long-standing popular items. Figure 7 shows the temporal frequency of the top six tags of a sample time-oriented topic discovered from Delicious. It can be observed that the topic concerns swine flu. The temporal distributions of three bursty tags, "flu," "mexico," and "swineflu," undergo sharp spikes. Although the trends of the three tags do not always synchronize, they each go through a drastic increase and reach a peak in July 2009. The bursts in these curves are triggered by a real-world event, that is, the swine flu outbreak in Mexico. The other three tags, "news," "health," and "death," maintain high frequency throughout the year. However, they convey little information about the event. Although they are relevant to the event, they are also related to many other topics. Hence, it is desirable to rank bursty items higher than popular items when representing time-oriented topics.

To address the challenge posed by the popular items, we propose an item-weighting scheme to reduce the importance of popular items while promoting weights for salient,

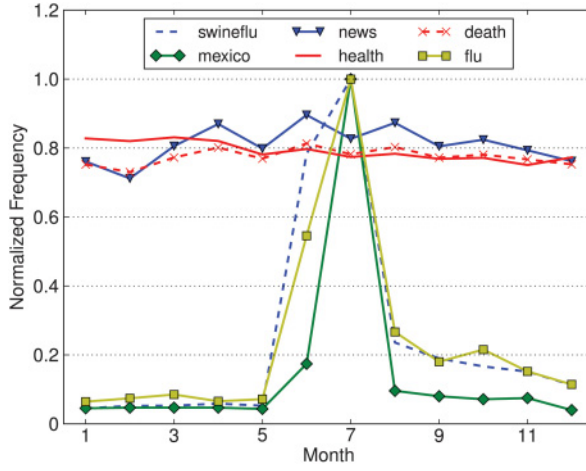


Fig. 7. An example of bursty tags and popular tags.

but infrequent, and bursty items in computing generation probability. From the view-point of information theory [Cover and Thomas 1991], the entropy of an item v is defined as follows:

$$E(v) = - \sum_u P(u|v) \log P(u|v).$$

Suppose that the item v is preferred by users with equal probability $P(u|v) = \frac{1}{N(v)}$, and then the maximum entropy is

$$E(v) = \log N(v).$$

Generally, the entropy of an item tends to be proportional to its frequency/popularity $N(v)$. Hence, in the following analysis, we use the maximum entropy to approximate the exact entropy to simplify the calculation.

To allow salient items to be ranked higher in user-oriented topics, the weights of items should be inversely proportional to the entropy, as discussed earlier. Hence, we propose a concept called *inverse user frequency* to measure the ability of items to represent salient information. Let N be the total number of users in the entire dataset; the *inverse user frequency (IUF)* for the item v is defined as follows:

$$iuf(v) = \log N - \log N(v) = \log \frac{N}{N(v)}, \quad (36)$$

which is similar to the inverse document frequency for a term in text mining.

To take into account the bursty information of items, we propose to compute the *bursty degree* of an item v using the following equation:

$$B(v, t) = \frac{N_t(v)}{N_t} \frac{N}{N(v)}, \quad (37)$$

where $N_t(v)$ represents the popularity of item v at time slice t , that is, the number of users who rate item v at time slice t ; N_t is the number of active users at time slice t ; $N(v)$ is the overall popularity of v across all time slices; and N is the total number of users in the dataset.

Combining the inverse user frequency and the bursty degree of items, we assign weight to the item v as follows:

$$w(v, t) = iuf(v) \times B(v, t). \quad (38)$$

Integrating the weights of items defined in Equation (38), we obtain the weighted user-time-item cuboid \tilde{C} from the original C as follows:

$$\tilde{C}[u, t, v] = C[u, t, v]w(v, t), \quad (39)$$

which can be used in all of our proposed models such as TCAM and DTCAM.

It should be noted that the item-weighting scheme makes TCAM and DTCAM no longer correspond to a well-defined probabilistic generative process since the values stored in the cuboid C are no longer integers, but it actually improves the empirical performance of TCAM and DTCAM in the tasks of both temporal recommendation and topic discovery by inserting IUF and bursty weights as heuristic factors into the model inference procedures, as shown in the experiment section. From the perspective of information theory, an item with lower entropy conveys more information about a user's intrinsic interests, and the one with a higher bursty degree is more capable of representing the temporal context at some specific time. TCAM and DTCAM enhanced by IUF and bursty weights incorporate these observations and intuitions.

7. TEMPORAL CONTEXT-AWARE RECOMMENDER SYSTEM

The conventional top- k recommendation task can be stated as follows: given a user, the recommender system should recommend a small number, say, k , of items from all the available items. Note that the conventional top- k recommendation task does not consider the temporal information. However, in reality, user rating behaviors, influenced by both user interests and the temporal context, are dynamic. For example, user u rating item v in time slice t does not mean that u still favors v in time slice $t + 1$. Each item has its own lifespan, especially for time-sensitive items such as news. It is undesirable to recommend outdated news. Hence, an ideal recommender system is expected to have the ability to recommend the right item v to user u in the right time slice t , rather than in other time slices. This article proposes the task of temporal top- k recommendation as follows: given a query $q = (u, t)$, that is, a querying user u with a time slice t , the recommender model recommends k items that match u 's interests and the temporal context at t .

To make a temporal recommendation, we design a temporal context-aware recommender system based on our proposed user models (e.g., DTCAM) in this section.

7.1. Computation of Ranking Score

As shown in Figure 8, TCARS consists of two main parts: modeling component and recommendation component. The modeling component is responsible for learning user interest θ_u^t , temporal context θ_t^t , user-oriented topics ϕ_z , time-oriented topics ϕ_x^t , and mixing weight λ_u . Once those model parameters are estimated, given a query $q = (u, t)$, the recommendation component computes a ranking score $S(u, t, v)$ for each item v according to Equation (41) and then returns the top- k items with the highest ranking score. Specifically, when receiving a query $q = (u, t)$, a new multinomial distribution ϑ_q is first constructed for the query q by combining θ_u^t and θ_t^t . Since θ_u^t and θ_t^t have different topic spaces (i.e., the user-oriented topic space vs. the time-oriented topic space), we need to transform them to be the same topic space by the means of topic space expansion. Specifically, if there are K_1 user-oriented topics and K_2 time-oriented topics, the joint topic space will have $K = K_1 + K_2$ topics. Figure 9 illustrates an example of topic space expansion, and there are two user-oriented topics and three time-oriented topics, so the joint topic space has five topics. In the joint topic space,

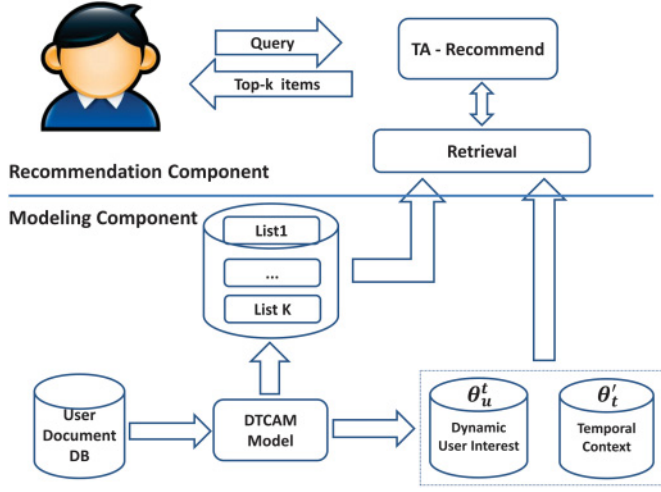


Fig. 8. The architecture framework of TCARS.

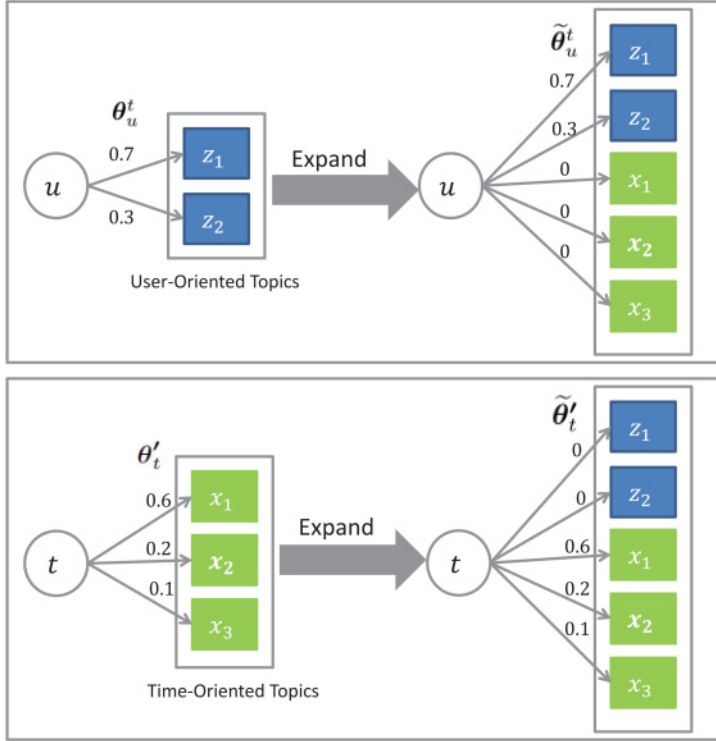


Fig. 9. Intuitive explanation of topic space expansion.

user u 's interest distribution at t is redefined as $\tilde{\theta}_u^t = \langle \theta_{u1}^t, \dots, \theta_{uK_1}^t, 0, \dots, 0 \rangle$, where we set 0 on the time-oriented topics. Similarly, we redefine the temporal context at t to be $\tilde{\theta}'_t = \langle 0, \dots, 0, \theta'_{tK_1+1}, \dots, \theta'_{tK} \rangle$, where we set 0 on the user-oriented topics. Based on the expanded topic space, a query q can be represented by a vector ϑ_q , which is constructed by linearly combining $\tilde{\theta}_u^t$ and $\tilde{\theta}'_t$, that is, $\vartheta_q = \lambda_u \tilde{\theta}_u^t + (1 - \lambda_u) \tilde{\theta}'_t$.

For mathematical simplicity and convenience, we introduce a new notation \tilde{z} to index the topic in the expanded topic space. \tilde{z} corresponds to either a user-oriented topic or a time-oriented topic, which depends on the value of \tilde{z} . As shown in Figure 9, if \tilde{z} is no larger than the number of user-oriented topics (i.e., K_1), \tilde{z} corresponds to a user-oriented topic; otherwise, \tilde{z} corresponds to a time-oriented topic. The weight of query q on topic \tilde{z} is denoted as $\vartheta_{q\tilde{z}}$. The weight of item v on topic \tilde{z} is denoted as $\varphi_{\tilde{z}v}$ which is computed as in Equation (40). Thus, both a query q and an item v can be represented as a vector with K ($K = K_1 + K_2$) dimensions in the expanded topic space. The ranking score $S(u, t, v)$ for item v given a query q is computed as the inner product of the two vectors, as shown in Equation (41):

$$\varphi_{\tilde{z}v} = \begin{cases} \phi_{zv} & \tilde{z} \leq K_1 \\ \phi'_{xv} & \tilde{z} > K_1 \end{cases} \quad (40)$$

$$S(u, t, v) = \sum_{\tilde{z}=1}^K \vartheta_{q\tilde{z}} \varphi_{\tilde{z}v}. \quad (41)$$

7.2. Fast Top-k Recommendation

The straightforward method of generating the top- k items needs to compute the ranking scores for all items according to Equation (41), which is computationally inefficient, especially when the number of items becomes large. To speed up the process of producing recommendations, we extend the Threshold-based Algorithm (TA) [Fagin et al. 2001], which is capable of finding the top- k results by examining the minimum number of items.

We first precompute the ordered lists of items, where each list corresponds to a latent topic learned by DTCAM. For example, given K topics (K_1 user-oriented topics plus K_2 time-oriented topics), we will compute K lists of sorted items, $L_{\tilde{z}}$, $\tilde{z} \in \{1, 2, \dots, K\}$, where items in each list $L_{\tilde{z}}$ are sorted according to $\varphi_{\tilde{z}v}$ as defined in Equation (40). Given a query $q = (u, t)$, we run Algorithm 1 to compute the top- k items from the K sorted lists and return them in the priority list L . As shown in Algorithm 1, we first maintain a priority list PL for the K lists where the priority of a list $L_{\tilde{z}}$ is the ranking score (i.e., $S(u, t, v)$) of the first item v in $L_{\tilde{z}}$ (Lines 2–6). In each iteration, we select the most promising item (i.e., the first item) from the list that has the highest priority in PL and add it to the resulting list L (Lines 9–16). When the size of L is no less than k , we will examine the k th item in the resulting list L . If the ranking score of the k th item is higher than the *threshold score* (i.e., S_{Ta}), the algorithm terminates early without checking any subsequent items (Lines 18–21). Otherwise, the k th item v' in L is replaced by the current item v if v 's ranking score is higher than that of v' (Lines 22–25). At the end of each iteration, we update the priority of the current list as well as the threshold score (Lines 28–33).

Equation (42) illustrates the computation of the threshold score, which is obtained by aggregating the maximum $\varphi_{\tilde{z}v}$ represented by the first item in each list $L_{\tilde{z}}$ (i.e., $\max_{v \in L_{\tilde{z}}} \varphi_{\tilde{z}v}$). Consequently, it is the maximum possible ranking score that can be achieved by the remaining unexamined items. Hence, if the ranking score of the k th item in the resulting list L is higher than the threshold score, L can be returned immediately because no remaining item will have a higher ranking score than the k th item:

$$S_{Ta} = \sum_{\tilde{z}=1}^K \vartheta_{q\tilde{z}} \max_{v \in L_{\tilde{z}}} \varphi_{\tilde{z}v}. \quad (42)$$

ALGORITHM 4: Threshold-based algorithm

Input: A query $q = (u, t)$; inferred model parameters θ_u^t , θ'_t , and λ_u ; ranked lists (L_1, \dots, L_K) ;
Output: List L with all the k highest ranked items;

```

1 Initialize priority lists  $PQ$ ,  $L$ , and the threshold score  $S_{Ta}$ ;
2 for  $\tilde{z} = 1$  to  $K$  do
3    $v = L_{\tilde{z}}.getfirst()$ ;
4   Compute  $S(u, t, v)$  according to Equation (41);
5    $PQ.insert(\tilde{z}, S(u, t, v))$ ;
6 end
7 Compute  $S_{Ta}$  according to Equation (42);
8 while true do
9    $nextListToCheck = PQ.getfirst()$ ;
10   $PQ.removefirst()$ ;
11   $v = L_{nextListToCheck}.getfirst()$ ;
12   $L_{nextListToCheck}.removefirst()$ ;
13  if  $v \notin L$  then
14    if  $L.size() < k$  then
15       $L.insert(v, S(u, t, v))$ ;
16    end
17    else
18       $v' = L.get(k)$ ;
19      if  $S(u, t, v') > S_{Ta}$  then
20        break;
21      end
22      if  $S(u, t, v') < S(u, t, v)$  then
23         $L.remove(k)$ ;
24         $L.insert(v, S(u, t, v))$ ;
25      end
26    end
27  end
28  if  $L_{nextListToCheck}.hasMore()$  then
29     $v = L_{nextListToCheck}.getfirst()$ ;
30    Compute  $S(u, t, v)$  according to Equation (41);
31     $PQ.insert(nextListToCheck, S(u, t, v))$ ;
32    Compute  $S_{Ta}$  according to Equation (42);
33  end
34  else
35    break;
36  end
37 end

```

8. EXPERIMENTS

In this section, we experimentally evaluate the performance of our proposed models. In particular, we evaluate the following: (1) how the proposed TCAM fares in comparison with state-of-the-art time-aware recommendation systems, (2) how the proposed DTCAM that fully exploits the dynamics of user interests performs in comparison with the TCAM, (3) whether our designed social-temporal regularization technique alleviates the problem of data sparsity confronted by DTCAM, (4) whether the proposed item-weighting scheme improves the performances of TCAM and DTCAM in time-aware recommendation and topic discovery, and (5) how our designed efficient query-processing technique for the TCARS performs in speeding up the process of producing the top- k

Table III. Basic Statistics of the Four Datasets

	Digg	MovieLens	Douban Movie	Delicious
# of users	139,409	71,567	33,561	201,663
# of items	3,553	10,681	87,081	2,828,304
# of ratings	3,018,197	10,000,054	5,257,665	36,966,661
time span (year)	2009–2010	1998–2009	2005–2010	2008–2009

recommendations from large social media data. Besides, we also explore other applications for our TCAM and DTCAM beyond time-aware recommendations, such as user profiling and topic discovery, through several illustrations.

8.1. Datasets

Our experiments are conducted on four real datasets: Digg, MovieLens, Douban Movie, and Delicious. The basic statistics of the four datasets are shown in Table III. Only the implicit feedback data can be available in the Digg and Delicious datasets, so we compute the cell value $C[u, t, v]$ for these two datasets according to the frequency/number of the interaction between user u and item v at time t . For the Douban Movie and MovieLens datasets, the explicit feedback information is available. Hence, the user-time-item rating cuboid \mathbf{C} can be directly derived from users' star ratings.

- Digg.** Digg is a popular social news aggregator, which allows users to vote news stories up or down, called *digging* or *burying*, respectively. The Digg dataset used in our experiment is Digg2009 [Lerman and Ghosh 2010], a publicly available dataset containing 3,018,197 votes on 3,553 popular stories cast by 139,409 distinct users. This dataset also records the friendship network of these Digg users. Although this dataset contains only the IDs of news stories (the titles and the contents of stories are excluded), it is sufficient to evaluate the effectiveness of user behavior modeling in our work.
- Douban Movie.** Douban⁸ is the largest movie review website in China. In total, we crawled 33,561 unique users and 87,081 unique movies with 5,257,665 movie ratings.
- MovieLens.** MovieLens is a publicly available movie dataset from the web-based recommender system MovieLens. The dataset contains 10M ratings on a scale from 1 to 5 made by 71,567 users on 10,681 movies. We selected users who had rated at least 20 movies.
- Delicious.** Delicious is a collaborative tagging system where users can upload and tag web pages. We collected 201,663 users and their tagging behaviors during the period February 2008 through December 2009. The dataset contains 2,828,304 tags. Topics on technology and electronics account for about half of all web pages. Most of the other web pages are about breaking news with strong temporal features.

Note that the Douban Movie and Delicious datasets are collected by ourselves, and we make them publicly available.⁹

8.2. Comparisons

TCAM was outlined in Section 3. DTCAM was outlined in Section 4, and the DTCAM enhanced by social-temporal regularization technique outlined in Section 5 is called RDT CAM. All of these models can be enhanced by the item-weighting scheme, which leads to three optimized versions: *W-TCAM*, *W-DTCAM*, and *W-RDT CAM*. We compare them with four categories of competitor approaches.

⁸<http://douban.com>.

⁹<http://net.pku.edu.cn/daim/hongzhi.yin/>.

- User-Topic Model (UT)**. We implemented a user-topic model following previous works [Michelson and Macskassy 2010; Stoyanovich et al. 2008]. This model is similar to the classic author-topic model (AT model) [Rosen-Zvi et al. 2004], which assumes that topics are generated according to user interests. A user document D_u is regarded as a sample of the following mixture model:

$$P(v|u; \Psi) = \lambda_B P(v|\theta_B) + (1 - \lambda_B) \sum_z P(z|\theta_u) P(v|\phi_z),$$

where v is an item (or word) in user document D_u , and $P(z|\theta_u)$ is the probability of user u choosing the z th topic ϕ_z . θ_B is a background model and λ_B is the mixing weight for it. The purpose of using a background model θ_B is to make the topics learned from the dataset more discriminative; since θ_B gives high probabilities to nondiscriminative and noninformative items or words, we expect such items or words to be accounted for by θ_B and thus the topic models to be more discriminative. In a nutshell, the background model θ_B is used to capture common items or words.

- Time-Topic Model (TT)**. Following previous works [Mei and Zhai 2005; Wang et al. 2007], we implemented a time-topic model. This model considers only the temporal information and ignores user interests. TT assumes that topics are generated by the temporal context and that user behaviors are influenced by the temporal context. The probabilistic formula of the time-topic model is presented as follows:

$$P(v|t; \Psi) = \lambda_B P(v|\theta_B) + (1 - \lambda_B) \sum_x P(x|\theta'_t) P(v|\phi'_x),$$

where $P(x|\theta'_t)$ is the probability of the general public choosing the x th topic during time period t , and θ_B is a background model that plays the same role as the one in the previous UT model.

- BPRMF**. This is a state-of-the-art matrix factorization model for item ranking that is optimized using BPR [Rendle et al. 2009]. This model outperforms most of the existing recommender models in the task of top- k item recommendation. We used the BPRMF implementation provided by MyMediaLite, a free software recommender system library [Gantner et al. 2011].
- BPTF**. This is a state-of-the-art recommender model for rating prediction that uses a probabilistic tensor factorization technique by introducing additional factors for time [Xiong et al. 2010]. This model outperforms most of the existing recommender models that consider time information.

8.3. Evaluation Methods of TCARS

There are two main objective evaluation methods, namely, *online evaluations* and *offline evaluations*, to measure recommender systems' quality [Ricci et al. 2011]. In online evaluations, the system is used by real users that perform real tasks. Recommendations are shown to real users of the system during their sessions. We then observe how often a user accepts a recommendation. Acceptance is most commonly measured by click-through rate (CTR), that is, the ratio of clicked recommendations.¹⁰ For instance, if a system displays 10,000 recommendations and 100 are clicked, the CTR is 1%. Online evaluation provides valuable information about user feedback regarding recommendations, and it also captures the influence of the recommender system. However, it is not always a feasible option due to the need of having an operative system deployed and a high cost, requiring a large number of users to use the system. Such

¹⁰Besides clicks, other user behavior can be monitored, for example, the number of times recommendations were downloaded, purchased, and so forth.

a real system platform is not available for most of the common recommender system researchers [Campos et al. 2014].

An offline experiment is performed by using a precollected dataset of users choosing or rating items. Using this dataset, we can try to simulate the behavior of users who interact with a recommendation system. Specifically, the precollected datasets generally contain a list of users and their ratings of items. To evaluate a recommender system, some ratings are held out as the test set, and the recommender system creates recommendations based on the information remaining (i.e., the training set). The more of the held-out items the recommender accurately finds, the better the algorithm is. Offline evaluations measure the accuracy of a recommender system. The test set is considered as the ground truth that represents the ideal set of items to be recommended. Compared with the online evaluation, offline evaluation brings a low cost and makes it easy to reproduce the experimental environment for testing new algorithms. Because of these advantages, most of the past work on recommender systems has been focused on offline evaluation protocols. In this article, we also adopt the offline evaluation protocol to measure the recommendation accuracy. In the following, we will present our *evaluation methodology and evaluation metrics*.

8.3.1. Evaluation Methodology. To make the evaluation process fair and reproducible, we adopt the *methodological description framework* proposed in Campos et al. [2014] to describe our evaluation conditions. We will present our evaluation conditions by answering the following methodological questions:

- (1) What *base set* is used to perform the training-test building?
- (2) What *rating order* is used to assign ratings to the training and test sets?
- (3) How many *ratings* make up the training and test sets?
- (4) Which items are considered as *target items*?
- (5) Which items are considered as *relevant items* for each user?

Base Set Condition. The base set conditions state whether the splitting procedure of training and test sets is based on the whole set of ratings \mathbf{C} or on each of the subdatasets of \mathbf{C} independently. We adopt the *user-centered base set condition* where we perform the splitting independently on each user's ratings, ensuring that all users will have ratings in both the training and test sets.

Rating Order and Size Conditions. We adopt the *time-dependent rating order condition*. Specifically, for each user u , his or her ratings $S(u)$ are ranked according to their rated timestamps. We use the 80th percentile as the cutoff point so that ratings before this point will be used for training and the rest are for testing; that is, $S(u)$ is divided into the training set $S^{train}(u)$ and test set $S^{test}(u)$.

Target Item Condition. To simulate a real-world setting, we require each tested recommender system to rank all the items except the target user's training items. In other words, given a target user u , each tested recommender system has to find the top- k items from all available items except those in the set $S^{train}(u)$.

Relevant Item Condition. Relevant item conditions select the items to be interpreted as relevant for the target user. The notion of relevance is central for information retrieval metrics applied to evaluate the top- k recommendations. We adopt the *test-based relevant items* condition in which the set of relevant items for target user u is formed by the items in u 's test set $S^{test}(u)$.

The previous condition combination is also called “uc_td_prop” for short. We repeat our experiments on four different social media datasets for increasing the generalization of the evaluation results, and we use a hold-out procedure on each dataset.

Note that all the experimental results reported in Section 8.4 are obtained based on the same experimental conditions without further explanations.

Table IV. Temporal Recommendation Accuracy on Digg Dataset

Methods	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
UT	0.091	0.086	0.084	0.093	0.091	0.088	0.007	0.028	0.044
TT	0.182	0.149	0.126	0.178	0.148	0.139	0.017	0.041	0.071
BPRMF	0.048	0.045	0.040	0.048	0.040	0.037	0.002	0.015	0.022
BPTF	0.194	0.166	0.152	0.195	0.176	0.165	0.017	0.050	0.080
TCAM	0.237	0.210	0.179	0.234	0.203	0.188	0.017	0.056	0.093
W-TCAM	0.258	0.220	0.201	0.252	0.224	0.208	0.019	0.063	0.098

Table V. Temporal Recommendation Accuracy on MovieLens Dataset

Methods	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
UT	0.343	0.252	0.211	0.338	0.257	0.234	0.036	0.099	0.136
TT	0.260	0.193	0.168	0.248	0.198	0.186	0.024	0.070	0.093
BPRMF	0.342	0.239	0.192	0.303	0.229	0.195	0.034	0.084	0.119
BPTF	0.383	0.270	0.224	0.365	0.290	0.261	0.035	0.103	0.141
TCAM	0.385	0.304	0.259	0.406	0.325	0.286	0.037	0.115	0.155
W-TCAM	0.401	0.324	0.264	0.427	0.350	0.313	0.040	0.123	0.165

8.3.2. Evaluation Metrics. To make the experimental results comparable and reproducible, we use multiple well-known metrics to measure the ranked results. Similar to evaluations in information retrieval, we first use Precision@ k to assess the quality of the top- k recommended items as follows:

$$Precision@k = \frac{\#relavances}{k},$$

where $\#relavances$ is the number of relevant items in the top- k recommended items. We also consider NDCG, a widely used metric for a ranked list. NDCG@ k is defined as

$$NDCG@k = \frac{1}{IDCG} \times \sum_{i=1}^k \frac{2^{r_i} - 1}{\log(i + 1)},$$

where r_i is 1 if the item at position i is a “relevant” item and 0 otherwise. IDCG is chosen for the purpose of normalization so that the perfect ranking has an NDCG value of 1. Considering that some users may have a large number of items in the test data while some have just a few, we also adopt the $F1$ score as our metric.

8.3.3. Evaluation of Recommendation Efficiency. Besides the evaluation of recommendation effectiveness, we also evaluate the efficiency (i.e., time cost) of producing recommendations in order to test our proposed query-processing technique in Section 7.2. We use the time costs of producing recommendations to measure the efficiency. The recommendation efficiency mainly depends on (1) the number of items available in the dataset and (2) the number of items recommended. Therefore, we test the efficiency of our proposed methods over these two factors.

8.4. Performance on Recommendation

This section provides our evaluation of both the effectiveness of the suggested recommendations and the efficiency of generating the top- k recommendations.

8.4.1. Effectiveness Performance. Tables IV through VII report the performance of the proposed models and other competitors in terms of Precision@ k , NDCG@ k , and F1@ k

Table VI. Temporal Recommendation Accuracy on Douban Movie Dataset

Methods	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
UT	0.141	0.104	0.087	0.139	0.106	0.097	0.015	0.041	0.056
TT	0.105	0.078	0.068	0.101	0.080	0.075	0.010	0.028	0.038
BPRMF	0.138	0.101	0.085	0.136	0.103	0.094	0.015	0.040	0.055
BPTF	0.158	0.111	0.092	0.151	0.119	0.108	0.015	0.043	0.058
TCAM	0.168	0.133	0.113	0.177	0.142	0.125	0.016	0.050	0.068
W-TCAM	0.175	0.141	0.115	0.186	0.153	0.137	0.018	0.054	0.072

Table VII. Temporal Recommendation Accuracy on Delicious Dataset

Methods	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
UT	0.086	0.076	0.073	0.082	0.081	0.078	0.006	0.025	0.039
TT	0.104	0.085	0.072	0.102	0.085	0.080	0.010	0.024	0.041
BPRMF	0.065	0.059	0.051	0.064	0.062	0.060	0.005	0.019	0.030
BPTF	0.111	0.095	0.087	0.112	0.101	0.095	0.010	0.029	0.046
TCAM	0.136	0.120	0.103	0.134	0.116	0.108	0.010	0.032	0.053
W-TCAM	0.148	0.126	0.113	0.144	0.128	0.119	0.011	0.036	0.056

on Digg, MovieLens, Douban Movie, and Delicious datasets, respectively. From the reported results, we observe that:

- (1) Our proposed models TCAM and W-TCAM consistently outperform other competitors such as UT, TT, BPRMF, and BPTF on all four datasets. This observation shows that recommendation accuracy, especially temporal recommendation accuracy, can be improved by simultaneously considering both user intrinsic interests and the temporal context.
- (2) BPTF performs better than other competitor methods such as BPRMF, UT, and TT because it also exploits the temporal context information when recommending items, but our proposed TCAM and W-TCAM consistently outperform BPTF. This may be because BPTF is designed for rating prediction rather than the top- k recommendation. It relies on high-quality explicit feedback data (e.g., users' explicit star rating for items), however, which is not always available [Rendle et al. 2009; Hu et al. 2008]. In contrast, our proposed TCAM and W-TCAM are suitable for both explicit and implicit user feedback data.
- (3) W-TCAM achieves higher temporal recommendation accuracy than TCAM, which demonstrates the benefits gained by the item-weighting scheme.
- (4) Comparing UT and TT, we find that UT performs better than TT on the MovieLens and Douban Movie datasets, while TT beats UT on the Digg dataset. This may be because news is a type of time-sensitive item, while movies are not so time sensitive and have a longer lifespan.

There are three parameters in our models, namely, the length of time slice, the number of user-oriented topics (K1), and the number of time-oriented topics (K2). Tuning these model parameters is critical to the model performance. The experimental results presented earlier are obtained with the optimal parameter settings: (1) the optimal time slices are 1 month for the MovieLens and Douban Movie datasets, 1 week for Delicious, and 3 days for the Digg dataset, respectively; (2) the default values for K1 and K2 are 60 and 40 in TCAM and W-TCAM, respectively. We study the impacts of varying the three parameters next in detail.

Table VIII. Performance of Varying Length of Time Slice on Digg Dataset

Length of Time Slice	TT	TCAM	W-TCAM	BPTF
1 day	0.105	0.142	0.157	0.121
2 days	0.134	0.183	0.202	0.155
3 days	0.149	0.203	0.224	0.172
4 days	0.134	0.183	0.202	0.155
5 days	0.125	0.171	0.188	0.145
6 days	0.125	0.171	0.188	0.145
7 days	0.111	0.150	0.166	0.128
8 days	0.108	0.146	0.162	0.124
9 days	0.106	0.144	0.159	0.122
10 days	0.104	0.142	0.157	0.121

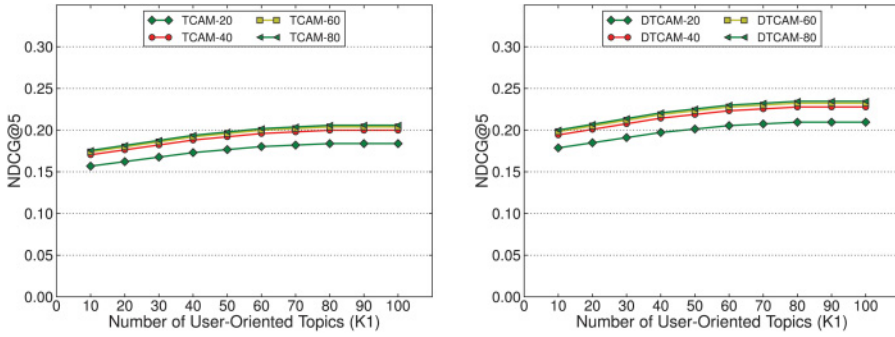


Fig. 10. Performance of varying number of topics.

8.4.2. Effect of the Length of Time Slice. This experiment studies the effect of the length of time slice. The length of time slice controls the time granularity of temporal recommendations. A larger length of time slice implies that the recommendation results will be less time aware. To focus on the impact of the length of time slice, we only consider the models that utilize temporal influence. We report NDCG@5 on the Digg dataset in Table VIII. The table provides the following two observations:

- The first is that as the length of time slice increases, the NDCG values of all methods first increase and then decrease. One possible reason for early increasing NDCG is that increasing the length makes the data in a time slice denser. Later on, NDCG decreases as the length of the time slice becomes larger, because increasing the length of time slice reduces the temporal influence. All methods achieve their best performance when the length of time slice is set to 3 days on this dataset, which could be a tradeoff of the other two factors.
- Another important observation is that, for all lengths of time slices, our proposed methods outperform other comparative methods. Among our proposed methods, W-TCAM outperforms TCAM, which demonstrates the benefits gained by our proposed item-weighting technology.

8.4.3. Effect of the Number of Topics. This experiment studies the effect of the number of user-oriented topics (K1) and the number of time-oriented topics (K2) on the Digg dataset. Figure 10 reports the results (i.e., NDCG@5) of varying K1 from 10 to 100 when fixing K2 to 20, 40, 60, and 80, respectively. For example, TCAM-40 represents the model TCAM with 40 time-oriented topics. Figure 10 indicates that the performance of our proposed model TCAM first increases with the increasing number of user-oriented

Table IX. Effect of Dynamic User Interest Modeling on MovieLens Dataset

Methods	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
TCAM	0.385	0.304	0.259	0.406	0.325	0.286	0.037	0.115	0.155
DTCAM	0.405	0.320	0.273	0.427	0.343	0.301	0.041	0.122	0.164
W-TCAM	0.401	0.324	0.264	0.427	0.350	0.313	0.040	0.123	0.165
W-DTCAM	0.421	0.341	0.278	0.449	0.368	0.330	0.042	0.130	0.175

Table X. Effect of Dynamic User Interest Modeling on Digg Dataset

Methods	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
TCAM	0.237	0.210	0.179	0.234	0.203	0.188	0.017	0.056	0.093
DTCAM	0.268	0.235	0.201	0.263	0.229	0.212	0.019	0.063	0.103
W-TCAM	0.258	0.220	0.201	0.252	0.224	0.208	0.019	0.063	0.098
W-DTCAM	0.287	0.244	0.224	0.281	0.249	0.231	0.021	0.070	0.109

topics (K1) and remains nearly stable when K1 is larger than 60. By comparing TCAM-20, TCAM-40, TCAM-60, and TCAM-80, we find that the performance of TCAM-20 is poorest while the other three perform almost equally well and their curves almost overlap. The performance of the TCAM on this dataset does not change much when the number of time-oriented topics (K2) is larger than 40. We also observe similar curve trends for DTCAM.

8.4.4. Effect of Dynamic User Interest. This experiment studies the effect of dynamic user interest modeling. Tables IX and X depict the comparison results between TCAM, DTCAM, W-TCAM, and W-DTCAM on the MovieLens and Digg datasets, respectively. The only difference between TCAM and DTCAM (W-TCAM and W-DTCAM) is that TCAM (W-TCAM) assumes that user interests are stable over time, while DTCAM (W-DTCAM) exploits the dynamics of user interests. From the results, we observe that DTCAM and W-DTCAM outperform TCAM and W-TCAM, respectively, by achieving higher recommendation accuracy values. This shows that DTCAM and W-DTCAM model users' temporal rating behaviors more accurately on social media because users' interests are actually dynamic in reality. Another observation is that the performance difference between TCAM and DTCAM on the Digg dataset is larger than that on the MovieLens dataset. DTCAM achieves approximately a 5% relative improvement over TCAM on the MovieLens dataset, while DTCAM achieves a 12% relative improvement on the Digg dataset. This may be because users' interests in news change more rapidly, while their interests in movies are relatively stable because news is a type of time-sensitive item and movies are not so time sensitive.

8.4.5. Effect of Similarity Functions on Social Regularization Framework. This experiment studies the impact of different similarity functions on our social regularization framework. The similarity function $\pi(u, u')$, defined in Section 5.1.3, measures how similar users u and u' are. It can help distinguish friends with different tastes. In this article, we employ three popular similarity functions: Jaccard Index, PCC, and VSS. In order to examine how much the similarity function $\pi(u, u')$ contributes to the whole social regularization framework, we conduct an experimental analysis on some special similarity settings. We are especially interested in the following two cases:

- (1) What is the performance of our social regularization framework if we set all the similarities between friends to 1?
- (2) What if we assign a random similarity to any pair of friendship?

Table XI. Impact of Similarity Functions on Digg Dataset

Similarity Function	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
S-1	0.272	0.239	0.207	0.268	0.234	0.218	0.018	0.063	0.105
S-Random	0.273	0.241	0.208	0.270	0.236	0.219	0.018	0.064	0.107
S-Jaccard	0.278	0.245	0.211	0.276	0.240	0.224	0.019	0.065	0.108
S-VSS	0.284	0.250	0.214	0.280	0.243	0.226	0.021	0.067	0.110
S-PCC	0.283	0.248	0.216	0.278	0.245	0.228	0.022	0.066	0.111

Table XII. Effect of Social-Temporal Regularization on Digg Dataset

Methods	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
DTCAM	0.268	0.235	0.201	0.263	0.229	0.212	0.019	0.063	0.103
RDTCAM	0.284	0.250	0.214	0.280	0.243	0.226	0.021	0.067	0.110
W-DTCAM	0.287	0.244	0.224	0.281	0.249	0.231	0.021	0.070	0.109
W-RDTCAM	0.301	0.257	0.235	0.96	0.263	0.244	0.022	0.074	0.115

We evaluate the results based on our RDTCAM, and the comparison is shown in Table XI. In this table, S-1 means we set all the similarities between friends to 1, while S-Random indicates that all the similarities are replaced by random values within the range [0, 1]. S-Jaccard, S-VSS, and S-PCC mean that the similarities between friends are computed by Jaccard Index, VSS, and PCC, respectively. We can see that RDTCAM with S-1 and S-Random performs worse than that with Jaccard, VSS, and PCC. This observation demonstrates the importance of similarity function $\pi(u, u')$. We cannot either naively set all the similarities between friends to be equal or simply use some random values to represent the friend relationships. Another observation is that the Jaccard Index performs worse than VSS and PCC. That is because the computation of the Jaccard Index results in the information loss when transforming the rating scores (real values) in the cuboid \mathbf{C} to binary values. In other words, the Jaccard Index ignores the preference degrees of users for items. VSS and PCC achieve almost the same performance, but the computation of VSS is more simple and efficient.

8.4.6. Effect of Social-Temporal Regularization. This experiment studies the effect of social-temporal regularization where we adopt VSS as the social similarity function due to its excellent performance. Table XII depicts the comparison results between DTCAM, RDTCAM, W-DTCAM, and W-RDTCAM on the Digg dataset. RDTCAM is the DTCAM enhanced by the social-temporal regularization technique proposed in Section 5. From the results, we observe that RDTCAM and W-RDTCAM achieve more accurate recommendation results than DTCAM and W-DTCAM, respectively. For example, RDTCAM achieves approximately a 5% relative improvement over DTCAM, which indicates that the social-temporal regularization is effective in improving temporal recommendations, showing the benefits of exploiting the network structure and temporal correlation information. The RDTCAM has two parameters λ and ξ , which control how much our methods should incorporate the social and temporal correlation information. In our experiment, RDTCAM achieves its optimal performance with $\lambda = 0.01$ and $\xi = 0.001$. This may be because the social network plays a more important role than the temporal correlation in the temporal recommendation.

Cold-Start Problem. In order to further study the effect of social-temporal regularization in alleviating the problem of data sparsity, we test the recommendation performance for cold-start users. We use the same training set as before (Section 8.4.1) and consider those users who have less than five ratings in the training set as cold-start users. Table XIII reports the performance of DTCAM, RDTCAM, W-DTCAM,

Table XIII. Recommendation Performance Comparison for Cold-Start Users

Methods	Precision			NDCG			F1 Score		
	P@1	P@5	P@10	N@1	N@5	N@10	F1@1	F1@5	F1@10
DTCAM	0.177	0.156	0.133	0.174	0.152	0.141	0.012	0.042	0.069
RDTCAM	0.244	0.215	0.183	0.24	0.209	0.194	0.017	0.058	0.095
W-DTCAM	0.189	0.161	0.148	0.186	0.165	0.154	0.014	0.047	0.073
W-RDTCAM	0.261	0.223	0.204	0.256	0.228	0.212	0.019	0.064	0.112

and W-RDTCAM for cold-start users on the Digg dataset. By comparison between Tables XII and XIII, we observe that, although the recommendation accuracy of all models decreases to various degrees, for cold-start users, our proposed RDTCAM and W-RDTCAM still perform the best, and the performance disparity between DTCAM (W-DTCAM) and RDTCAM (W-RDTCAM) becomes even larger. For example, RDTCAM achieves approximately a 38% relative improvement over DTCAM for cold-start users, while the former achieves only a 12% improvement over the latter for regular users. The cold-start user's interests are hard to capture because only a few items are rated by this user. RDTCAM and W-RDTCAM overcome the lack of a user's ratings by exploiting the preferences or rating behaviors of the user's neighborhoods (e.g., friends) in a social network. The preferences of users' friends can supply many valuable references and clues that are potentially useful for item recommendations due to the phenomenon of homophily. So, RDTCAM and W-RDTCAM achieve significant improvement over DTCAM and W-DTCAM, respectively, showing the advantages of exploiting social and temporal correlation information by our proposed social-temporal regularization technique.

8.4.7. Efficiency Performance. We next proceed to perform an efficiency comparison of different temporal recommendation algorithms on Douban Movie and MovieLens datasets. It is worth mentioning that there are different numbers of movies in these two datasets, that is, 69,908 and 10,681, respectively. All the recommendation algorithms are implemented in Java (JDK 1.6) and run on a Linux Server with 32G RAM. In this section, we report their recommendation time costs.

In the efficiency study, we adopt two methods to utilize the knowledge learned by DTCAM to produce recommendations. The first is called DTCAM-TA and uses the proposed TA-based query-processing technique outlined in Section 7.2 to produce the top- k recommendations. The second is called DTCAM-BF and uses a brute-force algorithm to produce the top- k recommendations. In DTCAM-BF, we scan all items within the dataset and compute their ranking scores and then recommend k items with the highest scores. It should be noted that the state-of-the-art temporal recommender model BPTF also needs to scan all items to produce the top- k recommendations because the ranking function in BPTF does not have the nice property of monotonicity, which is required by the TA [Fagin et al. 2001].

Figures 11(a) and 11(b) present the average time costs of different methods with a varying number of recommendations for datasets Douban Movie and MovieLens, respectively. For example, on average, our proposed DTCAM-TA finds the top 10 items (that would most interest a user) from the Douban Movie dataset in 46ms and from the MovieLens dataset in 9ms. The figures indicate that (1) DTCAM-TA outperforms DTCAM-BF and BPTF significantly in both datasets, justifying the benefits gained by the proposed TA-based query-processing technique; (2) DTCAM-BF is more efficient than BPTF in both datasets because BPTF computes the rating score that a user u will assign to item v at time t using the inner product of three vectors (i.e., user, item, and time latent representations in a shared low-dimensional space) [Xiong et al. 2010], while DTCAM computes the ranking score using the inner product of two vectors (i.e.,

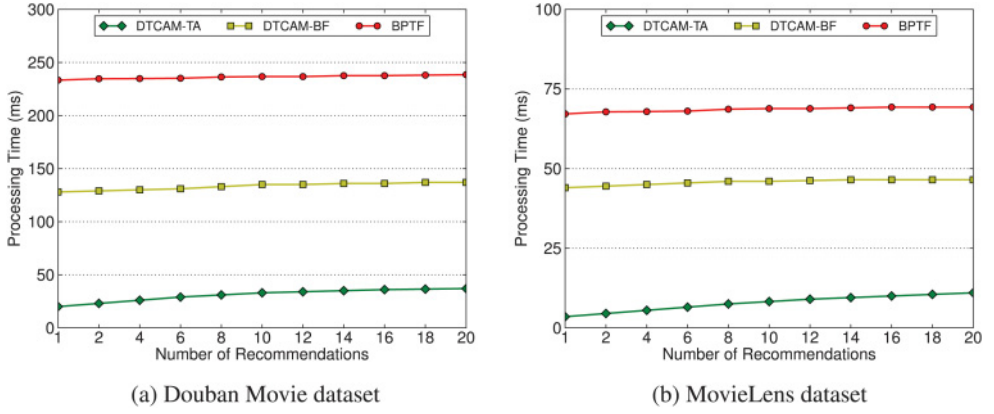


Fig. 11. Efficiency w.r.t online recommendations.

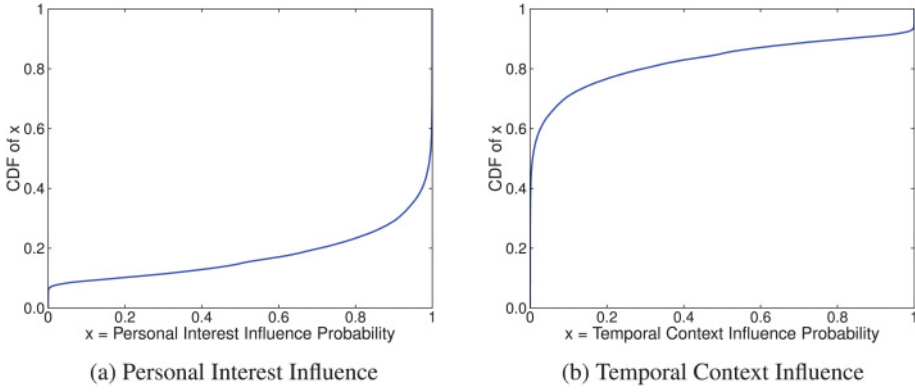


Fig. 12. Temporal context influence result (MovieLens).

the query and item latent representations), as shown in Equation (41); (3) the time cost of DTCAM-TA increases with the increasing number of recommendations because DTCAM-TA needs to scan more items to find the k items with the highest ranking scores, but DTCAM-TA is still much more efficient than DTCAM-BF and BPTF since the number of recommendations (i.e., k) is often constrained in a small range (e.g., $[1, 20]$); and (4) the time cost (TC) of each algorithm in Douban Movie is more expensive than that in MovieLens, showing that if a dataset has more items available, it requires more processing time to produce the top- k recommendations.

8.5. Temporal Context Influence Study

This section studies the influence degrees of users' personal interests and the temporal context on users' decision making. The user interest influence probability λ_u and the temporal context influence probability $1 - \lambda_u$ are learned automatically in TCAM and DTCAM. Due to the similar influence results, we only present the temporal context influence of DTCAM in this study. We are interested in how significantly the temporal context influences the user's decisions on different social media platforms.

Since different people have different mixing weights, we plot the distributions of both the personal interest and the temporal context influence probabilities across all users. The results on the MovieLens dataset are shown in Figure 12, where Figure 12(a)

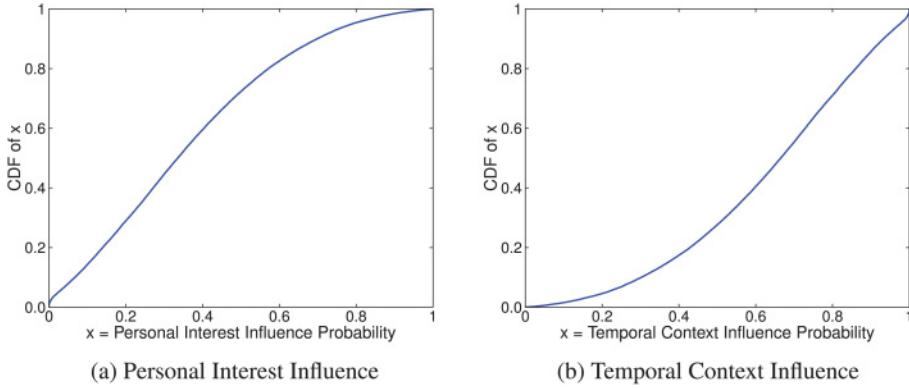


Fig. 13. Temporal context influence result (Digg).

plots the cumulative distribution of personal interest influence probabilities, and Figure 12(b) shows the temporal context influence probabilities. It is observed that, in general, people's personal interest influence is significantly higher than the influence of the temporal context. For example, Figure 12(a) shows that the personal interest influence probability of more than 76% of users is higher than 0.82. This observation indicates that most movies consumed by users are selected in accordance with their interests and tastes.

Figures 13(a) and 13(b) show respectively the personal interest influence probabilities and temporal context influence probabilities learned from the Digg data. As shown in Figure 13(a), the personal interest influence probability is smaller than the temporal context influence probability. For example, the temporal context influence probability of more than 70% of users is higher than 0.5. The implication of this finding is that people are mainly influenced by the temporal context when choosing news to read. By comparing the analysis results obtained from the two datasets, we observe that the temporal context influence on users' choice of news to read is much more significant than it is on the selection of movies to watch. This is probably because news is a time-sensitive item that is driven by offline social events, while movies are not so time sensitive.

8.6. User Profile Analysis

Both the user interests and temporal context, as well as their influences on users' decision making, can be learned by our TCAM to build user profiles. This section first analyzes two sample user profiles to enable a better interpretation of user rating behaviors. Figure 14 shows the profiles of user 102 and user 384 learned by TCAM from the Digg dataset. As shown in the figure, users 102 and 384 are influenced by the temporal context with influence probability values of 0.88 and 0.76, respectively. We also show the top-4 user-oriented topics with the highest probabilities in θ_u . The weights on the edges indicate users' preferences for the topics. Note that we only choose the top-4 user-oriented topics for demonstration, and thus the sum of the weights on the edges is not equal to 1. There is only one overlapping user-oriented topic for users 102 and 384, and the dominating user-oriented topics for them are different (i.e., $U1$ vs. $U8$).

Figure 15 shows the dynamic profiles of user 102 at two adjacent time slices (i.e., $t = 6$ and $t = 7$), which are learned by our DTCAM from the Digg dataset. Similarly, we present the top-4 user-oriented topics with the highest probabilities in θ_u^t . The weights on the edges indicate the preference degrees of the sampled user for the chosen four

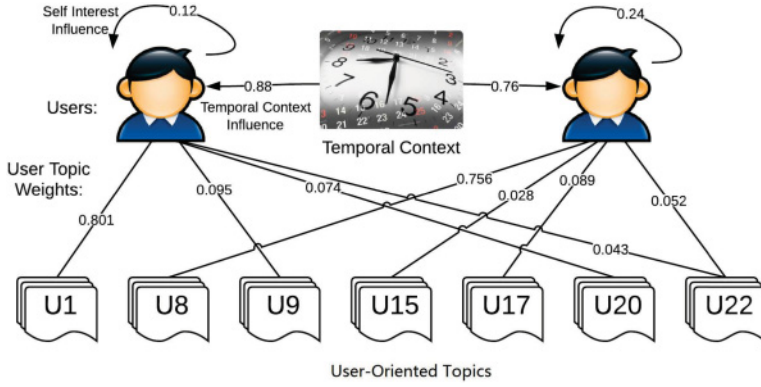


Fig. 14. Sample user profiles and temporal context influence learned by TCAM.

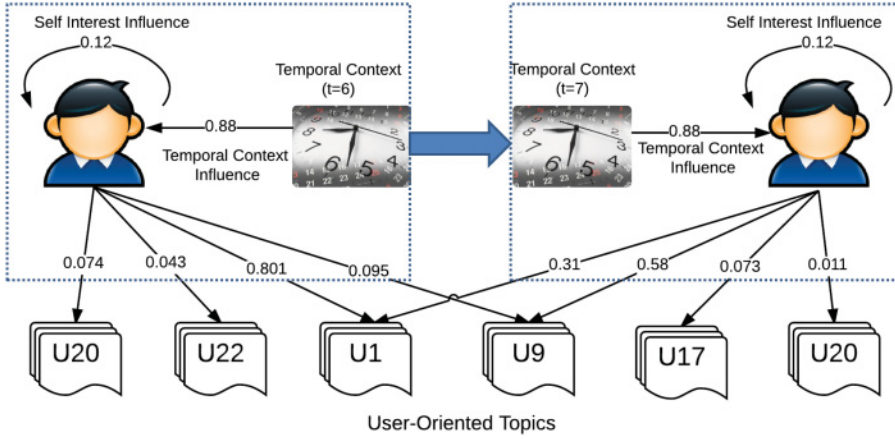


Fig. 15. Sample user profiles and temporal context influence learned by DTCAM.

user-oriented topics. By comparing the profiles of user 102 at two adjacent slices, we find that the user's interest distribution θ'_u changes over time. His or her main focus changes from topic "U1" to "U9," and he or she begins to become interested in topics "U17" and "U20." These discovered time-varying features for each user are useful for timely targeting of users with items.

We also show two sample temporal context profiles for time slices 6 and 7 in Figure 16. We present the top-4 time-oriented topics with the highest probabilities in each θ'_t . The weights on the edges indicate the preference degrees of the general public for the chosen four time-oriented topics. Since the temporal context profiles inferred by TCAM and DTCAM are similar, we only choose two temporal context profiles learned by TCAM from the Digg dataset for demonstration. By comparing the two adjacent temporal context profiles, we observe that the general public's preferences for time-oriented topics evolve over time. While the two adjacent time slices share the time-oriented topics $T1$ and $T16$, the general public focuses more on topic $T1$ at time slice 6 and shows more interest in topic $T6$ at time slice 7.

8.7. Analyzing Latent Topics

To compare topics detected by different topic models, Tables XIV and XV present several typical topics detected by different models on the datasets of Delicious and Douban

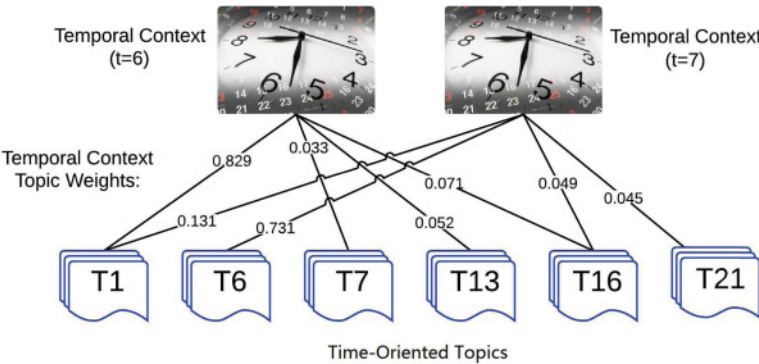


Fig. 16. Sample temporal context profiles.

Table XIV. Comparison of Topics Detected by Different Models on Delicious Dataset

Topic “Michael Jackson’s Death”					
UT	TT	TCAM	W-TCAM	DTCAM	W-DTCAM
music	latest	news	michaeljackson	headline	michaeljackson
pop	headline	world	mj	news	death
rock	news	death	moonwalk	death	homicide
hip	investigative	jackson	death	breaking	investigative
robot	michaeljackson	michaeljackson	investigative	july	breaking
michaeljackson	event	headline	news	michaeljackson	grief

Topic “Mexico’s swineflu”					
UT	TT	TCAM	W-TCAM	DTCAM	W-DTCAM
health	news	health	swineflu	health	swineflu
disease	death	disease	flu	news	mexico
flu	disease	news	mexico	flu	flu
H1N1	health	flu	disease	swineflu	influenza
influenza	swineflu	outbreak	mexico	mexico	pandemic
symptom	outbreak	mexico	death	pandemic	health

Table XV. Comparison of Topics Detected by Different Models on Douban Movie Dataset

Topic “Sci-Fi”				
UT	TT	TCAM	DTCAM	W-DTCAM
The Butterfly Effect (2004)	Total Recall (2012)	Inception (2010)	Avatar (2009)	The Black Hole (2006)
Inception (2010)	Looper (2012)	Avatar (2009)	X-Men (2011)	Bugs (2003)
Resident Evil (2002)	Life of Pi (2012)	The Matrix (1999)	Transformers (2009)	The Secret Number (2012)
The Hunger Games (2012)	Django	Cloud Atlas (2012)	Source Code (2011)	Babylon 5 (1999)
Avatar (2009)	Unchained (2012)	District 9 (2009)	Iron Man (2008)	Ghosts of the Abyss (2003)
The Matrix (1999)	Les Miserables (2012)	Iron Man (2008)	Battleship (2012)	Avatar (2009)
	Skyfall (2012)			

Movie. We make the following observations from the results: (1) On the Delicious dataset, the time-oriented topics of “Michael Jackson’s death” and “Mexico’s swineflu,” detected by TT, TCAM, and DTCAM, rank popular tags with abstract semantics like “event,” “headline,” “health,” and “world” in the top positions because of their high frequencies. As a matter of fact, these tags are of little value in describing the events and users may not be interested in them. In contrast, our proposed W-TCAM and W-DTCAM clearly promote concrete words like “moonwalk,” “michaeljackson,” “mexico,”

Table XVI. Time-Oriented Topics Detected on Delicious

T1	T4	T7	T9	T16
2009.1.12-2009.1.31	2009.6.15-2009.6.27	2009.4.24-2009.5.6	2009.5.27-2009.6.6	2009.1.24-2009.1.27
obama	moon	flu	google	droid
inauguration	space	swineflu	googlewave	go
bush	apollo11	pandemic	wave	dragonage
president	apollo	swine	bing	android
gaza	nasa	health	apps	tricks
whitehouse	competition	disease	realtime	jailbreak

Table XVII. User-Oriented Topics Detected on Douban Movie

U1	U15	U10
Same-Sex	Horror/Thriller	Chinese Martial Arts Drama
Shelter (2007)	Eden Lake (2008)	The Condor Heroes (1995)
Starcrossed (2005)	Dead Silence (2007)	Demi-Gods and Semi-Devils (1997)
Get Real (1999)	See prang (2008)	The Duke of Mount Deer (1998)
Maurice (1987)	The Hills Have Eyes (2006)	Legend of Dagger Lee (1999)
For a Lost Soldier (1992)	Dawn of the Dead (2004)	The Legend of the Condor Heroes (1994)
The Trip (2002)	Silent Hill (2006)	Swordsman (1990)
Lucky Blue (2007)	The Last House on the Left (2009)	The New Sword and the Dragon Sabre (1986)

Table XVIII. Time-Oriented Topics Detected on Douban Movie

T2010	T2009	T2008
Salt (2010)	District 9 (2009)	Eagle Eye (2008)
Inception (2010)	The Boat That Rocked (2009)	Biohazard: Degeneration (2008)
The Expendables (2010)	The Founding of A Republic (2009)	Quantum of Solace (2008)
The Twilight Saga: Eclipse (2010)	Sophie's Revenge (2009)	The Duchess (2008)
Temple Grandin (2010)	Eternal Beloved (2009)	The Dark Knight (2008)
Sex and the City 2 (2010)	Empire of Silver (2009)	WALL.E (2008)
Sherlock Season 1 (2010)	Overheard (2009)	Kung Fu Panda: Secrets of the Furious Five (2008)

and “swineflu,” which shows that our proposed item-weighting technique can cluster correlated bursty tags into a time-oriented topic, enabling the time-oriented topics to be represented by tags that are more relevant to the real events. Besides, we also observe that the topics detected by the UT model cannot capture and describe the real events accurately, although the top-ranked tags are semantically related. (2) On the Douban Movie dataset, the user-oriented topic “Sci-Fi,” detected by UT, TCAM, and DTCAM, ranks popular movies like “Inception,” “Avatar,” “The Butterfly Effect,” and “The Matrix” in the top positions as a result of their high popularity. In contrast, most of the top movies in topic “Sci-Fi” detected by W-DTCAM are niche movies that can bring more novelty and serendipity to users [Yin et al. 2012; Celma 2010], showing that our proposed item-weighting technique has the potential to help users discover and explore the long-tail world.

To examine whether the user-oriented topics and time-oriented topics detected by the DTCAMs can really capture user interest and the temporal context, we present both user-oriented and time-oriented topics detected by DTCAM on the Douban Movie and Delicious datasets in Tables II, XVI, XVII, and XVIII. Comparing Table II with Table XVI, we can clearly tell the difference between user-oriented and time-oriented

topics on the Delicious dataset. The detected user-oriented topics are related to a certain interest, such as the topics “jobs,” “loan,” “vehicle,” and “housing” in Table II, while time-oriented topics are closely related to specific social events during a certain period of time. Referring to Table XVI, the five time-oriented topics shown are “U.S president inauguration,” “Apollo 11 ceremony,” “swineflu,” “googlewave,” and “android,” respectively. All of them correspond to real-life events. The time during which the popularity of these topics reached their peak, shown in the second row of the table, is very close to the time at which these events happened in real life.

Comparing Table XVII and Table XVIII, we can easily tell the difference between the user-oriented and time-oriented topics on the Douban Movie dataset. From Table XVII, we can see that user-oriented topics capture the genres of films by clustering similar-taste movies into a topic. The movie types captured by each user-oriented topic are shown in the second row of the table. It is worth mentioning that user-oriented topics detected by our model can capture subtle interests that are beyond the capability of the well-designed Film Genres.¹¹ For example, movies in topic U10 have distinctive Chinese cultural characteristics and most are about Chinese Kung Fu and Jianghu. From Table XVIII, we observe that movies under each time-oriented topic share a similar release time and the popularity of the corresponding time-oriented topic also reaches its peak during that period.

9. CONCLUSION AND FUTURE WORK

In this article, we focused on the problem of dynamic user behavior modeling in social media systems and its applications in temporal recommendations. Based on the intuition and observations that users’ rating behaviors are influenced by two factors—user intrinsic interests as an internal factor and the temporal context (i.e., the public’s attention during a time period) as an external factor—we proposed a temporal context-aware mixture model (TCAM) that explicitly introduces two types of latent topics to model user interests and temporal context, respectively. The basic experimental results and analysis on four large real-world social media datasets demonstrated the superiority of our TCAM over existing methods in the task of temporal recommendation, which verified our motivation.

TCAM assumes that users’ interests are stable and do not change over time, while in reality this is not necessarily the case. Owing to the flexibility of the proposed probabilistic mixture model framework, we extended TCAM to a dynamic temporal context-aware mixture model (DTCAM) to explicitly model the dynamics of users’ interests. We conducted an empirical comparison of the effect of modeling the dynamics of user interests. The comparison results showed that capturing the dynamics of user interests is essential for accurately modeling users’ dynamic behaviors and improving the temporal recommendation. Besides, the user representation/profile learned by DTCAM was experimentally proven to be effective in computational advertising. However, the sparsity of users’ rating data generated in a time slice raises a great challenge, because users’ time-dependent interest distributions are easily overestimated. To alleviate the problem of data sparsity, we proposed a social-temporal regularization technique to exploit the social and temporal correlation information to enhance the prior knowledge about users’ interest distributions. The experimental results showed that our proposed social-temporal regularization is an important technique to overcome the problem of data sparsity.

Based on our proposed models, we designed a temporal context-aware recommender system (TCARS) that exploits both user interests and the temporal context. Given a target user u with a time slice t , the traditional approach to produce the top- k

¹¹<http://www.imdb.com/genre>.

recommendations is to first compute a ranking score for each item and then rank all of items. However, when the number of available items becomes large (e.g., millions), producing a top- k ranked list by the traditional method is very time consuming. To speed up the process of producing a top- k ranked list from the large social media data, we developed an efficient query-processing technique by extending the Threshold Algorithm (TA). This technique has the nice property of generating the top- k recommendations by computing ranking scores only for the minimum number of items instead of all.

We also explored other applications for our TCAM and DTCAM beyond time-aware recommendations, such as user profiling and topic discovery, in an illustrative way in the experiment section.

There are several directions for future research. Online learning has been actively studied in the machine-learning community due to its high efficiency to large and streaming datasets. One issue that arises with our DTCAM for dynamic user behavior modeling is how to perform the online model updates without loss of prediction quality. Although our current models are able to generate high-quality time-aware recommendations, coping with fast-changing trends in the presence of large-scale data is still a big challenge, since retraining our models from batch is costly. Thus, one promising future research direction is to study new algorithms and strategies to online update the models according to the newly observed users' rating data, so that our models can better fit the real-time recommendation scenarios. Although our current models take into account time factor, they do not explicitly exploit and capture temporal cyclic patterns, such as daily, monthly, seasonal, or yearly effects. Correspondingly, the time-oriented topics detected by TCAM and DTCAM mix up one-time events (e.g., Michael Jackson's death) and cyclic events (e.g., American Independence Day). In our future work, we will fully exploit the temporal cyclic patterns and further distinguish different types of time-oriented topics (e.g., one-time events vs. cyclic events). Another interesting future work is to evaluate our proposed TCAM and DTCAM online. We only adopted the offline evaluation method in this article; we'd like to deploy our models into a real system platform and to evaluate them in more detail with user studies or an online evaluation.

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