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A microblog recommendation algorithm based on social tagging and a temporal interest evolution model*

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Abstract: Personalized microblog recommendations face challenges of user cold-start problems and the interest evolution of topics. In this paper, we propose a collaborative filtering recommendation algorithm based on a temporal interest evolution model and social tag prediction. Three matrices are first prepared to model the relationship between users, tags, and microblogs. Then the scores of the tags for each microblog are optimized according to the interest evolution model of tags. In addition, to address the user cold-start problem, a social tag prediction algorithm based on community discovery and maximum tag voting is designed to extract candidate tags for users. Finally, the joint probability of a tag for each user is calculated by integrating the Bayes probability on the set of candidate tags, and the top *n* microblogs with the highest joint probabilities are recommended to the user. Experiments using datasets from the microblog of Sina Weibo showed that our algorithm achieved good recall and precision in terms of both overall and temporal performances. A questionnaire survey proved user satisfaction with recommendation results when the cold-start problem occurred.

Key words: Recommender system, Collaborative filtering, Social tagging, Interest evolution model
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1 Introduction

Microblogging has become a convenient way for Internet surfers and average users to communicate with their friends and family members, or to express intimate emotions or feelings. Using a microblog also has gradually become a habit for a massive amount of users, which leads to an exponential explosion of information in the virtual microblog society on the Internet, making retrieving and identifying needed microblog or related information extremely difficult. Therefore, more and more microblog services are developing novel engines dedicated to recommending user-specific information (Meng *et al.*, 2013).

The recommendation algorithm based on collaborative filtering (CF) has been widely used in industry and E-commerce, such as Amazon, CDNow, and Drugstore. However, the cold-start phenomenon and interest evolution of topics are two open problems of the CF approach. The cold-start phenomenon occurs when users or items have too few ratings or visiting records, which results in difficulties in finding similar ones due to the lack of adequate clues for user activities. Meanwhile, the popularity of topics varies over time along with the changes of current social hotspots and users' interests, which

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results in difficulties in more accurately modeling the item preferences.

Facing these problems, we propose in this paper a CF method based on social tagging and a temporal interest evolution model. The interest evolution model is introduced to solve the problem when interests change over time (Jain *et al.*, 2013). We use community discovery and maximum of tag votes to predict user preferences when the user cold-start problem occurs. Our work starts with the user-tag-microblog tensor, which can be decomposed into three matrices: user-tag matrix, microblog-tag matrix, and user-microblog matrix. After that, the score of each tag for a microblog is adjusted according to the interest evolution model. Then the preferred candidate tags of the target user are predicted according to the tags that are commonly labeled by people in the community they are in. Finally, a Bayesian probability of each microblog for a certain user is calculated according to the closeness between the candidate tags and this microblog, and the microblogs with top n probabilities are recommended to the user.

2 Related work

Traditional recommendation systems can primarily be classified into three categories: CF-based, content-based, and hybrid recommendation systems. The CF method was proposed by Goldberg *et al.* (1992), applied to the Tapestry system. There are two types of CF-based algorithms: user-based (Breese *et al.*, 1998) and item-based (Karypis, 2001; Sarwar *et al.*, 2001; Deng *et al.*, 2003). The user-based recommendations focus on the modeling of user preferences. This method introduces user similarity measurement and the sum of the weighted similarity to predict users' interests (Wen *et al.*, 2012). The item-based recommendations are very similar to the user-based ones, based on the assumption that a user prefers to the items that are similar to those they are interested in. Such recommendation systems calculate the similarity among items for a specific user and can effectively improve the accuracy and coverage of the recommendations. Although the CF method is widely used in practice, it still encounters difficulties such as the cold-start problem.

To overcome the cold-start problem, content-based recommendation algorithms have been proposed to model item preferences using the content of items (Balabanović and Shoham, 1997). Generally, the content-based algorithm is composed of three components (Yang and Rim, 2014). The first component is the content analyzer, which extracts the content description of the items. The second one is the profile learner, which generates the user's profile by learning the contents of user-concerned items. For example, the relevance feedback algorithm can be used to generate the user's profile in webpage recommendation. The third one is the filtering component, from which the relevant items are recommended by ranking the similarity distances between items in the user's profile and candidate items (Pazzani and Billsus, 2007). However, for content-based methods, the semantic gap is still a problem when representing the high-level semantic of the item with limited low-level features.

The hybrid recommendation algorithms (Kim *et al.*, 2006; Yu *et al.*, 2006; Koren, 2008; Wen *et al.*, 2012) consider not only the content of the items, but also users' viewing history and their interest preferences (Koren, 2010). Recommendations for microblogs usually apply hybrid methods because of the characteristics of microblogs, including short text, social authoring, and temporal effectiveness. Short text causes difficulties for building word vector models due to the fact that effective information is hard to obtain with few words and repeats, which could be partially solved with social tagging and temporal information.

Social annotation is an important clue to improve semantic understanding for short text of microblogs. Guy *et al.* (2010) proposed personalized item recommendations within an enterprise social media application, which are collected and aggregated across different data sources including blogs, bookmarks, communities, Wikis, and shared files. The system recommends items and tags to linked people using graph clustering. Chen *et al.* (2012) made recommendations based on collaborative ranking while considering three major elements on Twitter: tweet topic level factors, user social relation factors, and quality of the tweet.

Taking temporal interest evolution into consideration, Ding and Li (2005) proposed a time weight CF algorithm, which traces each user's buying history and introduces a personalized decay factor for different items according to the user's purchase behavior. Xing *et al.* (2007) proposed the time-based data weight and item similarity based data weight to adaptively track the change of user interests. Cataldi *et al*. (2010) defined emerging terms and leveraged a navigable topic graph to connect the emerging terms with other semantically related keywords to detect the emerging topics.

However, most research focused on only one aspect of the microblog's characteristics. The fusion of multiple factors in a unified framework and the cold-start problem of users are still unsolved issues.

3 Method

Four stages of our CF recommendation algorithm are illustrated in Fig. 1, including model preparation, optimizing tags of the microblog with the interest evolution model, social tag prediction for users, and microblog recommendation. Model preparation can be viewed as social microblog data preparation. Then the generated matrices are optimized based on the modeling for tags, and finally used for a Bayes based recommendation. The interest evolution model plays a key role in the optimization procedure to guide the algorithm to amend the preferences of the microblog. Social tag prediction is the solution to the user cold-start problem.

3.1 Model preparation

Assume the microblog database consists of three parts of data: the users that are organized in the social network, tags for each microblog, and microblogs. Formally, all of the k users are represented as $U=\{u_1, u_2, \ldots, u_k\}$ and all of the n microblogs represented as $B=\{b_1, b_2, \ldots, b_n\}$. Another set is $T=\{t_0, t_1, \ldots, t_m\}$, including all the tags $\{t_1, t_2, \ldots, t_m\}$ and an indicator t_0 that represents the status of reading or not. From these three parts, a three-mode tensor $\boldsymbol{X}_{m,n,k}$ is generated. Each of its element x is initialized with 0 or 1 according to the rules in Eq. (1):

$$X_{m,n,k}=\begin{cases} x_{t_0,b_\varepsilon,u_\theta}=1, & u_\theta \text{ viewed } b_\varepsilon, \\ x_{t_\delta,b_\varepsilon,u_\theta}=1, & u_\theta \text{ labeled } t_\delta \text{ for } b_\varepsilon, \\ x_{t_0,b_\varepsilon,u_\theta}(\text{or } x_{t_\delta,b_\varepsilon,u_\theta})=0, & \text{otherwise.} \end{cases} \tag{1}$$

The three-mode tensor is then factorized into three 2D matrices (Fig. 2), which represent the pairwise relationships between the users, tags, and microblogs. Instead of using a complex tensor factorization algorithm, the three matrices are simply formed by compression along each axis of $\boldsymbol{X}_{m,n,k}$.

The microblog-tag matrix $\boldsymbol{Q}$ is generated by summing each element of the tensor along the user axis. It represents the microblog preferences by tags. After summing along the other two axes, the user-tag matrix $\boldsymbol{A}$ representing the user preferences by their marked tags and the user-microblog matrix $\boldsymbol{R}$ representing the microblogs read by each user are generated, respectively.

In traditional recommendation systems, many prediction algorithms, such as the singular value decomposition (SVD) based algorithm, are then conducted directly on these sparse matrices to fill out the missing elements. Considering the cold-start problem, before prediction and recommendation, we optimize

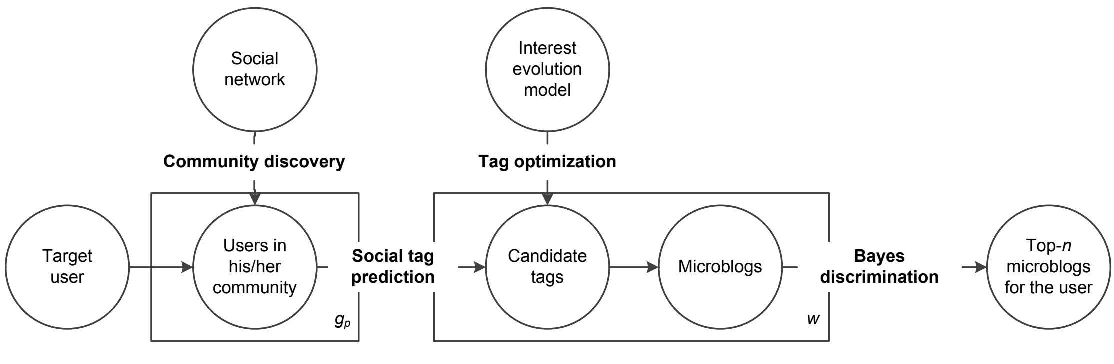

Fig. 1 An overview of our microblog recommendation algorithm (model preparation omitted)

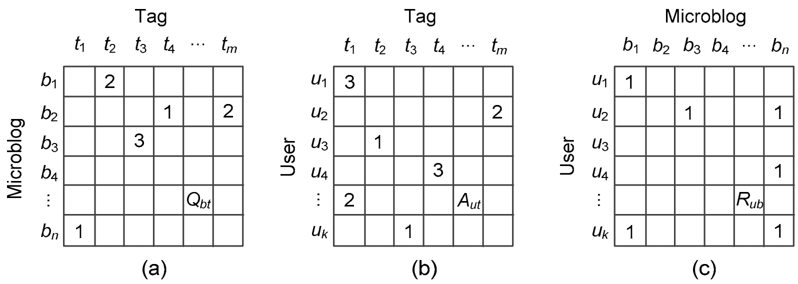

Fig. 2 The microblog-tag matrix $\boldsymbol{Q}$ (a), user-tag matrix $\boldsymbol{A}$ (b), and user-microblog matrix $\boldsymbol{R}$ (c)

the tags of microblogs using the interest evolution model and initialize user preference with the cold-start problem by social tag prediction.

3.2 Tag optimization based on the interest evolution model

The degree of interest on each tag changes over time. The term 'heat of a tag' is defined as the number of tags labeled during a certain period of time. The heat of a tag can be illustrated with an exponential curve, in which the X-axis represents days and Y-axis the labeling frequency. Fig. 3 gives the interest curves for three tags 'Steve Jobs', 'Nobel Prize', and 'SNS'. The data are depicted from the CADAL digital library, which is the portal of the Chinese Academic Digital Associative Library. A large number of tag samples show that the shapes of the interest curves are close to the Ebbinghaus forgetting curve (Chi *et al.*, 2011), which extrapolates the hypothesis of the exponential nature of forgetting, especially for the short-term behavior of tags. Therefore, the curves are fitted for each tag and the heat at a particular time is used as the weight to optimize the microblog preference in the microblog-tag matrix.

Generally, the Ebbinghaus forgetting curve can be formed as

$$W_j(\tau)=\alpha_j\tau^{\beta_j}, \tag{2}$$

where $W_j(\tau)$ is the labeling frequency of the jth tag, τ is time, and α_j and β_j are parameters of the curve (Wu *et al.*, 2012). Considering that the heat of the same tag for different users may result in different curves, the interest evolution curve is redefined as

$$W_{ij}(\tau)=\alpha_{ij}\tau^{\beta_{ij}}, \tag{3}$$

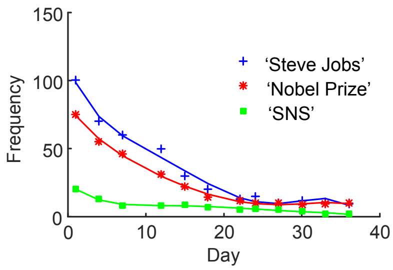

Fig. 3 Interest curves for three different tags

where τ is the number of days, $W_{ij}(\tau)$ represents the heat of the jth tag for the ith user, and α_{ij} and β_{ij} are two parameters of the tag forgetting curve for the ith user. The interest evolution model for each tag can be fitted by minimizing the following cost function:

$$J(\theta)=\frac{\lambda}{m}\tau^2+\frac{1}{m}\sum_{j=1}^{m}\mathrm{Cost}(W_{ij}(\tau),\ y_{ij}(\tau)) \tag{4}$$

with $\mathrm{Cost}(W_{ij}(\tau),\ y_{ij}(\tau))=\frac{1}{2}(W_{ij}(\tau)-y_{ij}(\tau))^2,$

where $\lambda\tau^2/m$ is the regularization term, λ is the regularization factor, and $y_{ij}(\tau)$ is the observation value of the heat of the jth tag for the ith user .

Since the optimization is applied to the microblog-tag matrix, we have to synthesize all of the users' $W_{ij}(\tau)$ to obtain $W_j(\tau)$ for the jth tag. $W_j(\tau)$ is computed as the average of k users:

$$W_j(\tau)=\frac{1}{k}\sum_{i=1}^{k}W_{ij}(\tau). \tag{5}$$

Then the microblog-tag matrix $\boldsymbol{Q}$ is updated by multiplying each of its elements with a factor of $W_j(\tau)$:

$$Q'_{m,k}(\tau)=Q_{m,k}\cdot W_j(\tau), \tag{6}$$

where $Q'_{m,k}(\tau)$ is the element of the updated matrix $\boldsymbol{Q}$ at time τ.

3.3 Social tag prediction

The cold-start problem of the CF algorithm may occur in two scenarios. One is when many items do not have any rating records, which leads to the difficulty of item modeling. Under such circumstances, initialized tags, with their metadata or keywords extracted by natural language processing, can be used to build microblog preferences (Zhou *et al.*, 2011; Armentano *et al.*, 2013). The other is when users do not have any rating or labeling records, which is called the user cold-start problem in this paper. Fortunately, a microblog system is an online social network (Weigang *et al.*, 2014). Based on the hypothesis that "the users within the same social community have similar interest", a social tag prediction algorithm is designed to assign tags for the users when the user cold-start problem occurs. The algorithm is composed of three steps. In the first step, the social network is divided into several communities. After that, a user's rating for a certain tag is predicted based on ratings from users in his/her community. Finally, the tags are ranked and the candidate tags are assigned to the user.

3.3.1 Community discovery in a social network

In a social network, the vertices are the users, and actions such as making friends, viewing, and commenting can be denoted as the edges. The community discovery algorithm is based on the Girvan-Newman algorithm (Newman, 2004). Assume that we have a network community with n vertices. First, initialize n groups for all users and define e_{vw} and a_v as

$$e_{vw}=\begin{cases}1/(2E), & \text{if users } v \text{ and } w \text{ are friends,}\\ 0, & \text{otherwise,}\end{cases} \tag{7}$$

$$a_w=d_v/(2E), \tag{8}$$

where E is the total number of edges of the network and d_v is the degree of the ith vertex. Second, stable communities are merged during an iterative optimization procedure, in which every merging step is going to maximize the increments or minimize the decrease of ΔD, where ΔD is defined as the increments of model degree D:

$$\Delta D=e_{vw}+e_{wv}-2a_va_w=2(e_{vw}-a_va_w). \tag{9}$$

After community discovery, the social network is partitioned into p groups $\{g_1, g_2, \ldots, g_p\}$.

3.3.2 Tag prediction for users

According to the interest of other users in the same community, tags that may attract a specific user can be inferred. Assume that user u belongs to group g_p, and that he/she has not annotated any tag. The degree of interest that user u prefers tag t is measured as

$$A_{u,t}=\frac{1}{n_p}\sum_{u'\in g_p}A_{u',t}, \tag{10}$$

where $A_{u',t}$ is an element of matrix $\boldsymbol{A}$, representing the labeling frequency of tag t by group user u', and n_p is the number of users in g_p. Otherwise, if the target user has annotated some tags, the degree value is modified by the similarity between the pairs of users:

$$A_{u,t}=\sum_{u'\in g_p}A_{u',t}\cdot\mathrm{sim}(u,u'). \tag{11}$$

Herein sim(u, u') represents the cosine similarity distance between the target users u and u':

$$\begin{aligned}\mathrm{sim}(u,u')&=\cos(u,u')\\&=\frac{\sum_{t\in T}A_{u,t}\cdot A_{u',t}}{\sqrt{\sum_{t\in T}(A_{u',t})^2}\sqrt{\sum_{t\in T}(A_{u,t})^2}},\end{aligned} \tag{12}$$

where $A_{u,t}$ is an element of matrix $\boldsymbol{A}$, and T is the set of tags. After ranking the scores of all the tags, the tags with the top w scores are selected as the set of candidate tags for the target user.

3.4 Microblog recommendation based on Bayes classification

After optimization of microblog-tag matrix $\boldsymbol{Q}$ with the interest evolution model and prediction of the candidate tags for target user u with the social tag prediction model on user-tag matrix $\boldsymbol{A}$, microblogs are recommended to user u based on Bayes classification on user-microblog matrix $\boldsymbol{R}$. The user-microblog matrix $\boldsymbol{R}$ can be decomposed into three matrices using SVD-based matrix decomposition (Xing *et al.*, 2007):

$$\boldsymbol{R}=\boldsymbol{U}\cdot\boldsymbol{S}\cdot\boldsymbol{V}^{\mathrm{T}}. \tag{13}$$

We choose the h largest values from matrix $\boldsymbol{R}$ to decompose the diagonal matrix $\boldsymbol{S}$ into $\boldsymbol{S}_h$, and then the user-microblog matrix $\boldsymbol{R}$ can be reconstructed as $\tilde{\boldsymbol{R}}$ to fill the missing elements in $\boldsymbol{R}$:

$$\tilde{\boldsymbol{R}} = \boldsymbol{U}_h \cdot \boldsymbol{S}_h \cdot \boldsymbol{V}_h^{\mathrm{T}}, \tag{14}$$

where $\boldsymbol{V}_h$ are the eigenvectors corresponding to the h largest eigenvalues.

Using the same method, matrix $\boldsymbol{Q}'$ can be reconstructed as a new matrix $\tilde{\boldsymbol{Q}}$. Assuming the candidate microblog is b_ε and the related tag is t_δ, the prior probability of the candidate microblog is $p(B=b_\varepsilon)$, which is defined in Eq. (15). The posterior probability is $p(t_\delta|B=b_\varepsilon)$ as in Eq. (16).

$$p(B=b_\varepsilon) = \frac{\sum_{\theta=1}^{k} \tilde{R}_{\theta,\varepsilon}}{\sum_{\varepsilon=1}^{k} \sum_{\theta=1}^{k} \tilde{R}_{\theta,\varepsilon}}, \tag{15}$$

$$p(t_\delta \mid B=b_\varepsilon) = \frac{1+\tilde{Q}_{\delta,\varepsilon,\tau}}{m+\sum_{\delta=1}^{m} \tilde{Q}_{\delta,\varepsilon,\tau}}, \tag{16}$$

where $\tilde{R}_{\theta,\varepsilon}$ represents the degree of user u preferring microblog ε, $\tilde{Q}_{\delta,\varepsilon,\tau}$ is the number of microblog b_ε annotated by tag t_δ in microblog-tag matrix $\boldsymbol{Q}$, and τ is the recommendation time. Then the joint probability $P_{\theta,\varepsilon}$ of recommending microblog b_δ to user θ is calculated by integrating the Bayes probability on the set of candidate tags. Finally, the top n microblogs with the highest $P_{\theta,\varepsilon}$ are recommended to the target user θ:

$$P_{\theta,\varepsilon} = p(B=b_\varepsilon)\prod_{\delta=1}^{w} p(t_\delta \mid B=b_\varepsilon). \tag{17}$$

4 Experiments and results

Three experiments have been designed to evaluate the performance of the algorithm under different circumstances. The first experiment was to compare the overall recommendation accuracy of our algorithm with those of several classical ones. The second one was to study the temporal accuracy trends of the recommendation algorithms. The last experiment studied user satisfaction when the cold-start problem occurs by performing a questionnaire survey.

4.1 Dataset

To evaluate the recommendation performances on the social tagged microblog data, crawlers were designed to collect social network datasets from Sina Weibo, which is one of the largest microblog systems in China. The datasets include not only the microblogs, but also the social network. Each microblog includes messages, timestamps, tags, comments, etc. The dataset of the social network contains users, the following relationships, and the forwarding actions. Table 1 shows the numbers of microblogs and comments in our database. Fig. 4 shows the heat histogram of 50 selected keywords.

Table 1 Numbers of microblogs and comments

Microblog category	Number of microblogs	Number of comments
Life	23049	209837
Health	17893	27895
TCM	9870	19890
Psychology	5098	13798
Technology	40598	124980
Education	59480	173740

TCM: traditional Chinese medicine

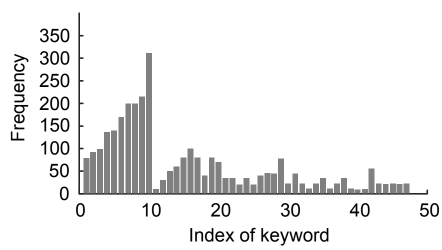

Fig. 4 Heat histogram of 50 selected keywords

The experimental datasets were sampled randomly from the database, in which there are totally 512 users, 123534 microblogs, and 6987 tags. To avoid the redundancy of datasets, 5-fold cross-validation was adopted, by which the original sample was randomly partitioned into five equal-sized subsamples. The cross-validation process was repeated five times. Each time a single subsample was retained as the validation data for testing the model, the remaining four subsamples were used as training data.

4.2 Experiments

4.2.1 Experiment 1: overall accuracy of recommendation

We compared our algorithm with four other algorithms to study the overall recommendation accuracy, including an item-based CF algorithm, which computes the adjusted cosine between similar items to predict the interest of a user (Sarwar *et al.*, 2001), a user-based CF algorithm, which uses Bayesian clustering and vector similarity (Breese *et al.*, 1998), a PLSA algorithm, also known as probabilistic latent semantic indexing (PLSI) (Ding *et al.*, 2006), and an old hybrid algorithm (Yuan *et al.*, 2011), without optimization by the interest evolution model. Precision, recall, and F1 measure are used to evaluate the performance of the top-*n* recommendations.

Recall and precision are two classical benchmarks for evaluating the performance of a recommendation system. They are ratios calculated from the number of recommendations from the test data and the total number of test sets:

$$\text{hit-ratio-recall}(u) = \frac{|\text{Test}_u \cap \text{Top}N_u|}{|\text{Test}_u|}, \tag{18}$$

$$\text{recall} = \frac{1}{k}\sum_{u=1}^{k} \text{hit-ratio-recall}(u) \times 100\%, \tag{19}$$

$$\text{hit-ratio-precision}(u) = \frac{|\text{Test}_u \cap \text{Top}N_u|}{|\text{Top}N_u|}, \tag{20}$$

$$\text{precision} = \frac{1}{k}\sum_{u=1}^{k} \text{hit-ratio-precision}(u) \times 100\%, \tag{21}$$

where Test_u represents the set of items that are annotated by target user u from the test set, $\text{Top}N_u$ is the set of recommended items, and k is the total number of users. Here we set the number of candidate tags to 10.

Fig. 5a shows the value of recall for each algorithm with a different number n. When n is relatively small, the recall performance for each algorithm is poor; when n increases, the recall improves significantly. The proposed algorithm achieves the highest recall among all the algorithms. Fig. 5b shows the precision curves of different algorithms. The precision of user-based CF is the worst one. Although all curves decrease with the increase of n, our algorithm maintains the largest precision among all.

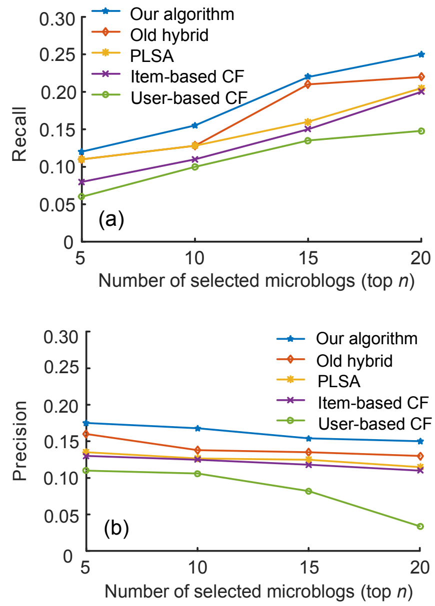

Fig. 5 Recalls (a) and precisions (b) with varying numbers of selected microblogs (top *n*) under different algorithms

The harmonic mean of precision and recall, F1, was also used to compare the overall performance of different recommendation algorithms:

$$\text{F1} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}. \tag{22}$$

Fig. 6 shows that the overall performance of the proposed algorithm is the best one compared with those of other algorithms. When n is less than 15, F1 increases with n except for the CF-based algorithms, and F1 decreases while n continued to increase.

4.2.2 Experiment 2: temporal accuracy of recommendation

Temporal accuracy, or recommendation accuracy which varies with time, is studied in the second experiment. Taking into account the dynamic evolution of interest, we append the microblogs and comments into the test sets according to their timestamps, and then compare the F1 measure for each algorithm.

Fig. 7 shows that the F1 measure of the proposed algorithm is the highest during all the time periods, while the difference between the F1 measure of our algorithm and those of other algorithms becomes larger.

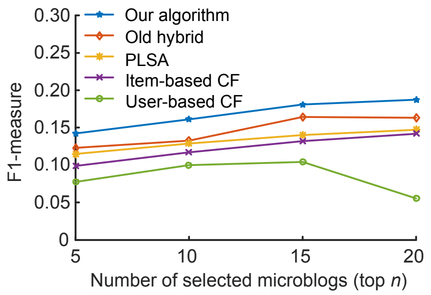

Fig. 6 F1 measures with varying numbers of selected microblogs (top n) under different algorithms

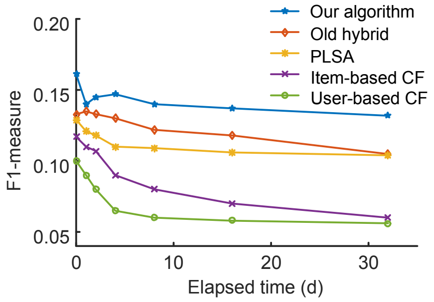

Fig. 7 F1 measures with varying elapsed time under different algorithms

4.2.3 Experiment 3: cold-start recommendation

It is difficult to evaluate the recommendation algorithm when a cold-start problem occurs. We used satisfaction questionnaires to investigate the change in users' satisfaction along with the increased number of microblogs. We invited 50 students as the new users of Sina Weibo and asked them to build some connections in the social network. Two sets of microblogs were recommended to them, one generated using the item-based algorithm and the other using our algorithm. The students were asked to rate their satisfactions for each microblog recommended to them. Three measures were designed for ratings in the range of 0 to 5: satisfied, surprised, and uninterested.

A satisfaction metric was used to evaluate whether the recommended microblog successfully attracted the students. The metric synthesizes the degree of satisfaction, surprise, and uninterest as

$$\text{Satisfation} = \frac{1}{5\times 50}\sum_{i=1}^{50}(s_i + f_i - u_i)\times 100\%, \quad (23)$$

where s_i, f_i, and u_i are the satisfaction, surprise, and uninterest ratings of the ith recommended microblog, respectively.

As we can see in Fig. 8, the satisfaction rate of the two algorithms both increases with the increasing number of recommended microblogs. The traditional item-based algorithm receives an almost 20% satisfaction rating when the number of recommended microblogs is 140. In contrast, our algorithm achieves an about 35% satisfaction rating, which proves the superiority of our algorithm in solving the cold-start problem.

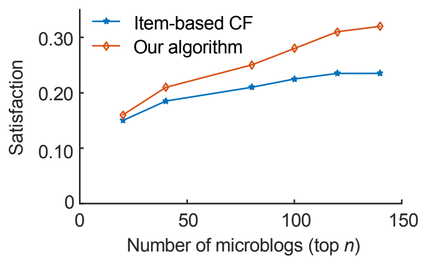

Fig. 8 Satisfaction rates of item-based CF algorithm and our algorithm

5 Conclusions and future work

We have proposed a CF recommendation algorithm based on a temporal interest evolution model and social tag prediction. The interest evolution model was used to optimize the scores of tags for each microblog. Community discovery and maximization of social tag voting were implemented to predict the tag candidates for a target user. The joint probabilities of microblogs for users were computed with the help of these tag candidates.

In the future, methods for more accurately predicting social tags for target users will be further investigated. A recommendation for multi-modal microblog content to improve the semantic representation of microblogs is also one of our future directions.

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