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Xuwei Pan
Department of Qixin Honors & Entrepreneurship, Zhejiang Sci-Tech University, Hangzhou, China

Ling Ding
Department of Management Science and Engineering, Zhejiang Sci-Tech University, Hangzhou, China

Leimin Ye
Department of Management Science and Engineering, Zhejiang Sci-Tech University, Hangzhou, China

Considering correlation retarded growth for personalized recommendation in social tagging

Xuwei Pan[1], Ling Ding[2], Leimin Ye[2]*
[1]Department of Qixin Honors & Entrepreneurship, Zhejiang Sci-Tech University, Hangzhou, China
[2]Department of Management Science and Engineering, Zhejiang Sci-Tech University, Hangzhou, China

Abstract: Due to the massive amounts of data, finding social media suited to their need is a challenging issue. To help such users retrieve useful social media content, we propose a new model of personalized recommendation system by using annotating information from relationship among users, tags, and items. However, the frequency of users' tagging has strong or weak correlation, which affects the dynamic interest mining of users. In this paper, CRGI is proposed to describe the correlation between users and tags or tags and items. Our approach has two phases, in the first phase, we describe the correlation between users, items and tags by CRGI and in the second phase, we build a tag-item weight model and a user-tag preference model on the basis of the first phase. Then we utilize the two models to find the suitable items with the highest scores. The experimental results demonstrate that the item recommendation performance is improved in both the accuracy and the diversity, and validate that the proposed personalized approach is effective for improving the social media recommendation.

Keywords: social tagging, collaborative tagging, personalized recommendation, correlation retarded growth

1. INTRODUCTION

Nowadays, there are huge amount of information that are available for users. The expansion of information has become a double-edged sword. Users can not only get more abundant contents, but also spend a long time to find the contents needed. Researchers started to utilize social tagging known as Folksonomy to solve the problem of finding the suitable resource for each user query according to his own taste. In social tagging system, users are allowed to add one or more tags to items freely. Due to that flexibility in Folksonomy, it can be used as a good tool to organize and share items on the web.

As a core component of Web 2.0 [1], social tagging is consists of users, tags and items. These three elements are combined together to form a complex dynamic network. The statistical properties and evolution mechanism of the network are helpful to reveal the structural characteristics and behavior characteristics [2].Some studies, Yang et al. [3] analyzed a large number of data in Folksonomy experimentally and found a pile of tags contain much information to identify the core ideas of Multimedia content. In a word, the tag has two functions in social tagging system: 1) the tag can help users organize and manage content, and 2) users use tags to discover the similar content that others share [4]. Therefore it is very crucial to studying collaborative tagging as a tool to improve personalization in social media recommendation.

User's tagging activities show the relationship among users, tags and items. And the closeness of the relationship is affected by many factors, such as annotation frequency, tagging time. The acquisition of users' preference is directly affected a lot without an accurate description of tight correlation. Tagging behavior is the concentrated embodiment of user's participation in annotation and interactive behavior. However, there is a correlation upper limit of user's annotation ability [5]. So it is not true to recognize the correlation between user-resource-tag is infinitely increasing proportionally with the raise in the number of annotations. This paper introduces the logistic population growth model [6] to construct an index of correlation retarded growth (CRGI)

* Corresponding author. Xuwei Pan, Email: panxw@zstu.edu.cn

to convert the labeling frequency of the user, tag and resource, which provides a favorable basis for next work. We compute first the tag-item weight model with respect to similar tags and the user-item weight model with respect to similar items. Then we combine both weights to give a personalized recommendation result according to anyone's own preference.

2. LITERATURES REVIEWING

2.1 social tagging system

At present time, there exists so many popular social tagging systems, such as Delicious, Flickr, You tube, etc. Users can not only organize and manage items, but also acquire items of interest according to the sharing of other users. In the Internet, the a large number of annotation links not only users, tags and items, but also forge links between one and the other user, so as items and tags[7]. Among the multimedia content, there are two ways to mark them [8]: manual annotations, which are edited entirely by the user with appropriate words; semi-automatic tagging, social tagging systems that recommend the appropriate list of tags for the user to select. Social tagging has become an indispensable tagging behavior in the modern network. More and more researches have been conducted, mainly focusing on the patterns and characteristics of social tagging, usage characteristics of social tags and the recommendation model based on social tagging [9]-[15].

2.2 tag based recommendation

The widely used approach is forming weighting vector to build user interest model with tags. Centering on the information such as the tagging frequency, number of times, characteristic and so on from users, it is easy to calculate the laws of these information by using probability computing model, etc. Researchers regard folksonomy as a graph-based perspective to provide personalized service. Some of these studies use a tripartite hyper-graph in which each hyper edge connects a user, tag and items [16]-[17]. Hotho et al. [16] proposed graph based algorithms. It is basic thought is making use of potential information between tags and resource, tags and users. Nonetheless, the algorithm doesn't consider the personalized message of tags well so that can't recommend personalized tags to different users. Firan et al. [18] put forward a music recommendation system basing on tags which expresses user's preference by frequency of tags. The tags not only reflect types and characteristic of music, but also reflect the user's preference for music. Symeonidis et al. [19] built a new model to recommend basing tensor decomposition which represented social tagging data-set as three-order tensor and then use higher-order singular value decomposition (HOSVD) to mine the potential semantic among users, tags and resource. Yeung et al. [20] built user model with frequent tags set that used just tag co-occurrence. The model reflects the varying degree of users among different interests.

The above researches all use annotation frequency to express the tightness between users, tags and items. However, the ability of users to annotate items changes at a variable rate over time. In this paper, CRGI (correlation retarded growth index) is proposed to describe the correlation between them. Integration of this indicator into a tag-based recommendation model would get better recommendation results.

3. CORRELATION RETARED GROWTH INDEX

The unit nodes of the users, tags and items in the social tagging system are the indicators that reflect the correlation characteristics among these elements. The association feature index establishes the connection between the user, label and item according to the associated activity. The degree and intensity of this connection are affected by many factors, such as tagging frequency, etc. We find that the rate of change of user tagging ability is similar to that of Logistic population growth model, so we construct the indicator to describe the correlation between users and tags and between tags and items. The establishment of correlation indicators can measure the close relationship between them more accurately.

The correlation index is used to describe the degree of correlation between user U_u and tag T_t, item I_i

and tag T_t. Take the correlation index $a'_{u,t}$ between user U_u and tag T_t as an example. The correlation index has the following characteristics:

(1). The number of related activities $a_{u,t}$ between user U_u and tag T_t is independent variable, the correlation index $a'_{u,t}$ is dependent variable. The data range of $a_{u,t}$ is natural numbers N, that means $a_{u,t}$=0,1,2,…. In order to simplify the calculation, we normalize the result of $a'_{u,t}$, that is the data range of $a'_{u,t}$ is [0,1].

(2). $a'_{u,t}$ is the increasing function of $a_{u,t}$ that is the more number of related activities between user U_u and tag T_t, the higher the degree of correlation.

(3). When $a_{u,t}$=0, $a'_{u,t}$=0. In the initial stages of $a_{u,t}$ changes from 1, $a'_{u,t}$ grows faster. Then $a'_{u,t}$ grows slowly. Finally, after a certain stage, $a'_{u,t}$ gradually stops increasing. Obviously, $a'_{u,t}$ is not the linear function of $a_{u,t}$.

Logistic retarded growth model was discovered by Pierre François Verhulst in 1844-1845 while he was studying the law of population growth. The model is near exponential growth in the initial stages, and then its growth slows with the saturated increasing. At last, the growth stops after maturity. Logistic function has a typical statistical significance, its standard form is:

$$f(x) = \frac{L}{1+e^{-r(x-x_0)}} \tag{3-(1)}$$

The growth rules of correlation index $a'_{u,t}$ are very similar to Logistic function. The related activities between user U_u and tag T_t are similar to the population growth in bio-system. Its correlation is not only influenced by the number of related activities, but also has upper limit that is the correlation could not increase infinitely. So we use the variant of Logistic function to define the correlation index $a'_{u,t}$.

$$a'_{u,t} = \begin{cases} 0 & , \; a_{u,t} = 0 \\ \frac{1}{1+e^{-r(a_{u,t}-a_0)}} & , a_{u,t} > 0 \text{ and } a_{u,t} \in N \end{cases} \tag{3-(2)}$$

The *r* in the function is growth rate, the larger the *r* is, the faster the growth of $a'_{u,t}$ is. The a_0 is defined as the median of dependent variable, when $a_{u,t} = a_0$, $a'_{u,t}$ =0.5. r and a_0 can be defined as different values according to different application scenarios. The definitional domain of standard Logistic function is $(-\infty, +\infty)$, the range is[0,L]. The function 3-(2) limits the definitional domain to natural numbers N, and limits range to [0,1] by setting up L=1. In the standard Logistic function, when x tends to $-\infty$, f(x) tends to 0.

4. PROPOSED MODEL

The recommendation system recommends items which users may interested according to recommendation algorithm and user model. We propose a reference algorithm by analyzing the relationship among users, items and tags. As shown in the Figure 1:

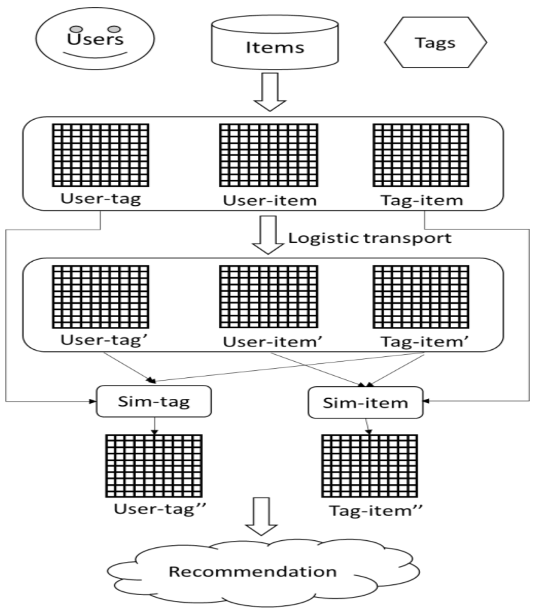

Figure 1. The algorithm process of the users, tags and items

4.1 Tagging system decomposition

A tag system is a three-dimensional system consisted of user, tag and item. Users can label an item with multiple tags while the same tag can be used to label multiple items. Obviously, tag is a link between the user and the item. All users in the network application system form the user set $U = \{u_1, u_2, u_3, \ldots, u_{|U|}\}$. All items in the network application system form the item set $I = \{i_1, i_2, i_3, \ldots, i_{|I|}\}$. All tags in the network application system form the tag set $T = \{t_1, t_2, t_3, \ldots, t_{|T|}\}$. |U|,|I|,|T|represent the number of users, items and tags. The U represents the users who can select and use the items in I under the tag in T. Because of the relationship among user, item and tag, U, I, T form into a three-dimensional matrix which is complex to make recommendation. We reduce the three-dimensional matrix to three two-dimensional matrices.

The User-tag matrix $A = [a_{u,t}]_{|U|,|T|}$ represents the number of items chosen by U_u with T_t. The User-item matrix $B = [b_{u,i}]_{|U|,|I|}$ represents that if the users $U_u$tags item I_i, marking "1" and otherwise marking "0". The Tag-item matrix $C = [C_{t,i}]_{|T|,|I|}$ represents the number of users who choose item I_i with T_t.

To compute the degree of correlation between item I_i and tag T_t, we employ CRGI in section 3. Figure 2. illustrates the calculation process of building the correlation index.

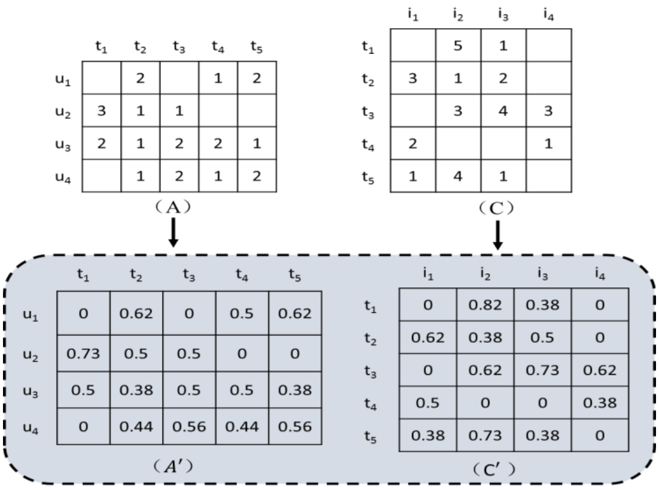

Figure 2. Concrete numerical demonstration of Logistic transformation

4.2 Similarities analysis

Computing the similarity between tags or items is an important part. In the tagging system, items and items are linked together by users and tags. By projecting into the tag space, we can get user-based item-item relational network, and by projecting into the user space, we can get tag-based item-item relational network. Therefore, the similarity between items depends on the user-based item-item similarity N_{user} and the tag-based item-item similarityN_{tag}. There are many algorithms to compute similarities including cosine similarity, adjusted cosine similarities and Pearson correlation coefficient. In the paper, we use cosine similarity which has obvious advantage process huge data with high speed.

In order to compute the Item-Item similarity matrix $N_{|I|\times|I|}$, we divide the process up into three steps. Frist, we utilize the User- Item correlation matrix B' by computing the weights of users tag items. Then we use the cosine similarity according to 3-(4) to compute the user-based item-item similarity N_user and the tag-based item-item similarity N_tag respectively. Finally, we define the item-item similarity according to 3-(3)：

$$N_{(i_x,i_y)} = \lambda N\_user_{(i_x,i_y)} + (1-\lambda) N_{tag_{(i_x,i_y)}} \qquad 3\text{-}(3)$$

where i_x and i_y represent the row and column of item i_x and item i_y, $\lambda \in (0,1)$. In this article, the value of λ is set of 0.5 due to the fact that the two types of cosine similarities follow a similar distribution.

$$n_{i_x,i_y} = \cos(i_x, i_y) = \frac{i_x . i_y}{\|i_x\| . \|i_y\|} = \frac{\sum_{s=1}^{|I|}(n_{i_x,s} . n_{i_y,s})}{\sqrt{\sum_{s=1}^{|I|}(n_{i_x,s})^2} . \sqrt{\sum_{s=1}^{|I|}(n_{i_y,s})^2}} \qquad 3\text{-}(4)$$

s represents a particular tag, and |T| represents the number of tags. If the similarity value jumps to the top of *k* among the similarities in a given column, we keep the similarity value. Otherwise the similarity value is set to 0.

As a result, get the N^k similar items, where k is the number of the top Item-Item similarities.

we follow the same steps as in computing the Item-Item similarity matrix N to compute Tag-Tag similarity matrix M. In the end, we can get the M^k similar tags, where k is the number of the top Tag-Tag similarities.

4.3 Building the recommendation model

We build two models to reflect the user-item relationship in a given tag. The first model called user-tag preference model reproduces the answer to the following question:

(1)How to judge the level of interest of users in similar tags to a specific tag?

The model computes the users' potential preference for tags denoted as $\mathrm{E}_{|U|\times|T|}$,which is deduced by the result of User-tag correlation matrix A' and Tag-tag similarity matrix M as shown:

$$\mathrm{E}_{|U|\times|T|} = \mathrm{A}' \times \mathrm{M}^{\mathrm{k}} \qquad 3\text{-}(5)$$

The model shows that the potential impact from the similar tags to a tag. The result reflects that the degree of users' favor to tags as shown in Figure 3.

$$\underset{(A')}{\begin{array}{cccccc} & t_1 & t_2 & t_3 & t_4 & t_5 \\ u_1 & 0 & 0.62 & 0 & 0.50 & 0.62 \\ u_2 & 0.73 & 0.50 & 0.50 & 0 & 0 \\ u_3 & 0.50 & 0.38 & 0.50 & 0.50 & 0.38 \\ u_4 & 0 & 0.44 & 0.56 & 0.44 & 0.56 \end{array}} \times \underset{(M^{\mathrm{k}})}{\begin{array}{cccccc} & t_1 & t_2 & t_3 & t_4 & t_5 \\ t_1 & 1 & 0.64 & 0.78 & 0.17 & 0.58 \\ t_2 & 0.64 & 1 & 0.69 & 0.70 & 0.87 \\ t_3 & 0.78 & 0.69 & 1 & 0.50 & 0.66 \\ t_4 & 0.17 & 0.70 & 0.50 & 1 & 0.66 \\ t_5 & 0.58 & 0.87 & 0.66 & 0.6 & 1 \end{array}} = \underset{(E)}{\begin{array}{cccccc} & t_1 & t_2 & t_3 & t_4 & t_5 \\ u_1 & 0.84 & 1.51 & 1.09 & 1.34 & 1.49 \\ u_2 & 1.44 & 1.31 & 1.41 & 0.72 & 1.19 \\ u_3 & 1.44 & 1.73 & 1.65 & 1.35 & 1.66 \\ u_4 & 1.12 & 1.62 & 1.45 & 1.40 & 1.60 \end{array}}$$

Figure 3. An illustration of the process of computing the user-item matrix E

The second model reproduces the answer to the following question:

(2)How to judge the connection degree between tags and items?

The model called tag-item weight model and computes the connection degree between tags and items denoted as $\mathrm{F}_{|T|\times|I|}$,which is deduced by the product of Tag-item correlation matrix C' and Item-item similarity matrix N **.**The model shows that the potential impact from the similar items to an item. The result reflects that the degree of connection between tags and items as shown in Figure 4.

$$\underset{(C')}{\begin{array}{ccccc} & i_1 & i_2 & i_3 & i_4 \\ t_1 & 0 & 0.82 & 0.38 & 0 \\ t_2 & 0.62 & 0.38 & 0.5 & 0 \\ t_3 & 0 & 0.62 & 0.73 & 0.62 \\ t_4 & 0.5 & 0 & 0 & 0.38 \\ t_5 & 0.38 & 0.73 & 0.38 & 0 \end{array}} \times \underset{(N^{\mathrm{k}})}{\begin{array}{ccccc} & i_1 & i_2 & i_3 & i_4 \\ i_1 & 1 & 0.36 & 0.44 & 0.47 \\ i_2 & 0.36 & 1 & 0.50 & 0.64 \\ i_3 & 0.44 & 0.50 & 1 & 0.44 \\ i_4 & 0.47 & 0.64 & 0.44 & 1 \end{array}} = \underset{(F)}{\begin{array}{ccccc} & i_1 & i_2 & i_3 & i_4 \\ t_1 & 0.46 & 1.01 & 0.79 & 0.69 \\ t_2 & 0.98 & 0.85 & 0.96 & 0.76 \\ t_3 & 0.84 & 1.38 & 1.31 & 1.34 \\ t_4 & 0.68 & 0.42 & 0.39 & 0.62 \\ t_5 & 0.81 & 1.06 & 0.91 & 0.81 \end{array}}$$

Figure 4. An illustration of the process of computing the tag-item matrix F

Our goal is getting the preference degree of users to items in a specific tag. We build the final model shown as user-item matrix which is computed by combining the two models E and F. We call our final model as Tag-Based-Recommend (TBR). For a given set of tags in a query q, $\mathrm{q} = \{t_1, t_2, \ldots, t_n\}\ \mathrm{n} \le |\mathrm{T}|$, the relevance score of item I_y for user U_x can be computed as:

$$\mathrm{TBR_U}(\mathrm{i},\mathrm{t}) = \sum_{\mathrm{t}\in\mathrm{q}} \mathrm{E_{u,t}} \times \mathrm{F_{t,i}} \qquad 3\text{-}(6)$$

By utilizing both models, E and F, items that fit a user's needs rank higher in the recommendation list.

5. EVALUATED MEASUREMENTS

In this section we describe the experiments conducted. In the first phase, we present how the user data are used to train a model and corresponding results. In the second phase, we evaluate and compare the performance of the different recommendation methods. Traditional item based collaborative filtering method is compared to explore that weather annotating information from relationship among users, tags, and items makes contribution to recommendation. Besides, we compare our approach with ICM approach .The ICM approach [21] connects users, tags and items through the number of tagging directly, which ignores the tagging ability of the user changes over time by varied rate.

In this experiment, a MovieLens dataset is used to evaluate our algorithms. It contains 35163 tags applications across 19545 movies. And it is created by 7801 users between December 24, 2005 and March 31, 2015. During the testing phase, it is divided into two groups containing training set and testing set. We withhold 20% records for testing while the remaining 80% is used for training. In order to make the experimental results more accurately, we use the 10% cross-validation method.

We adopt precision and recall, which can be used to measure the relevance between a set of ranked results and the user. The collection of k items recommended to user u is $R(u)$, user u favorite collection of items on the testing set is $T(u)$. Accuracy and recall show the effect of recommendation from different point of view. In evaluating the model, the higher the accuracy and recall are, the better. But in some extreme cases, there are some contradictions between the two indicators. So, we need to consider them together. F1-measure is a weighted average of precision and recall. F1 is higher, test method is more effective. Three indicators can be seen in 4-(1),4-(2),4-(3).

$$\mathrm{Precision} = \frac{\sum_{u=1}^{|U|}|R(u) \cap T(u)|}{\sum_{u=1}^{|U|}|R(u)|} \tag{4-(1)}$$

$$\mathrm{Recall} = \frac{\sum_{u=1}^{|U|}|R(u) \cap T(u)|}{\sum_{u=1}^{|U|}|T(u)|} \tag{4-(2)}$$

$$\mathrm{F1} = \frac{2\times\mathrm{Precision}\times\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \tag{4-(3)}$$

6. CONCLUSION AND RECOMMENDATION

In total, we have tested 3000 different queries. After that we compute for the whole queries, the average precision related to our approach, and the average precision related to the other two approaches.

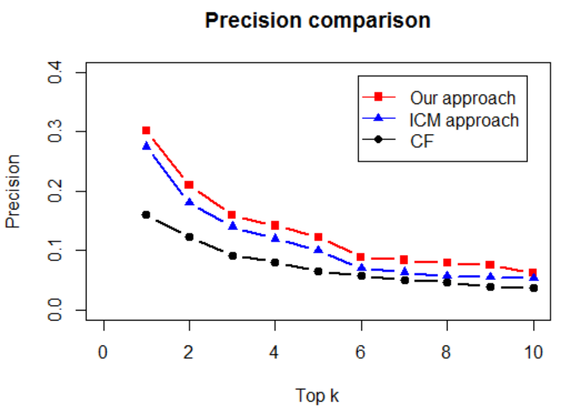

Figure 6. Precision comparison at top k

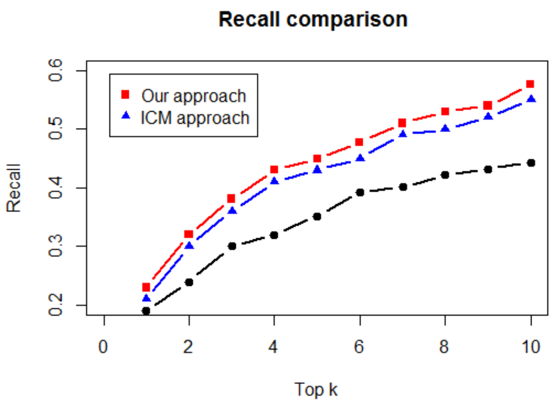

Figure 7. Recall comparison at top k

First, Figure 6 shows the results of the precision performance with respect to different values of k (top item recommended) according to 4-(1). The results show that the item based CF approach has worst performance compared to the other two approaches. Then examine recall of each algorithm as shown in Figure 7 using 4-(2). Our method obtained approximately 2.3 % on recall (at top 10).Finally, we examine F1-measure of each algorithm as shown in Figure 8 using 4-(3).

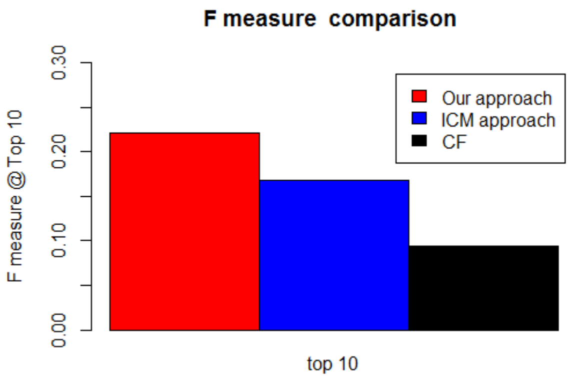

Figure 8. The F-measure at top10 of each approach

Considering that it is difficult to obtain scoring information when we recommend items to users in a context-aware environment, this article attempts to use tag information to make recommendations. Through tagging information, this paper excavates the potential relationship between users and items. Moreover, considering the correlation intensity , the numbers of tagging are not directly proportional in the actual applications. Therefore, we convert the relationship of users, tags and items into a more reasonable correlation index through the logistic population growth formula. Experiment shows that the quality of proposed model is higher than other models.

The work presented here shows prospects for further research. In fact, the quality of recommendation also relates to time and number of repeated tagging, so we are now developing a more perfect algorithm which considers tagging time and number of repeated tagging. We hold that the relational strength of items that are marked recently is higher than items marked previous. Similarly, we also recognize that the stability strength item which is marked many times is higher than the item marked only once. Although our investigation has provided promising results, we believe that our contribution is an initial step in the study of tag-aware RS. Additional research in this field is still to be explored.

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