Personalized Paper Recommendation Based on User Historical Behavior

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Abstract. With the increasing of the amount of the scientific papers, it is very important and difficult for paper-sharing platforms to recommend related papers accurately for users. This paper tackles the problem by proposing a method that models user historical behavior. Through collecting the operations on scientific papers of online users and carrying on the detailed analysis, we build preference model for each user. The personalized recommendation model is constructed based on content-based filtering model and statistical language model.. Experimental results show that users' historical behavior plays an important role in user preference modeling and the proposed method improves the final predication performance in the field of technical papers recommendation.

Keywords: Personalized Recommendation, User Historical behavior, Similarity, Recommendation Model.

1 Introduction

With the rapid development of the Internet, researchers tend to share and search for papers in Digital Libraries (DLs). Most latest papers first appear on the Internet for researchers to search for and to read, which means DLs are stepping into a golden age. Nowadays there are some famous platform providing researchers rapidly sharing academic achievements, such as arXiv.org, sponsored by Cornell University and Science Paper Online(www.paper.edu.cn),sponsored by the Ministry of Education of China. However, the number of papers on the Internet grows exponentially, bringing the problems of information overload, which makes it difficult for researchers to find useful information efficiently. Faced up with these problems, recommendation technique is one of the most effective means. So far, Elsevier, PubMed and SpringLink have offered recommendation service for their users. These sites offer paper recommendation that meets users' personal interests by sending them emails or through RSS subscription. But all the recommendation requires users to state their interests explicitly, either to provide information about their interested categories initiatively.

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In this paper, we proposed a personalized recommendation model based on researchers' expressions of interest through analysis of their historical behavior in which users do not need to specify their preference explicitly. In a paper sharing system, the users are usually researchers from different areas, and they have specific preference for certain areas. Therefore, we hypothesize that the users' interests can be excavated from their behaviors on the site that are accumulated spontaneously when they browse the pages, which does not need extra provision. By collecting and analyzing users' behavioral information bearing users' interests, we built a personalized recommendation model and choose candidate papers for recommendation. The experiment shows that our recommendation model based on users' behaviors improves the accuracy of paper recommendation.

For newly registered and inactive users whose behavioral information is scarce and easy to be noisy, we cannot get thorough knowledge about their preference, so it's hard to provide service for them well. Meanwhile, such as user A and user B share same preference, user B and user C have close preference, but A and C share a little same content or papers. So it is hard for us to find some correlation between A and C ,which ignoring potential association between the two . To solve this problem, we further optimize our model, which will be showed in detail in Section 3. In the experiment section, we discussed the optimization of our model.

The paper is organized as follows. Section 1 introduces related work. Section 2 discusses how to build personalized recommendation model based on users' behaviors. Section 3 makes an analysis on relationship of user preference transmission and we go further into how to optimize the model for new and inactive users. Section 4 verifies the accuracy of our personalized recommendation model to recommend through experiments. The last section briefly comes to some conclusions and proposes future work.

2 Related Work

Personalized Recommendation is an active service technique, in which servers collect and analyze user information to learn about their behaviors and interests to build a model, and provide services that meet their personal needs based on the personalized interest model. Nowadays, many personalization systems have been built to achieve personalized service in different ways, among which information filtering is a relatively successful one. There are two mainly approaches in filtering: collaborative filtering and content-based filtering.

Collaborative filtering approach[1] is to filter information based on the similarity of users. AT&T Lab built PHOAKS[2] and REFERRAL Web[3] recommendation system in 1997. Kurt[4] introduced personalized recommendation based on collaborative filtering approach to CiteSeer search engine in 2000. Being able to filter some complex concepts such as information quality and taste, which are hard to express, this approach is mainly used in commercial recommendation systems like Amazon[1] , eBay[2] and Douban[3] . However, because of large resource sets and the sparseness of rating data, collaborative filtering fails to solve the problems of cold start and others. Recently researches focus on creating virtual users to augment grading for items[5], explain new products with fuzzy natural language processing[6], or cluster users and apply collaborative filtering to clustered groups[7].

Content-based filtering approach has a simple and effective structure, which is mainly used in text recommendation system[8] and hybrid collaborative filtering recommendation[9]. The earliest recommendation system was based on content-based filtering including Web Watcher[10], LIRA[11], Leticia[12] and et al. All of them recommended resources by evaluating the similarity between resource content and user interest.

Personalized recommendation for scientific papers draws the attention of providing service for researchers. McNee[13] realized recommendation by building paper reference graph with collaborative filtering. Torres[14] combined collaborative filtering with content-based filtering. Since Torres accepted recommendation results from other systems before filtering, it was difficult to implement such input, thus preventing it from being applied to practical applications. Yang [15]proposed a sort-oriented collaborative filtering approach, which extracted users' behavioral preference from users' web log and coped with the cold start problem in collaborative filtering. But noises we mentioned above in web log reduced the credibility of web data and affected the results of recommendation.

Notice that scientific papers consist of text and text can imply rich information. Taking into account the issues of sparse data and cold start in collaborative filtering, we believe that content-based filtering is more effective. Up to now, recommendation by extracting text reflecting users' preference from the log and building preference model for users has proved to be effective. Based on statistical principles, Chu and Park[16]built users' personalized model with metadata, which means treat papers users read as a unit. Kim[17] et al. designed user frequency model according to terms' weight through users' web log to recommend based on content.

The methods mentioned above mainly based on inter-citation by the historical papers[13][18], or based on use of user's browse log [16][17][14]. While modeling based on references between papers didn't take each researcher's interest into all-sided consideration. When considering web log, they treat user as a center, but overlook the noise problem inside. The method we propose in this paper utilizes users' structured behavioral information on the scientific paper sharing site with content-based filtering to provide personalized recommendation for registered users.

[1] http://www.amazon.com/
[2] http://www.ebay.com/
[3] http://www.douban.com/

3 Personalized Recommendation Model

To implement user-centered personalized recommendation, we first need to track users' behavior to collect sufficient information and figure out what can reflect users' features. The selection of behaviors has a great influence on modeling user preference. By analyzing the structure of the site and its records as well as existing data, we chose the following behaviors to represent users' preference: publishing a paper, marking a paper as favorite, rating a paper, making a comment, and tagging a paper. All above are users' active operations on papers. For each user, we extract the title, abstract and keywords of papers that they operate on to form a text file as their configuration file. The personalize recommendation model we propose in this paper is to use users' profile, according to which the paper sets are filtered by content and then recommendation sets are formed.

We define recommendation task as a triple relationship: (D_i, D_x, U), in which U refers to the current user, D_x is the document set the user is viewing, and D_i is the document set to be recommended to the user. We adopt probability model to calculate the probability that we recommend D_i, given the current user U and the document set D_x being viewed. We define the similarity between our recommended resource and user as:

$$P\left(d_i|u_k, d_x\right) = \frac{P\left(u_k, d_x|d_i\right) \cdot P\left(d_i\right)}{P\left(u_k, d_x\right)} \tag{1}$$

To make it easier to calculate $P\left(d_i|u_k, d_x\right)$, we suppose that users and documents draw from independent identical distribution. Then,

$$P\left(d_i|u_k, d_x\right) = \frac{P\left(u_k|d_i\right) \cdot P\left(d_x|d_i\right) \cdot P\left(d_i\right)}{P\left(u_k, d_x\right)} \tag{2}$$

Given that the current user is viewing the current paper, $P\left(u_k, d_x\right)$ is constant. Therefore the similarity between user and paper is proportion to the numerator:

$$P\left(d_i|u_k, d_x\right) \propto P\left(u_k|d_i\right) \cdot P\left(d_x|d_i\right) \cdot P\left(d_i\right) \tag{3}$$

Then the solution to the model can be achieved by calculating $P\left(u_k|d_i\right)$, $P\left(d_x|d_i\right)$, $P\left(d_i\right)$, in the condition of current user u_k and the paper d_x being viewed now. In Equation (3), $P\left(u_k|d_i\right)$ denotes users' preference. Without $P\left(u_k|d_i\right)$, it will become statistical language model which acts as a baseline. We define the above three as similarity between the user and the paper, similarity between papers and the priori probability of a document respectively. We discuss details about them in the following part.

3.1 Priori Probability of Paper

The priori probability of paper here means to evaluate the probability that a document will be selected. It is evaluated by users' historical behaviors to grading papers throughout the global website. We make a reasonable assumption that a document is more valuable when global users operate more on it. First, we define users' behavior set: A= {down, keep, visit, tag, score, comment, collect,$\cdots$} which refers to downloading, marking as favorite, viewing, tagging, scoring, commenting and so on. D is the set of all documents in the corpus. Then we have:

$$P\left(d_i\right) = \prod_{a\in A} P\left(d_i|a\right) = \prod_{a\in A} \frac{C\left(d_i|a\right)}{\sum\limits_{d_j\in D} C(d_j|a)} \tag{4}$$

In the equation, a iterates all behaviors in A, and $C\left(d_i|a\right)$ is the number of operations users had on document d_i. We assume that all behaviors are independent because of the randomness of users' behaviors. The normalized probability of behaviors is used as an overall evaluation for documents.

Considering that records for user-registered users are sparse, or that bad-quality documents might have few users' behavior records, the value of Eigen function $C\left(d_i|a\right)$ is 0. To avoid this situation, we adopted a technology named absolute discount smoothing[19]. It is to subtract a constant value from events in the model, and distribute the subtracted values evenly into events that do not appear. In this paper, the value of Eigen function is term frequency and we do not have to add up the probabilities to 1 when discounting. We assign a small value (0.1 in this paper) to those whose Eigen function values are 0 to achieve absolute discount smoothing, so that they can get a lower score.

$$C(d_i|a) = \begin{cases} C(d_i|a) & , C(d_i|a) \neq 0 \\ 0.1 & , C(d_i|a) = 0 \end{cases} \tag{5}$$

3.2 Similarity between Papers

We mention $P\left(d_x|d_i\right)$ as the similarity between paper d_x and paper d_i. We can easily apply statistical language model on it. The title, abstract, keywords can give a graphic description of the document, while the domain of area of it is decided by users who was submitters. So we use the title, abstract, keywords and domain of area as documents' feature, and calculate the similarity through word segmentation:

$$P\left(d_x|d_i\right) = \sum_{w\in d_x} P\left(w|d_i\right) = \sum_{w\in d_x} ((1-a)\cdot \frac{tf\left(w,d_i\right)}{tf\left(d_i\right)} + a\cdot \frac{tf\left(w,D\right)}{tf\left(D\right)}) \tag{6}$$

where w refers to any word in the document d_x. $tf\left(w,d_i\right)$ is the frequency in which w appears in d_i. $tf\left(d_i\right)$ means the frequency of all words in d_i. $tf\left(w,D\right)$ is the frequency that w appears in all documents, and $tf\left(D\right)$ is the total frequency that all words appear in all documents. a is a parameter used for smoothing (we use 0.1 here).

3.3 Similarity between User and Paper

The similarity between the user and the document is represented $P\left(u_k|d_i\right)$, where users' preference information becomes fully integrated into personalized recommendation model. According to VSM (Vector Space Model), we discompose user information and document information into terms, to calculate the similarity based on probability statistics language model. The representation of document is the same as discussed in 3.2. Users are represented, as mentioned above, through the characteristic of preference model built according to users' behaviors. We can get the similarity between the two:

$$P\left(u_k|d_i\right) = \sum_{w \in W_k} P\left(w, u_k|d_i\right) = \sum_{w \in W_k} P\left(u_k|w, d_i\right) \cdot P\left(w|d_i\right), \tag{7}$$

where W_k refers to the entry set in user k's Eigen space. Since the one-dimensional characteristic of user and document is independent, we have:

$$P\left(u_k|w, d_i\right) \approx P\left(u_k|w\right), \tag{8}$$

Under our assumption, the final equation is:

$$P\left(u_k|d_i\right) = \sum_{w \in W_k} P\left(w, u_k|d_i\right) \approx \sum_{w \in W_k} P\left(u_k|w\right) \cdot P\left(w|d_i\right), \tag{9}$$

where $P\left(u_k|w\right)$ refers to the ratio of w appears in user u_k and in all users.

$$P\left(u_k|w\right) = \frac{tf\left(w, u_k\right)}{tf\left(u_k\right)} \tag{10}$$

The measurement of $P\left(w|d_i\right)$ is the same as what is mentioned in 3.2.

4 The Optimization of the Model

In practical applications, the amount of terms in documents and the number of users are quite huge-larger than a hundred thousand. Despite the enormous total amount, the term vectors for each user are usually rather sparse. For one user: Firstly, a user has a specific area of interest, and he does not care about other areas. Therefore, terms in other areas are meaningless for the user, making the user-word matrix global sparse, local dense. Secondly, if a user has just registered or has little information, almost all values of his terms are 0. The above two points both will lead to data sparse. With sparse data, content-based recommendation will not get a good performance. For example, we suppose three users:A,B and C, where B focuses on interdisciplinary. When A and B have high relevance to each other, while B and C share same interests. But because A and C have a few common preference, we directly consider A and C don't have any relevance, which ignores potential associations between them [20]paper21. When recommendation papers for A, it will male recommendation results confined to a certain field without C's field blind to A. This problem is also recommendation technical difficult problem. Under this circumstance, we need to get relevant information from other users as global information to make up complement users with less information. To cope with the problem of insufficient information, we have to increase the density of the third part of our model.[20] predicted the missing items by diffusion and iterative optimization method to smooth the original matrix, so as to increase the density of matrix. Here we redefine user-word matrix based on random walk. In Equation (9), $P(u_k|w)$ needs to be calculated from the whole domain. We built a UW matrix, *i.e.,* user-word matrix as follows:

$$C(U,W) = \begin{pmatrix} C_{u_1w_1} & \cdots & C_{u_1w_m} \\ \vdots & \ddots & \vdots \\ C_{u_kw_1} & \cdots & C_{u_kw_m} \end{pmatrix} \tag{11}$$

In Matrix (11),$C_{u_iw_j}$ refers to the frequency in which w_j appears in u_i. Normalize the matrix by column, and we can get

$$P(U,W) = \begin{pmatrix} P_{u_1w_1} & \cdots & P_{u_1w_m} \\ \vdots & \ddots & \vdots \\ P_{u_kw_1} & \cdots & P_{u_kw_m} \end{pmatrix} \tag{12}$$

In Matrix (12), $P_{u_iw_j}$ is the percentage of the number of occurrence of w_j in u_i to that of w_j in all user configuration files, i.e., the value of $P(u_k|w_j)$.

We normalize $C(U,W)$ by row, and get a new matrix:

$$P(W,U) = \begin{pmatrix} P_{w_1u_1} & \cdots & P_{w_1u_k} \\ \vdots & \ddots & \vdots \\ P_{w_mu_1} & \cdots & P_{w_mu_k} \end{pmatrix} \tag{13}$$

where $P_{w_iu_j}$ is a ratio of the number of occurrence of w_j in u_i to the number of that of all words in u_i.

In order to reduce the number of 0 in the matrix, we randomly walk on UW matrix which means multiply $P(W,U)$ and $P(U,W)$ to get a new $C^n(U,W)$, it's defined as follows:

$$C^n(U,W) = C(U,W) \cdot [P(W,U) \cdot P(U,W)]^{n-1} \tag{14}$$

where $C^1(U,W) = C(U,W)$, as the number of iteration increases, the matrix will become denser and denser. But on the other side, the deviation with the original term frequency matrix becomes larger, and comes to a constant number in the end. Therefore, the number of tighten is determined by the equation (15):

$$n = \arg\min_n |C^{n+1}(U,W) - C^n(U,W)| \tag{15}$$

If the change exceeds a given threshold, it stops. Maintain each tighten matrix and we mix the primitive matrix with it. As equation (16) shows, a is influence factor, which measures the original matrix and iterative matrix how effect the description in the user preferences.

$$C^{final}(U,W) = (1-a)\cdot C(U,W) + a\cdot C^{n}(U,W) \tag{16}$$

In this section, we optimize the original user preference modeling based on random walk model, where the potential association between users is taken into account. After optimization, the content for new or inactive users can be complemented, so that we can provide better content-based recommendation. Meanwhile we take advantage of delivery relationship among users' content, which improve the performance in predicting users' potential preference. Beyond that, we filter more interesting things to recommend to users.

5 Experiments

In this section, we will examine the performance of our content-based method personalized recommendation model based on users' behaviors. Here we carry on three groups of experiments. The first experiment compared the recommendation results of considering users' preference and without considering. Beyond that, we analysis the optimal model based on random walk with different iteration times. Finally, combining preference information after optimal iteration and original preference, we get a fusion model to find the better solution for select better technique papers to recommend. The results show that the optimized model has a good performance for recommendation as well as good robustness.

5.1 Dataset

Our dataset is provided by Science Paper Online (www.paper.edu.cn), which is a well-known scientific paper sharing system. On this platform, researchers can fast share their papers, do some reviewing, tagging, etc. Especially, the section of "the First Publications " shares the first published scientific research from users. Users in the website can publish, keep, download, visit, tag, score and make comments about papers. In the experiments , we choose five actions to represent users' preference: publishing, keeping, tagging, commenting and scoring. The data we use include users' behavioral information and first publish of papers from October 1, 2010 to March 1, 2011.

According to the practical situation of the website, we got test data as (U, D_x, D_i, L) after processing the original data. U refers to user id. D_x is the paper the user is currently reading, while D_i is the paper to be recommended and L refers to a label. In this paper, we assign L the value 1 when users are interested in the recommended paper with clicking and the value 0 when they are not interested. There are 638 data samples, 339 labeled with 1 and 299 with 0. Involved are 26 users and 93 papers. We divide them into 108 groups.

In our personalized recommendation model, papers with a higher probability mean more confidence to recommend, while papers with a lower probability are not recommended to users.

5.2 Quantitative Evaluation

In recommendation, it is necessary as IR to evaluation the top recommendation results. We utilize the *MAP* and *NDCG* in information retrieval to evaluate our recommendation model. *MAP* is short for Mean Average Precision:

$$MAP = \frac{\sum_{k} avgP_k}{N_d}, \tag{17}$$

where N_d is the total number of papers currently viewed , $avgP_k$ is the average accuracy of recommended papers when paper k is viewed. It is defined as:

$$avgP_k = \sum_{j=1}^{M} \frac{p(j) \cdot l(j)}{C(d_i)}, \tag{18}$$

where M is size of recommended paper set, $p(j)$ is the accuracy of first j recommended papers, $l(j)$ is label information, which is 1 if the recommended paper is relevant and 0 if not.$C(d_i)$ is the total number of related papers to the viewed one d_i.MAP reflects the accuracy of recommendation and evaluates the global effectiveness of personalized model.

The second criterion is *NDCG* (Normalized Discounted Cumulative Gain), which is sort-oriented.*NDCG* is applied to evaluate the accuracy of top results in recommendation set.

Given a sorted paper sequence, the *NDCG* of the nth paper $NDCG@n$ is:

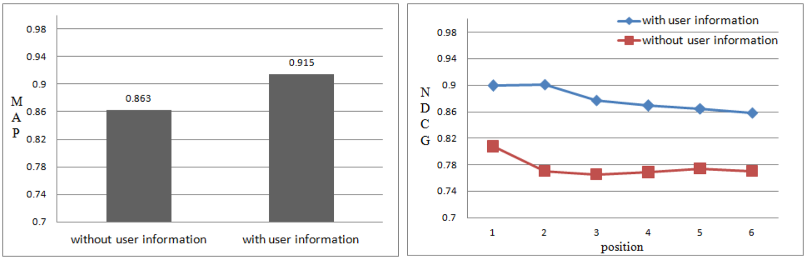
$$NDCG@n = Z_n \sum_{i=1}^{n} \frac{(2^{r(i)-1})}{\log(1+i)}, \tag{19}$$

where $r(i)$ refers to the relevant grade of ith paper and Z_n is a normalized parameter, which assures and the values $NDCG@n$ of top results add up to 1. If the number of result set is less than r, the value of $NDCG@n$ is re-calculated. In this paper, we experiment with the evaluation from $NDCG@1$ to $NDCG@6$.

5.3 Experiment Results

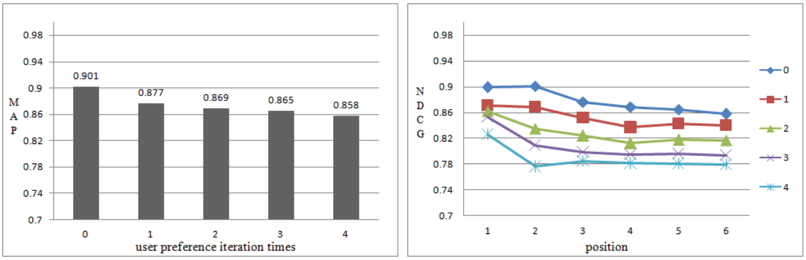
Three groups of experiments have been designed. The first experiment compared the recommendation results of considering users' preference and without considering. In this group experiment, we use original user-word matrix to represent users' preference. The following is the comparison:

The result of comparison shows that the MAP of personalized recommendation model is improved from 86% to 91%, increased by nearly five percent . Figure 1(b) shows the recommendation accuracy evaluated using $NDCG@1$ to $NDCG@6$, and the average improvement of *NDCG* is 10.2%. It verifies the effectiveness of our recommendation model with users' preference based on their behavior .



(a) (b)

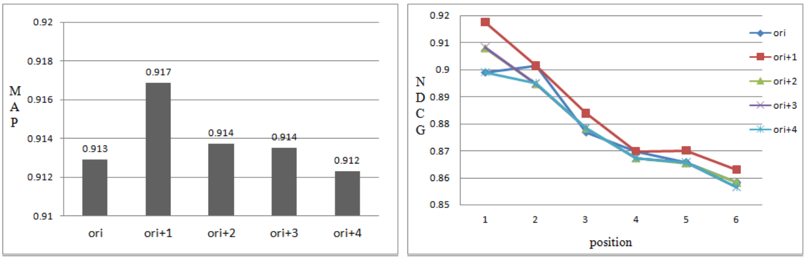
Fig. 1. Comparision on MAP (a) and NDCG (b)



(a) (b)

Fig. 2. Comparision between different iterations on MAP (a) and NDCG (b)

For the optimized part of the model, we test different setting of parameter n of dense matrix with experiment, and results are shown in Fig. 2(different graphic symbol means different iteration times). Fig. 2 reveal that the performance of the model declines as the number of interations increases. When the number of iterations are 0, 1, 2, 3, the degrees of decrease are similar to each other. The more iterations, the sharper MAP declines. This is because that the original information is lost as the number of iterations increases. Users' personalized information will be lost when we random walk on the user-word matrix.So we adopt the method of weighting to evaluate the model. Having compare original user preference to fusion model with weighted iteration information, as per equation(16). The generalized cross-validation leads to a good selection of regularization parameters a (In equation (16), here is set 0.35). we get Fig. 3(a) and Fig. 3(b)(represent as $ori + n$, where ori means original model, n means the iteration times): Figure 3(a) shows that when we take the original information into account and iterate the user-word matrix once, the effect is better than that without iteration information. When iterating more than twice (such as twice and third), fusion model get increasement compared with original model, approximately 0.1%. But iterating more than three times result in performance degradation(see in Fig. 3(a) column 5). It's concluded that fusion model with one time iteration has got a best performance under our algorithm.



(a) (b)

Fig. 3. Comparision between fusion model on MAP (a) and NDCG (b)

This section conducted experiments to evaluate the personalized recommendation model based on users' behavior and got relatively good results, which verified the effectiveness of the model. It can be concluded from the experiment results that analyzing users' behaviors is useful to recommendation model, because it makes the recommendation more personalized and can satisfying to users' different needs.

6 Conclusion

In this paper we proposed a personalized recommendation model based on users' historical behavior, which can effectively represent researchers' interests. With users' preference profile extracted from historical behavior, this paper generates recommendation with the help of content from user model and paper information. Try to avoid recommending one-sided due to modeling only based on single user himself and ignore the relationship between them, we introduce random walk model in original model to helping correlation transformation between users. Therefore new users and inactive users both benefit from it. Experimental results verified the effectiveness of our model in the field of technique papers recommendation. But as the amount of data increases, it is unnecessary to conduct global recommendation for users within specific areas. Clustering before analysis can help to reduce the recommendation set. In the future we will think about clustering based on content and filtering preference-deviating information to improve the performance further.

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