Effective Personalized Recommendation using United Auxiliary Domain based Weighted Rating Model in Large-Scale BT Download Datasets

Yue Liu, Binkai Shi, Guobing Zou, Zhe Xu
School of Computer Engineering and Science, Shanghai University, Shanghai 200444, China
yliu@staff.shu.edu.cn

Abstract

In a personalized recommendation system, users can conveniently access information that they really need along with the exponential growth of different kinds of Web data. Currently, most sophisticated off-the-shelf personalized recommendation techniques are based on the idea of collaborative filtering which can help users to find their favorites and interests. However, many important research issues still exist and need to be solved in collaborative filtering for effective personalized recommendation, especially including sparse data and "cold start". To address these research issues, this paper first proposes a novel transfer learning model, called UADWR (United Auxiliary Domain based Weighted Rating model) for collaborative filtering, where an united auxiliary domain is defined and acquired by cross-domain clustering, and then the transfer algorithm is applied to generate a weighted rating model so that it can be used for personalized recommendation. Extensive evaluation on large-scale online BT dataset shows that the effectiveness of the proposed method and its applicability for personalized recommendation.

Keywords*: Personalized Recommendation, Data Sparse, Weighted Rating Model, United Auxiliary Domain, Transfer Learning*

1. Introduction

Personalized recommender systems have become extremely common in recent years because they can help users find their favorite information by producing a list of recommended items for each given user. There are some representative examples: Book Matcher recommendation from Amazon, We Predict recommendation from Movie Finder [1]. A variety of recommendation techniques has been developed in recent years, such as rule-based recommendation, content-based recommendation, collaborative filtering recommendation, hybrid recommendation, and network-based recommendation [2]. Collaborative filtering (CF) is based on collecting and analyzing a large amount of information on users' behaviors, activities or preferences and predicting what users will like based on their similarity to other users. CF has been known to be the most successful recommendation technique, which includes Model-based collaborative filtering algorithm and Memory-based collaborative filtering algorithm (including user-base and item-based)[3]. User-based collaborative filtering algorithm always includes three steps: rate dataset representation, neighborhood formation and recommendation generation [4]. In the item-based collaborative filtering algorithm, we can forecast items rate using rates from the similar items [5]. CF has been used in a number of different applications such as recommending web pages, movies, products, and so on[6-9]. However, despite their success, their widespread use has exposed two major limitations. The first is related to data sparse. The number of ratings already obtained is very small compared to the number of ratings that need to be predicted because typical collaborative filtering requires explicit non-binary user ratings for similar products. As a result, collaborative filtering based recommendations cannot accurately compute the neighborhood and identify the products to recommend. The second is related to the cold start. In a recommendation system, the new items and new users are constantly increasing. When the new one joins in, there is little information about them. So the system cannot generate the recommendation effectively by collecting the similar rate from the new items or users.

Recent studies have suggested transfer learning an effective way to overcome these. Li et al [10] who used Co-Clustering algorithm to train a feature transfer dictionary- codebook, and solved the data sparse problem in recommendation system. Furthermore, Li et al [11] proposed a rating-matrix generative model (RMGM) for effective cross-domain collaborative filtering and achieved better results than the previous method. Pan et al [12] proposed a model based matrix factorization- CTC, and solved the sparse data by clustering users and items simultaneously. Including, the RMGM provides a new effective way for solving data sparse problem, but there are still limitations in the traditional transfer learning, such as target data transfer loss and the ambiguous weights in shared cluster-model.

In this paper, a novel weighted rating model named UADWR (United Auxiliary Domain based Weighted Rating model) is proposed to overcome the difficulty of data sparse and limitations in traditional transfer learning. Firstly, there is some marked information in the target domain which will do good to improve the efficiency of transfer and accuracy of personalized recommendation. A new weighted rating model combining the similarity of the auxiliary domain and the target domain, data sparse, size and other factors is proposed, in which weights impact factor is introduced and different weights are used for different auxiliary domains. And then, the adverse effects of the target domain from low similarity of the auxiliary domain are effectively weakened, and the effective function of the target domain from high similarity of the auxiliary domain is enhanced [13].

However, target domain and auxiliary domain are used independently in the traditional transfer learning. In our proposed method, a new conception called united auxiliary domain is defined, which is composed of the auxiliary domain and the marked data from target domain.

The new united auxiliary domain can improve the similarity of the data, reduce the sparse data of target domain effectively and elevate the efficiency of transfer learning. Secondly, when choosing more auxiliary domains in the traditional transfer learning, people do not consider the effect of different auxiliary domains for the target domain. However, different auxiliary domains have different distributions and different data similarity, which will produce different influence to the target domain. Furthermore, it can influence the accuracy of transfer learning.

Therefore, a new weighted rating model combining the similarity of the auxiliary domain and the target domain, data sparse, size and other factors is proposed, in which weights impact factor is introduced and different weights are used for different auxiliary domains. And then, the adverse effects of the target domain from low similarity of the auxiliary domain are effectively weakened, and the effective function of the target domain from high similarity of the auxiliary domain is enhanced. Finally, the experiments based on the real data of LehuBT show that UADWR provides better recommendations than the traditional collaborative filtering methods.

The remainder of the paper is organized as follows. In Section 2, the new definition of united auxiliary domain is presented. In Section 3, our proposed novel weighted rating model based united auxiliary domain is studied in detail. Section 4 depicts the experiments on large-scale online BT website by comparing with other traditional methods. Finally, conclusions are drawn.

2. United auxiliary domain

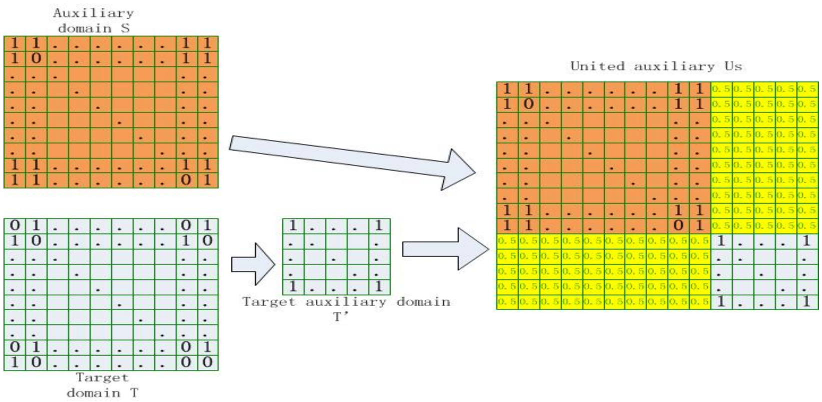

Figure 1. The Principle of United Auxiliary Domain

In transfer learning methods, the data of our target domain is always sparse, and not enough to train a reliable model. So we need choose an auxiliary domain that is a dense data set and highly similar with target domain to help train a reliable model. It is unfortunately that the target domain and auxiliary domain were mostly used independently, which make part of marked information of target domain was lost when cross-domain transfer occurred. In order to use the marked information of target domain effectively, this paper proposes a joint model called united auxiliary domain as shown in Figure 1 to integrate of auxiliary and target domains.

Here, S is a dense $x * y$ rating matrix, S={s_{11}, s_{12}, s_{13}, ……, s_{xy} } is the auxiliary domain, s_{ij} ={q_1, q_2, q_3, ……, q_l }, which s_{ij} is the rating given by user *i* on item *j*, *x* is the user number of the auxiliary domain, y is item number, q_i is an attribute of s_{ij}.

T is a sparse m*n rating matrix, T={ t_{11}, t_{12}, t_{13} , ……, t_{mn} } is the target domain, t_{ij} ={q_1, q_2, q_3, ……, q_z }, which t_{ij} is the rating given by user *i* on item *j*, *m* is the user number of the target domain, y is item number, q_i is an attribute of t_{ij}.

And then, the definition of the united auxiliary domain is given as Definition 2.1.

Definition 2.1 (United auxiliary domain). A united auxiliary domain U_S is a k*l rating matrix, including k users and *l* items. And the data is from all data of auxiliary domain *S* and part of marked data of target domain *T*, and then complement the missing user and item information of the auxiliary domain *S* and the target domain *T* in the expansion process.

$$U_S = S \cup T' \cup \bar{S} \quad (1)$$

We can learn the value of the united auxiliary domain by using the learning process shown in the Algorithm 1.First, we analyze the sparse target domain data, extract dense part of rating data to be a new auxiliary matrix *T'*, and then integrate the auxiliary domain *S* and *T'* to form a new united auxiliary domain U_S, which lost part of united auxiliary filled with rate mean $\bar{S}$. So the data quality of our united auxiliary domain is much higher and further reduced the sparse of data. The new composed auxiliary domain is more similar with the target domain data, but useful to facilitate our following prediction algorithm in transfer learning.

Algorithm 1. United auxiliary domain

Input: target domain *T*, auxiliary domain *S*;
Output: United auxiliary domain U_S.
Step 1: Initialize the united auxiliary domain U_S.
Step 2: Get a new auxiliary matrix *T' (m'*n')* by extracting the target domain *T.*
Step 3: Calculate the average rate $\bar{r}$ of the auxiliary *S*.
Step 4: For *i*← 1, …, *m'*; *j*← 1, …*n'* do
    Update $\bar{S}$ using $\bar{r}$.
  End For
Step 5: For *i*← 1, …, *x*+*m'*; *j*← 1, …, *y*+*n'* do
    Update U_S using Eq (1).
  End For

3. Transfer Learning for Weighted Rating Model

3.1 Problem Formulation

When using cluster rating model [13], all collaborative filtering tasks share a co-cluster rating model to generate rates. However, our data of collaborative filtering tasks is always similar with huge differences. If all tasks share the same rating model, it will reduce the results of forecast rating. So, in order to get better forecast results, we must change the shared cluster-rating model by the concrete data. UADWR is considered as an extension on the task of choosing cluster rating model RMGM [11], which not only shares a rating matrix on multiple tasks, but also strengthens the study of primary task by weight.

Suppose that there are two collaborative filtering tasks. One is used as the primary task, marked as R_T, and its data is used as target domain *T*. Another is the one for the auxiliary task, marked as R_S, accordingly its data is used as auxiliary domain *S*. On the basis of these two tasks, dense data as auxiliary part *T'* is extracted from the target domain, and then a united auxiliary domain U_S is built with the auxiliary domain *S*. As a result, the united auxiliary domain U_S is generated as the new auxiliary task domain by replacing the auxiliary domain *S*.

Here, the weight W is defined as Formula 2.

$$\mathrm{W} = \mathrm{sim}(R_S, R_T) + \mathrm{sim}\,(U_S, T) \tag{2}$$

Where $\mathrm{sim}(R_S, R_T)$ formulated as Formula 2 represents the similarity of the auxiliary task R_S and the primary taskR_T.

$$\mathrm{sim}(R_S, R_T) = \frac{|N_S - N_T| * |M_S - M_T| * \overline{r_S}}{N_T * M_T * \overline{r_T}} \tag{3}$$

Where N_S and N_T are the number of items in the auxiliary domain *S* and the target domain *T* respectively, M_S and M_T are the number of users in the auxiliary domain *S* and the target domain *T* respectively, $\overline{r_S}$ represents the mean rate of the auxiliary domain *S*, $\overline{r_T}$ represents the mean rate of the target domain *T*.

Similarly, $\mathrm{sim}\,(\mathrm{U}_S, \mathrm{T})$ represents the domain similarity of the united auxiliary domain U_S and the target domain *T*, defined as:

$$\mathrm{sim}(U_S, T) = \frac{U_S \cap T}{T} \tag{4}$$

In this way, $U_S \cap T$ represents the intersection of the auxiliary domain U_S and target domain *T*.

3.2 Transfer Learning for Weighted Rating Model

In the cluster rating model[13], the data of each rating matrix can be recognized as a triple $(\mathrm{u}_i^n, \mathrm{v}_i^n, r_i^n)$, which represents the rate r_i given by user u_i on item v_i in the rating matrix *n*. Expectation Maximization (EM) algorithm [14]is used to find the maximum likelihood parameters of a statistical model in cases where the equations cannot be solved directly. Here, it is employed to train the weighted rating model by the cluster rating model.

The learning process of the united auxiliary domain based weighted rating model is shown in the Algorithm 2.

Algorithm 2. United auxiliary domain based weighted rating model (UADWR)

Input: target domain *T*, united auxiliary domain U_S, weight *W*;
Output: Complete target domain prediction matrix $\tilde{T}$;
Step 1: Randomly initialize core function *B*, set clustering parameters *K*, *L*.
Step 2: For *m*← 1, …, *M*; *n*← 1, …*N* do
 Update P_u^T, B, P_v.
 End For
Step 3: For *r*← 1, …*R*; *m*← 1, …, *M*; *n*← 1, …*N* do
 Calculate $\mathrm{P}\,(c_u^k), \mathrm{P}\,(c_v^l)$ and $\mathrm{P}(r|c_u^k, c_v^l)$ using Eqs (6~10).
 End For
Step 4: For *p*← *1*, …, *P*
 Calculate $\mathrm{P}(c_u^k, c_v^l\,|\mathrm{u}_i^n, \mathrm{v}_i^n, r_i^n)$ using Eq (5).
 End for
Step 5: Calculate missing rate $f_R(u, \mathrm{v})$ using Eq (11).

In UADWR, the joint posterior probability of co-cluster (c_u^k, c_v^l) in a given rating triples $(\mathrm{u}_i^n, \mathrm{v}_i^n, r_i^n)$ is defined as $\mathrm{P}(c_u^k, c_v^l\,|\mathrm{u}_i^n, \mathrm{v}_i^n, r_i^n)$ in the E-step[14].

$$P(c_u^k, c_v^l\,|\mathrm{u}_i^n, \mathrm{v}_i^n, r_i^n) = \frac{\mathrm{P}\,(c_u^k)\,\mathrm{P}\,(c_v^l)\,P(u_i^n|c_u^k)P(v_i^n|c_v^l)\mathrm{P}(r_i^n|c_u^k, c_v^l)}{\sum_{k,\mathrm{l}} \mathrm{P}\,(c_u^k)\,\mathrm{P}\,(c_v^l)\,P(u_i^n|c_u^k)P(v_i^n|c_v^l)\mathrm{P}(r_i^n|c_u^k, c_v^l)} \tag{5}$$

At the same time, in the M-step of EM algorithm in our process, M_S and M_T are the effective rate number of the rating matrix *S* and *T respectively*. And then our rate *r* in the co-cluster (c_u^k, c_v^l) is acquired by adding the weight *W* as Formula 6-9.

$$P(c_u^k) = \frac{\sum_l \sum_i \left(\mathrm{W} * \mathrm{P}\left(c_u^k, c_v^l\,|\mathrm{u}_i^S, \mathrm{v}_i^S, r_i^S\right) + \mathrm{P}\left(c_u^k, c_v^l\,|\mathrm{u}_i^T, \mathrm{v}_i^T, r_i^T\right)\right)}{W * M_S + M_T} \tag{6}$$

$$P\,(c_v^l) = \frac{\sum_k \sum_i \left(\mathrm{W} * \mathrm{P}\left(c_u^k, c_v^l\,|\mathrm{u}_i^S, \mathrm{v}_i^S, r_i^S\right) + \mathrm{P}\left(c_u^k, c_v^l\,|\mathrm{u}_i^T, \mathrm{v}_i^T, r_i^T\right)\right)}{W * M_S + M_T} \tag{7}$$

$$P(u_i^n|c_u^k) = \frac{\sum_l \sum_\mathrm{i} \mathrm{P}\left(c_u^k, c_v^l\,|\mathrm{u}_i^n, \mathrm{v}_i^n, r_i^n\right)}{\mathrm{P}\left(c_u^k\right)(W * M_S + M_T)} \tag{8}$$

$$P(v_i^n|c_v^l) = \frac{\sum_k \sum_\mathrm{i} \mathrm{P}\left(c_u^k, c_v^l\,|\mathrm{u}_i^n, \mathrm{v}_i^n, r_i^n\right)}{\mathrm{P}\left(c_v^l\right)(W * M_S + M_T)} \tag{9}$$

$$P(r|c_u^k, c_v^l) = \frac{\sum_{i:\, r_i^n = r} \left(W * P\left(c_u^k, c_v^l \,|\, u_i^S, v_i^S, r_i^S\right) + P\left(c_u^k, c_v^l \,|\, u_i^T, v_i^T, r_i^T\right) \right)}{\sum_i \left(W * P\left(c_u^k, c_v^l \,|\, u_i^S, v_i^S, r_i^S\right) + P\left(c_u^k, c_v^l \,|\, u_i^T, v_i^T, r_i^T\right) \right)} \tag{10}$$

Through calculating in the E-step and M-step, we can get a weighted rating model by applying the multiple related tasks. So the rating triples (u_i^n, v_i^n, r_i^n) of arbitrary tasks can be recognized as the sampling from UADWR. After training UADWR, the missing rates of the given rating matrix are generated by learning five set of model parameters.

$$f_R(u, v) = \sum_r r \sum_{k,l} P(r|c_u^k, c_v^l) P(c_u^k|u) P(c_v^l|v) \tag{11}$$

Finally, we get missing data of target rating matrix based on formula 11.

4. Experimental Evaluation on LEHUBT

4.1. Experimental Data

Nowadays, there are some Ipv6 based download websites in colleges, such as neu6 (http: //bt.neu6.edu.cn/), byrBT (http://bt.byr.cn/), CGBT (http://cgbt.cn/), and so on. Our experimental dataset originates from the history download records of LehuBT (http: //bt.shu6.edu.cn), which is an official forum at Shanghai University with huge number of visiting data by the faculty and students. The movie download records and the music download records of LehuBT between February, 2012 and April, 2012 are chosen as the experimental dataset.

The movie data includes 723659 records downloaded by 10979 users on 5392 torrents, where each user downloads 15 torrents at least and each torrent is downloaded by 15 users at least, and data sparse is about 98.78%. The music data includes 146777 records downloaded by 4129 users on 1676 torrents, where each user downloads 10 torrents at least and each torrent is downloaded by 10 users at least, and data sparse is approximately 97.88%. To be convenient for calculating and enhancing the effectiveness of the experiments, the representative download records given by 100 users (movie100, music100) and 200 users (movie200, music200) are chosen to verify the effectiveness of our algorithm UADWR.

4.2. Experimental Steps and Results

4.2.1. Experimental Results of Data Sparse

Both the movie data and the music data have high data sparse which significantly affects the recommendation accuracy. Before the recommendation, our proposed united auxiliary domain is applied to pre-process the data. The results are shown in Figure 2, where movie-UAD represents the sparse of processing movie data by the united auxiliary domain and music-UAD represents the sparse of processing music data by the united auxiliary domain.

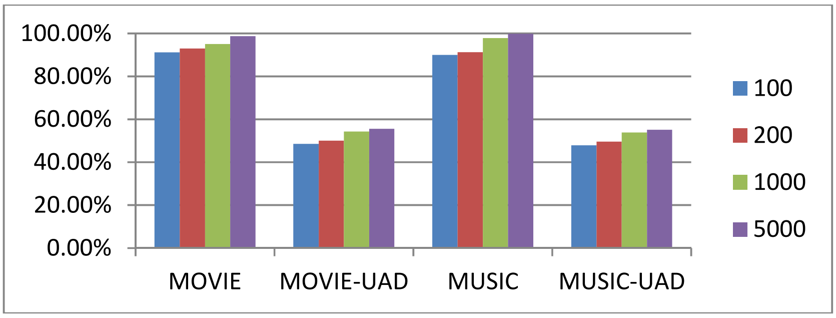

Figure 2. The comparison of the data sparse

From the Figure 2, it can be seen that the sparse of the 100, 200, 1000, 5000 movies and music are all more than 90%, the sparse of the 5000 music is even almost 99.99%, while the sparse of the movie-UAD and music-UAD are both dropped to almost 50%. The sparse is reduced greatly through using the united auxiliary domain.

4.2.2 The Experimental Results of the Rate Prediction

Experiments are performed on the above processed data to the cross domain collaborative filtering tasks. The RMGM transfer learning [11] and traditional collaborative filtering (CF) algorithm [5] are taken as the compared methods. The evaluation metrics we adopt are mean absolute error (MAE), coverage rate and recall rate [1].

The mean absolute error (MAE) is represented as Formula 12.

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}\left|f_{ij} - r_{ij}\right| \tag{12}$$

Where, n denotes the number of test ratings, f_{ij} represents the predicted rating, r_{ij} is true rating. A smaller value of MAE means a better performance.

For user i, the *Recall* is defined as the Formula 13.

$$\mathrm{Recall} = \frac{N_{\mathrm{rs}}}{N_s} \tag{13}$$

Where N_{rs} is the number of torrents in the recommendation list and downloaded by users. N_s is the number of torrents downloaded by user.

The coverage rate is formulated as Formula 14.

$$\mathrm{Coverage} = \frac{N_{\mathrm{r}}}{N} \tag{14}$$

where, N represents the number of all the items, N_{r} represents the number of the torrents downloaded by the user.

Table 1. The comparison of MAE

	Music 100	***Music 200***	***Movie 100***	***Movie 200***
CF	0.8249	0.8030	0.8208	0.7631
RMGM	0.8018	0.8162	0.7985	0.7750
UADWR	0.7892	0.8127	0.7820	0.7703

The experimental results of MAE on the four music and movie datasets are listed in the Table 1. The MAEs of UADWR on the four datasets are all less than those of the other two compared method. For example, on Music 100, the MAE of UADWR is 0.7892 which is 0.0126 and 0.0357 smaller than that of RMGM and CF.

It is shown that the effects of transfer learning we proposed are better than the traditional CF algorithm when the data is with high sparse such as Music 100 and Movie 100. We also find that UADWR does not work better than CF when the data is dense (such as Music 200, Movie 200). However, UADWR still performs better than RMGM.

The comparisons on coverage rate and recall rate are shown in Table 2 and Table 3 respectively. UADWR gets best coverage rates with 1.26%, 0.53%, 1.650%, and 0.47% improvement on the four dataset over RMGM which explains the effectiveness of our proposed method. We also observed that UADWR brings 0.87, 0.69, 1.13, and 0.32 percent improvement of the recall rates over RMGM. It can be concluded that the coverage rate and the recall rate of UADWR are both better than the shared cluster model-RMGM after adding weight to our model.

Table 2. The comparison of coverage rate

	Music 100	***Music 200***	***Movie 100***	***Movie 200***
RMGM	19.82%	18.38%	20.15%	22.50%
UADWR	21.08%	18.91%	21.80%	22.97%

Table 3. The comparison of recall rate

	Music 100	***Music 200***	***Movie 100***	***Movie 200***
RMGM	16.54%	15.21%	16.77%	18.37%
UADWR	17.41%	15.90%	17.90%	18.69%

5. Conclusions

In order to solve the problem of data sparse in the traditional collaborative filtering algorithm for personalized recommendations, this paper proposed a novel transfer learning model called UADWR. First, UADWR method employs the united auxiliary domain to decrease data sparse, and solves the target data transfer loss in the traditional transfer learning. And then, in the cross domain transfer learning, a weighted rating model is applied which gives different weights for the different tasks. It does not like that the traditional transfer learning method which uses the same clustering model and the ambiguous weights for all tasks.

Finally, by extensive experiments that are conducted on large-scale LehuBT download datasets, the effectiveness of the proposed transfer algorithm for personalized services is verified. From the experimental results, it can be concluded that UADWR can generate different weights according to different kinds of tasks, so that the weight of the target domain performs better than the auxiliary domains. Meanwhile, the weight of the auxiliary domain high similar to target domain is also higher than other auxiliary domains.

For our further work, the effectiveness of the algorithm need to be improved and social relationships among the users can be used to the model which can improve the accuracy of the personalized recommendation.

6. Acknowledgments

This research is supported by the National Natural Science Foundation of China (Grant No. 70972106), Shanghai Municipal National Natural Science Foundation (Grant No. 09ZR1412600), Shanghai Leading Academic Discipline Project (Grant No. J50103), and Innovation Foundation of Shanghai University (Grant No. A.10-0108-12-005).

7. References

[1] Luo Xin, Ouyang Yuanxin, Xiong Zhang, Yuan Man, “The Effect of Similarity Support in K-Nearest-Neighborbood Based Collaborative Filtering”, “Chinese Journal of Computers”, Science Press, vol. 33, no. 8, pp. 1437-1445, 2010.

[2] Liu Jianguo, Zhou Tao, Wang Binghong, “Personalized Recommendation System in Progress”, “Progress in Natural Science”, Science China Press, Vol.19, No. 1, pp.1-15, 2009.

[3] John. S. Breese, David Heckerman, Carl Kadie, “Empirical Analysis of Predictive Algorithms for Collaborative Filtering”, In Proceedings of the 14th Conference on Uncertainty in Artificial Intelligence, pp. 43-52, 1998.

[4] Wu Yifan, Wang Haoran, “Collaborative Filtering Algorithm Using User Background Information”, “Journal of Computer Applications”, Science Press, vol. 28, no. 11, pp. 2972-2974, 2008.

[5] Francesco Ricci, Lior Rokach, Bracha Shapira, Paul B Kantor (Eds.), “Recommender Systems Handbook”, Springer, New York, USA, 2011.

[6] Anirban Kundu, Sutirtha Kr. Guha, Tanmoy Chakraborty, Subhadip Chakraborty, Snehashish Pal, and Debajyoti Mukhopadhyay, “Multi-Agent System for Search Engine based Web Server: A Conceptual Framework”, “JDCTA: International Journal of Digital Content Technology and its Applications”, Advanced Institute of Convergence Information Technology Research Center, vol. 3, no. 4, pp. 44-59, 2009.

[7] Zhang Yao, Feng Yuqiang, “Hybrid Recommendation method IN Sparse Datasets: Combining Ccontent Analysis and Collaborative Filtering”, “JDCTA: International Journal of Digital Content Technology and its Applications”, Advanced Institute of Convergence Information Technology Research Center, vol. 6, no. 10, pp. 44-59, 2012.

[8] Cheng Gongxun, Liu Lilan, Lei Huahuan, Lin Zhiqi, Li Manping, Yu Tao, “QoS-Prediction Cloud Service Recommendation by Collaborative Filtering in Cloud Manufacturing Platform”, “AISS: Advances in information Sciences and Service Sciences”, Advanced Institute of Convergence Information Technology Research Center, Vol. 5, No.3, pp. 295-304,2013.

[9] Wu Yekui, Yao Jianrong, Tang Zhihao, Meng Jinqi, “Collaborative Filtering Based on Multi-level Item Category System”, “JCIT: Journal of Convergence Information Technology”, Advanced Institute of Convergence Information Technology Research Center, Vol. 7, No. 7, pp. 64-71, 2012.

[10] Li Bin, Yang Qiang, Xue X, “Can Movies and Books Collaborate? Cross-Domain Collaborative Filtering for Sparsity Reduction”, In Proceedings of the 20th International Joint Conference on Artificial Intelligence, pp. 2025-2057, 2009.
[11] Li Bin, Yang Qiang, Xue Xiangyang, “Transfer Learning for Collaborative Filtering via a Rating-Matrix Generative Model”, In Proceedings of the 26th International Conference on Machine Learning, pp. 617-624, 2009.
[12] Pan Weike, Evan W.Xiang, Nathan N.Liu and Yang Qiang, “Transfer Learning in Collaborative Filtering for Sparsity Reduction”, In Proceedings of the 24th AAAI Conference on Artificial Intelligence (AAAI-10), pp. 230-235, 2010.
[13] Wu H, Wang YJ, Wang Z, Wang XL, Du SZ, “Two-Phase Collaborative Filtering Algorithm based on Co-clustering”, “Journal of Software”, Science Press, vol. 21, no. 5, pp. 1042-1054, 2010.
[14] Dempster AP, Laird NM, Rubin DB, “Maximum Likelihood from Incomplete Data via the EM Algorithm”, “Journal of the Royal Statistics Society, Series B (Methodological)”, Wiley-Blackwell, vol. 39, no. l, pp. l-38, 1977.