

Hybrid Recommendation Algorithm for E-commerce Website

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Abstract—Traditional recommendation algorithms face some serious problems, including data sparsity, cold start and inefficiency. To better address the problems above, the paper proposes a hybrid recommendation algorithm based on improved collaborative filtering of user context fuzzy clustering and content-based. For collaborative filtering, firstly, user classification is based on fuzzy clustering according to user context, and then collaborative filtering is used to recommend products for similar users. And the improved content-based algorithm sets up feature vectors for users and items dynamically. Experiments show that the hybrid algorithm can avoid defects of single algorithm and improve the performance in both recommendation quality and efficiency, which opens up exciting avenues for future research.

Keywords—Collaborative filtering; Content filtering; Hybrid recommendation

I. INTRODUCTION

As e-commerce grows and provides more and more goods, so that it also makes consumers hard to find products user interested. In this case, a variety of recommendation systems came into being. E-commerce recommendation system suggests products and provides consumers with information to help them decide which products to purchase[1]. It makes personalized recommendations for information or products adapted to individual customers' preferences and tastes by analyzing historical data[2].

The core part of the recommendation system – recommendation method, faces some key challenges, including data sparsity, cold start and inefficiency, which seriously affect recommendation.

In order to solve the issues well, the paper provides a hybrid recommendation algorithm. We first improve the two methods of collaborative filtering and content-based, and then combine the two recommend results in a certain proportion. Finally we carry on experiments of comparing with other methods, which suggest that the new algorithm can efficiently solve these problems above and improve recommendation quality and efficiency.

II. RELATED WORK

So far, four common recommendatory technologies are used by e-commerce recommendation systems, namely collaborative filtering, content-based, knowledge-based and hybrid recommendation. There are also some non-

mainstream recommendation technologies: statistics-based and rule-based etc.

Collaborative filtering is one of the most successful personalized recommendation technologies and it is an algorithm based on the comparison of one user's behavior with other user's behavior, to find his nearest neighbors, and according to his neighbor's interests or preferences to predict his interests or preferences[3].

Content-based recommendation algorithm is derived from the information-access field[4]. The main idea of it is to recommend an item to a user based upon a description of the item and a profile of the user's interests.

However, there are advantages and limitations of each recommendation method. For example, collaborative filtering can find users' potential interests by analyzing the historical data, but suffer from serious sparsity, cold start problems. Although the content-based can avoid all these problems and can also make a list of features of recommended products to explain recommendation reasons, it can be constrained by information extraction technologies and hard to find users' potential interest preferences. Thus the study of hybrid recommendation is proposed, which is the hottest research field[5]. There are two main hybrid types: recommendation algorithms hybridization and recommendation results hybridization. Hong Wenxing et al. proposed a hybrid recommendation method based on user clustering and association rules[6]. Li Ying et al. presented a personalized hybrid recommendation method based on commodity keywords[7]. Hou Zhiping proposed a e-commerce website personalized recommendation based on user behavior[8]. Guo Feipeng and Lu Qibei presented a novel contextual information recommendation model in e-commerce[9]. The above methods achieved a certain effect for the specific e-commerce website, but the combination and applicability of recommendation methods have not been considered comprehensively.

We analyze the feature of existing e-commerce site and products and put forward a novel hybrid recommendation algorithm. The method can overcome data sparsity, cold start well with high coverage, accuracy. At the same time, it can improve the recommendation efficiency.

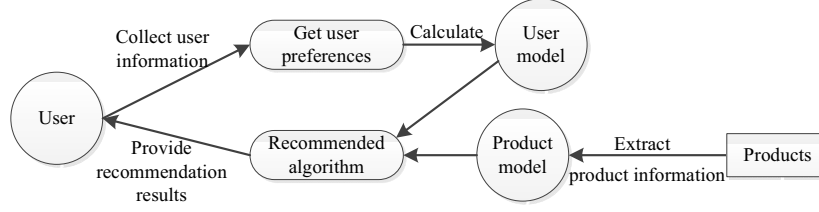


Figure 1. The flow of personalized recommendation

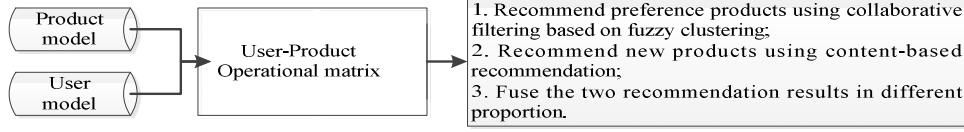


Figure 2. The hybrid recommendation model for e-commerce

III. HYBRID RECOMMENDATION MODEL

A. Recommendation Model Building

Personalized recommendation model mainly includes three modules: user modeling, product modeling and recommendation algorithm. Figure 1 shows the flow of personalized recommendation model. It provides item recommendation or predictions based on the match of users' interests with item features.

B. Recommendation Model Realization.

The flow of hybrid recommendation model for e-commerce is shown as Figure 2

1) Build product model

Extract important product characteristic dimensions like brand, category, price level etc., so product feature vector is shown as formula (1).

$$D = (D_1, D_2, \dots, D_1, \dots, D_n), i \in (1, n) \quad (1)$$

Where D_i represents different dimensions of product characteristics.

2) Build user model

a) First find out all products operated by user k and then extract their properties with repetition to compose a characteristic vector (2).

$$D^k = (D_{11}, D_{12}, \dots, D_{1l}, D_{21}, D_{22}, \dots, D_{2m}, \dots, D_{ij}, \dots, D_{n1}, D_{n2}, \dots, D_{nq}) \quad (2)$$

If product p has one characteristic of them above, the corresponding position of the characteristic vector is set to 1, otherwise to 0. According to the principle, compose a vector D^{k_p} for product p operated by user k .

So user feature vector is shown as formula (3).

$$U_k = \frac{\sum_1^n R_p D^{k_p}}{\sum_1^n R_p} \quad (3)$$

Where stands for rating or operation type user made for product p and n stands for the number of products user operated.

b) Build user-product operational matrix R .

$$R = \begin{bmatrix} R_{1,1} & \dots & R_{1,k} & \dots & R_{1,n} \\ \dots & \dots & \dots & \dots & \dots \\ R_{i,1} & \dots & R_{i,k} & \dots & R_{i,n} \\ \dots & \dots & \dots & \dots & \dots \\ R_{m,1} & \dots & R_{m,k} & \dots & R_{m,n} \end{bmatrix}$$

Where R_{ij} stands for rating or operation style user i made for product j , $R_i = (R_{i1}, R_{i2}, \dots, R_{in})$, $i \in [1, m]$ stands for user-product operating value vector.

3) According to historical data, on the one hand, recommend products adapted to individual customers' preferences and tastes, using the collaborative filtering based on user context fuzzy clustering; on the other hand, recommend new products applying content-based. For the reason that user's interest preference changes over time and there is a huge amount of historical data, thus, we can choose history data for modeling over a certain time period according to actual circumstances.

4) Mix the two recommended results in different proportion which can be adjusted to achieve the optimal effect.

C. Recommendation Algorithm Module

Below are the two improved recommendation algorithm.

1) Collaborative filtering based on user context fuzzy clustering.

In order to reduce data sparsity and dimensions of the user-product operation matrix, firstly, fuzzy clustering based on user personalized information is used to construct the user set which is similar with current user context, and then take collaborative filtering for a certain user set. Fuzzy clustering is different from traditional clustering methods, it can consider the properties of samples comprehensively and cluster more accurately[10]. The core idea of it is to calculate similarity coefficient between samples firstly to establish a fuzzy similar matrix and then generate fuzzy equivalence matrix by transforming the above fuzzy similar matrix, finally, according to different cutting level to classify fuzzy equivalence matrix. The transitive closure is a significant

method of fuzzy clustering. Lee optimized the transitive closure based on fuzzy similar matrix[11].

a) *Describe user personalized contextual information*

Extract user personalized contextual information flexibly according to the styles of e-commerce and consumption objects. For instance, we can extract gender, age, occupation as user personalized context for consumers of film. And user personalized context is used to establish the Matrix C_u :

$$C_u = \begin{bmatrix} I_{11} & I_{12} & \cdots & I_{1n} \\ I_{21} & I_{22} & \cdots & I_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ I_{m1} & I_{m2} & \cdots & I_{mn} \end{bmatrix}$$

Where stands for corresponding values of personalized context dimension j for user i.

b) *Standardize data*

Step1: The average and standard deviation of dimension j for m users are separately described as formula (4) and (5):

$$\bar{I}_j = \frac{1}{m} \sum_{i=1}^m I_{ij} \quad (4)$$

$$S_j = \left[\frac{1}{m} \sum_{i=1}^m (I_{ij} - \bar{I}_j)^2 \right]^{1/2} \quad (5)$$

Step2: After standardized, the raw data becomes

$$I'_{ij} = (I_{ij} - \bar{I}_j) / S_j \quad (6)$$

Step3: Compress standardized data to [0,1] using extreme standardization formula (7):

$$\bar{I}'_{ij} = (I'_{ij} - I'_{\min j}) / (I'_{\max j} - I'_{\min j}) \quad (7)$$

Where $I'_{\max j}$ and $I'_{\min j}$ are the maximum and minimum value of respectively.

c) *Construct fuzzy similar matrix*

$$D^f = \begin{bmatrix} D_{11} & D_{12} & \cdots & D_{1m} \\ D_{21} & D_{22} & \cdots & D_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ D_{m1} & D_{m2} & \cdots & D_{mm} \end{bmatrix}$$

If $i=j$, $D_{ij}=1$, or else D_{ij} stands for the similarity between two users. D is a $m \times m$ symmetric matrix. For convenience, simplify it into upper triangular matrix D. And then construct fuzzy equivalent matrix using transitive closure

$$t(D) = D^{2^k} \quad (k \geq 1)$$

d) *Conduct fuzzy clustering*

Find out the optimal cutting level λ using statistic F and then users whose similarity is bigger than λ are organized by category.

e) *Collaborative filtering*

Step1: Construct user-product feature vector R_i in every user set.

Step2: Identify k most similar users for a target user and use Pearson similarity coefficients to accurately measure the similarities between users.

Step3: Predict ratings of target user for products and chose the top N items. More specially, the predicted rating can be calculated by the formula below[12].

$$\text{pred}(a, p) = \bar{R}_a + \frac{\sum_{b \in N} \text{sim}(a, b) \times (R_{b,p} - \bar{R}_b)}{\sum_{b \in N} \text{sim}(a, b)} \quad (8)$$

Where $\text{sim}(a, b)$ stands for the similarity between user a and user b, $R_{b,p}$ stands for the rating of nearest neighbor user b for item p. \bar{R}_a and \bar{R}_b is the mean rating of user a and user b.

2) *Content-based recommendation*

Initially, establish feature vector H_i for new product according to each user feature vector U_i , and then compute the similarity between H_i and U_i , the calculation is a key step and the method is shown as the formula (9)[13].

$$u(c, s) = \text{score}(\text{userprofile}, \text{content}) \quad (9)$$

There are many methods to calculate $u(c, s)$, and more specially, it is usually calculated by the vector angular cosine as the formula (10)[13].

$$u(c, s) = \cos(U_c, H_s) = \frac{\sum_{i=1}^k U_{i,c} H_{i,s}}{\sqrt{\sum_{i=1}^k U_{i,c}^2} \sqrt{\sum_{i=1}^k H_{i,s}^2}} \quad (10)$$

IV. EXPERIMENTAL EVALUATION

A. Data Set

In order to investigate the performance of our method, we conducted an experiment using MovieLens Dataset, which includes user ratings, item attribute contents and user personality information. The data set was randomly divided into a training set and a test set in the ratio of 4:1.

B. Evaluation Metrics.

In this paper, we chosen precision/recall and coverage to evaluate our method.

1) *Precision/recall is to evaluate the accuracy of recommended results. Assume that $R(u)$ stands for the number of recommended results, $T(u)$ stands for the number of items in the test set. The calculation methods are shown as the formulas (11) and (12)[14].*

$$\text{Precision} = \frac{\sum_u |R(u) \cap T(u)|}{\sum_u |R(u)|} \quad (11)$$

$$\text{Recall} = \frac{\sum_u |R(u) \cap T(u)|}{T(u)} \quad (12)$$

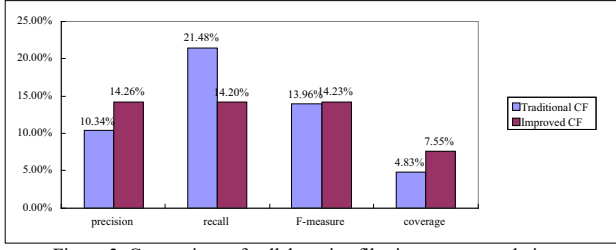


Figure 3. Comparison of collaborative filtering recommendation

And the F-measure is the harmonic mean of precision and recall, which can comprehensively reflect the accuracy of a algorithm. The calculation formula is shown as below:

$$F = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (13)$$

2) Coverage[14] refers to the ratio of recommended results in all products. The formula is shown as:

$$COV_R(L) = \frac{N_d(L)}{N} \quad (14)$$

Where L is the number of the recommended results for each user, $N_d(L)$ is the number of recommended results for all users without repetition, N is the number of all items.

C. Experimental Results

In this paper, we conduct experiments by comparing our hybrid recommendation algorithm with the traditional collaborative filtering method and content-based.

Initially, experiment compares the results of improved collaborative filtering algorithm with the traditional method. The results are given in Figure 3.

Although the recall of improved algorithm declined, the other three metrics are significantly better. The following is the analysis of experimental results. The experimental results prove that clustering considers from users' information directly better and more sensitively reflects users' intention of purchase.

Furthermore, experiment compares the results of improved content-based recommended method and traditional algorithm. The results are given in Figure 4.

As shown in the figure, the four metrics are better, especially, the coverage of recommendation increases significantly and higher than collaborative filtering, which means that content-based algorithm can solve the cold start of new products well.

Except that precision and coverage, the time complexity of improved algorithms also reduced significantly.

V. SUMMARY

In this paper, the hybrid recommendation methods can avoid defects of single algorithm, and it is more suitable for recommend application of e-commerce. It significantly improves the recommendation quality and efficiency, provides great user experience.

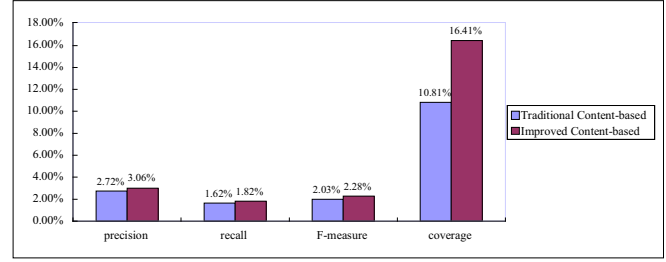


Figure 4. Comparison of content-based recommendation

ACKNOWLEDGMENT

This research was financially supported by the National Natural Science Foundation of China (71071041) and the Heilongjiang Natural Science Foundation (G201306).

REFERENCES

- [1] P. Resnick, H. Varian, Recommender systems, J. Communication of the ACM, 1997(3)56-58.
- [2] Wang Yonggu, Qiu Feiyue, Zhao Jianlong, Liu Hui, Research on personalized recommendation of learning resources based on collaborative filtering recommendation technology, J. Journal of Distance Education, 2011(3)66-71.
- [3] Song Yating, Xu Tianwei, Overview of personalized recommendation technologies based user interest, J. Journal of Yunnan University, 2012, 34(S1)20-23.
- [4] Liu Wei, Research on information recommendation in e-commerce, J. Information Science, 2006, 24(2)300-303.
- [5] Zhu Yan, Lin Zenan, A review of e-business recommendation system, J. Soft Science, 2009(2)183-192.
- [6] Hong Wenxing, Weng Yang, Zhu Shunzhi, Li Maoqing, Hybrid recommender system for vertical e-commerce website, J. Systems Engineering Theory&Practice, 2010, 30(5) 929-935.
- [7] Li Ying, Wang Bo, Sui Zhanli, Yu Juan, Research on personalized recommendation technologies for e-commerce, J. Fujian Computer, 2015(1)29-30.
- [8] Hou Zhiping, Research of e-commerce website personalized recommendation based on user behavior, J. Computer and Information Technology, 2011, 19(4)4-7.
- [9] Guo Feipeng, Lu Qibei, A novel contextual information recommendation model and its application in e-commerce customer satisfaction management, J. Discrete Dynamics in Nature and Society, (2015)1-11.
- [10] Gao Xinbo, Xu Chunguang, Xie Weixin, Fuzzy partitioning of feature space for pattern classification based on supervised clustering, J. Journal of Electronics(China), 2000, 17(2)170-177.
- [11] Lee, Hsuan-Shih, An optimal algorithm for computing the max-min transitive closure of a fuzzy similarity matrix, J. Fuzzy Sets and Systems, 2001, 123(1)129-136.
- [12] Xiang Liang, Recommended system practice, M. Beijing:Posts and Telecom Press, 2012:44-59.
- [13] Adomavicius, G. Tuzhilin, A, Toward the next generation of recommender systems:a survey of the state-of-the-art and possible extension, J. IEEE Trans on Knowledge and Data Engineering, 2005, 17(6)734-749.
- [14] Karafyllis, Lason, Finite-time global stabilization by means of time-varying distributed, J. SIAM Journal on Control and Optimization, 2006, 45(1)320-342.