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RESEARCH ON PERSONALIZED RECOMMENDATION ALGORITHM BASED ON USER'S ATTENTION BEHAVIOR

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Abstract. *Nowadays, how to deal with mass data and to perform personalized recommendation for users has become a research hotspot. Collaborative filtering recommendation algorithm has been widely used since it was proposed. However, there is still more room for improvement in the computation of similarity. This paper introduces user's attention behavior on the basis of the traditional homogeneity measure, and puts forward a personalized recommendation algorithm based on user's attention behavior which combines with the low rank matrix factorization technique to improve the accuracy of the predictions. We named the algorithm pTrust. Through contrast experiments on a public dataset, the pTrust algorithm shows better effectiveness both on accuracy and time complexity in the trust network.*
Keywords: Recommendation algorithm, Trust prediction, Matrix factorization, Attention behavior

1. **Introduction.** Nowadays, the quantity of information is growing at an exponential rate. Vast amounts of information has completely changed the way that people live and analyze the problem; however, the use efficiency of information is low, and the reason is that users often need to browse a lot of irrelevant information before finding the information they need. Recommendation system is generated in the context of such a problem, and is widely used in many websites. The core part of the recommendation system is the recommendation algorithm. A relatively successful recommendation algorithm applied currently is the collaborative filtering recommendation algorithm. This algorithm assumes that the users who have similar behavior in the past will have similar behavior in the future. The measure of similarity is the key step of the collaborative filtering algorithm.

Most studies about recommendation algorithm are based on content, which has great difficulty in feature extraction and recommendation accuracy [1]. In this paper, the user's attention behavior is introduced into the calculation of homogeneity measure on the basis of the existing recommendation algorithm and a more reasonable user correlation measurement method is applied to describing the homogeneity among the users, and then combined with the low rank matrix decomposition technique to make the recommendation, hoping to improve the accuracy of the recommendation system by this method.

This paper is organized as follows: Section 1 states the background of trust prediction in social network; Section 2 introduces the related work of the homogeneity measurement method based on social relationship; Section 3 discusses a collaborative filtering recommendation algorithm based on user's attention behavior; Section 4 conducts experiments to verify the above assumptions and analyzes the experimental results; Section 5 summarizes the algorithm proposed in this paper and discusses its future prospect.

2. Related Work.

Researchers combine different information sources, using clever methods, and continuous improvement of collaborative filtering algorithm, in order to get a better characterization of the user's model [2]. In recent years, great progress and results have been made while adding the social relationship to the collaborative filtering algorithm.

Kuter and Golbeck did a probabilistic interpretation of the display for the social network, and designed the SUNNY framework to recommend a trusted relationship for the specified user [3]. Hamed and Bashah conducted work related to research, comparison and summary of the methods of trust prediction and the methods used in the evaluation of trust prediction [4]. Guha and Kumar established the formal framework of trust relation, and formed a scheme of communication based on trust network structure [5]. Liu and Lim found that the interaction between the user behavior is more important than the individual behavior while recommending friends to the users [6]. Kiyana and Abdollah proposed a social trust generating factor algorithm which leads to trust formation [7], and its feasibility is proved. Borzymek and Sydow improved the social network of trust prediction model by the combination of the score correlation between users [8]. Tang and Liu through the study of trust relationship prediction problems, and the use of low rank matrix decomposition technology, built a trust relationship prediction model called hTrust [9]. Meng and Liu studied cold start problems in the recommended system and improved the performance of the recommendation system using user's social attributes information, providing a theoretical guide for the application of the social attribute information [10]. Deng and Huang studied trust relationship between users and analyzed technology of web services and proposed trust based on service recommendation model, to provide users with personalized recommendation service [11]. Wang and Wang put forward a forecasting model based on the study of the theory of sociology [12]. Studies on predictions made by combining the sociological theory and the traditional method of homogeneity were rare, and it is far from satisfactory in terms of accuracy and efficiency. This paper wants to further explore these problems.

3. Personalized Recommendation Algorithm Based on User's Attention Behavior.

3.1. Design idea of pTrust algorithm.

Homogeneity has a profound influence on the interaction of individuals in society [13]. The user's attention behavior can reflect the trust relationship among the users, and trustor has an important influence on trustee's future behavior and also reflects that the user may have similar interests. This paper holds the opinion that the user's attention behavior should be considered, which can further improve the accuracy of homogeneity measurement. The equation of Pearson correlation coefficient is shown in Equation (1). A new method of homogeneity measurement can be obtained by introducing the user's attention behavior as shown in Equation (2).

$$p = \alpha \frac{\frac{\sum_{k \in I(i) \bigcap I(j)} \left(R_{ik} - \overline{R_i}\right)\left(R_{jk} - \overline{R_j}\right)}{\sqrt{\sum_k (R_{ik} - \overline{R_i})^2} \sqrt{\sum_k \left(R_{jk} - \overline{R_j}\right)^2}} + 1}{2} \tag{1}$$

$$\zeta(i,j) = p + (1-\alpha)\left(\beta\frac{|T(i)\bigcap T(j)|}{|T(i)\bigcup T(j)|} + (1-\beta)\frac{|F(i)\bigcap F(j)|}{|F(i)\bigcup F(j)|}\right) \quad (2)$$

In Equation (1), R_{ik} and R_{jk} respectively represent the scores graded by user i and user j for item k. $\overline{R_i}$ and $\overline{R_j}$ respectively represent the average score of user i and user j. In Equation (2), $T(i)$ and $T(j)$ are the user set to which are paid attention by user i and user j. $F(i)$ and $F(j)$ are the user set that pays attention to user i and user j. α and β are the influencing factors whose range is 0 to 1. α is used to control the effect of correlation of score on the coefficient of homogeneity. $1-\alpha$ is used to control the effect of trust on homogeneity coefficient. β is used to control the user proportion that is trusted by two users. $1-\beta$ is used to control the user proportion that trusts two users at one time.

3.2. **Algorithm process description.** This section describes the input, output and detailed process of the algorithm based on the above ideas.

Input: The score relationship of user to item; relationship of user's attention behavior; target user u; parameter α which controls the effect of correlation of scores on the coefficient of homogeneity; parameter β which controls the user proportion that is trusted by two users.

Output: Item list L is recommended to target users.

The concrete process of the algorithm is divided into the following steps.

(1) Take out all the user's score data for the item and build score matrix R that is user to item. R is a score matrix whose dimension is $n \times d$. n is the number of users, and d is the number of items. The corresponding r_{is} indicates the user i's score for the item s. The score value can be two element attribute value or score levels defined by users.

(2) Introduce the user's attention behavior into the homogeneity measurement, build user's attention behavior matrix which is expressed by M, M is a scoring matrix whose dimension is $e \times f$, e is trustee, and f is trustor. The corresponding M_{ij} indicates the attention behavior of user i to user j. The user's attention behavior contains a lot of information among the users, such that trustor has an important influence on trustee's future behavior.

(3) Based on Pearson correlation coefficient, the traditional method of homogeneity measurement can be obtained combing with the user's rating for the item. On this basis, the introduction of user's attention behavior can improve the homogeneity measurement method, and a new method of homogeneity measurement is obtained as shown in Equation (2). The accuracy and rationality of the similarity between users can be improved by the introduction of user's attention.

(4) Using homogeneous regularization method in trust prediction, we can get the regularization form of homogeneity measurement method got in front, as shown in Equation (3).

$$\sum_{i=1}^{n}\sum_{j=1}^{n}\zeta(i,j)\|U(i,:)-U(j,:)\|_2^2 \quad (3)$$

In the above Equation, $\zeta(i,j)$ represents calculation equation of the homogeneity measurement got from Equation (2). $U(i,:)$ represents the trust relationship obtained from the user i's attention behavior, and $U(j,:)$ represents the trust relationship from the user j's attention behavior. The greater the value of the homogeneity coefficient is, the easier trust relationship builds. Therefore, we should try our best to make the implicit expression of two users who have the larger value in homogeneity coefficient in low rank space closer, and make the implicit expression of two users who have the smaller value in homogeneity coefficient in low rank space farther [14]. For a particular user, the implicit expression of the homogeneous regularization is shown in Equation (4).

$$\sum_{j=1}^{n} \zeta(i,j) \|U(i,:) - U(j,:)\|_2^2 \tag{4}$$

Matrix form of homogeneous regularization term is shown in Equation (5).

$$\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \zeta(i,j) \|U(i,:) - U(j,:)\|_2^2 = \sum_{k=1}^{d} U^T(:,k)(D-Z)U(:,k) = Tr\left(U^T LU\right) \tag{5}$$

In the above equation, Z is the matrix of homogeneity coefficient, D is diagonal matrix, each diagonal element is the element sum of the corresponding column in the matrix Z of the homogeneity coefficient, which is expressed as $D(i,j) = \sum_{j=1}^{n} Z(j,i)$, and L is a Laplasse Matrix which can be expressed by $D - Z$.

(5) Put the matrix form of homogeneous regularization term add in the matrix factorization model, we can get Equation (6).

$$\begin{aligned} &\min_{U,V} F = \|G - UVU^T\|_F^2 + \alpha\|U\|_F^2 + \beta\|V\|_F^2 + \lambda T\gamma\left(U^T LU\right) \\ &\text{s.t. } U \geq 0,\ V \geq 0 \end{aligned} \tag{6}$$

In order to make the cost function reach the optimal value in the matrix U and matrix V. According to Karush-Kuhn-Tucker constraints [15] and applying the rule of stochastic gradient descent [16], the update equation of matrix U and matrix V can be obtained, as shown in Equation (7) and Equation (8).

$$U(i,k) \longleftarrow U(i,k)\sqrt{\frac{G^T UV + GUV^T + \lambda ZU}{UV^T U^T UV + UVU^T UV^T + \alpha U + \lambda DU}} \tag{7}$$

$$V(i,k) \longleftarrow V(i,k)\sqrt{\frac{[U^T GU](i,k)}{[U^T UVU^T U + \beta V](i,k)}} \tag{8}$$

Use the update equation to make the iteration until the results converge or meet the accuracy of the experiment. Because of the original trust relationship matrix G, the homogeneity coefficient matrix Z and the diagonal matrix D are all non-negative, so the matrix U and matrix V are also non-negative in the process of updating and the final fitting matrix UVU is also non-negative. The possibility of building trust relationships among all users can be represented by matrix UVU^T, each element representing the possibility of users in the line trust users in the column. The default trust relationship can be predicted by using value of the new fitting matrix. Finally, sort from large to small according to the possibility of building the trust relationship in the fitting matrix. The steps of recommendation algorithm pTrust are listed in Table 1.

4. **Experiments and Discussion.**

4.1. **Data set and result evaluation criteria.** The experimental data in this paper is a set of public data set from Ciao website, including trust relationship data set between users and users rating date set. The experiment of this paper selects the data set whose comment number is more than ten thousand and establishes trust relationship which can be expressed by $T = \{< i, j > |G(i,j) = 0\}$. Select $x\%$ of the trust relationship as the experimental set T_Train randomly and the remaining $1 - x\%$ that removed the trust relationship as the evaluation set T_Test. Then we build trust between users predicted by T_Train, sorting the pairs of users in $N + T\_Test$ who have not established the trust relationship. Selecting the top $|T\_Test|$ pair of users expressed by set P, T_Test represents the number of elements in the collection T_Test. The equation for calculating

TABLE 1. The steps of recommendation algorithm pTrust

Algorithm 1 The Proposed Personalized Recommendation Algorithm pTrust

Input: Trust relations G and parameters α, β, λ
Output: Item list L is recommended to target users
Begin

```
    Build score matrix R
    Build user's attention behavior matrix M
    Initialize U randomly
    Initialize V randomly
    Build matrix form of homogeneous regularization according to Equation (6)
    While not convergent do
      for i = 1 to n do
          for k = 1 to d do
              Update U(i, k) using Equation (7)
          end for
      end for
      for i = 1 to d do
          for k = 1 to d do
              Update V(i, k) using Equation (8)
          end for
      end for
  Ranking pairs of users according to matrix UVU^T
```

End

the accuracy of the recommendation called trust prediction accuracy (TPA) is shown in Equation (9).

$$TPA = \frac{|P \bigcap T\_Test|}{|T\_Test|} \tag{9}$$

4.2. **Experimental result analysis.** Four kinds of homogeneity measurement methods were used to compare and verify, including:

(1) socialTrust: Use sociological theory and non-negative matrix factorization model to predict the recommendation.

(2) hTrust: Use Cosine correlation equation to calculate homogeneity coefficient.

(3) $pTrust\_1$: Introduce user's attention behavior into the homogeneity measurement method of cosine correlation, and the equation for calculating the homogeneity coefficient is shown in Equation (10).

$$\zeta(i,j) = \alpha \frac{\sum_{k=1}^{n} R_{ik}R_{jk}}{\sqrt{\sum_{k=1}^{n} R_{ik}^2}\sqrt{\sum_{k=1}^{n} R_{jk}^2}} + (1-\alpha)\left(\beta \frac{|T(i) \bigcap T(j)|}{|T(i) \bigcup T(j)|} + (1-\beta)\frac{|F(i) \bigcap F(j)|}{|F(i) \bigcup F(j)|}\right) \tag{10}$$

(4) pTrust: Introduce user's attention behavior into the homogeneity measurement method of Pearson correlation coefficient, and the equation for calculating the homogeneity coefficient is shown in Equation (2).

The comparison experiment of four methods on accuracy of trust predicts in ten areas. Results in Ciao_Books are shown in Figure 1.

Figure 1 shows that the higher the proportion of the trust relationship that is in the training, the worse the prediction effect is received. The reason is that the trust relationship needed to predict is gradually reduced with the increase of x, but the very sparse trust relationship makes the proportion of trust relationship in whole relationship further reduce and increase the difficulty of prediction. A better prediction effect can be received

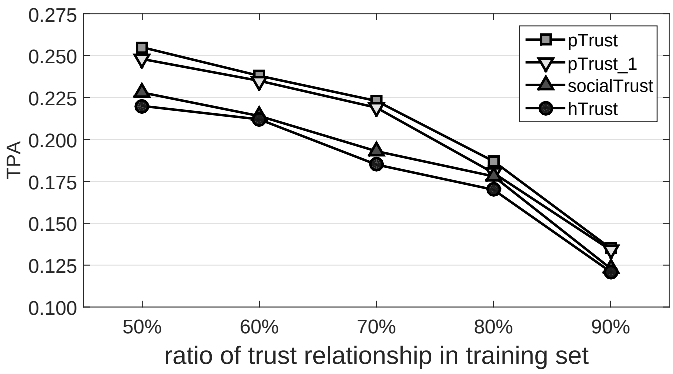

Figure 1. Comparison about accuracy of trust prediction in Ciao_Books

Table 2. Ciao_Books comparison on time consuming (s)

Relationship Ratio	pTrust	socialTrust	hTrust
50%	792.229	3181.300	712.499
60%	825.392	3190.152	679.038
70%	846.243	3276.588	704.012
80%	884.044	3265.304	695.226
90%	906.073	3271.806	702.649

by combining the user's rating behavior with the attention behavior to measure the homogeneity comparing with the method just considering the rating, and the accuracy of pTrust is higher than that of $pTrust\_1$. Thereby, we can get better accuracy of recommended prediction by introducing user's attention behavior into method of homogeneity coefficient which uses Cosine correlation. The time complexity of the algorithm is further considered after considering the accuracy of the recommendation. Because pTrust and $pTrust\_1$ are similar, and the accuracy of $pTrust\_1$ is higher than that of pTrust, so this paper considers to carry on an experiment to compare PTrust, hTrust and socialTrust on time complexity. Some results of three methods comparing in trust prediction on time consumption are shown in Table 2.

4.3. **Effect of coefficient on accuracy in pTrust algorithm.** We choose the user's comments and user's attention behavior to measure the homogeneity among users, see Equation (2). As mentioned above, α and β are the influencing factors whose values range from 0 to 1, α is used to control the effect of correlation of rating behavior on the coefficient of homogeneity, and $1-\alpha$ is used to control the effect of trust object's situation on homogeneity coefficient. β is used to control the user proportion that is trusted by two users. $1-\beta$ is used to control user proportion that trusts two users at one time. In this section, we have carried on the experiment to the value of influence factors α and β. The experimental results are shown in Figure 2.

In order to get the relationship between α and accuracy of prediction, we set β as 0.4, 0.6, 0.8, then adjust α and find that when α takes 0.3 makes accuracy of prediction reach the best with β takes 0.8. In the same way, when β takes 0.9 makes accuracy of prediction reach the best with α takes 0.4. The initial values of α, β and the relationship between parameters and accuracy of prediction still needs further research and the best result reached may not be the best globally. The situation that the value of β is relatively large indicates that analyzing user set trusted by two users has a more accurate description of the homogeneity between users than that of analyzing user set that trusts two users at the same time.

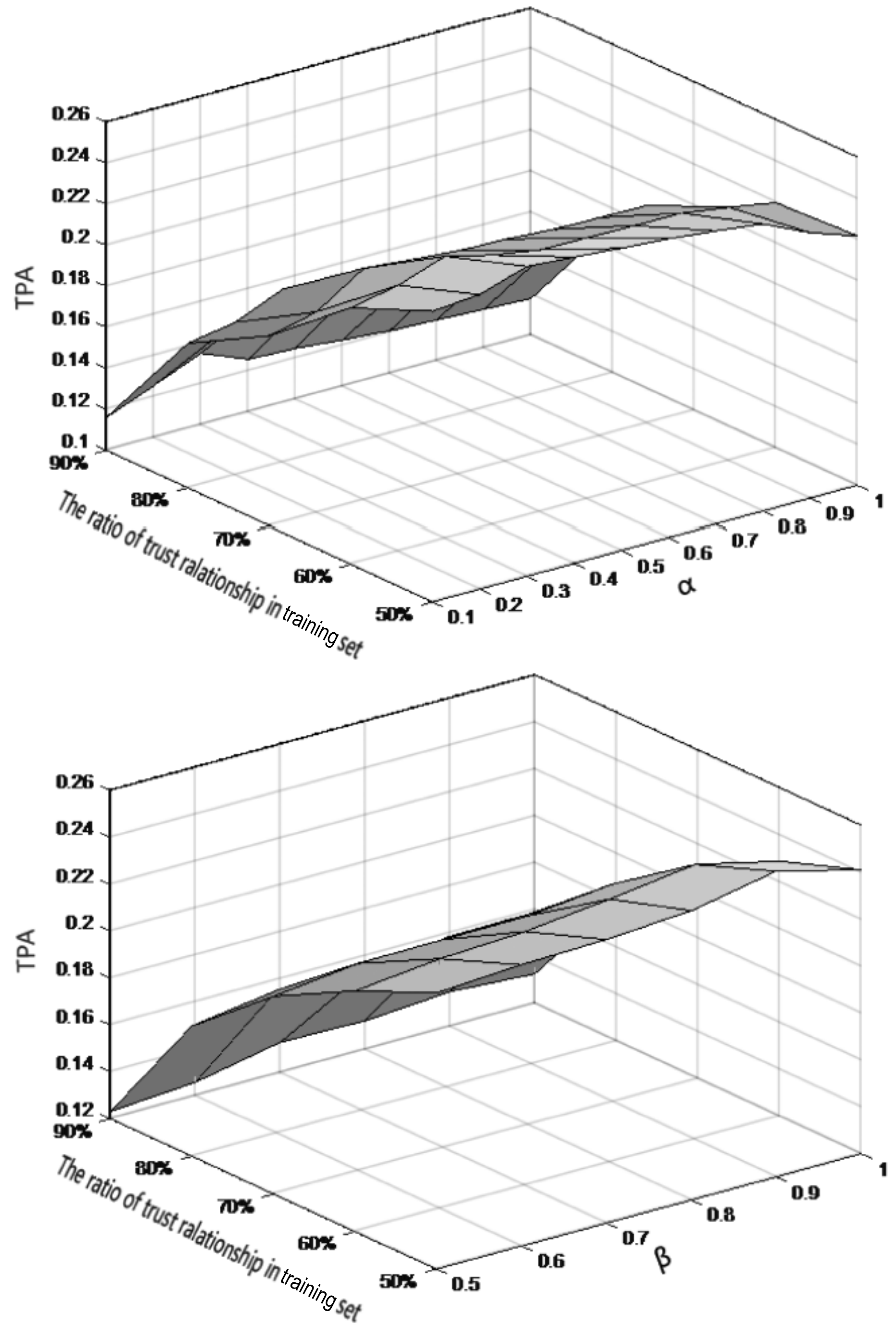

FIGURE 2. The effect of α and β on the accuracy of trust prediction

5. **Conclusion and Future Work.** In this paper, a recommendation algorithm which is named pTrust based on user's attention is put forward. The algorithm improves the accuracy and time complexity of homogeneity measurement by introducing user's attention into the homogeneity measure and combining matrix decomposition technique. Experiment shows that this algorithm is suitable to personalized recommendation in the trust network, and at the same time, it improves the accuracy of personalized recommendation and makes full use of user's behavior, so as to provide more reasonable and accurate personalized recommendation service and improve the quality of recommendation. However, there may be some problems if transplanted to other networks. The next step will be to compare the pTrust with other algorithms in other networks; meanwhile, the deficiency of pTrust in other networks will be improved.

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