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A modified iterative ranking method based on trust network*

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***Abstract*— How to evaluate the intrinsic quality of products and the user reputation becomes a significant yet difficult problem. In this paper, considering the trust relationship between users, we improve the traditional iterative ranking methods by combining the traditional iterative methods with the TrustRank method. The user's reputation depends on the user's rating behavior and the TrustRank value. Our simulations demonstrate that the modified methods posses a better robustness and performance than the existing methods.(AMS subject classifications: 05C82, 91D30)**

***Keywords*— Reputation system, Trust network, User reputation**

I. INTRODUCTION

In the presence of unfair rating attacks, most works focus on building a reputation system to evaluate the product quality. However, these works only consider the rating network regardless of the relationship of users[1]. In this paper, we modify the traditional iterative methods to investigate the intrinsic quality of products in the consideration of both rating network and trust network. We take users' trust relationships into account and improve the traditional iterative ranking methods by combining these methods with the TrustRank method [2]. The user reputation is relevant with the user's rating behavior and trust relationships.

II. METHOD

At first, we introduce some basic notations used in this paper. The bipartite rating network is represented by a matrix A, where the element $A_{i\alpha}$ denotes the rating value assigned to product o_α by user u_i. We use O_i to denote the set of products rated by u_i before. U_α denotes the set of users who has rated product o_α. In addition, user u_i is assigned with the reputation value R_i, and the quality of product o_α is denoted by Q_α.

We use a directed graph to model the trust network which describes the trust relationships between users with its adjacent matrix M. Suppose we use $k_{out}(i)$ to denote the out-degree of user u_i. The transition matrix T is represented as

$$T_{i,j} = M_{j,i}/k_{out}(i). \tag{1}$$

Traditional iterative ranking methods analyze the user reputation and product quality purely based on the rating network. In this paper, by using both the rating network and trust network, we combine the iterative ranking methods with the TrustRank algorithm to evaluate the user reputation and product quality.

First, all the users have the same reputation value, e.g. $R_i = 1$. The quality of product O_α is determined by the weighted average rating as follows

$$Q_\alpha = \frac{\sum_{i \in U_\alpha} R_i A_{i\alpha}}{\sum_{i \in U_\alpha} R_i}. \tag{2}$$

Second, we obtain get an estimated user reputation $\bar{R}1$ according to the iterative ranking method. And then we adopt the normalization method to process $\bar{R}1$

$$R1 = \frac{\bar{R}1 - min(\bar{R}1)}{max(\bar{R}1) - min(\bar{R}1)}, \tag{3}$$

where $max(\bar{R}1)$ and $min(\bar{R}1)$ are the maximum and minimum value of $\bar{R}1$.

Third, we use the TrustRank algorithm to evaluate the user reputation precisely,

$$\bar{R}2 = 0.85 \cdot T \cdot \bar{R}2 + 0.15 \cdot r, \tag{4}$$

where r is the normalized vector for the good seed set. Initially, we set $\bar{R}2$ to be $R1$. $\bar{R}2$ is updated iteratively until the variation of $\bar{R}2$, $\|\bar{R}2 - \bar{R}2'\|_2/m$ is smaller than the threshold $\Delta = |10^{-4}|$, where $\bar{R}2'$ is the reputation calculated in the previous step and m is the number of users.

We further adopt the normalization method to process $\bar{R}2$,

$$R2 = \frac{\bar{R}2 - min(\bar{R}2)}{max(\bar{R}2) - min(\bar{R}2)}, \tag{5}$$

where $max(\bar{R}2)$ and $min(\bar{R}2)$ are the maximum and minimum value of $\bar{R}2$, respectively.

At last, we combine $R1$ and $R2$ to evaluate the user reputation,

$$R = \alpha \cdot R1 + \beta \cdot R2, \tag{6}$$

where α and β are two parameters. And then, by repeating the previous steps, the reputation R is updated iteratively until it reaches stability.

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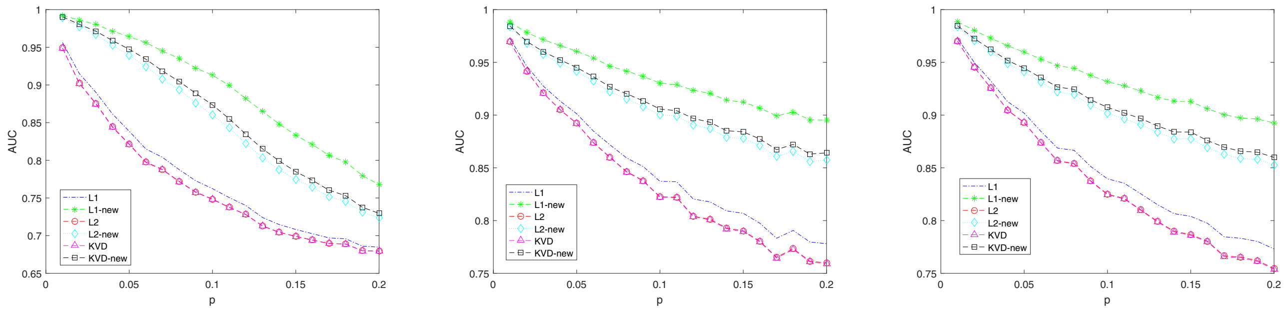

(a) AUC under the first type of attack (b) AUC under the second type of attack (c) AUC under the third type of attack

Fig. 1: The performance of different methods

III. Results for Real Network

A. Data set

We apply our method to a real dataset called Filmtrust Dataset. This dataset consists of the rating network and trust relationships between users. The basic statistical properties of the data set are summarized in Table I, where m and n are the number of users and products, respectively. However, it's hard to know the intrinsic quality of products. Thus we select the top-100 products as the benchmark set according to their average ratings. An effective method should give these products higher scores. By adding some attackers, we calculate the product quality to see whether the products in the benchmark set can get high rankings or not. We add d attackers into the rating network and trust network. In the rating network, attackers choose 20 products randomly to give unfair ratings. The unfair rating attacks are categorized in 3 types. The first type is that the attackers always give the lowest rating 0.5 to products. The second type is that the attackers give 4 or 0.5 rating to products with identical probability. The third type is that the attackers choose one integer from $\{0.5, 2, 3, 4\}$ with identical probability to products. As for the trust network, for each attacker, randomly choosing two users from top 30 users with high in-degree and adding two directed edges from him to them. Next, randomly choose two attackers and add two directed edges from him to them. Meanwhile, randomly choose a normal user and then decide whether to add a directed edge from this normal user to him with the probability of 0.5. Thus the proportion of attackers is p, and $p = d/m$.

TABLE I: Filmtrust dataset

Dataset	m	n	rating edges	trust edges
Filmtrust Dataset	704	1056	16939	1623

B. Metric

To evaluate the ranking accuracy and the robustness of methods, we apply a widely used metric called AUC. The AUC measures the accuracy of the method as a whole. To calculate the AUC value, we should compare the quality of products from the benchmark with other products' here. Among the N times independent comparisons, there are $N^{'}$ times that the quality of products from the benchmark is higher than the others' quality and $N^{''}$ times that the quality of products from the benchmark is equal to that of the others. Then we can obtain

$$AUC = \frac{N^{'} + 0.5N^{''}}{N}. \tag{7}$$

Larger value of the AUC indicates the higher accuracy of the method.

C. Result

First, we modify the existing three iterative methods (L1, L2 [3], KVD [4]). Then we calculate the AUC value to analyze the performance of the original and improved methods. The parameters α and β are set equal to 0.5. The results are averaged over 50 independent realizations as shown in Fig. 1. The horizontal axis is the proportion of attackers p in the network, and the vertical axis is the AUC value. In Fig. 1, we can find that the AUC value of the improved methods is always larger than that of the original methods under any attack strategies. The results illustrate that the improved methods possess a better performance than the existing ones.

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