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An enhanced trust propagation approach with expertise and homophily-based trust networks

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ABSTRACT

The transitivity property of trust enables the propagation of a trust value through a chain of trusting users in social networks and then provides an expected trust value for another user. Logically, a user in social networks can assess a large number of other users, even if two users have not been directly connected previously. However, a large percentage of trust propagation efforts fail to find reliable trust paths from a source user to a target user because the web of trust in real-world online social networks is too sparse. The success (both quality and quantity) of a trust propagation algorithm strongly relies on the density of a web of trust. The more trust paths that are able to reach the given target user, the more reliable will be the trust estimates based on the trust path with the highest strength. In this paper, we propose an enriched trust propagation approach by combining a homophily-based trust network with an expertise-based trust network, which enhances the density of the trust network. We then evaluate the prediction accuracy and coverage of trust propagation based on various aggregation methods and highlight the most promising method.

1. Introduction

In social networks, users have incomplete knowledge of others, including those who have devious intentions [17]. Tracking trust is useful for predicting future behavior in a reliable manner and for deterring malicious users by encouraging good behavior and discouraging bad behavior. With the proliferation of Web-based social networks, users are allowed to directly express who they trust and how much they trust other users based on previous interactions. Given such information, trust transitivity enables us to propagate a trust value through a chain of trusting users and then provide an expected trust value for another user [4]. Logically, a user in social networks can assess a large number of users through trust propagation, even if two users were not directly connected previously.

However, trust propagation is not always successful for any two random users of social networks. If a web of trust (i.e. a network consisting of trust connections) is not dense enough to be propagated, it is difficult to find reliable and trustworthy paths from a source user to a target user [7]. Practically speaking, a significant percentage of trust propagation efforts fail to find reliable trust paths from a source to a target user in online social networks. Thus, the success (both quality and quantity) of trust propagation is strongly affected by the density of a web of trust. The more trust paths that are able to reach the given target user, the more likely it is to determine reliable trust estimates by choosing the trust path with the highest strength.

In recent years, considerable numbers of studies have been done on reliable trust propagation models in social networks. The main objective of these models is to discover reliable trust paths from a given source user to an unknown target user by mathematically combining recommendations from trusting users with minimum error, resulting in a trust prediction [8]. Few researchers have noted to the failure of trust propagation due to a sparse web of trust.

In order to reduce the sparsity problem in a web of trust, we adopt the property of homophily in social interactions. Homophily refers to the tendency of people to have non-negative ties with similar other users in social networks. In online social networks, homophily is a fundamental characteristic. In a trust effective community, users trust some people more than others, thus they are more influenced by them and share similar tastes. In addition, in a homophily effective community, similar users might share mutual trust, so the similarity of trust might induce trust among other people. Then trust and similarity will be influenced by each other [11].

A homophily property-based network is able to enlarge network connections over an entire network and help a user to find more trust paths and more trustworthy neighbors who know a

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target user. In the context of trust propagation, however, there are challenges to adopting homophily-based trust and combining it with a web of trust in which trust is directly issued by users. Compared to a homophily-based trust, this second web of trust, with connections directly given by users, is constructed by evaluating another user's knowledge or expertise based on each user's limited direct experiences. In this paper, we will call this web of trust an 'expertise-based trust,' as compared to a 'homophily-based trust.' We will discuss these definitions further in Section 2.

First, we face the issue of adjusting the level of two types of trust scores. Expertise-based trust is assessed by evaluating and analyzing the actions that a user performs over the domain content. Moreover, since this trust judgment is a very subjective opinion given by each user, there exists a trust subjectivity issue in an expertise-based trust network [5]. On the contrary, homophily-based trust is determined by evaluating the similarity between two users' opinions. It is difficult to compare an expertise-based trust score of 0.9 and a homophily-based trust score of 0.8 without eliminating the distinction between them. In other words, the evaluation metric of a homophily-based trust is different from an expertise-based trust, so these two kinds of trust scores cannot be compared and propagated simultaneously into a raw score.

Second, aggregation is an important issue in simultaneously propagating two types of trust values. In current research, expertise-based trust is considered the most reliable source, since it is directly given by each user. However, no studies have evaluated the reliability of a homophily-based trust score as compared to an expertise-based trust score. Several aggregation methods are possible, including mean aggregation, max aggregation and priority aggregation. In summary, it is imperative to find an effective method to adjust and aggregate these two types of trust knowledge during trust propagation.

In this paper, we propose an enriched trust propagation approach by combining a homophily-based trust network and an expertise-based trust network, which enhances the density of the trust network. We normalize and transform both trust values so they can be compared with each other through a long chain, as well as through a single user. We then evaluate the prediction accuracy and coverage of trust propagation based on various aggregation methods and highlight the most promising method. In our experiments with the FilmTrust dataset, we discover that homophily-based trust is a more important metric than expertise-based trust in terms of trust propagation. Our proposed combined trust propagation approach could significantly outperform current proposed models, which rely only on expertise-based trust networks, for prediction accuracy and coverage.

This paper is organized as follows. Section 2 briefly describes the definition of trust in various perspectives and presents the previous studies on trust propagation. Section 3 discusses our proposed method, while Section 4 explains the details of our experiment results. Finally, Section 5 summarizes our work and provides directions for future work.

2. Related works

Ding et al. [1] insist that knowing 'user A trusts user B in domain X' does not fully capture the meaning of trust without considering the provenance and usage of trust knowledge [1,14,15]. They identified five types of trust and classified them into two categories, referral trust and associative trust. Referral trust represents trust in the other agent's knowledge in a certain domain. For example, user A trusts user B's knowledge in a movie domain. In most cases, this is estimated by an agent's direct experiences of using the other agent's knowledge. Associative trust reflects the similarity between two agents, such as their trust knowledge or domain knowledge. For example, this type of trust might be derived by measuring the similarity of user A's and user B's referral trust toward other users in common. As Ding et al. mention, referral trust and associative trust can both be used to propagate referral trust [1]. In this paper, expertise-based trust and homophily-based trust correspond to referral trust and associative trust, respectively.

In recent years, a few researchers have explored the interaction between trust and similarity [2,18,19]. They discovered a strong positive correlation between trust and profile similarity in online communities. The similarity of profile features, including overall ratings, has been found to induce a degree of trust. Matsuo and Yamamoto [11] measured the bidirectional effects of trust and profile attributes, such as ratings for movies. They empirically demonstrated that users made trust connections due to their ratings' similarities. In addition, the rating of a user is influenced by the ratings of trusted users. This bidirectional effect influences community dynamics, including the evolution of trust relationships, thus increasing the density of the community.

Shakeri and Bafghi [14,15] employed the similarity of opinions between two users as a measure of confidence in the value of trust. They calculated the mean of absolute difference between two users' opinions on the trust values of all users in common. Next, they proposed an approach for propagating trust with confidence and improved the accuracy of prediction. While their approach might reduce uncertainty through a chain of trust, it does not resolve the sparsity issue in a trust network.

Considerable numbers of studies have been done on trust propagation regarding the ways that trust is transferred, combined and then estimated in online social networks. The main objective of these models is to predict a level of trust from a certain user to distant others with high reliability. In order to achieve a credible estimation of trust, they worked to discover reliable paths and mathematically combined multiple recommendations from reliable users.

Golbeck [3] proposed a trust inference model called TidalTrust, which infers a trust value in continuous trust networks. However, the TidalTrust algorithm confines the search to the shortest paths with trust values higher than a threshold value to discover a reliable trust path from a source user to a target user. This model aggregates recommendations from users on the strongest trust paths. By contrast, the MoleTrust algorithm [10] discovers all paths within a given maximum-distance and aggregates all recommendations from all chains of users by calculating the weighted average. Lesani and Montazeri [9] selected the path with a maximal propagated trust value as the most trustworthy trust path. Kim and Song [8] questioned the accuracy of trust propagation as affected by the length of the trust paths and the different aggregation approaches. Their research evaluated four types of strategies: weighted mean aggregation among the shortest paths, min–max aggregation among the shortest paths, weighted mean aggregation among all paths, and min–max aggregation among all paths. In this paper, we adopt the best optimal strategy from their empirical results (refer to Section 3.3).

Eliminating the subjectivity of trust propensity is another issue related to increasing trust inference accuracy through trust propagation. Hasan et al. addressed the issue of propagating trust using subjective personal views, experiences or backgrounds [5]. Since the perception of trustworthiness is subjective, the meaning of a trust recommendation might be misinterpreted. Moreover, the inferred trust value gained from propagating a misinterpreted recommendation would be far from the true meaning of the initial trust recommendation. The authors eliminated trust subjectivity by converting an absolute trust value into its percentile value based on the disposition of the trust of each user. However, their