

RATE: Recommendation-aware Trust Evaluation in Online Social Networks

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Abstract—In online social networks (OSNs), it is an open challenge to select proper recommenders for predicting the trustworthiness of a target. In real life, people who are close and influential to us can usually make more proper and acceptable recommendations. Based on this observation, we present the idea of recommendation-aware trust evaluation (RATE). We further model the recommender selection problem into an optimal problem, with the objectives of higher accuracy, lower risk (uncertainty), and less cost. Four metrics, *trustworthiness*, *influence*, *uncertainty*, and *cost*, are identified to measure the quality of recommenders. Experimental results, with the real social network data set of Epinions, validate the effectiveness of RATE: it can predict trust with higher accuracy (at least 22.4% higher), lower risk, and less cost.

Keywords—*recommendation-aware*, *recommender selection*, *trust evaluation*, *online social networks (OSNs)*

I. INTRODUCTION

Online social networks (OSNs) are organized around users. In (OSNs), various applications have motivated the tremendous attention of trust evaluation, such as hiring managers who want to recruit new employees, service consumers who are looking for service providers, etc. In other words, trust issues exist in any application whenever a person (e.g., source s) needs to estimate the trust level of another (e.g., target t), so as to decide whether or not to conduct further interactions.

The Motivation. A single person usually has a limit of known persons, due to his limited time and energy [1]. Hence, friends take an important role of recommendation (Fig. 1). Several models have been proposed to estimate the trustworthiness of a given target from a source, taking the advantage of the transitive property of trust: if s trusts u , and u trusts t , then it is with high probability that s trusts t . Many useful findings have been made. However, most of the existing trust models deal with the information aggregation in small trusted graph, for which several challenges remain open: (1) It is unclear which users should be selected into the trusted graph. (2) There is no ground truth on how much the real trust s falls on t , especially when s knows little about t . (3) Existing models are solely based on trust ratings. Other closely related concepts in practical applications, e.g., social relationships, the possible cost, and the risk (uncertainty) are usually overlooked.

In reality, it usually happens that a user has many friends; selecting different subsets of these friends may lead to making different decisions, paying different costs, and taking different risks. Therefore, we focus on exploring the factors that are involved in the process of trust evaluation, and developing an efficient scheme to solve the recommender subset selection

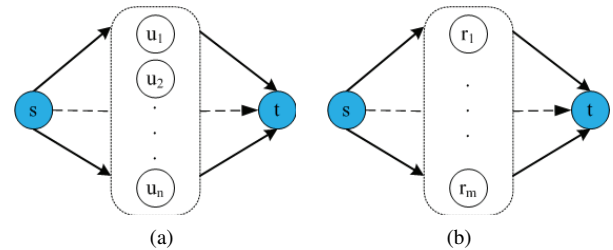


Fig. 1. (a) An example social network showing s has many friends who can provide recommendations on t ; (b) The objective graph, in which a subset of friends are selected as recommenders, $\{r_1, \dots, r_m\} \subseteq \{u_1, \dots, u_n\}$.

problem, to meet the goals of higher prediction accuracy, lower risk (uncertainty), and less cost.

Main Ideas. “It is not what you know, but who you know that makes the difference.” Our basic idea is to find people who are the most suitable for becoming a recommender, as to help the source make a proper decision. That is, choosing the one who can enhance the visibility of the source. To make it simple, we are coping with “How do you find the users that reflect your tastes the most?” We try to apply the idea of recommendation [2] to trust evaluation, based on the observation that people who are close and influential to us can make more proper and acceptable recommendations for us.

Our Contributions. We propose a novel model to select proper neighbors, which we call recommenders, for evaluating a target’s trustworthiness. Our goal is to develop a comprehensive model, which can tell what the trust level of a target is; more importantly, it can provide through whom the goal can be realized. Our contributions are as follows: (1) To the best of our knowledge, we are the first to propose the idea of recommendation-aware trust evaluation (RATE for short). Since trust itself is usually personalized, it is natural to identify some proper recommenders who often have similar ideas or opinions as the source, as to estimate the trustworthiness of the target. (2) We evaluate RATE using a real trust network, Epinions (www.epinions.com). The results demonstrate how each metric can impact the performance of RATE, and show that RATE can predict trust with higher accuracy (at least 22.4% higher), lower risk, and less cost.

II. PROBLEM FORMULATION

Recommender Selection Problem (RSP). Given a social network $G = (V, E)$, V is the set of nodes and E is the set of edges. For two nodes, s and t in V , s is the source and t is the target. For the safety of user interactions in OSNs,

we wonder how to design an efficient scheme to select the best recommenders $R = \{r_1, \dots, r_m\}$, from the neighbor set of s $N_s = \{u_1, \dots, u_n\}$ ($m \leq n$), with the goals of making a proper decision (to trust or not trust t), meeting the optimal requirements of higher accuracy, lower risk (uncertainty), and less cost.

According to the distance from recommenders to the source, the problem can be divided into two sub-issues, to cope with 1-hop neighbors (the direct neighbors of source) and multi-hop chains, respectively. The task of selecting 1-hop neighbors is similar to, but more challenging than, the Jury Selection Problem (JSP) [3]. For the determination of multi-hop chains, it can be modeled as a Multi-Constrained Optimal Path (MCOP) selection problem [4].

Preliminary: Jury Selection Problem (JSP). It is used to choose the most reliable and feasible subset of all possible “jurors” to vote on a question. In JSP of [3], each juror has only two choices of 0 or 1; some jurors are selected by considering the two factors of the jury error rate and the cost. In our problem of RSP, each recommender may give a trust level in $[0, 1]$, i.e., more choices; and we consider more metrics to measure the quality of recommenders.

Related Work. Cao et al. [3] studied the Jury Selection Problem (JSP) by utilizing crowdsourcing for decision-making tasks on micro-blog services. Liu et al. proposed H_OSTP [5] and MFPB-HOSTP [4] to deal with the multi-constrained optimal trusted path selection problem. In previous work [6], we focused on generating small trusted graphs for large OSNs.

III. SOLUTION OVERVIEW

The goal of trust evaluation is to estimate the trustworthiness of an unknown target, through proper intermediate recommenders. Our solution framework is as follows:

Step 1: Metrics identification. We identify some metrics to describe the trust related user features, and to regulate the trust evaluation systems.

Step 2: 1-hop recommender selection. We aim to explore a rational approach to select an optimal subset of recommenders, when there are enough 1-hop (or direct) neighbors of s who know t . Many issues need to be addressed, such as “what kind of neighbor can be deemed as a good one,” “how many neighbors should be selected,” and “what can we do if the selected neighbors have different opinions towards t ?”

In addition, we also consider multi-hop scenario when it need multi-hops for s to reach t .

Metrics. For the recommender selection of 1-hop neighbors, a similar approach to the recommender system can be applied. That is, we choose people who are most likely to be selected as a recommender to current user u . A key step is to calculate the metric values of a neighbor v from the view of u . We present the following four metrics: (1) The trustworthiness of v , denoted as t_{uv} . (2) The influence between u and v , denoted as w_{uv} . (3) The uncertainty of v , denoted as u_{uv} . (4) The cost of v , denoted as c_{uv} . We combine the four metrics as a metric vector $\mathcal{M}_{uv} = \langle t_{uv}, w_{uv}, u_{uv}, c_{uv} \rangle$. All the variables are normalized into the range of $[0, 1]$.

Trustworthiness. We use trustworthiness to represent two things: honesty, and the capability to provide real information. This metric is a subjective opinion of current user u , according to his direct experience of interactions with v .

Influence. Unlike trustworthiness, which is usually subjective, the metric of influence is a more objective measure according to the historical contacts. The closer the relationship exists between two persons, the larger the possibility that one’s opinion will influence the other’s [7].

Uncertainty. Uncertainty increases the risks of transaction. Our objective is to reduce the uncertainty so that risk of failure is lowered and a long-term exchange relationship is sustained. This metric indicates an accumulative measure of the fluctuation of v , according to the historical interactions.

Cost. Just as in daily life, the source wants to contact the target. Regardless of whether it contacts directly or indirectly, some cost will be charged. Note that direct contacts may lead to a larger cost than indirect contacts. In an extreme case, a source can conduct multiple direct contacts to any target, as to test the trustworthiness himself, which may be quite resource-consuming. Therefore, the essence of trust prediction is to search the proper recommenders, who already know the target well, through their previous experiences.

Utility Functions and the Objective. In our model, we define two utility functions, denoted as \mathcal{F} and \mathcal{G} , as the measurements of the quality and the risk/cost of social trusted paths, respectively. The functions take the above four metrics t, w, u , and c as the arguments in the following two equations:

$$\mathcal{F}_{P(a_1, \dots, a_n)} = \omega_t \cdot t_{P(a_1, \dots, a_n)} + \omega_w \cdot w_{P(a_1, \dots, a_n)} \quad (1)$$

$$\mathcal{G}_{P(a_1, \dots, a_n)} = \omega_u \cdot u_{P(a_1, \dots, a_n)} + \omega_c \cdot c_{P(a_1, \dots, a_n)} \quad (2)$$

where $\omega_t, \omega_w, \omega_u$ and ω_c are the weights of t, w, u , and c , respectively (the weights are determined by the source s); Moreover, $0 < \omega_t, \omega_w, \omega_u, \omega_c < 1, \omega_t + \omega_w = 1, \omega_u + \omega_c = 1$.

We combine \mathcal{F} and \mathcal{G} in a normalized utility function as $\lambda \cdot \mathcal{F} + (1 - \lambda) \cdot (1 - \mathcal{G})$, with $\lambda \in [0, 1]$. The objective is to select the neighbors that satisfies multiple constraints and yields the best utility (maximize \mathcal{F} and minimize \mathcal{G} , i.e., maximize the normalized utility), with the weights specified by the source participant.

IV. RATE: 1-HOP RECOMMENDER SELECTION

In this section, we focus on how to select the 1-hop recommenders, for which two issues need to be addressed:

Issue 1: How to measure the quality of a recommender? We should know what kind of recommender can be taken as ‘good’, before identifying good ones.

Issue 2: How many recommenders are enough, and are efficient for, decision-making? Intuitively, it will be much safer if we select more recommenders, to avoid bias and make a comprehensive decision. Then comes the question “when to stop (selecting more)?”, i.e., deciding the size of the optimal recommender set.

The Quality of Recommenders. Incited by the well-known concept of “quality of service (QoS)”, which consists of several attributes, and is used to illustrate the ability of services

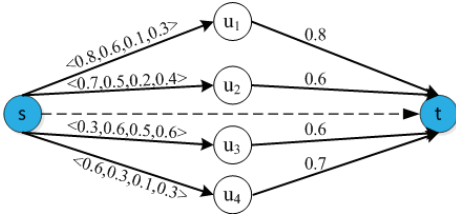


Fig. 2. A toy example of 1-hop recommender selection.

to guarantee a certain level of performance, we present a new concept, quality of recommender (QoR).

Definition 1: Quality of recommender (QoR) comprises requirements on a recommender, taking *trustworthiness*, *influence*, *uncertainty*, and *cost*, as attributes.

In RATE, users can set multiple quality constraints, denoted as $Q^\theta (\theta \in \{t, w, u, c\})$. Only neighbors who meet all the requirements can be selected as recommenders. We use QoR constraints as the thresholds of the four metrics. Taking Fig. 2 for instance, s may specify $Q^t > 0.5$, $Q^w > 0.4$, $Q^u < 0.3$, $Q^c < 0.5$, then u_1 and u_2 can be selected. In another case, s , who cares more about trustworthiness, may even specify $Q^t > 0.8$; then, only u_1 can be selected. From the example, we can see that there is a tradeoff between the quality requirements and the availability of qualified recommenders. We take a neighbor as “qualified” if he meets the quality requirements specified by the source.

The Size of an Optimal Subset. Suppose there are n neighbors, then the possible size of a subset has 2^n cases. Generally speaking, the more recommenders we select, the higher the probability that we may predict properly; however, this will lead to a higher cost to pay, and more complexity in the aggregating of different options. Therefore, we expect to select less recommenders, while guaranteeing a higher utility (larger \mathcal{F} and smaller \mathcal{G}). There are many choices: (1) Selecting all qualified neighbors. (2) Selecting a fixed number of qualified neighbors, e.g., 3, 6, etc. (3) Selecting a fixed proportion of qualified neighbors, e.g., 1/3, 1/6, etc. (4) Flexibly selecting some top m qualified neighbors, $m \leq n$.

For Choice 4, we present a heuristic approach (lines 5-8, Algorithm 1): we continue to select qualified recommenders until the number of next hop neighbors is larger than the current ones. The basic intuition comes from the view of information diffusion [8], which says the information can be propagated if there are more next hop neighbors than current ones. Algorithm 1 shows the process of 1-hop recommender selection. It takes a total time complexity of $O(n \cdot \log n)$.

Trust Aggregation. We make use of the aggregation method in the reliability model (e.g., [6]), where the trust value in the last hop to t is the direct trust, and the trust value from the source to the last intermediate node is taken as the reliability (of direct trust). Trust aggregation calculates the final trust value. Two commonly used aggregation functions are *MaxT* and *WAVEt*. *MaxT* takes the trust value of the most reliable neighbor of t . *WAVEt* takes the weighted average value of all qualified neighbors of t . Taking Fig. 2 for instance, $t_{u_i t}, i \in \{1, 2, 3, 4\}$ are direct trust, while $t_{s u_i}, i \in \{1, 2, 3, 4\}$ are their reliability. Suppose u_1 and u_2 are selected qualified recommenders. Taking *MaxT* aggregation, we will get

Algorithm 1 BasicRATE(G, s, t)

Input: G , a social network; s , source; t , target.

Output: R_s , an optimal subset of referrals.

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1: for each neighbor  $u$  in  $N_s$  do
2:   Calculate the metric vector  $\mathcal{M}_{su}$ .
3:   Keep the qualified neighbors who meet constraints.
4: end for
5: Sort the qualified neighbors in descending order.
6: for  $i : [0, m]$  do
7:   Add the best recommender  $r_i \in N_s$  to  $R_s$ .
8:    $i \leftarrow i + 1$ .
9:   if the neighbor set of  $R_s$  is larger than  $N_s$  then
10:    End the selection process.
11: end for
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$t_{st} = t_{u_1 t} = 0.8$; taking *WAVEt* aggregation, we will get $t_{st} = (0.8 \cdot 0.8 + 0.7 \cdot 0.6) / (0.8 + 0.7) = 0.7067$.

V. EXTENSION: MULTI-HOP SCENARIO

When it needs multi-hops to reach the target, the propagation operations of the four metrics, *trustworthiness*, *influence*, *uncertainty*, and *cost*, should be determined. We define the four equations for a trusted path.

Trustworthiness of a path. Again, we use the idea of the reliability model, in which trust propagation calculates the reliability of a trusted path. A commonly used method is *Multi*, which takes the product of trust values in all edges, as in the following: $t_{P(a_1, \dots, a_n)} = \prod_{e(a_i, a_{i+1}) \in P(a_1, \dots, a_n)} t_{a_i, a_{i+1}}$.

Influence of a path. We use a similar method with trustworthiness when calculating the influence through a path, as in the following: $w_{P(a_1, \dots, a_n)} = \prod_{e(a_i, a_{i+1}) \in P(a_1, \dots, a_n)} w_{a_i, a_{i+1}}$.

Uncertainty of a path. If we take uncertainty as the probability of failure, then the uncertainty of a path is defined as the following: $u_{P(a_1, \dots, a_n)} = 1 - \prod_{e(a_i, a_{i+1}) \in P(a_1, \dots, a_n)} (1 - u_{a_i, a_{i+1}})$.

The above equation can be seen like this: the probability that the trusted path $P(a_1, \dots, a_n)$ comes to a success, is the same that all intermediate nodes behave well and finally come to a success, i.e., $\prod_{e(a_i, a_{i+1}) \in P(a_1, \dots, a_n)} (1 - u_{a_i, a_{i+1}})$. Then the probability of failure is what remains.

Cost of a path. It is natural to summarize all the costs of each intermediate recommender to get the cost of a path, as in the following: $c_{P(a_1, \dots, a_n)} = \sum_{e(a_i, a_{i+1}) \in P(a_1, \dots, a_n)} c_{a_i, a_{i+1}}$. It is straightforward that a shorter path will lead to less cost if the average cost on each edge is the same.

The process of the multi-hop scenario is as follows: Start from s , and do a local greedy bread-first search with Algorithm 1. If there exist paths from s to t , calculate the metric vector for the paths. Then aggregate their results by *MaxT* or *WAVEt*, as mentioned before.

VI. EXPERIMENTAL EVALUATION

In this section, we evaluate the performance of RATE with experiments in a real trust network data set, Epinions.com (www.epinions.com). We use the subset and the same method

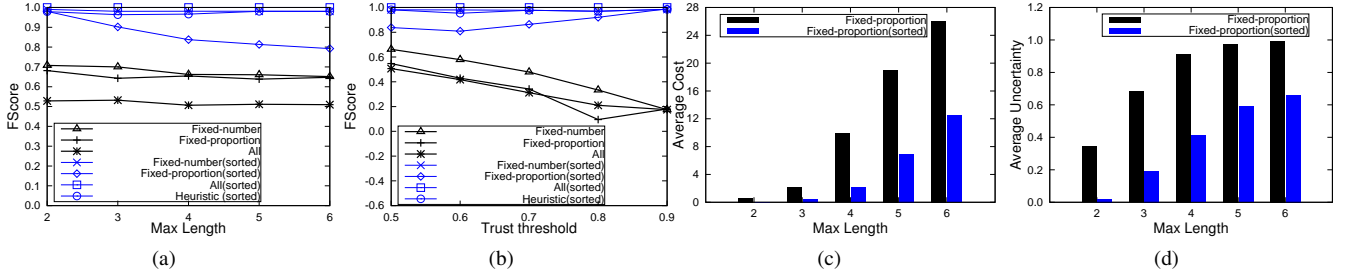


Fig. 3. The comparison of accuracy, average cost, and uncertainty.

to treat trust values in [6]. We use a standard evaluation technique in machine learning: leave one out. If there is an edge between two nodes, that edge is masked, and trust is calculated through algorithms; then, we compare the calculated value with the masked value.

We mainly consider the metric of *trust accuracy* [6], which represents the ability to predict whether a user will be trusted or not: (1) Precision: $A_t \cap B_t / B_t$, (2) Recall: $A_t \cap B_t / A_t$, (3) FScore: $2 \cdot \text{Recall} \cdot \text{Precision} / (\text{Recall} + \text{Precision})$, where A_t is the number of edges on which s trusts d directly, and B_t is the number of edges on which s trusts d , by trust calculated through an algorithm. The FScore metric is used to measure the accuracy using recall and precision jointly.

In the experiments, we implement four trust prediction strategies for comparison, they are: AveR-MaxT, AveR-WAveT, MaxR-MaxT, and MaxR-WAveT. If there are multiple paths from s to a node in N_t , AveR will take the average path weight as the reliability, while MaxR will take the maximal one. Experimental parameters are set as the following: $L \in [2, 6]$, $th \in [0.5, 0.9]$, $w_t = w_w = w_u = w_c = 0.5$, $\lambda = 0.8$, and $(Q^t, Q^w, Q^u, Q^c) = (0.5, 0.5, 0.5, 0.7)$. For the fixed-number approach, we select at most 6 qualified neighbors. For the fixed-proportion approach, we select at most 1/3 of all qualified neighbors. For all the strategies, we select the first 20 trusted paths to construct the trusted graph. To test the effects of RATE, we conduct experiments for the four strategies. Since all the results show similar patterns, we only present the result using AveR-MaxT in Fig. 3.

The Effects of QoR. Figs. 3(a) and 3(b) show the results of prediction accuracy. We gain several findings: (1) It shows significant improvements by sorting qualified neighbors with their QoR, which indicates the effects of RATE. It gains at least 22.4% higher accuracy. (2) Also, the fixed-number strategy shows its advantage when compared to the heuristic and fixed-proportion strategies. The reason is that it actually uses more qualified neighbors than other two strategies. We also record the uncertainty and cost. Here, only the results of fixed-proportion selection, are shown in Figs. 3(c) and 3(d). The results indicate that both the average uncertainty and the average cost are decreased with sorted neighbors, which shows the advantage of RATE. In all the possible parameters settings, the least improvement occurs when $L = 6$; it is 33.45% for uncertainty, and 52.13% for cost (Note that it is only a rough estimation since some edges may be counted multiple times).

The Effects of Max Length. If the max length is large, then there will be more hops from source to destination. Also see the results in Fig. 3. With the increase of max length,

the prediction accuracy is decreased. Taking the fixed-number selection (without sorting) strategy for instance, the decrease percentage is at least 2.55% comparing $L = 6$ to $L = 2$. Meanwhile, the uncertainty and the cost are increased. The increased percentages are 232.94% and 148.03%. The finding is consistent with real life, i.e., shorter path is better, since people tend to trust close friends rather than strangers.

The Effects of Trust Threshold. Fig. 3(b) shows the effects of increasing trust threshold. The prediction accuracy decreases more significantly compared to that of increasing max length. Taking fixed-number (without sorting) for instance, the FScore of $Q^t = 0.5$ is 0.6622, while $Q^t = 0.9$, only 0.1754 remains. We analyze the reason to be that, too large of a trust threshold makes many paths as not trustful, and less information can be used to predict trust. This finding validates that there is a tradeoff between the quality of recommenders and the availability of qualified recommenders.

VII. CONCLUSION

We propose a recommendation-aware trust evaluation (RATE) scheme, where we take a new perspective on the selection of good recommenders, to help people make proper decisions. The experiments in a large social network data set validate the effectiveness of RATE. In the future work, we will analyze the theoretical bounds of the size of an optimal recommender subset and the probability of success to make a trust decision.

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