Generalized Trust Propagation with Limited Evidence

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Abstract

Trust underlies effective interactions among autonomous parties. Ideally, a truster would base its trust in a trustee on the evidence of prior experiences with the trustee. But, such experiences arise between only a few trusters and trustees. Thus, a truster must rely upon the *propagation of trust* through a path of intermediary agents, each providing a trust assessment in the next. However, existing propagation approaches fail in settings such as social communities and product evaluations where a forward path isn't available and we must consider a backward path from a rated entity to a rater.

We propose Shin, a generalized trust propagation approach that incorporates a recent probabilistic method for revising trust estimates in trustees. Shin yields higher prediction accuracy than traditional approaches.

Keywords: Trust, trust propagation, social networks, bipartite networks

In settings such as e-commerce and social networks, trust provides the basis for interaction among autonomous agents [1, 2, 3, 4, 5, 6]. We define a truster's trust in a trustee as the truster's belief that a future interaction with the trustee will yield expected outcomes [7].

Trust relationships naturally form a *trust network*, a weighted directed graph whose vertices represent agents and whose edges represent directed trust relationships, weighted with the level of trust. Each edge weight is affected by the outcomes of prior interactions and determines whether its source agent elects to pursue a future interaction with its target. A centralized reputation system consolidates the trust network. In a decentralized setting, each agent knows of only its own out-edges.

A *truster* can reasonably decide whether to interact with a (prospective) *trustee* based on its estimation of the latter's trustworthiness. A truster that lacks direct experience with a trustee would rely upon referrals leading to *witnesses* who provide testimony of their experiences with the trustee. Restricting the witnesses to direct experience helps avoid double counting evidence.

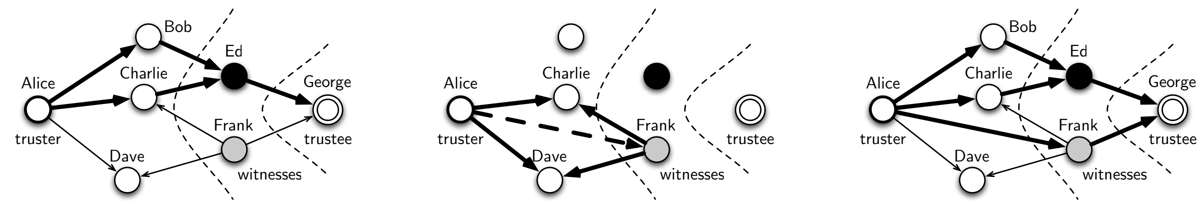
Trust propagation [8, 9] means estimating trust over referral paths. Existing approaches consider only forward paths wherein each agent trusts the next. Our propagation technique, Shin (from the Chinese word for trust), applies even if no suitable forward path exists provided a path from both the truster and trustee to a common neighbor exists.

Approach, Briefly

A *witness* is a party who can provide the truster with testimony about the trustee. A witness is *reachable* provided there is a trustworthy forward (generally, short [8]) path to it; and *unreachable* otherwise. Even unreachable witnesses are physically reachable to have been considered. A witness is *evaluable* if it shares acquaintances with the truster (thus its trustworthiness can be evaluated); and *inevaluable* otherwise.

Figure 1a illustrates how traditional approaches propagate trust through reachable witnesses. Existing approaches fail in two important settings:

- When reachable witnesses cannot be found. For example, suppose Alice is a recruiter looking for a potential software engineer. She finds candidate Ed referred to by her accountant Bob. However, Alice does not fully trust Ed because she does not trust Bob's expertise in assessing software engineers. Thus, there is no high-quality forward path. Alice interviews Ed to estimate his expertise. Thus, Alice finds Ed via an untrustworthy path but evaluates his trustworthiness herself.
- When reachable witnesses don't exist. In user-item rating networks, an edge corresponds to a user rating an item: no edges end at users or originate from items. A user can reach no other users and only a few items. For example, suppose Alice needs a recommendation for a smartphone. Her friends don't own smartphones, and don't know anyone who does. Thus no reachable witnesses exist for Alice. Instead, she browses reviews on smartphone forums. Alice does not know the reviewers directly, but trusts reviewers who have similar opinions as hers on the phones she has used. Thus, Alice propagates trust through her past phone models and their reviewers to identify unreachable new phone models.



(a) Traditionally trust propagation follows (bold) edges from *truster* Alice to *trustee* George through *reachable witness* Ed.

(b) Shin estimates Alice's trust in *unreachable witness* Frank by comparing Frank and Alice's ratings of their common acquaintances Charlie and Dave.

(c) For propagation, Shin treats witnesses Ed and Frank equally.

Figure 1: Shin illustrated. The bold, black, and double-circled vertices represent the truster, witnesses, and trustee, respectively. Bold edges indicate trust propagation.

Shin estimates the trustworthiness of unreachable witnesses based on their trust in common acquaintances with the truster, and propagates trust through all witnesses. In Figure 1b, the truster establishes trust in an unreachable witness by comparing the trust relationships to these common acquaintances. Figure 1c shows Shin propagates trust through all witnesses.

Shin is decentralized in that each truster unilaterally pursues referrals and estimates its trust in others. Shin proves beneficial as long as sufficiently many witnesses are cooperative.

Sidebar: Mathematical Background

Following Jøsang [10] and Wang and Singh [11], we define trust in dual representations of *evidence* and *belief*. First, Alice's trust in Bob is modeled as the pair $\langle r, s\rangle$ of the counts of Alice's positive (r) and negative (s) experiences with Bob. We adopt Wang and Singh's formulation using (i) the probability of the next outcome being positive:

$$\alpha = \frac{r}{r+s}$$

and (ii) the certainty as the confidence in the probability:

$$c = \frac{1}{2}\int_0^1 |f(x|\langle r, s\rangle) - 1|\, dx$$

Here, $f(x|\langle r, s\rangle)$, the conditional probability of a positive outcome given $\langle r, s\rangle$, is

$$f(x|\langle r, s\rangle) = \frac{x^r(1-x)^s}{\int_0^1 x^r(1-x)^s dx}. \tag{1}$$

The certainty of $\langle r, s\rangle$ is the probability mass above $\langle 0, 0\rangle$, the no-evidence distribution.

Second, *belief-based* trust is a triple $\langle b, d, u\rangle$ of *belief*, *disbelief*, and *uncertainty*, where $b = c\alpha$, $d = c(1-\alpha)$, and $u = 1-c$. Evidence and belief map to each other [11].

Figure 1b explains trust in unreachable witnesses. Charlie is a common acquaintance of Alice and Frank. Suppose that Alice's trust in Charlie is $\langle r_{AC}, s_{AC}\rangle$, and Frank's trust in Charlie is $\langle r_{FC}, s_{FC}\rangle$. From these, we compute Alice's trust in Frank as $\langle 1-q, q\rangle$, where q captures Frank's "error" from Alice's perspective [12].

Recall that Frank's trust in Charlie carries the certainty based on $f(x|\langle r_{FC}, s_{FC}\rangle)$ (Equation 1). Alice's trust in Charlie carries the probability α_{AC}. Wang et al. [12] define the average error q as the integral over x of $f(x|\langle r_{FC}, s_{FC}\rangle)(x-\alpha_{AC})^2$, and approximate it by

$$1 - \sqrt{\left(\alpha_{AC} - \frac{(r_{FC}+1)}{(r_{FC}+s_{FC}+2)}\right)^2 + \frac{(r_{FC}+1)(s_{FC}+1)}{(r_{FC}+s_{FC}+2)^2(r_{FC}+s_{FC}+3)}}.$$

Suppose Alice and Frank have N common acquaintances. For each acquaintance, we compare Alice and Frank's trust reports, computing a piece of evidence $\langle 1-q, q\rangle$ of Alice's trust in Frank. Alice's trust in Frank is the aggregation

$$\langle \sum_{n=1}^{N}(1-q_n), \sum_{n=1}^{N} q_n\rangle.$$

Suppose the average numbers of unreachable witnesses and common relations per witness are uw and cr, respectively. The complexity of calculating the trustworthiness of all unreachable witnesses approximates $O(uw \times cr)$. The complexity of Shin depends not only on evaluating the unreachable witnesses, but also on the choice of the forward propagation method and the propagation depth. For example, CertProp [9] requires calculating rw (number of reachable witnesses) $\times depth$ integrals.

Generalized Trust Propagation

We define a trust network $T(V, E, d)$, where V is a set of agents; $E \subseteq V \times V$ a set of direct trust relationships between the agents; and $d : V \times V \mapsto [0, 1]$ is a function such that $d(a, b)$ is the amount of direct trust placed by truster a in trustee b, and $(a, b) \in E$ if and only if $d(a, b) \neq 0$.

In addition, we define a function $t : V \times V \mapsto [0, 1]$ such that for $a, b \in V$, if $(a, b) \in E$ then $t(a, b)$ is the amount of (direct or indirect) trust placed by truster a in trustee b. In simple terms, trust propagation is the problem of computing $t(u, v)$ given $T(V, E, d)$. The sidebar describes our trust representation.

Shin can be readily combined with any forward propagation approach. For concreteness and because of its good results, we adopt CertProp [9] and two of its operators, *concatenation* $\otimes$ and *aggregation* $\oplus$. (CertProp's third operator *selection* does not yield better accuracy.) Concatenation discounts trust values along a referral path. Aggregation combines trust from referral paths to different witnesses.

Trust Propagation through Reachable Witnesses

Consider Figure 1a again. Alice's trust in Ed through Bob is computed as $t(\text{Alice}, \text{Ed})' = t(\text{Alice}, \text{Bob}) \otimes t(\text{Bob}, \text{Ed})$. Alice's trust in Ed through Charlie is computed as $t(\text{Alice}, \text{Ed})'' = t(\text{Alice}, \text{Charlie}) \otimes t(\text{Charlie}, \text{Ed})$. To determine $t(\text{Alice}, \text{Ed})$, Alice aggregates $t(\text{Alice}, \text{Ed})'$ and $t(\text{Alice}, \text{Ed})''$ by $t(\text{Alice}, \text{Ed})' \oplus t(\text{Alice}, \text{Ed})''$. Then Alice's trust in George through Ed equals $t(\text{Alice}, \text{George})' = t(\text{Alice}, \text{Ed}) \otimes t(\text{Ed}, \text{George})$. Once Alice determines $t(\text{Alice}, \text{Frank})$, as Figure 1b shows, she can calculate her trust in George through Frank as $t(\text{Alice}, \text{George})'' = t(\text{Alice}, \text{Frank}) \otimes t(\text{Frank}, \text{George})$. Finally, Alice determines $t(\text{Alice}, \text{George})$ as $t(\text{Alice}, \text{George})' \oplus t(\text{Alice}, \text{George})''$.

Establishing Trust in Unreachable Witnesses

We establish the truster's trust in an unreachable witness by comparing the (extent of) trust the truster places in a common acquaintance with the trust the witness places in the same acquaintance. Wang et al.'s [12] method for *trust update* incorporates a way for a truster to compare its trust value with that of a given witness: an agent evaluates the trustworthiness of a referrer by comparing its own experience with a referral provided by the referrer. In intuitive terms, the closer the referral is to the truster's own experience the more trustworthy would the truster consider the referrer. Similarly, the truster evaluates the trustworthiness of an unreachable witness based on the trust the witness places in a common acquaintance. Then the truster aggregates its trust estimates about the witness after considering all common acquaintances. The sidebar presents additional details.

Evaluation

We evaluate Shin using two types of datasets: (i) bipartite networks and (ii) social networks. Table 1 shows the datasets and their corresponding weight-trust translations. To model datasets as trust networks, we translate edge weights $d(u, v)$ (single integer) to our trust representation $t(u, v) = \langle r, s \rangle$, using the *linear* transformation [9].

Category	**Social network**		**Bipartite network**
Name	FilmTrust	Advogato	Epinions
Type	Users $\mapsto$ Users		Users $\mapsto$ Items
Vertices	528	5,406	1,000+139,738
Edges	823	51,839	105,754
Weights (d)	{1,2,3,. . . ,10}	{1,2,3,4}	{1,2,3,4,5}
Trust (t)	$\langle e-1, 10-e \rangle$	$\langle e-1, 4-e \rangle$	$\langle e-1, 5-e \rangle$

Table 1: Summary of the datasets used in our evaluation. Advogato is scaled down using random-walk sampling [13], and Epinions by selecting first 1,000 users.

FilmTrust (`http://trust.mindswap.org`) is a social network of film buffs; its edges represent a user's estimation of the quality of the movie tastes of another user. Advogato (`http://www.advogato.org/`) is a trust network built from a social network site. Epinions.com is a web-site where consumers can submit their reviews about products. The Epinions dataset (`http://www.trustlet.org/wiki/Epinions_dataset`) contains consumers' reviews of products including numerical ratings. We represent Epinions as a bipartite network whose vertices are consumers and products, and edges are consumers' reviews of the products.

Bipartite Networks

We evaluate our approach on bipartite (user-item) networks by three-fold cross validation. For each of three bipartite datasets, we randomly divide the edges into three independent subsets of equal size. We take each subset and the remaining two subsets as the test set and the training set, respectively. For each user-item pair in the test, we consider either all or at most five random (to simulate the cases where evidence is limited) witnesses, each of which is evaluated based on either all or at most five random common trust relations.

To measure accuracy, we translate the propagated trust $t(u_i, v_i) = \langle r_i, s_i \rangle$ back to an edge weight $d(u_i, v_i)$, as defined by the dataset. For example, in FilmTrust, $d(u_i, v_i) = 9 * \alpha_i + 1$, where $\alpha_i = \frac{r_i}{r_i + s_i}$.

Our accuracy metric is root mean square error ($RMSE$). Given the predicted $P = \{p_1, \ldots, p_n\}$ and actual values $A = \{a_1, \ldots, a_n\}$ in the test set,

$$RMSE(P,\ A) \quad = \quad \sqrt{\frac{\sum_{i=1}^{n}(p_i - a_i)^2}{n}}. \tag{2}$$

We calculate the RMSE of trust predictions by propagating trust through all user-item pairs in each test set, and average RMSE over three test sets. We compare Shin with the user-oriented neighborhood-based collaborative filtering approach (CF) [14]. We choose CF because it considers users individually. CF provides rating predictions based on a weighted average of ratings from users with similar tastes, which are measured by Pearson correlation. When there are few distinct ratings, Pearson correlation is ineffective due to the lack of evidence, but our approach is robust because such situations result only in the trust relationships having low confidence without affecting their accuracy.

Our results show that Shin yields more accurate predictions (RMSE: 1.12) than CF (RMSE: 1.35) when considering all available witnesses and common relations. Besides, Shin provides solid predictions (RMSE: $\approx$ 1.25) with at most five random common trust relations (CF yields RMSE: $\approx$ 1.50).

We conclude Shin is effective in evaluating the trustworthiness of a witness based on limited common trust relations in a partially observable setting. Moreover, Shin's accuracy improves when we consider more witnesses. The details are in the Appendix.

Social Networks

We evaluate the approaches through the leave-one-out cross-validation technique on unipartite datasets. We select an edge $e = (u, v)$ from a given dataset $G(V, E)$, and consider that edge as a test set in itself. First, we remove e from E to construct the corresponding training set. Second, we calculate the propagated trust between truster u and trustee v, $t(u, v)$, based on the training set and each approach. Third, we measure the effectiveness of an approach by comparing $t(u, v)$ with the actual trust value of the test edge e. When an approach fails to make a prediction, we treat the mean value of edge weights as the prediction (FilmTrust: 5.5; Advogato: 2.5).

We find that Shin yields results similar to CertProp over these datasets because most of witnesses are reachable (details in the Appendix).

Sparse Networks

To further demonstrate the benefits of Shin, we modify CertProp and Shin such that each considers only a fraction γ of the reachable witnesses (treating the other witnesses as unreachable). The motivation for doing so is that we wish to consider settings where social networks are sparse, such as because they are only just emerging or exist in specialized domains. Our intuition is that the traditional methods would be less useful than Shin in such settings because the traditional methods rely upon a rich network in order to make effective predictions.

Let us consider a simple example. Given a truster u and a trustee v, suppose there are 28 witnesses of v in total, eight unreachable and 20 reachable from u. With $\gamma = 50\%$, the γ-parameterized CertProp and Shin propagate trust through only ten of these 20 reachable witnesses. In addition, Shin tries to establish trust from u to 18 witnesses (ten of the reachable witnesses treated as unreachable plus all eight truly unreachable ones) based on common acquaintances. Suppose Shin successfully builds trust in five (evaluable) out of the 18 such witnesses. As a result, γ-parameterized CertProp calculates propagated trust based on the ten witnesses, whereas the γ-parameterized Shin estimates trust based on 15 witnesses.

We vary γ from 0% to 100%. Figures 2 and 3 show the results for FilmTrust and Advogato, respectively. We also compare to a well-known referral-based propagation approach, TidalTrust [8], because it is clearly described and is feasible to reimplement and apply in our setting. The black, white, and gray areas show the numbers of the unreachable and inevaluable, reachable, and unreachable but evaluable witnesses, respectively. As γ increases, the number of reachable witnesses decreases, and the number of evaluable witnesses increases. We find that as γ increases, the accuracy of CertProp decreases due to the lack of witnesses. Shin provides stable predictions regardless of γ by benefiting from additional evaluable witnesses. TidalTrust produces the highest error. As γ increases, the accuracy of TidalTrust improves because when TidalTrust fails to provide a prediction due to the lack of witnesses, simply guessing 5.5 yields better accuracy.

We define an *untrustworthy* path as a referral path with belief b of concatenated trust lower than a threshold ψ. Given a trust value $\langle r, s \rangle$, recall from the sidebar that belief incorporate both probability and certainty. Specifically, $b = c\alpha$, where c is the certainty of the trust value, and $\alpha = \frac{r}{r+s}$.

We now show how Shin improves trust predictions by reevaluating the trustworthiness of witnesses that are reached by untrustworthy referral paths. Figure 4 compares Shin with different thresholds ψ. Here Shin ignores the untrustworthy referral paths $b < \psi$ and reevaluates the trustworthiness of the witnesses reached by those paths by comparing the trust values to the common acquaintances between the truster and the witnesses. TidalTrust is not compared here because it uses a different belief measurement in its trust

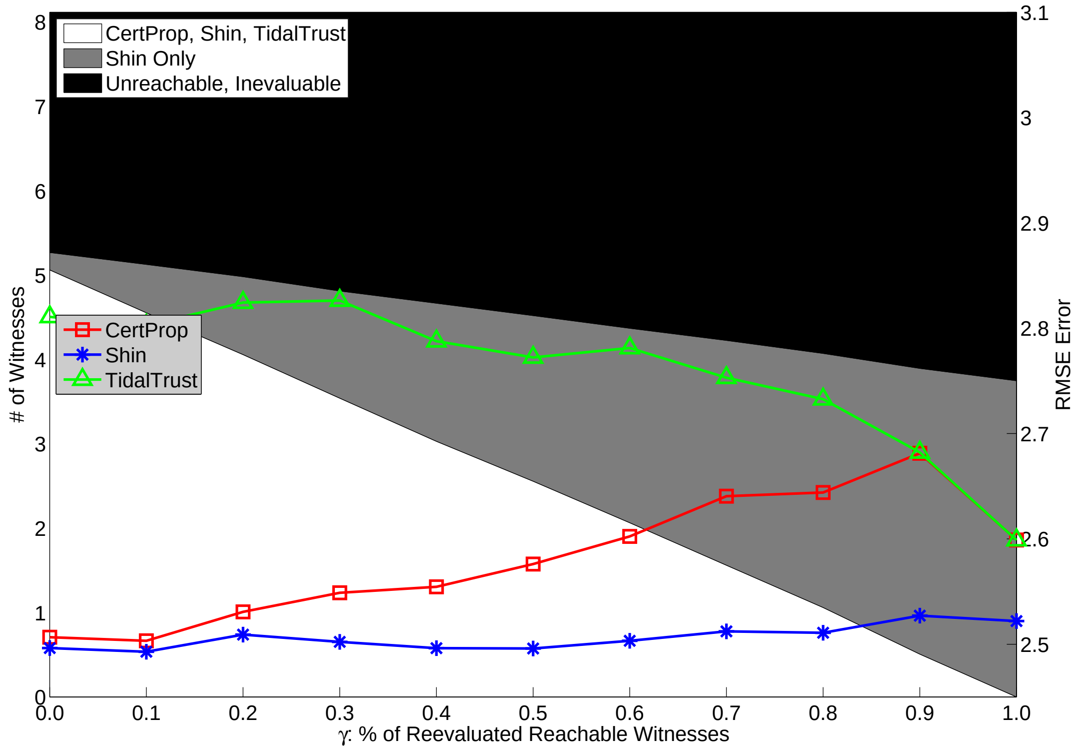


Figure 2: Prediction errors on FilmTrust by varying the percentage (x-axis) of unreachable witnesses. Despite the small number of reachable witnesses, Shin yields reliable predictions by benefiting from additional evaluable witnesses. (In all figures, the white, gray, and black areas show the numbers of reachable, unreachable but evaluable, and unreachable and inevaluable witnesses, respectively.)

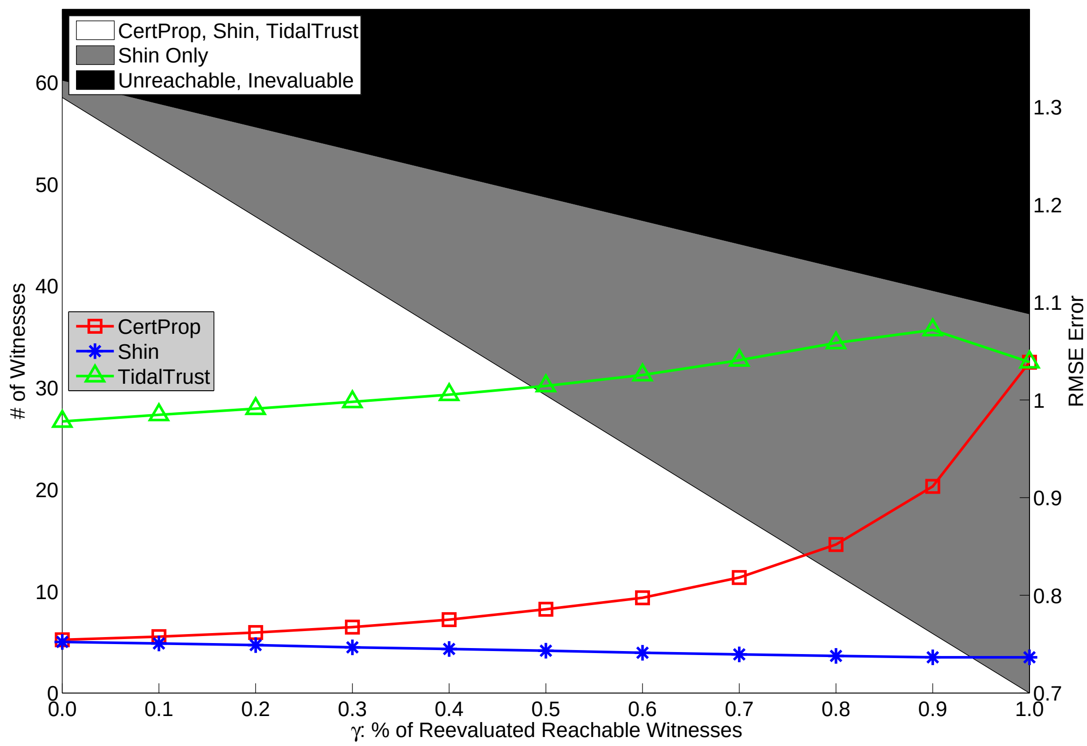


Figure 3: Prediction errors on ADVOGATO by varying the percentage (x-axis) of unreachable witnesses. Despite the small number of reachable witnesses, Shin yields more accurate predictions by benefiting from additional evaluable witnesses.

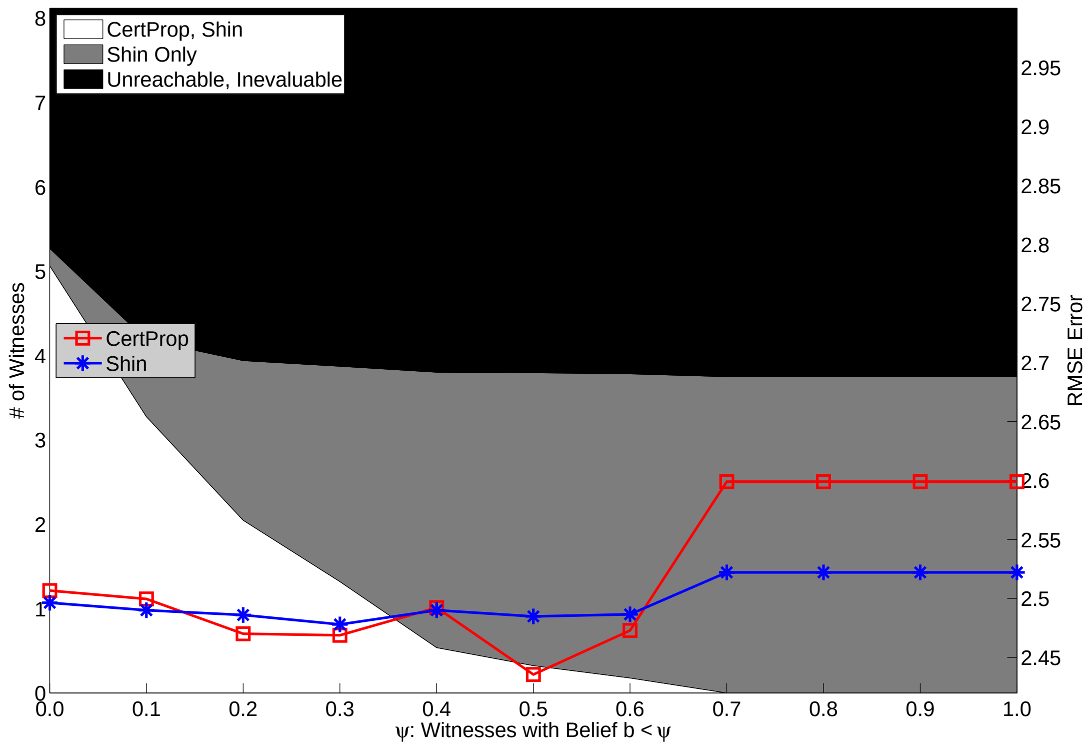


Figure 4: Comparing Shin and CertProp with various values of ψ in FilmTrust. By reevaluating the witnesses reached by paths with $b < \psi$, Shin yields more accurate prediction when $\psi \geq 0.7$.

representation.

Figure 4 shows that Shin yields improvement when reevaluating all the witnesses ($\psi \geq 0.7$). The white area verifies that there are almost no paths having $b \geq 0.7$. For $\psi < 0.7$, CertProp and Shin produce similar results, although Shin is less volatile with respect to ψ (the Appendix provides additional details). This result indicates that, in FilmTrust, the witnesses should be evaluated by the common relations with the truster rather than by the referral paths. For Advogato, Figure 5 shows that, when $\psi \in [0.2, 1.0]$, reevaluating the witnesses reached by referral paths having $b < \psi$ with Shin yields better prediction. In Advogato, there exist no paths having $b > 0.5$. This result indicates that, in Advogato, the witnesses reached by trustworthy paths help, but the witnesses reached by untrustworthy paths can sometimes worsen the predictions compared to reevaluating every reached witness.

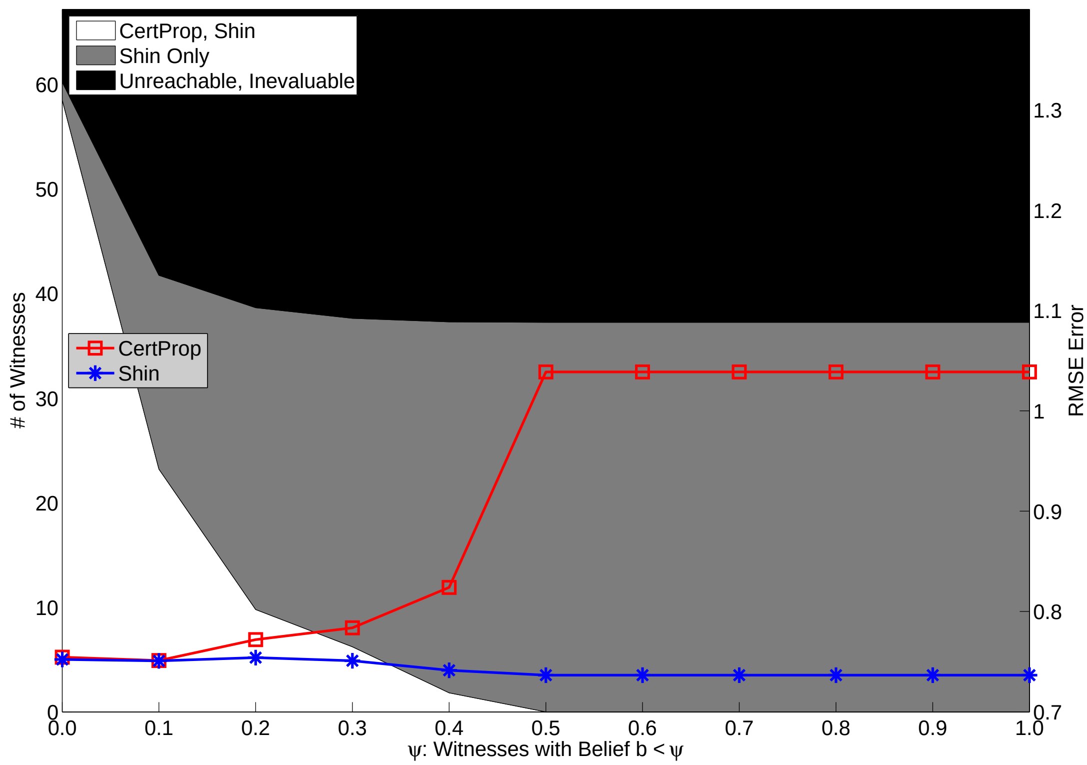


Figure 5: Comparing Shin and CertProp with various values of ψ in ADVOGATO. By reevaluating the witnesses reached by paths with $b < \psi$, Shin yields more accurate prediction when $\psi > 0.1$.

Conclusions

Traditional trust propagation suffers when the witnesses of a trustee are unreachable or reachable only by untrustworthy referrals. Our approach, Shin, considers those witnesses by establishing trust between them and the truster agent.

We evaluate Shin over both bipartite and unipartite datasets. In bipartite datasets, where all witnesses are unreachable, Shin provides results competitive with collaborative filtering even with a small amount of evidence. The trust relationships Shin builds follow the trust relationships people establish in social networks. These results indicate our approach is effective in building accurate trust relationships between a truster and unreachable witnesses. In unipartite datasets, where some witnesses can be reached from the truster, Shin provides more accurate results than CertProp and TidalTrust for a sparse network as the ratio of reachable to unreachable witnesses goes down.

A possible limitation is that Shin models trustworthiness as two parameters, whereas many real systems only capture one value. Translating between one-value and two-value representations may lose valuable information, leading to inaccurate prediction. We advocate that future systems provide a two-value representation of trust.

To summarize, our contributions are two-fold. First, our approach estimates the trustworthiness of an unreachable witness or a witness reachable in untrustworthy referrals based on the common trust relations the witness shares with the truster. Second, our approach improves the accuracy of trust propagation.

Future Directions

We would like to formalize network properties that can serve as useful indicators of the relative effectiveness of Shin and traditional approaches. For example, in FilmTrust, almost all witnesses can be reached by referrals. We would like to explore the network properties FilmTrust from networks where witnesses are mostly unreachable. For example, we would like to retrieve the frequent patterns from a network. A witness in a network with more frequent path-of-three pattern could be more reachable than the one in a network with less frequent such pattern.

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Online Appendix: Additional Results

We compare our trust propagation Shin with CF on EPINIONS, a bipartite dataset. Figure 6 shows the prediction error by varying the number of common trust relations considered when we evaluate a witness. The result shows generally Shin outperforms CF when the evidence is limited. Besides, Shin is robust against the number of common trust relations considered, whereas CF requires more evidence to improve accuracy.

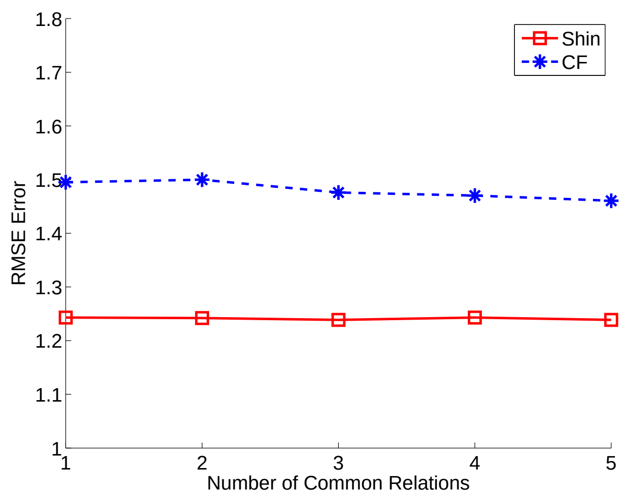

Figure 6: Comparing Shin with CF on EPINIONS with limited evidence. Both Shin and CF make predictions by only evaluating three witnesses. Each witness is evaluated based on one to five common trust relations.

Figure 7 varies the number of witnesses considered. Each witness is evaluated based on at most two common trust relations. Shin yields better prediction error than CF. Shin produces more accurate prediction with more considered witnesses, whereas CF is less sensitive to the number of considered witnesses. Shin is an evidence-based approach, which makes prediction by aggregating evidence without modifying the evidence. With more evidence, Shin leads to more accurate prediction. CF adjusts evidence based on correlation. The prediction accuracy of CF depends on the accuracy of the correlation rather than the amount of evidence.

We further evaluate the accuracy of the trust established between trusters and witnesses. On Epinions.com, a user can explicitly state that he trusts the trustee's reviews. We use these explicit statements (as the test set) to verify the trust we compute from the ratings (as the training set).

For any two users u and v with at least one common rated acquaintance, we establish a trust relationship from u to v based on their respective trust relationships with their

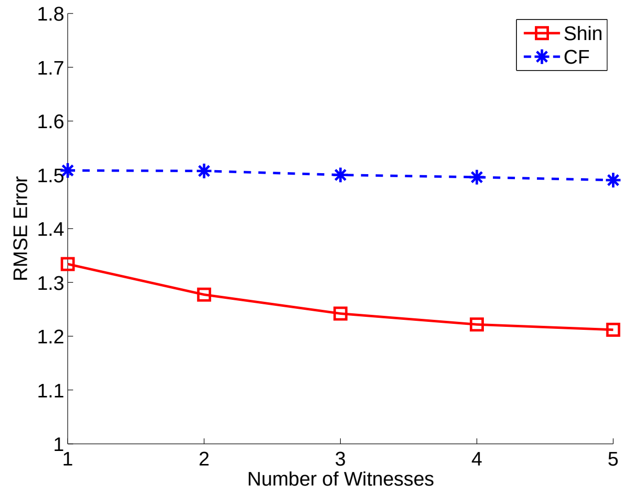

Figure 7: Comparing Shin with CF on Epinions with limited evidence. Both Shin and CF make predictions by only evaluating one to five witnesses. Each witness is evaluated based on one to two common trust relations.

Table 2: Confusion tables for Shin and CF on Epinions dataset. Shin yields higher numbers of true-positive and true-negative predictions.

	Positive		*Negative*	
	Shin	CF	Shin	CF
Positive	**3.77**%	2.60%	9.60%	10.77%
Negative	9.60%	10.77%	**77.03**%	75.86%

common acquaintances. Hence, we build a trust network where edges exist between any two users that have acquaintances in common. Then we compare the built trust network with the test set. First, we count the number of "real" trust relationships that exist in the test set. The number is $25,257$. Then, in the training set, we rank the top $25,257$ strongest trust relations predicted by Shin and CF. Table 2 shows the confusion matrix of Shin and CF. Shin accurately predicts the trust relations by having more positive-positive and negative-negative cases (correct predictions) than CF. This result indicates that Shin better follows the actual trust relationships that people tend to establish.

Table 3 shows the comparison of our trust propagation (Shin), Naïve, TidalTrust [8], and CertProp [9]. Naïve takes the product of ratings along a referral path, and computes propagated trust by averaging trust from multiple referral paths. The result shows that Shin and CertProp outperform Naïve and TidalTrust significantly. However, Shin yields similar results as CertProp because there are few unreachable witnesses. On average, there are only 0.21 and 1.71 unreachable witnesses out of a total of 8.12 and 67.17 witnesses in FilmTrust and Advogato, respectively.

Table 3: Comparing our trust propagation (Shin) with Naïve, TidalTrust [8], and CertProp [9] on social network datasets. Shin *witnesses* means the average number of witnesses considered only by Shin. Shin outperforms Naïve and TidalTrust but yields limited improvement (< 0.01) over CertProp, because of the paucity of unreachable witnesses.

		FilmTrust	Advogato
RMSE	CertProp	2.51	0.75
	Shin	2.50	0.75
	TidalTrust	2.81	0.98
	Naïve	4.68	1.54
	Total witnesses	8.12	67.17
	CertProp,Trust *witnesses*	5.06	58.50
	Shin *witnesses*	0.21	1.71

Figure 8 is the detailed version of Figure 4. Figure 8 compares Shin and CertProp with $\psi = 0.00, 0.01, 0.02, \ldots, 1.00$. When $\psi < 0.7$, CertProp and Shin produces similar results, although Shin is less volatile with respect to ψ.

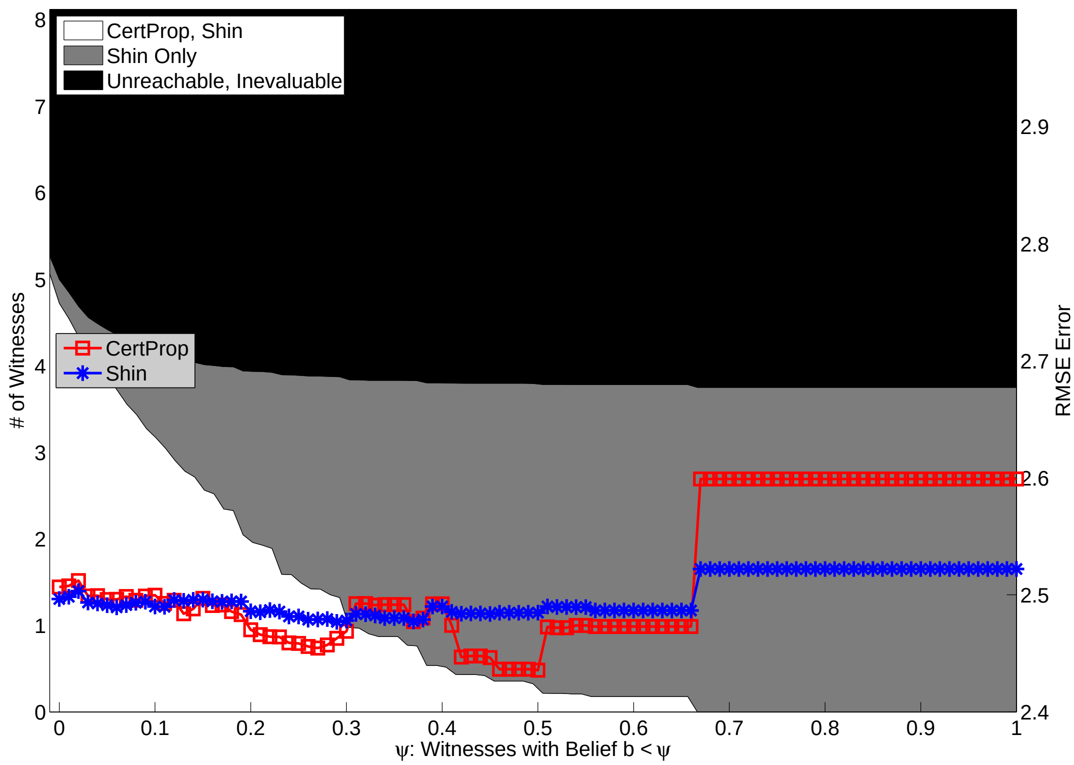

Figure 8: Comparing Shin and CertProp with $\psi = 0.00, 0.01, 0.02, \ldots, 1.00$ in FilmTrust. By reevaluating the witnesses reached by paths with $b < \psi$, Shin yields more accurate prediction when $\psi \geq 0.7$. Shin is less volatile with respect to ψ.