



We describe two primary trust propagation strategies in which the proposed new *message-passing mechanisms*, motivated from the idea of belief propagation [1], facilitate the integration of explicit trust & review ratings and the prediction of the probability of an edge. We define a *source link* to be an edge from which a trust-message originates and a *target link* to be an edge to which a trust-message is delivered. Thus, we estimate trust degrees of target links after applying the trust-message passing mechanisms. For the sake of simplicity, the status of a target link in the following figures is represented by  $p_{ij}$ .

As the first primary strategy, *direct propagation* is a trust propagation strategy in which, when  $u_i$  trusts  $u_k$  and then  $u_k$  trusts  $u_j$ , the probability that  $u_i$  trusts  $u_j$  increases by way of  $u_k$ . Figure 2(a) explains the direct propagation strategy. When both  $p_{ik}$  and  $p_{kj}$  are greater than 0.5, we increase the probability that  $u_i$  trusts  $u_j$ ,  $p_{ij}$ , to reflect  $p_{kj}$ .

As the second primary strategy, when  $u_i$  trusts  $u_k$  and also  $u_j$  trusts  $u_k$ , *transpose trust* involves with increasing the probability  $p_{ij}$  that  $u_i$  trusts  $u_j$  by way of  $u_k$ . Figure 2(b) explains the strategy of transpose trust. When  $p_{ik} > 0.5$  and  $p_{jk} > 0.5$ ,  $p_{ij}$  increases by receiving trust-message from  $p_{jk}$ . When  $p_{jk} \leq 0.5$ , the trust relationship between  $u_j$  and  $u_k$  does not influence  $p_{ij}$ .

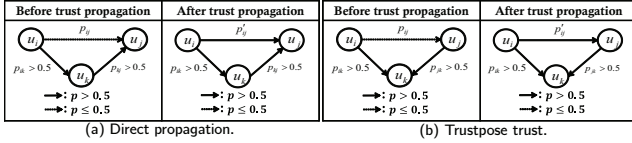


Figure 2: Propagation strategies.

The following equations (1) and (2) describe the computation of evolving trust degree through the trust-messages passing for the two primary strategies, respectively. The trust-messages passing, in effect, is realized by a propagation matrix  $\psi$ , shown in Table 2, connecting the status of a source link to that of a target link. Propagation matrix  $\psi$  can control the level of connectedness between the two links by parameter  $\epsilon$ .

The equations (3) describe the computation of trust probabilities for the proposed models *ITD*. The initial trust probabilities are denoted by  $I$  and direct propagation and transpose trust are denoted by  $D$  and  $T$ , respectively. In the equations,  $n$  represents general constants to normalize the message vector because the sum of the elements should be equal to one. The parameter  $\epsilon$  in the propagation matrix is preset through experiments.

Table 2: Initial trust probabilities

Target link	Source link	
	$p > 0.5$	$p \leq 0.5$
$p_{ij} > 0.5$	$\epsilon$	$1 - \epsilon$
$p_{ij} \leq 0.5$	$1 - \epsilon$	$\epsilon$

$$\mathbf{m}_{ik,kj \rightarrow ij}^d = \psi \times \mathbf{p}_{kj}, p_{ik} > 0.5 \text{ and } p_{kj} > 0.5 \quad (1)$$

$$\mathbf{m}_{ik,jk \rightarrow ij}^t = \psi \times \mathbf{p}_{jk}, p_{ik} > 0.5 \text{ and } p_{jk} > 0.5 \quad (2)$$

$$ITD: \mathbf{p}_{ij} = \alpha_I \mathbf{p}_{ij}^{(0)} + (\alpha_T \times \mathbf{n} \left[ \prod \mathbf{m}_{ik,jk \rightarrow ij}^t \right]) + (\alpha_D \times \mathbf{n} \left[ \prod \mathbf{m}_{ik,kj \rightarrow ij}^d \right]) \quad (3)$$

### 3. EXPERIMENTS

In our experiments, we used Epinions dataset<sup>1</sup> which has 131,828 users, 841,372 trust relations, and 13,668,319 review ratings. We demonstrated the excellence of *ITD* by the performance comparison of two previously proposed methods, *ABIT\_L* [4] and *MoleTrust* [3]. We empirically found the

<sup>1</sup><http://www.Epinions.com>

parameter  $\epsilon$ , 0.7 and 0.8 for the proposed strategies of direct propagation and transpose trust, respectively, in such a way that accuracy for the training data set is maximized.

To assess the performance of *ITD*, we basically followed [4]; We randomly selected 1,000 user pairs which are trust pairs and review-rating pairs at the same time, denoted by Answer set. As for the training, among pairs of users providing information on review ratings, we selected 2,000 pairs: 1,000 pairs in Answer set and random 1,000 pairs of users who have not built trust. Then, using each of the trust prediction models, we estimated trust probabilities for the selected 2,000 pairs.

In the training phase, the initial probabilities, provided in Table 1, were assigned for the 2,000 pairs. For the user pairs other than the users from the selected 2,000 pairs,  $p_{ij}^{(0)} = 1$  is assigned if explicit trust formation exists. Otherwise, the initial probabilities as in Table 1 were assigned.

For each model, the predicted probabilities for the 2,000 pairs are sorted in descending order, and then trust probabilities of the top 1,000 pairs from the sorted list are selected. By comparing the estimated results of the top 1,000 pairs with the 1,000 pairs in Answer set, we computed the accuracy of the model, which is a ratio of the number of correct pairs to 1000. For *ITD*, *ABIT\_L*, and *MoleTrust*, the above-stated testing was repeated five times, and the average was used for the model's accuracy.

Table 3 shows the accuracy of the trust prediction models as well as the used weights in *ITD*,  $\alpha_I$ ,  $\alpha_T$ , and  $\alpha_D$ , which maximized the accuracy. The accuracy of *ITD* is higher than that of *ABIT\_L* and *MoleTrust* by 12.5% and 29.1%, respectively. The result is not surprising because, while the *ABIT\_L* model relies on user interactions and the *MoleTrust* model depends on information on explicit trust, the proposed *ITD* model takes into account information on both user interactions and explicit trust.

Table 3: Accuracy of the proposed model in comparison with the previous models

Model (weights)	Accuracy
<i>ITD</i> ( $\alpha_I = 0.2, \alpha_T = 0.7, \alpha_D = 0.1$ )	<b>0.932</b>
<i>ABIT_L</i>	0.797
<i>MoleTrust</i>	0.609

### 4. CONCLUSIONS

This paper has proposed a new model for trust prediction. In experiments using real-life data, we have demonstrated that the proposed model *ITD* outperforms *ABIT\_L* and *MoleTrust* in accuracy by 12.5% and 29.1%, respectively.

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