# Building a Web of Trust without Explicit Trust Ratings


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***Abstract*— A satisfactory and robust trust model is gaining importance in addressing information overload, and helping users collect reliable information in online communities. Current research on trust prediction strongly relies on a web of trust, which is directly collected from users based on previous experience. However, the web of trust is not always available in online communities and even though it is available, it is often too sparse to predict the trust value between two unacquainted people with high accuracy. In this paper, we propose a framework to derive degree of trust based on users' expertise and users' affinity for certain contexts (topics), using users rating data which is available and much more dense than direct trust data. In experiments with a real-world dataset, we show that our model can predict trust connectivity with a high degree of accuracy. With this framework, we can predict trust connectivity and degree of trust without a web of trust and then apply it to online community applications, e.g. e-commerce environments with users rating data.**


## I. Introduction

As online communities that allow their users to share their knowledge and experiences are becoming popular, it is vital to provide a satisfactory trust model which resolves information overload, increased uncertainties and risk taking from unreliable information [1]. Since social interaction in online communities is conducted based on trust, people are able to collect reliable information from trustworthy people [2]. Trust is a subjective degree of belief about agents or objectives on users' previous experiences and knowledge [1], [3], [4]. Users in online communities are allowed to express who they trust or how much they trust based on their relevant prior experiences, and this *web of trust* is used as a primary and underlying source of inferring trust connectivity and the degree of trust value without prior interaction.

Recently, most of the work on 'trust prediction' has focused on developing a trust inference model which propagates trust values through a web of trust (a network connected by trust) to predict an opinion of another user without prior interaction. However, a user has limited experiences on online communities and tends to express trust in a small number of people. Moreover, since users' judgement on trust is intuitive and overall evaluation based on experiences [1], online communities ask users to evaluate if they trust another user or not. Therefore, a web of trust (i.e., a trust matrix) is too sparse and binary to calculate trust value between any two people with high accuracy [5].

In order to overcome the sparseness of a web of trust, we consider a user's reputation (i.e., expertise) and affiliation for contexts as main factors to derive trust connectivity and the degree of trust value. The main idea is that a user would trust an expert in the area of interest that matters greatly to her. For example, if a user A is mostly interested in movies, she is deeply involved in movie review communities and then will trust experts who share high quality reviews on movies in online communities.

Unlike trust, reputation is an opinion of online communities about a single user, so it would represent objective views of the user's expertise from online community members. Reputation is reflected by summarizing of the quality of information which a user produces. The quality of information can be calculated based on received ratings from other users. People's expertise usually varies across knowledge contexts, so a user's reputation should be calculated by context [6], [7]. A user who has a good reputation on movies will quickly gain trust on movie recommendations in the surrounding neighborhood of people who are interested in movies by word-of-mouth effects in online communities.

A user's affinity for a context can be captured from her history in an online community, such as reading and evaluating other users' reviews and writing reviews for some categories in which she is interested. For example, user A is interested in movies and electronic products according to her history of activity, and user B has developed a good reputation on movie recommendations by writing many helpful reviews. In this situation, if user A trusts user B, we can expect that user A's trust for user B comes from the movie context, and not the electronic product context.

A trust decision is based on the reputation of an information provider and affinity of an information consumer for each context. Moreover, users' reputation and affinity for contexts can be calculated based on rating data which is easily collected and is much larger than trust directly expressed by users. Therefore, we can compute a degree of trust by combining reputation and affiliation for contexts and ultimately get a denser web of trust with rating data in an online community.

In this paper, we will provide a framework for deriving degree of trust based on users' expertise (i.e., reputation) and affinity for contexts, using rating data and without the existence of a web of trust entry between them. Our framework is proposed for the online community which allows users to write text reviews for various products and to evaluate other users' reviews with numerical ratings.

The remainder of the paper is organized as follows. In Section 2, we provide an overview of the related work on trust inference models. In Section 3, we describe our framework for deriving degree of trust including detailed calculation models. In Section 4, we provide experimental results comparing the baseline model on a real world dataset. Section 5 concludes this paper.

## II. Related Work

Most recent work in the area of developing 'prediction models of trust' can be divided into global and local trust models. Global trust models compute a universal measure of trust in the social network [8], [9]. Reference [8] introduced the EigenTrust algorithm to calculate trust rating of each node in a network with a variation of the PageRank algorithm. Reference [9] proposes a trust algorithm which returns a trust ranking of all the nodes in the network based on finding the principal eigenvector. The objective of the global trust model is to rank all nodes with a universal trust value, rather than calculating the absolute trust value of each user in a network.

On the other hand, local trust models calculate personalized trust value for each user based on each user's historical experience and a web of trust [3], [5]. Reference [3] proposes a trust inference model called TidalTrust which infers trust value in continuous trust networks. In the TidalTrust algorithm, when the source node infers a trust rating for the sink, it asks the source's trusted neighbours the trust rating for the sink node, and then calculates a weighted average of trust rating of its neighbours to the sink node. This research has shown that highly trusted neighbours and closer neighbours are more accurate in predicting a user's trust value. The TidalTrust algorithm is also strongly affected by the density of a web of trust. If a web of trust is too sparse, it is hard to find paths from the source to the sink and highly trusted neighbours which have paths to the sink. Moreover, TidalTrust model is only applicable to a social network with continuous trust values. Reference [5] proposes a trust propagation algorithm which combines distrust with trust and propagates them through a network. The sparsity of a web of trust can be reduced by introducing the concepts of co-citation, transposition of trust and trust coupling. A relatively low error rate has been observed in predicting trust/distrust between two unknown users. However, it is not always possible to get distrust values in online social communities.

Most current research on trust inference models strongly relies on trust values (binary or continuous) directly collected from users. However, trust value is not always available and even if so, it may be too sparse to calculate trust connectivity and degree of trust between two random users in a network without direct interaction. Thus, there is need for an approach which is not handicapped by this requirement. This is the focus of our research.

## III. A Framework for Deriving Trust

In this section we describe our framework for deriving degree of trust starting with users rating data.

As shown in Fig. 1, our framework consists of three major steps: The first step is to compute users' expertise (i.e., reputation) for each category and then to construct the Users_Category Expertise matrix E. The second step is to construct the Users_Category Affiliation matrix A which shows how much a user is involved in each category. The last step is to derive a Trust matrix $\hat{T}$ by combining Users_Category Expertise matrix E and Users_Category Affiliation matrix A.

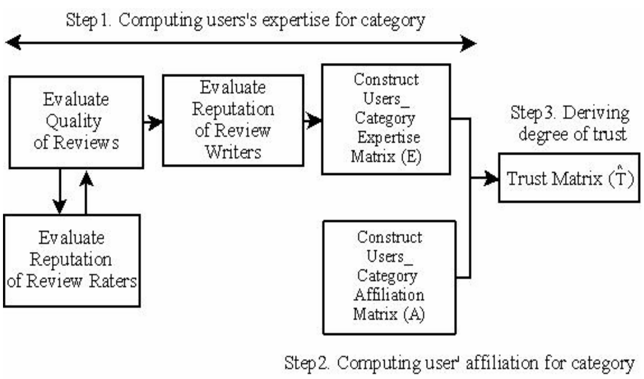


Fig. 1 A framework for deriving degree of trust

### A. Step 1. Computing Users' Expertise for Category

The general idea of the computation of a review writer's reputation (i.e., expertise) for each category is that good review writers are those who write many high quality reviews for a category. The quality of a review is the weighted average of ratings received from review raters. In the calculation of quality of reviews, we adopt Riggs' model [7] which considers how reliable a review rater is in terms of evaluation of reviews. As shown in Fig. 1, we calculate the quality of a review and the reputation of a review rater for each category, before calculating a review writer's reputation for each category. It is noted that the reputation of review rater, the quality of review and the reputation of review writer should be calculated for each category.

Fig. 2 illustrates how a review writer is connected to a review rater based on a review in an online community. A user, review writer $u_i^w$ writes a review $r_j$ on an object $o_j$ in a category $C_j$. A user, review rater $u_i^r$ gives a rating $\rho_{ij}$ to a review $r_j$.

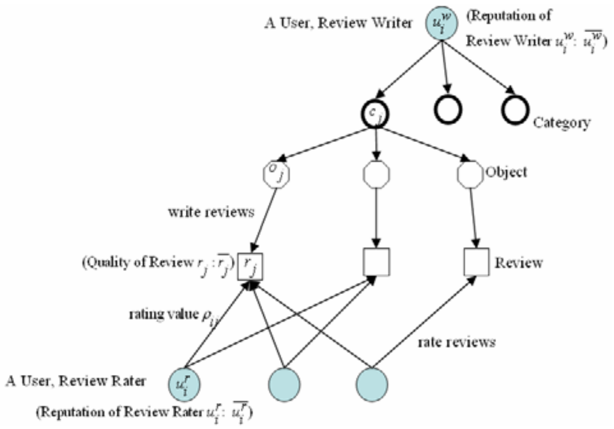


Fig. 2 The relationship between a review writer and a review rater

For ease of reference, we provide the description of major notation in Table 1.

TABLE I
THE GLOSSARY OF MAJOR NOTATION

| Notations | Meaning |
|---|---|
| $u_i^w$ | A user, *i*-th review writer |
| $\overline{u_i^w}$ | A reputation of *i*-th review writer |
| $u_i^r$ | A user, *i*-th review rater |
| $\overline{u_i^r}$ | A reputation of *i*-th review rater |
| $r_j$ | The *j*-th review on an object |
| $\overline{r}_j$ | A quality of the *j*-th review on an object |
| $\rho_{ij}$ | A rating value that the *i*-th rater gives to the *j*-th review on an object |

*1) Calculating Quality of a Review and Reputation of a Review Rater:* As mentioned earlier, we adopt Riggs' model [7] in order to calculate the quality of a review and reputation of a review rater. The quality of a review is a weighted average of received ratings. The rating value from a reliable rater is weighted more heavily than that from a less reliable rater, as follows:

$$\overline{r_j} = \frac{\sum_{i \in U^r(r_j)} \overline{u_i^r} \rho_{ij}}{\sum_{i \in U^r(r_j)} \overline{u_i^r}}$$

where $\overline{r_j}$ is the quality of a review $r_j$ $(0 \le \overline{r_j} \le 1)$,

$U^r(r_j)$ is the set of review raters that rate a review $r_j$ (1)

$\overline{u_i^r}$ is the reputation of a review rater $u_i^r$

$\rho_{ij}$ is a rating value that a rater $u_i^r$ gives to a revew $r_j$

According to Riggs' model, reliable review raters are those who consistently evaluate reviews near their ultimate weighted average (i.e., the final quality score of a review). The model also considers the number of reviews that a rater $u_i^r$ evaluates in a category (i.e., $n_{u^r}$ ) when computing the reputation of a review rater. Since, if a review rater has rated just one review close to the average, it is hard to conclude the rater is a reliable rater. Hence, it compensates for less experience of rating reviews by discounting the number of reviews as $1 - 1/(n_{u^r}+1)$.

The formula for calculating reputation of a review rater is defined as:

$$\overline{u_i^r} = \left(1 - \frac{1}{n_{u_i^r}+1}\right) \times \frac{\sum_{j \in R(u_i^r)} 1 - \left|\overline{r_j} - \rho_{ij}\right|}{n_{u_i^r}}$$

where $\overline{u_i^r}$ is the reputation of a review rater $u_i^r$ $(0 \le \overline{u_i^r} \le 1)$

$n_{u_i^r}$ is the number of reviews that a rater $u_i^r$ evaluates in a category (2)

$R(u_i^r)$ is the set of reviews that a rater $u_i^r$ evaluates in a category

*2) Calculating Reputation of a Review Writer:* We aggregate the quality of all reviews that a review writer has written in a category for the computation of reputation of a review writer as follows:

$$\overline{u_i^w} = \left(1 - \frac{1}{n_{u_i^w}+1}\right) \times \frac{\sum_{j \in R(u_i^w)} \overline{r_j}}{n_{u_i^w}}$$

where $\overline{u_i^w}$ is a review writer $u_i^w$'s reputation $(0 \le \overline{u_i^w} \le 1)$

$n_{u_i^w}$ is the number of reviews that writer $u_i^w$ writes in a category (3)

$R(u_i^w)$ is the set of reviews that a writer $u_i^w$ writes in a category

The reputation of a review writer is an average of the quality of all reviews that a review writer has written in a category. We also consider the number of reviews (i.e., $n_{u^w}$ ) in order to discount less experience of writing reviews as $1 - 1/(n_{u^w}+1)$. Therefore, review writers who write high quality reviews more than others have higher reputation as a review writer.

*3) Constructing Users_Category Expertise Matrix E:* After calculating reputation of review writers in each category, we can construct Users_Category Expertise matrix E. This is a U x C matrix where U is the number of all users in an online community and C is the number of all categories. $E_{ij}$ is the reputation of the *i*-th user *i* for a category $C_j$.

### B. Step 2. Computing Users' Affiliation for Category

In multi-context social networks like Epinions.com, users may be involved in multiple contexts (i.e., categories), but may not necessarily have the same level of affinity for or interests in all categories. So, we need to identify users' affinity by category, which will be used to identify all categories where a user's trust decision comes from, and weight review writers' expertise for each category when deriving the degree of trust. A users' affinity is measured by counting the number of rating of reviews and the number of writing of reviews in each category. In general, a user is able to rate multiple reviews on one object, but a user is often allowed to write only one review on an object. Thus, the number of ratings of reviews is much larger than the number of object reviews. Therefore, we calculate users' affiliation as follows:

$$A_{ij} = \left( \frac{a_{ij}^r}{\max\limits_{j \in all\ category} (a_{ij}^r)} + \frac{a_{ij}^w}{\max\limits_{j \in all\ category} (a_{ij}^w)} \right) \times \frac{1}{2}$$

$A_{ij}$ is the affiliation of a user $i$ for category $j$ $\left(0 \le A_{ij} \le 1\right)$ (4)

$a_{ij}^r$ is the total number of review that a user $i$ rates on a category $j$

$a_{ij}^w$ is the total number of review that a user $i$ writes on a category $j$

$A_{ij}$ is the average of the normalized value of $a_{ij}^r$ and $a_{ij}^w$. With users' affiliation by category, we construct Users_Category Affiliation matrix A which is a U x C matrix. Here U is the number of users in an online community and C is the number of categories. The element $A_{ij}$ in a matrix A is an affinity value of the *i*-th user for category $C_j$.

### C. Step 3. Deriving Degree of trust

Since we assume that a user *i* would trust a user *j* who is an expert in categories that are more important to the user *i*, we consider a user *j*'s expertise for a category and a user i's affinity for the category in order to derive the degree of trust between two users as follows:

$$\hat{T}_{ij} = \frac{\sum\limits_{category\ c} A_{ic} E_{cj}^T}{\sum\limits_{category\ c} A_{ic}}$$

$\hat{T}_{ij}$ is the degree of trust that a user $i$ holds for a user $j (0 \le \hat{T}_{ij} \le 1)$

$A_{ic}$ is an affiliation level of user $i$ for a category $c$ (5)

$E_{jc}$ is expertise value of user $j$ on a category $c$

The degree of trust of a user *i* on a user *j*, $\hat{T}_{ij}$ is calculated as a weighted average of a user *j*' expertise for all categories and a value of expertise for a category with which a user *i* more affiliates is more weighted with a user i's affiliation value.

Since our framework does not rely on a web of trust, which even when available is often too sparse. Based on our approach, even though there is no path, or a very long path from a user i to a user j, we can calculate degree of trust between two users. If degree of trust $\hat{T}_{ij}$ is zero, it means no overlap exists between categories with which a user *i* has affinity and categories in which a user *j* has expertise. Ultimately, we can have a denser trust matrix $\hat{T}$ with a continuous trust value without requiring explicit trust data.

## IV. Experiments

In our experiments we have two objectives: First, we verify our reputation model of both a review writer and a review rater. Second, we verify our derived trust matrix $\hat{T}$ with a real-world dataset from Epinions.

### A. Datasets

The dataset for experiments is obtained from an online community site, Epinions (www.epinions.com) which allows users to writes text reviews and to rate other users' reviews with numerical ratings. Epinions also gives a web of trust that would allow a user to express trust of other users based on his/her previous experience. Our framework can be applied to any online community where we can compute users' expertise and affiliation for category with users' rating data. However, for the validation of derived trust matrix, we need an original trust matrix and then decide to experiment with Epinions' dataset

Because of the limitation of computational cost and time, we select one category, Video & DVD category for experiments. Video & DVD category is appropriate for our experiments since it has 12 sub categories and has significant size of data. In this category, a single user could watch many movies and then write reviews for various movies and rate many reviews with 5 stages which is assigned a score from 0.2 to 1 (i.e., not helpful: 0.2, most helpful: 1). In our experiments, we calculate a user's expertise and affiliation in each sub category.

We first crawled all the reviews in all sub categories of Video & DVD. From those reviews collected, we extracted all the users (i.e., writers and raters), Based on that list of users, we proceeded to crawl all the users' pages, extracting their profiles such writing and rating reviews as well as their trust-networks and then retain only the rating and trust data related to Video & DVD category. The final dataset has 44,197 users who write at least 1 review in at least 1 sub category or rate at least 1 review in at least 1 sub category. The datasets has 429,955 trust connectivity among them.

### B. Evaluation of Reputation Models.

*1) Reputation of Review Rater:* Epinions regularly selects top active review raters called Advisors based on the quality and quantity of ratings in each category by human experts. When we collected the data in Movies & DVD category, Epinions selected 22 Advisors in the category

In order to validate the model in each sub category, we reselect Advisors of each sub category among 22 Advisors by removing Advisors who never rate reviews in a sub category. In each sub category, we calculate all review raters' reputation, rank raters by reputation values and divide them into 4 quartiles (i.e., top 25%, … , bottom 25%). Then, we count the number of Advisors falling into each quartile in order to validate the distribution of Advisors. If our model is useful to evaluate review raters' reputation, the higher rank groups would have higher percentage of Advisors. Table 2 shows the performance of review raters' reputation model in 12 sub categories. Since the 98% of Advisors are included into Top 25% high reputation group by our model, we can believe that our models is effective to evaluate review raters' reputation.

TABLE 2
THE PERFORMANCE OF REVIEW RATERS' REPUTATION MODEL

| Genre (Category) | Rater | Advisors | | | | |
|---|---|---|---|---|---|---|
| | | **Total** | **Q1(Top)** | **Q2** | **Q3** | **Q4** |
| Action/Adventure | 11940 | 22 | 22(100%) | 0 | 0 | 0 |
| Adult/Audience | 946 | 21 | 18(85.7%) | 3 | 0 | 0 |
| Comedies | 14406 | 22 | 22(100%) | 0 | 0 | 0 |
| Dramas | 18879 | 22 | 22(100%) | 0 | 0 | 0 |
| Educations | 3211 | 22 | 22(100%) | 0 | 0 | 0 |
| Foreign films | 4473 | 22 | 22(100%) | 0 | 0 | 0 |
| Horror/Suspense | 341 | 11 | 22(100%) | 0 | 0 | 0 |
| Musical | 4420 | 22 | 22(100%) | 0 | 0 | 0 |
| Religious | 1189 | 20 | 19(95%) | 0 | 1 | 0 |
| Science/Fiction | 9041 | 22 | 22(100%) | 0 | 0 | 0 |
| Sports/Recreation | 3365 | 21 | 21(100%) | 0 | 0 | 0 |
| Westerns | 2041 | 21 | 21(100%) | 0 | 0 | 0 |
| **Overall** | | **248** | **244(98.4%)** | | | |

*2) Reputation of a Review Wrtier:* Epinions regularly selects top good review writers called Top Reviewers based on the quality and quantity of reviews and other factors in each category. We have 40 Top Reviewers in Movies & DVD category and reselect Top Reviewers of each sub category by removing Top Reviewers who never write reviews in a sub category.

With the same validation way of review raters' reputation model, we validate the distribution of Top Reviewers in each sub category. Table 3 shows the performance of review writers' reputation model. Even though the performance is lower than review raters' reputation model, this result that 89.4% of Top Reviewers are included into Top 25% high reputation group is still good enough to validate the effectiveness of our model.

### *C. Evaluation of a Derived Trust Matrix*

In this section, we experiment how much accurately our model predicts trust connectivity in an original trust matrix $T$ collected from Epinions. We also compare the result of our derived trust matrix $\hat{T}$ with the result of a baseline matrix $B$ where $B_{ij}$ is an average rating by a user $i$ on a user $j$'s all reviews as a degree of trust value.

TABLE 3
THE PERFORMANCE OF REVIEW WRITERS' REPUTATION MODEL

| Genre (Category) | Rater | Advisors | | | | |
|---|---|---|---|---|---|---|
| | | **Total** | **Q1(Top)** | **Q2** | **Q3** | **Q4** |
| Action/Adventure | 7410 | 37 | 36(97.3%) | 1 | 0 | 0 |
| Adult/Audience | 52 | 1 | 1(100%) | 3 | 0 | 0 |
| Comedies | 9043 | 37 | 36(97.3%) | 0 | 0 | 0 |
| Dramas | 13286 | 39 | 38(97.4%) | 1 | 0 | 0 |
| Educations | 655 | 29 | 23(79.3%) | 5 | 1 | 0 |
| Foreign films | 1299 | 26 | 20(77%) | 5 | 1 | 0 |
| Horror/Suspense | 29 | 1 | 1(100%) | 0 | 0 | 0 |
| Musical | 1299 | 27 | 21(77.8%) | 6 | 0 | 0 |
| Religious | 118 | 5 | 4(80%) | 1 | 0 | 0 |
| Science/Fiction | 4502 | 34 | 33(97.1%) | 1 | 0 | 0 |
| Sports/Recreation | 682 | 8 | 6(75%) | 2 | 0 | 0 |
| Westerns | 259 | 11 | 9(81.8%) | 2 | 0 | 0 |
| **Overall** | | **255** | **228(89.4%)** | | | |

Fig. 3 illustrates the density of our trust matrix $\hat{T}$, a direct connection matrix $R$ where $R_{ij} = 1$ if a user $i$ rates any reviews of a user $j$ and an Epinions trust matrix $T$.. Among all trust connectivity in **T**, trust connectivity in **(T-R)** is constructed even though two users has no connection in Movie & DVD category. So, we consider trust connectivity in $(\mathbf{T} \cap \mathbf{R})$ as trust connectivity in our category.

Since a ground trust matrix $T$ has a binary trust value (i.e. trust is 1 and others 0), we need to convert continuous trust value of our model and a baseline model into a binary trust for the validation. Given the row vector $\hat{T}_i$, we judge that a user $i$ trusts a user $j$ and convert its value into 1 if $\hat{T}_{ij}$ is within the top $k_i(\%)$ of all derived connections in $\hat{\mathbf{T}}$ in Fig.3. The value of $k_i(\%)$ is determined based on the user $i$' relative fraction of trust connections vs. all direct connections (i.e. $(\mathbf{R} \cap \mathbf{T})/\mathbf{R}$ for each user i). The motivation behind this conversion is to consider each user's generousness of trust decision compared to total number of direct connection. Through this converted process for our trust matrix $\hat{T}$ and a baseline matrix $B$, we have new binary trust matrix $\hat{T}'$ and $B'$ where $\hat{T}'_{ij} = 1$ and $B'_{ij} = 1$ if a user i trusts a user j and others are zero.

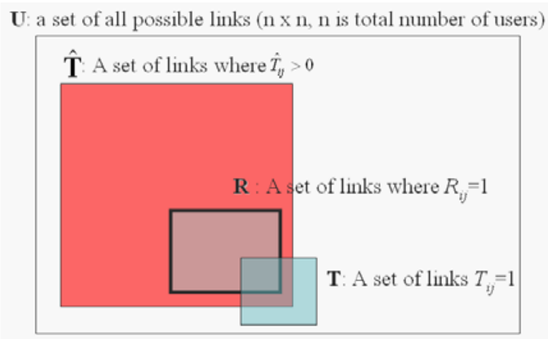


Fig. 3 The density of a derived matrix, a direct connection matrix and Epinions trust matrix

In Fig. 3, we can know about trust connectivity in $(\mathbf{T} \cap \mathbf{R})$ and direct connection but non-trust connectivity (not distrust) in **R.** So, we calculate 3 metrics with information in **R** for a validation as follows:

- Recall of trust= $\dfrac{\text{count}(\hat{T}'_{ij}=1 \ \& \ R_{ij}=1 \ \& \ T_{ij}=1)}{\text{count }(R_{ij}=1 \ \& \ T_{ij}=1)}$
- Precision of trust in **R**
$= \dfrac{\text{count}(\hat{T}'_{ij}=1 \ \& \ R_{ij}=1 \ \& \ T_{ij}=1\ )}{\text{count }(R_{ij}=1 \ \& \ \hat{T}'_{ij}=1)}$
- The rate of predicting non- trust as trust in **(R-T)**
$= \dfrac{\text{count}(\hat{T}'_{ij}=1 \ \& \ R_{ij}=1 \ \& \ T_{ij}=0\ )}{\text{count }(R_{ij}=1 \ \& \ T_{ij}=0)}$

Table 4 shows the results of validation for Trust matrix

TABLE 4
THE VALIDATION RESULTS FOR TRUST MATRIX

| Model | recall | Precision | The rate of predicting non-trust as trust |
|---|---|---|---|
| $\hat{T}$ (our model) | 0.857 | 0.245 | 0.513 |
| $B$ (a baseline) | 0.308 | 0.308 | 0.134 |

Our derived trust matrix $\hat{T}$ shows much better performance of recall than a baseline matrix $B$. It means our model can predict trust connectivity with high accuracy without a web of trust. We also see that the precision of our model is lower and the rate of predicting non-trust as trust in **(R-T)** is higher than a baseline model. The results looks like that our model is not good to predict trust connectivity in **(R-T).** However, we look into all connectivity where $\hat{T}'_{ij} = 1$ in **(R-T)** and all connectivity where $\hat{T}'_{ij} = 1$ in $(\mathbf{T} \cap \mathbf{R})$ in order to find how much different their trust value $\hat{T}_{ij}$ between two groups since we don't have correct information of trust connectivity in **(R-T)**. Then, we find that the average and minimum value of $\hat{T}_{ij}$ in **(R-T)** is higher than $(\mathbf{T} \cap \mathbf{R})$. It means that our model predicts a lot of connection in **(R-T)** as trust since it expects their connections would become trust connectivity in the future based on their expertise and affiliations. In summary, our framework can derive much denser trust connectivity with higher accuracy compared to a baseline model and an original trust matrix

## V. CONCLUSIONS

Many online social communities build and maintain a web of trust (trust network) that would allow users to express trust towards other users. With a web of trust, the idea is to (try to) predict the entire web of relationships to help users find high quality information without previous interaction [5]. However, a web of trust is not always available especially in e-commerce environments which have only raters' rating data on reviewers' reviews of items. Even though sometimes direct trust data is available, it is usually far too sparse to construct the entire web of trust, or predict specific relationships with high accuracy. In this paper, we propose a framework to derive degree of trust based on users' expertise for context and users' affinity for context, which shows good performance in predicting trust connectivity with a real-world dataset. With this framework, we can predict trust connectivity and degree of trust without a web of trust, and apply the computed pairwise to any online community including e-commerce environments with users rating data. For further research, we will propagate our derived web of trust and compare the propagation results between our web of trust and a web of trust constructed with users' explicit trust rating.

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