The Influence of Interaction Attributes on Trust in Virtual Communities

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Abstract. In virtual communities (*e.g.*, forums, blogs), modeling the trust of community members is an effective way to help members make decisions about whose information is more valuable. Towards this goal, we first formulate hypotheses on how various interaction attributes influence trust in virtual communities, and validate these hypotheses through experiments on real data. The influential attributes are then used to develop a trust ranking-based recommendation model called TruRank for recommending the most trustworthy community members. Contrary to traditional recommender systems that rely heavily on subjective manual feedback, our model is built on the foundation of carefully verified objective interaction attributes in virtual communities.

Keywords: Trust, reputation system, recommender system, virtual community.

1 Introduction

Since Web 2.0, virtual communities (also known as online communities such as forums, blogs, newsgroups, social networks, *etc.*) have spread over the Web, enabling different people to interact with one another. People share information, express opinions, and exchange ideas. The continuously growing size of members and information with widely varying quality in virtual communities has raised various issues among community members: Whom should I trust and whose information is more valuable to me?

To address this challenge, some virtual communities such as *Slashdot*[1] introduce features to enable their members to tag other members as either friend or foe and allow them to explicitly mark information resources trustworthy or untrustworthy in their own opinions. Obviously, such non-automatic mechanism requires community members to manually decide trustworthy people on their own, and thus, is not scalable as the size of a community can be very large, consequently information about friends and foes that is manually identified by users in *Slashdot* is incomplete. As a result, the topic of recommender and reputation systems where users generally make decisions based on automatically generated recommendations has received considerable attention in recent years.

[1] http://www.slashdot.org, is a famous news and comment based virtual community.

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Related Work. Many types of recommender systems were studied [20]: Such recommender systems rely heavily on ratings given by users in order to predict preferences [1]. For example, collaborative filtering systems require users to rate items to express their preferences. The systems then find users with similar preferences using different algorithms such as cosine similarity and pearson correlation to generate recommendations for users based on similarity among users. However, since these systems rely on subjective rating values, they suffer from the problems of unfair rating and discrimination[8].

Traditional reputation systems for e-commerce allow users to rate one another or rate products or services based on their quality [8]. From these ratings, reputation systems compute users' trust or reputation. Typically, interactions, especially communications among members, take place frequently in virtual communities. Therefore, without incorporating members' rich interaction information (*e.g.*, comments on others' postings, length of users' comments, and the timestamp when the comments are provided), rating-based reputation systems in e-commerce are not able to reflect a member's trustworthiness objectively and accurately in the context of virtual communities.

Recent research has also incorporated trust models into recommender systems to improve the accuracy of recommendation by taking into account user trustworthiness as well as preference similarity. Three typical types of trust-based recommender systems have been studied [18,7,5]. However, recently they have been proven to be vulnerable to various attacks through unfair ratings [4].

On members' interaction information, although several interaction attributes have been studied [10,13], their influence on trust has not been explored. Of these, few studies connect interaction attributes with trust [19]. In addition, they do not compute trust in virtual communities based on members' interaction information like *count* and *strength*, as well as neglecting to carefully verify how these interaction attributes influence trust and failing to incorporate other attributes [10,13].

Methodology. In our work, we first investigate various interaction attributes, including the ones studied by Kaltenbrunner *et al.* and Leskovec *et al.* [10,13]. We then propose hypotheses on how they influence trust in the context of virtual communities. We also process real data collected from *Slashdot* and conduct regression analysis to evaluate the relationship between the proposed interaction attributes and trust. Based on the validated hypotheses, we propose a novel trust ranking-based recommendation model called TruRank to recommend the most trustworthy community members based on interaction information.

Contributions of Our Work. Our investigation reveals four new interaction attributes that influence trust in virtual communities, and reinforces the fact that manual feedback are not accurate for evaluating the trust of community members. We extend user's view of trust in virtual communities by four additional perspectives: interaction quality, seriousness in interactions, consistency over a long period, and common interest. The proposed trust ranking-based recommendation model TruRank supported by the extended view of trust has several important advantages over traditional recommender systems for recommending trustworthy members in virtual communities.

Paper Structure. The rest of the paper is organized as follows. In Section 2 we discuss the concept of trust in virtual communities that guides our work. Section 3 formulates hypotheses on the influencing factors of trust from various interaction attributes. In Section 4 we prove our proposed hypotheses with extensive experiments on real data collected from *Slashdot*. A novel trust ranking-based recommendation model TruRank is proposed and discussed in Section 5. We then conclude in Section 6.

2 Trust in Virtual Communities

Before proposing our hypotheses, we first formulate an indicator for the trustworthiness of user A from the point of view of user B within a certain time period ΔT. Trust is a very broad concept and there is no commonly agreed definition that fits all purposes [15]. Jøsang *et al.* defined trust purpose as an "overarching concept that can be used to express any operational instantiation of the trust classes" [8]. Mui *et al.* defined trust as a "subjective expectation an agent has about another's future behavior based on the history of their encounters" [17]. Here, trust emphasizes a local view of an agent through direct interactions. Massa and Avesani [16] pointed out that due to the significant proportion of controversial users (who are trusted and distrusted by many), a global agreement of the trustworthiness value of these users cannot exist. They preferred a local view in the prediction of the trustworthiness of a user in a personalized manner; that is, user B develops a trust for A based only on B's personal view of her interactions with A.

In the context of virtual communities, we note that having a continuous supply of knowledge from members is the greatest challenge. Many virtual communities failed due to members' low willingness to share knowledge with others [3,14]. Following the interpretation of trust in virtual communities—which is "openness to discussion and willingness to share data" [19], we formulate a concept of the trustworthiness of user A from the point of view of another user B. From the concept of provision trust by Grandison and Sloman's classification [6], we use the number of replies $N^{\Delta T}(A, B)$ from user A to user B as the indicator for the trustworthiness of A from the point of view of B during the time period ΔT. Within a certain time period, if user A provides a larger number of direct replies than C to B, then from the view point of B, A is more open to discussion and more willing to share information (which also suggests more efforts in the "continuous supply of knowledge" [3]); thus, A is more trustworthy to B.

3 Hypotheses

In virtual communities, trust is influenced by many factors. Considering our view of trust in the context of virtual communities as formulated in the previous section, we explore five interaction attributes between a user pair: comment length, comment score, time difference between a posting and a reply, time variance of user A's comments to user B, and domain similarity of A's comments to B. Using these interaction attributes, we formulate 5 hypotheses of how these attributes influence the evaluation of the trustworthiness of A from B's perspective.

An interaction between users A and B is said to be of high quality if A provides useful and insightful information to B during the interaction, and/or *vice versa.* Interaction quality is of great importance when determining a user's trust with respect to another user. In other words, the higher interaction quality a user has with another, the more she can be trusted and relied on. Generally speaking, in virtual communities, interaction quality between two users can be reflected by the length of a comment from one user to another and the score the comment received. The longer a user's comment is, the higher the possibility that the comment contains rich and helpful information. Likewise, a user who usually writes long comments is perceived to be more trustworthy as the recipient is more likely to receive valuable information. On the score or rating of a comment received, a user whose comments always receive high scores tends to be perceived as more trustworthy. Hence, we propose two hypotheses:

- H1. During the time period ΔT, the average length of comments $X_{\ell}^{\Delta T}(A, B)$ provided by user A to B influences B's trust in A; the longer the comments from A, the higher is B's trust in A.
- H2. During the time period ΔT, the average score of comments $X_{s}^{\Delta T}(A, B)$ provided by user A to B influences B's trust in A; the higher the score of comments from A, the higher is B's trust in A.

Temporal patterns of time difference between a user's post and the comments (replies) provided by other users to the post have been analyzed in previous studies [9,10]. Although it was not verified, Skopik *et al.* suggested that the time intervals between a posting and its comments or replies may improve trust interpretation [19].

Consider the following scenario: When user B posts something, user C replies more quickly than user A to B's posting. From B's point of view, who is more trustworthy to him? There are two possibilities. Clearly, user C shows more eagerness to reply—this may suggest C's active involvement. On the other hand, an immediate reply from C may also indicate that C has not properly digested the posting from B; thus, user C can be seen to be exhibiting a casual attitude. Replies that came later could be due to more care and attention given to properly comprehend the posting from B. Thus, A could be seen to be more serious in the interaction. Based on these two possibilities, we propose the third hypothesis:

- H3. During the time period ΔT, the average time difference $X_{d}^{\Delta T}(A, B)$ between user A's reply to user B's post influences B's trust in A; the longer the time difference, the higher is B's trust in A.

In marketing, customers generally show a more positive attitude towards organizations which they have interacted with consistently over a long period of time. Lauterbach *et al.* claimed that interactions in virtual communities often carry great risk due to the lack of long-term relationships between parties [12]. In normal relationships, familiar old friends are usually more trustworthy. We incorporate long-term relationships into the study of trust, in the form of the "time variance" of users' interactions in virtual communities.

To clarify what we mean by "time variance", we first make the following assumption: Among users A, B, and C, if A's replies to B's posts are evenly spread out over a longer timeline while C's replies to B's posts are either (i) unevenly spread out over a short timeline, (ii) unevenly spread out over a long timeline, or (iii) evenly spread out over a short timeline, B sees A as more trustworthy than C. In this work, we compute time variance $X_v^{\Delta T}(A, B)$ from user A to user B during time period ΔT as follows:

$$X_v^{\Delta T}(A, B) = \prod_{i=1}^{n-1} |t_{i+1} - t_i| \tag{1}$$

where n is the number of replies from A to B during ΔT, and t_i is the time of A's ith reply to B. Eq. 1 has two interesting properties: (1) When the number of replies n and the time period ΔT are both fixed, $X_v^{\Delta T}(A, B)$ is maximum when A's replies are evenly spread out. Hence, when evaluating the interactions of different users in the same time frame and having the same message traffic, Eq. 1 ranks the most evenly spread out interactions the highest. (2) When the number of replies n is fixed but the time period ΔT may vary, $X_v^{\Delta T}(A, B)$ is larger when $|t_{i+1} - t_i|$ is larger[2]. Hence, when evaluating the interactions of different users having the same message traffic but across different lengths of periods of interactions, Eq. 1 ranks the longest period (history) of interaction the highest. To illustrate, if both user A and C reply 10 times to user B within 20 days: A replies evenly to B (say, every 2 days) while C replies unevenly to B (say, 5 replies in day 1 and the other 5 replies in day 20), B sees A as more trustworthy than C since A has interacted with B more consistently. If both user A and C reply 10 times evenly to user B across difference lengths of periods of interactions: A has interacted with B every 2 days within 20 days while C has interacted with B every day within 10 days, B sees A as more trustworthy than C since B has interacted with A for a longer time.

Thus, this calculation of time variance satisfies the above assumption. With this calculation, the fourth hypothesis is formulated as follows:

H4. During the time period ΔT, the time variance $X_v^{\Delta T}(A, B)$ among all of user A's replies to B influences B's trust in A; the larger the time variance is, the higher B's trust in A.

As mentioned in Section 1, traditional recommender systems generate recommendations to a user based on others sharing similar preferences with the user. In fact, virtual communities usually suggest friends to a user based on shared interest [13]. People tend to trust those who have common interest with them. We argue that the greater the proportion of user A's replies to B's posts falling

[2] We assume $|t_{i+1} - t_i| > 1$ by, for example, using milliseconds to represent time.

within A's favorite domain (*i.e.*, the domain of most of A's posts or replies), the more trustworthy A is from B's point of view. This can be further explained as follows. Previous work has shown that in this case user B plays the activator role [19] whose postings are worthy of discussion. Since B's posts attract replies from others (user A in this case), B is also considered to possess the expertise or competencies under this domain; this indicates that this domain is probably of B's interest too. Therefore, if most of A's interactions with B take place in A's favorite domain (which is also of interest to B), we can conclude that they share common interest and A is trustworthy to B.

In this paper, we use domain similarity to express similarity in users' interest. The domain similarity of user A from B's view point is determined as follows:

$$X_m^{\Delta T}(A, B) = s^{\Delta T}(A, B)/N^{\Delta T}(A, B) \tag{2}$$

where $s^{\Delta T}(A, B)$ is the number of replies (that are in the domain where A posts the most in the whole community) from A to B during time period ΔT and $N^{\Delta T}(A, B)$ is the number of replies from A to B during ΔT. Clearly, $X_m^{\Delta T}(A, B) = 1$ means that all of A's replies to B belong to both A and B's common domain of interest while $X_m^{\Delta T}(A, B) = 0$ means that there is maximum diversity between A and B's interest. As such, the fifth hypothesis is formulated as follows:

H5. During the time period ΔT, the domain similarity $X_m^{\Delta T}(A, B)$ of all of user A's replies to user B influences B's trust in A; the larger the domain similarity is, the higher B's trust in A.

4 Evaluation

In this section, we evaluate the five hypotheses proposed in the previous section using data from *Slashdot*. We first describe the data that are extracted from the website, then perform regression analysis to validate the hypotheses and analyze the results.

4.1 Data Collection

Slashdot is a forum for posting news and comments with a distinct, technology-centric culture. Once news has been posted, anyone may provide comments to the news or to other users' comments. Each news or comment can be posted in a various domain such as games, hardware, mobiles, stories, book reviews, and so on. Slashdot has introduced a moderation system to maintain the quality of postings. This consists of two layers where M1 is for moderating comments to news, and M2 is for moderating M1 moderators. In recent years *Slashdot* has been chosen as an ideal example in various studies on virtual communities [8,11]. To validate our hypotheses, we focus on the relationship between various interaction attributes and trust in *Slashdot*. We collected data from *Slashdot* comprising 102,199 comments written by 11,117 different users from December

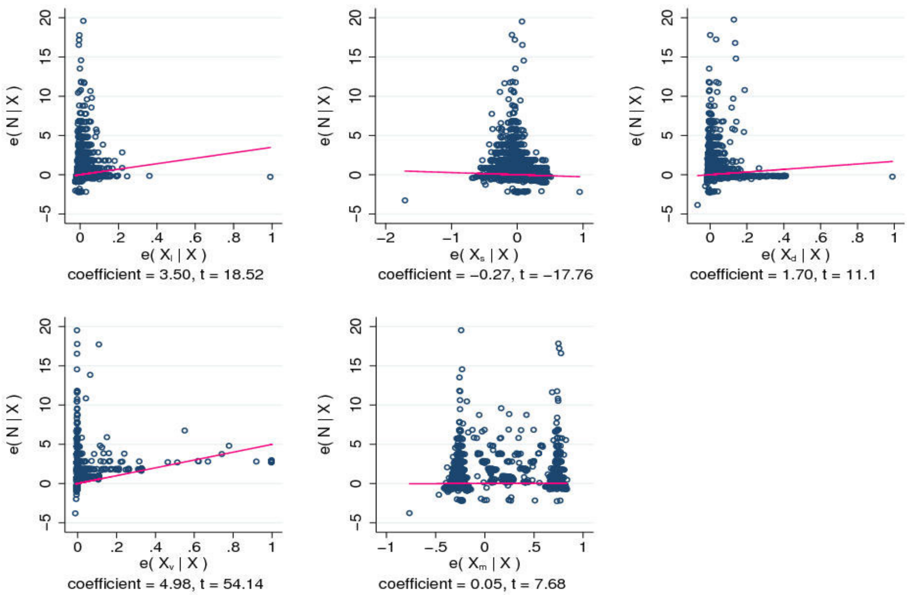

Fig. 1. Added-variable plots for each factor before filtering out outliers

20, 2003 to February 23, 2011 across all domains by random sampling users. The comments of each user are continuous with respect to certain time interval. The comment contents, comment scores, comment posted time, comment domains, and the user pairs (comment sender and comment recipient) are all included.

To improve the quality and representativeness of the data collected, we filtered out anonymous comments, replies to anonymous comments, and self-replies.

4.2 Experiments

After pre-processing the data as illustrated above, we continued to normalize data to ensure that they are in the same order of magnitude. To evaluate the influence of each interaction attribute on trust based on our hypotheses, we establish the following linear regression model:

$$N^{\Delta T}(A,B) = \beta_0 + \beta_\ell X_\ell^{\Delta T}(A,B) + \beta_s X_s^{\Delta T}(A,B) + \beta_d X_d^{\Delta T}(A,B) + \beta_v X_v^{\Delta T}(A,B) + \beta_m X_m^{\Delta T}(A,B) + \mu \tag{3}$$

In this model, β_ℓ, β_s, β_d, β_v, β_m are the coefficients of each factor (interaction attribute). The symbol β_0 is a constant and μ is an error term representing factors which cannot be directly observed or easily quantified.

Figure 1 shows the added-variable plots for each factor when performing regression analysis. It visually indicates that there exist individual points that are sufficiently remote from the bulk of the data when evaluating some of these factors. For example, due to the existence of extremely long or short comments,

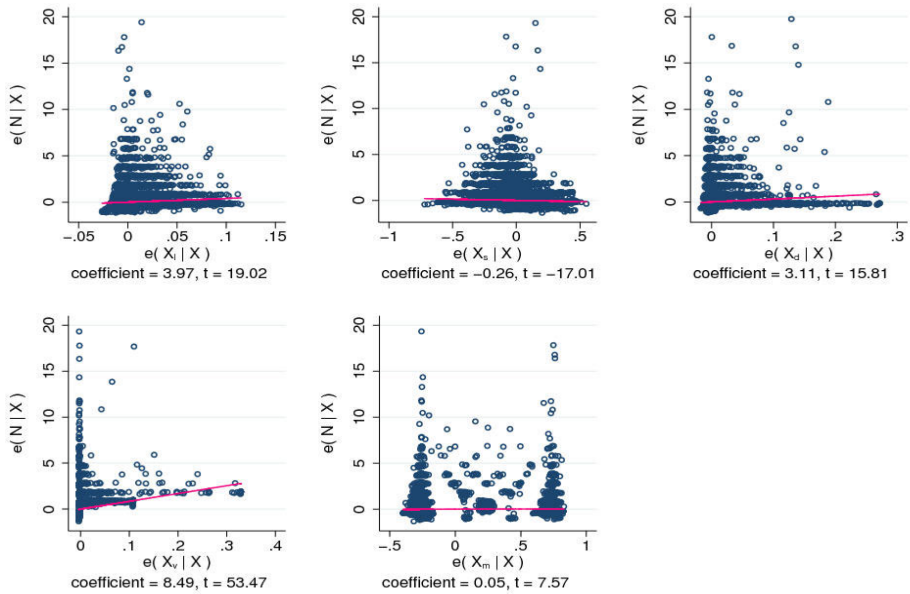

Fig. 2. Added-variable plots for each factor after filtering out outliers

there are outliers in the left-top plots (Figure 1) that seem most influential in determining the slope (they appear incidentally and often mislead the estimation of the coefficient). Hence, without distorting the overall distribution of data, we filtered out the top and bottom 0.1% comments ranked by length, time difference, and time variance where extreme values may appear. In Figure 2, most of these outliers have been removed. The notable increase in the coefficients of factors from comment length, comment time difference, and comment time variance justifies the use of outlier filtering.

Table 1. Regression Results of the Linear Model

Number of observations	42,104		
$F(5, 42098)$	781.05		
$Prob > F$	0.0000		
	Coefficient	t	$P > \|t\|$
Comment Length	3.97	19.02	0.000
Comment Score	-0.26	-17.01	0.000
Time Difference	3.11	15.81	0.000
Time Variance	8.49	53.47	0.000
Domain Similarity	0.05	7.57	0.000
Constant	1.21	126.45	0.000

4.3 Result Analysis

Regression results of our established model (Eq. 3) are presented in Table 1. The p values suggest that all the independent variables are significantly correlated with the dependent variable. This indicates that all the proposed interaction attributes in the model have significant influence on trust. In the following, we evaluate each of them based on the proposed hypotheses in Section 3.

From Table 1, given the positive coefficient (3.97), the comment length is positively correlated with trust, as measured by the number of replies. This validates the first hypothesis (H1). As an indicator of interaction quality, comment length determines whether a user is trustworthy or not. Our result shows that if user A always gives long comments (replies) to user B's postings in the past, B will regard A as trustworthy since from interactions with A, it is highly possible for B to gain a lot of valuable information.

As observed, comment score is negatively correlated with trust (coefficient is -0.26). This is contrary to Hypothesis H2. Previous studies showed low score comments may be hidden and comments with a score of 1 or 2 may not have been rated by many users [19,11]. Hence, we re-test our model after removing all low scored (-1 and 0) comments and filtering out potentially non-rated comments by sampling. From our experiment, the coefficient of $X_s^{\Delta T}(A, B)$ changes to -0.11 with the P value of 0.000. The negative coefficient still indicates the rejection of H2. To explain this, we review previous work that pointed out the limitations of the moderation system in *Slashdot*. According to Brennan *et al.*, classifying a comment into a specific score may involve much noise and the benefits of classifying a comment as 4 instead of 5 are negligible towards improving the interaction quality [2]. The study by Lampe and Resnick showed that low score comments, non top-level comments, or late posted comments are likely to be overlooked by moderators [11]. In other words, this reveals the existence of buried treasures; *i.e.*, comments that should have high scores but did not, also causes some trash to surfaced. Our experiment further reinforces that subjective manual feedback, and thus, models relying on them, may not be accurate or reliable.

The experiments support Hypothesis H3, as suggested by the positive correlation coefficient 3.11. We hence argue that a late reply suggests longer time incurred to digest comments and provide new insights. The serious attitude shown in late replies suggests their providers are trustworthy.

Among all the interaction attributes that influence trust, comment time variance is in a prominent position as indicated by the value of its coefficient 8.49, which is larger than any other interaction attribute. This is consistent with Hypothesis H4 and further shows that consistency over a long period of time is of great importance to evaluating an individual's trust.

Hypothesis H5 is validated by the positive correlation coefficient of 0.05. We may conclude that individuals with common interest can be trusted. As interest also indicates rich experiences or expertise, opinions on certain domains from people with common interest can be favored and considered as more trustworthy and valuable.

Alg. 1 : Trust Ranking-Based Recommendation Model: TruRank
Input : U, the user who wants to find trustworthy users;
$\overrightarrow{S}$, the users U has interactions with and wants to evaluate;
ΔT, the time period during which U interacted with $\overrightarrow{S}$;
$\overrightarrow{w_x}$, weighting values assigned by U according to his preferences;
Output: $\overrightarrow{S^k}$, the k most trustworthy users;

$R^{\Delta T}(U, \overrightarrow{S}) = \emptyset$;
$(w_n, w_\ell, w_d, w_v, w_m) \Leftarrow \overrightarrow{w_x}$;
foreach S_i *in* $\overrightarrow{S}$ **do**

$$R^{\Delta T}(U, S_i) = w_n R_n^{\Delta T}(U, S_i) + w_\ell R_\ell^{\Delta T}(U, S_i) + w_d R_d^{\Delta T}(U, S_i) + w_v R_v^{\Delta T}(U, S_i) + w_m R_m^{\Delta T}(U, S_i); \quad (4)$$

add $R^{\Delta T}(U, S_i)$ into $R^{\Delta T}(U, \overrightarrow{S})$;

sort($\overrightarrow{S}$, $R^{\Delta T}(U, \overrightarrow{S})$);
return $\overrightarrow{S^k}$: the k most trustworthy users;

5 Trust Ranking-Based Recommendation: TruRank

Section 3 and Section 4 have identified and validated that length of comments (interaction quality), time difference (seriousness in interactions), time variance (consistency over a long period), and domain similarity (common interest) influence the trustworthiness of a user from the view point of another user. These factors provide additional inputs to how one views trust arising from interactions in virtual communities. They lend new perspectives on existing recommender systems. Therefore, we propose a trust ranking-based recommendation model called **TruRank** (Alg. 1), in the context of virtual communities.

In this algorithm, Eq. 4 first calculates an aggregated ranking $R^{\Delta T}(U, S_i)$ for every user $S_i \in \overrightarrow{S}$. Then, based on the results from Eq. 4, the users in $\overrightarrow{S}$ are sorted in descending order. A number of the most trustworthy users (ranked top) will be recommended to the user U. Note that for each S_i in $\overrightarrow{S}$, $R_x^{\Delta T}(U, S_i)$ denotes the ranking number of S_i during ΔT when user U ranks S according to x where n is the number of replies, ℓ is the comment length, d is the time difference, v is the time variance, and m is the domain similarity.

Our TruRank demonstrates several advantages over traditional recommender systems. First, it is clear that TruRank provides a more comprehensive view of evaluating the trustworthiness of community members by integrating different carefully verified perspectives. Second, TruRank is highly configurable according to user's preferences. Users may configure the time period and set of members of their interest to be evaluated. Moreover, users may assign weighting values to each of the five interaction attributes according to their own preferred view of evaluating trust. For instance, in friend-based forums users may care more about common interest while ignoring other perspectives when choosing friends. However, in professional virtual communities, by evaluating potential work partners from the perspective of seriousness in interactions, user can expect to find serious colleagues to work together. After the ordered community members are generated, users may choose the top ranked members as trustworthy friends or colleagues. Therefore, the information (*e.g.*, book review) provided by their chosen friends, or knowledge (*e.g.*, about how the work can be done properly) shared by their chosen colleagues can also be trusted by users. Third, without considering subjective manual feedback (ratings) like what traditional recommender systems usually do, TruRank is objective and thus, more accurate.

6 Conclusions

In this paper we studied the influence of interaction attributes on trust in virtual communities. Compared with the state-of-the-art research literature, we make three unique contributions. First, we have identified and validated four new interaction attributes: comment length, time difference, time variance and domain similarity that influence trust in virtual communities by performing regression analysis on real data from *Slashdot*. We have further verified that subjective manual feedback (comment scores) are not accurate. Second, we have extended one's view of evaluating trust in virtual communities in four perspectives: interaction quality, seriousness in interactions, consistency over a long period, and common interest. With these new perspectives, trust in virtual communities can be evaluated in a more comprehensive way. Third, we have proposed a trust ranking-based recommendation model TruRank in the context of virtual communities. This novel model has several advantages over traditional recommender systems.

For future work, we will continue our efforts in evaluating whether TruRank reflects existing social relationships in virtual communities, such as the friends and foes directly identified by users in *Slashdot*. We also plan to verify our proposed hypotheses and TruRank using data from other virtual communities.

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