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# INTEGRATING INTERACTION AND SIMILARITY THRESHOLD OF USER'S INTERESTS FOR TOPIC TRUST COMPUTATION

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**Abstract**

This paper proposes a computational model of topic trust being constructed from users similarity and levels of their interaction. It is defined as function of similarity degrees in interests and levels of interaction in topics among users. Based on this model, we may estimate trustworthy values among peers in all cases with some direct and indirect interaction or without any interaction. The proposed approach may overcome limitation in the high computational cost of propagation methods based on graph models.

## 1 Introduction

Trust is a reliability which a user has on his partner in the process of its interaction. It is considered as an important factor for partners to share knowledge or to coordinate in actions with each others in distributed intelligent systems. There are various models of computational trust being proposed in literature

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[1][4][6][9][14]. However, they are mainly based on interaction experience among partners and lack of considering context for estimating the reliability.

In social networks, users utilize their own entries to annotate and organize items for searching or sharing viewpoints and opinions as well. Such entries are a kind of meta-data containing terms to introduce bookmarks, article titles, comments of items or digital images etc. They may contribute to discovering user interests for various applications such as recommender systems, searching engine, predicting customer preferences [11][12][13]. These entries also become contexts for performing estimation of trustworthiness among peers.

In our previous work [3][7][9], the computational topic trust in the social network is estimated via a function of connections and degrees of user's interests on topics among a *truster* on a *trustee*. However, these studies have paid no attention to the property of similarity of interests, which are considered as a critical factor for users connecting with each other in social networks [2]. Furthermore, our previous proposed algorithms must exhaustively find all possible paths in graph from a source truster to a sink trustee. Such a search computation needs to face with the high computational cost.

In this paper, we propose an enhanced approach in trust computation which is based on the combination of similarity of peers in degrees and levels of their interaction. The similar measure is constructed from interest degrees of users in topics. Whereas, interaction levels are the amounts of behaviors being given by peers such as like, share, post etc. on some topics. Such a integration method may overcome the limitation in the high computational cost of trust propagation in our previous models [3][8][9].

The remainder of this paper is structured as follows. Section 2 presents the background consisted of some concepts, definition and the representation of hierarchical structure of peers. Section 3 is devoted to modeling user's interests and similarity. Section 4 presents a definition of topic trust being formulated from direct interaction among peers, degree of user's interests on various topics and similarity among peers. Section 5 is conclusions.

# 2 Background

## 2.1 Notations and Definitions

This subsection presents some definitions and notations which are used in the rest of this paper.

- Each user in social media may be considered as an autonomous entity in the system. Let $\mathcal{U} = \{u_1, \ldots, u_m\}$ be a set of users being called *universe*, whose elements are also called a *peer*. In this paper, the terms of peer and user are used interchangeably;

- When a peer estimates a topic trust value on another peer then the former one is called a *source peer* or *truster* and the latter is a *sink peer* or *trustee*.
- Let $I_{ij}$ be a set of all interactions or connections between $u_i$ and $u_j$ and $\|I_{ij}\|$ be the number of such interactions. Each interaction between users $u_i$ and $u_j$ is a transaction at an instant time, which occurs when $u_i$ sends to $u_j$ via some "wall" messages such as post, comment, like, opinions etc.
- *Entry* is a brief piece of information dispatched from some user $u_i$ to make a description or post information/idea/opinions on an item such as a paper, a book, a film, a video etc. From such entries, we can construct a classification of them according to topics.

## 2.2 Hierarchical Structure of Peers

This subsection presents the concept of hierarchical structure in levels of peers being proposed in our previous work [3]. It is constructed from neighbors of peers as follows. If $u_i$ is source peer and has some direct interaction with $u_j$, then $u_j$ is called a neighbor of layer 1 or *1-neighbor* of $u_i$. With the convention that 0-neighbor of $u_i$ is $u_i$, we have a recursive definition of the concept of *k-neighbor* of $u_i$.

**Definition 1 ([3]).** *Given a peer $u_i$. A peer $u_j$ is a k-neighbor of $u_i$ ($k \geq 2$) iff two following conditions are satisfied:*

*(i) $u_j$ has no direct interaction from any peer of l-neighbor of $u_i$, for all $l \leq k-2$*

*(ii) There is at least a peer of (k-1)-neighbor of $u_i$, which has some direct connection with $u_j$.*

Denote $L_i^k$ for all $k \geq 1$ to be a set of k-neighbors of $u_i$. We have the following proposition.

**Proposition 1 ([3]).** *Given a source peer $u_i$. Then there exists a number $n_i$ such that $L_i^1 \ldots, L_i^{n_i}$ are k-neighbors of $u_i$ and satisfy the following conditions:*

*(i) For every $v \in L_i^k$ ($k = 2, \ldots, n_i$), $v$ not being interacted directly with any one in $\cup_{l=0}^{k-2} L_i^l$.*

*(ii) $L_i^k \cap (\cup_{l=0}^{k-1} L_i^l) = \emptyset$, for all $k \geq 1$.*

We call $L_i^1 \ldots, L_i^{n_i}$ to be a *taxonomy* or a *hierarchy* of neighbors of $u_i$. Estimation of trust value of a source peer on a sink peer depends on which level the sink one belongs to. This paper focuses first on investigating a class of functions for estimating a trust degree of a source peer on sink peers in 1-level. Then we consider to take advantage the similarity of 1-level users with sink peers (not of 1-level) for constructing trustworthiness.

## 3 Modeling User's Interests and Similarity

Suppose that $\mathcal{E} = \{E_1, \ldots, E_m\}$ be the set of entries dispatched by users $\mathcal{U} = \{u_1, \ldots, u_m\}$, where $E_i = \{e_{i1}, \ldots, e_{im_i}\}$ are entries given by $u_i$. Then we might classify these entries into classes w.r.t. the set of topics $\mathcal{T} = \{t_1, \ldots, t_n\}$. There are many techniques for such a classification e.g. in [12]. We denote $classifier(E_i, \mathcal{T})$ the function for classifying entries of $u_i$ into classes.

**Definition 2.** *Suppose that $n_i^t$ is the number of entries in some topic $t \in \mathcal{T}$ a user $u_i \in \mathcal{U}$ has dispatched. Then the interest degree of $u_i$ on topic $t$ is defined by the following formula*

$$interest_{topic}(i,t) = \frac{1}{2}\left(\frac{n_i^t}{\sum\limits_{l \in \mathcal{T}} n_i^l} + \frac{n_i^t}{\sum\limits_{u_k \in \mathcal{U}} n_k^t}\right) \tag{1}$$

Denote $u_i^k = interest_{topic}(i, t_k)$, each peer $u_i$ is then defined as a vector of interests on various topics.

**Definition 3.** *Degrees of user's interest on all topics is defined as a vector*

$$\mathbf{u_i} = (u_i^1, \ldots, u_i^n) \tag{2}$$

*in which $u_i^k$ is the interest degree of user $u_i$ in topics $t_k \in \mathcal{T}$ $(k = 1, \ldots, n)$.*

Based on this interest degree we can construct a similar measure as follows:

**Definition 4.** *Similarity degree of two peers $u_i$ and $u_j$ is defined as a cosine similarity of two vectors $\mathbf{u_i}$ and $\mathbf{u_j}$*

$$sim(u_i, u_j) = \frac{\mathbf{u_i} \cdot \mathbf{u_j}}{\|\mathbf{u_i}\| \times \|\mathbf{u_j}\|} \tag{3}$$

*in which $\cdot$ is the scalar product, $\times$ is the usual multiple operation and $\|.\|$ is the usual length of vector.*

**Definition 5.** *Given $L_i^k$ a k-level of $u_i$. The average similarity threshold of the k-level w.r.t. $u_i$ is defined by the formula*

$$\alpha_i^k = \frac{\sum_{v \in L_i^k} sim(u_i, v)}{\|L_i^k\|} \tag{4}$$

From this concept we can define *k-level close friend* as follows:

**Definition 6.** *A peer $v \in L_i^k$ is a k-level close friend of $u_i$ w.r.t. $\alpha$ iff its similarity with $u_i$ is greater than threshold $\alpha$. Denote $L_i^{k,\alpha} = \{v \in L_i^k | sim(u_i, v) \geq \alpha\}$*

In this paper, we focus on investigating the class of close friends in 1-level w.r.t.$\alpha$.

# 4 Reference Topic Trust based on Interaction Experience and Similarity

Based on similarity constructed in Section 3, we now develop an approach for estimating topic trust. Trustworthiness among peers is then represented with their interaction experience and the context of interests in various topics. In this section, we present a model of estimating trust values based on interaction experience and users interests. The model is considered as a complementary work with ones proposed by ourselves [7][3].

**Definition 7 ([3]).** *A function* $trust_{topic} : \mathcal{U} \times \mathcal{U} \times \mathcal{T} \rightarrow [0, 1]$ *is called a topic trust function, in which* $[0, 1]$ *is an unit interval of the real numbers. Given a source peer* $u_i$*, a sink peer* $u_j$ *and a topic* $t$*, the value* $trust_{topic}(i, j, t) = u^t_{ij}$ *means that* $u_i$ *(truster) trusts* $u_j$ *(trustee) of topic* $t$ *w.r.t. the degree* $u^t_{ij}$*.*

**Definition 8 ([3]).** *Experience trust of user* $u_i$ *on user* $u_j$*, denoted* $trust^{exp}(i, j)$*, is defined by the formula*

$$trust^{exp}(i, j) = \frac{\|I_{ij}\|}{\sum_{k=1,k\neq i}^{m} \|I_{ik}\|} \tag{5}$$

*where* $\|I_{ik}\|$ *is the number of connections* $u_i$ *with each* $u_k \in \mathcal{U}$*.*

Based on the degrees of interaction and of user's interests, we can define the *experience topic trust* for sink peers of 1-friend of $u_i$ as follows.

**Definition 9.** *Suppose that* $trust^{exp}(i, j)$ *is the experience trust of* $u_i$ *on* $u_j$ *and* $interest_{topic}(j, t)$ *is the interest degree of* $u_j$ *on the topic* $t$*. Then the experience topic trust of* $u_i$ *on* $u_j$ *of topic* $t$ *is defined by the following formula:*

$$trust^{exp}_{topic}(i, j, t) = \beta \times trust^{exp}(i, j) + \gamma \times interest_{topic}(j, t) \tag{6}$$

*where* $\gamma, \beta \geq 0,\ \beta + \gamma = 1$*.*

It is easy to see that

**Proposition 2.** *The function* $trust^{exp}_{topic}(i, j, t)$ *is a topic trust function.*

Thus values of topic trust, which source peers assign to sink peers, belong to the unit interval $[0, 1]$. **Definition 9** implies an important fact that the more a peer interacts with an opponent, the higher it is reliable on some topic; the higher interest degree of a peer is, the more trust on him it should be assigned. The formula (6) is also considered as a linear function of experience trust and interests compared with nonlinear functions in [3].

The degrees $\beta, \gamma$ are parameters which represents correlation of interest degrees and interaction in social networks. These parameters need to be measured by means of experiments. In this paper, we accept the couple of values $\beta = \gamma = \frac{1}{2}$ for presenting algorithms.

**Definition 10.** *Given a source peer $u_i$. Let $L_i^p$ be the $p-level$ of $u_i$ and $L_i^{p,\alpha}$ be the set of p-level close friends of $u_i$. Then, the reference topic trust is defined by the formula:*

$$trust_{topic}^{ref}(i,j,t) = \frac{\sum_{v \in L_i^{p,\alpha}} trust_{topic}^{exp}(i,v,t) \times sim(v,j)}{\|L_i^{p,\alpha}\|} \tag{7}$$

It is easy to prove the following proposition

**Proposition 3.** *The function $trust_{topic}^{ref}(i,j,t)$ is a topic trust function.*

The steps of computing reference topic trust of $u_i$ on $v$ via its interaction and similarity are described in **Algorithm 1**.

**Algorithm 1** Computing Topic Trust of $u_i$ on $u_j$ of topic $t$ via interaction and Similarity

**Input:** The set of topics $\mathcal{T} = \{t_1, t_2, ..., t_n\}$, the set of users $\mathcal{U} = \{u_1, u_2, ..., u_m\}$ and the set of entries $\mathcal{E} = \{E_i | i = 1, \ldots, m\}$
**Output:** $computeRefTopicTrust_{topic}^{ref}(i,v,t)$.

$C_i = \{C_i^t | t \in \mathcal{T}\} \leftarrow classifier(E_i, \mathcal{T})$ //classifying entries into classes
$n_i^t \leftarrow \|C_i^t\|$
$u_i^k \leftarrow interest_{topic}(i,t)$ //formula (1)
$\mathcal{P} \leftarrow constructTaxonomy(i)$ //constructing the set of $L_i^k$ $(k = 1, \cdots, n_i)$
**for all** $t$ in $\mathcal{T}$ **do**
  **for all** $p$ $(1 \le p \le n_i)$ **do**
    $\alpha_i^p \leftarrow \frac{\sum_{v \in L_i^p} sim(u_i,v)}{\|L_i^p\|}$ //formula (4)
    $L_i^{p,\alpha} \leftarrow \{v \in L_i^p | sim(u_i,v) \ge \alpha_i^p\}$ //Definition (6)
    **for all** $j$ in $L_i^{p,\alpha}$ **do**
      $e_{i,j}^t \leftarrow \beta \times trust^{exp}(i,j) + \gamma \times interest_{topic}(j,t)$ //formula (6)
    **end for**
    $r_{i,v}^t \leftarrow \frac{\sum_{u_j \in L_i^{p,\alpha}} e_{i,j}^t \times sim(u_j,v)}{\|L_i^{p,\alpha}\|}$ //formula (10)
  **end for**
**end for**
**return** $trust_{topic}^{ref}(i,v,t)$

# 5 Conclusions

In this paper, we have introduced a model of trust computation which is constructed from degrees of interaction of peers and similarity of user's interests.

When there is directed interaction among a peer and its friend, trust degree of the truster on its trustee is estimated as a function of interaction levels and degree of interests of opponents on on topics. Whereas, trust estimation from a truster on some trustee without direct interaction is computed via a function of friend based trust and similarity level the friend compared with the opponent. The approach may overcome the limitation in computational complexity that the method in trust propagation in graph has faced with. We are currently performing experimental evaluation and comparing with other models on trust propagation in social network. The research results will be presented in our future work.

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