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REFINED EXPERIENCE TOPIC-AWARE TRUST IN SOCIAL NETWORKS

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Abstract

Trust estimation among peers in social computing is usually interpreted as a function of parameters with interaction experience and some context. In this paper, we model the interaction among peers in factors: familiarity, common interests and degrees of feedbacks. Then we represent the experience topic-aware trust whose computation is based on these factors and the context of topic interests. The proposed computational model is considered as a refinement of our previous interaction based trust computation.

1 Introduction

Various models of trust computation, which have been developed in computer science and in social computing, make use of various factors including interaction, relationship among peers, propagation, contexts etc. ([1] [2] [3] [8] [4] [9] [10] [11]). In this paper, we propose a novel model of experience computational trust which is based on factors: (i) Familiarity among users; (ii) Degrees of

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responds given by users; (iii) Common interests in topics. The model is considered as a refinement of experience based trust computation, which has been proposed previously by ourselves ([12]).

The remainder of this paper is structured as follows. Section 2 describes the model of social network, entries and user's interests in their vectorial representations. Section 3 is first devoted to representing user's interaction with familiarity, common interests and degrees of responds. And then we present a formula of experience based topic trust computation, which is inferred from types of the proposed interaction. Section 4 is conclusions.

2 Background

This section describes first a graphical representation of social network and hierarchy of peers based on interaction. Then, we present vectorial models of topics and entries based on weights of word frequencies with tf-idf [5].

2.1 Social Network

A social network is defined as a directed graph $\mathcal{S} = (\mathcal{U}, \mathcal{I}, \mathcal{E}, \mathcal{T})$, in which

- $\mathcal{U} = \{u_1, \ldots, u_n\}$ is a set of users, whose elements are autonomous entities being called peers. In this paper, the terms of peer and user are used interchangeably;

- $\mathcal{I}$ is a set of all interactions or connections I_{ij} from u_i to u_j. $\|I_{ij}\|$ is denoted to 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.

- $\mathcal{E} = \{E_1, \ldots, E_n\}$ is the set of entries dispatched by users $\mathcal{U} = \{u_1, \ldots, u_n\}$ respectively, where $E_i = \{e_{i1}, \ldots, e_{in_i}\}$ are entries given by u_i. Each 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.

- $\mathcal{T} = \{t_1, \ldots, t_p\}$ is a collection of topics, in which each topic is defined as a set of terms or words.

2.2 Vectorial Representation of Entries and Topics

We utilize the technique of word frequency $tf - idf$ for representing vectors of entries and topics (refer to [5] for more detail). Let $V_T = \{v_1, \ldots, v_q\}$ be a set of q distinct terms in all $t_i \in \mathcal{T}$. A topic vector w.r.t. each topic t_i is a weighted one, which is defined as follows

$$\mathbf{t_i} = (w_{i1}, \dots, w_{iq}) \tag{1}$$

where $w_{ik} = tf(v_k, T_i) \times idf(v_k, \mathcal{T})$, $v_k \in V_T$.

With e_{il} dispatched by u_i, an entry vector of w.r.t. topics $\mathcal{T}$, briefly topic vector, is a weighted one, which is defined as follows

$$\mathbf{e^t_{il}} = (e^1_{il}, \dots, e^p_{il}) \tag{2}$$

where $e^r_{il} = tf(v_r, e_{il}) \times idf(v_r, E_i)$, $v_r \in V_T$.

Suppose that $E_i = \{e_{i1}, \dots, e_{in_i}\}$ and $E_j = \{e_{j1}, \dots, e_{jn_j}\}$ are sets of entries dispatched by users u_i, u_j, respectively. Let V_{ij} be a set of distinct terms occurring in E_i and E_j. Entry vectors $\mathbf{e^j_{il}}$, $\mathbf{e^i_{jk}}$ are defined as follows

$$\mathbf{e^j_{il}} = (e^1_{il}, \dots, e^{\|V_{ij}\|}_{il}),\ l = 1, \dots, n_i \tag{3}$$

$$\mathbf{e^i_{jk}} = (e^1_{jk}, \dots, e^{\|V_{ij}\|}_{jk}),\ k = 1, \dots, n_j \tag{4}$$

where $e^r_{il} = tf(v_r, e_{il}) \times idf(v_r, E_i)$, $e^r_{jk} = tf(v_r, e_{jk}) \times idf(v_r, E_j)$ $v_r \in V_{ij}$.

Thus, we can define a sequence of topic vectors $\mathbf{e^{t_1}_{il}}, \dots, \mathbf{e^{t_p}_{il}}$ w.r.t. each entry and a sequence of entry vectors $\mathbf{e^j_{i1}}, \dots, \mathbf{e^j_{in_i}}$ w.r.t. entries E_j. These vectors will be utilized for constructing measures of user's similarity and interests, which are presented in the next subsection.

2.3 Interest Degrees

We define correlation degrees $cor(\mathbf{e^t_{ij}}, \mathbf{t_k})$ among entries e_{ij} given by u_i w.r.t. topics t_k as follows:

$$cor(\mathbf{u}, \mathbf{v}) = \frac{\sum_i (u_i - \bar{u})(v_i - \bar{v})}{\sqrt{\sum_i (u_i - \bar{u})^2} \times \sqrt{\sum_i (v_i - \bar{v})^2}} \tag{5}$$

where $\bar{u} = \frac{1}{n}(\sum_{i=1}^n u_i)$ and $\bar{v} = \frac{1}{n}(\sum_{i=1}^n v_i)$. Since values of the function $cor(x, y)$ belong $[-1, 1]$. We may make use of the function $f(x) = \frac{(x+1)}{2}$ to bound values of function $cor(x, y)$ into the unit interval $[0, 1]$. It means that instead of the formula given in (5), the following one (6) will be applied in the paper.

$$cor(\mathbf{u}, \mathbf{v}) = \frac{\frac{\sum_i (u_i - \bar{u})(v_i - \bar{v})}{\sqrt{\sum_i (u_i - \bar{u})^2} \times \sqrt{\sum_i (v_i - \bar{v})^2}} + 1}{2} \tag{6}$$

Given a threshold $0 < \theta \leq 1$. An entry e_{ij} is called θ-entry w.r.t. topic t_k if and only if $cor(\mathbf{e^t_{ij}}, \mathbf{t_k}) \geq \theta$. The interest degree of u_i in topic t is defined by one of the following formulas:

$$intMax(u_i, t) = \max_j(cor(\mathbf{e^t_{ij}}, \mathbf{t})) \tag{7}$$

$$intCor(u_i, t) = \frac{\sum\limits_j cor(\mathbf{e^t_{ij}}, \mathbf{t})}{\|E_i\|} \tag{8}$$

$$intSum(u_i, t) = \frac{1}{2}\left(\frac{n_i^t}{\sum\limits_{l \in \mathcal{T}} n_i^l} + \frac{n_i^t}{\sum\limits_{u_k \in \mathcal{U}, l \in \mathcal{T}} n_k^l}\right) \tag{9}$$

where n_i^t is the number of θ-entries concerned about the topic t given by u_i.

For easy presentation, we denote $intX(u_i, t)$ to be one of the above formulas, in which X may be Sum, Cor, Max. The interest vector of users in various topics is defined by the formula:

$$\mathbf{u^t_i} = (u_i^1, \ldots, u_i^p) \tag{10}$$

in which $u_i^k = intX(u_i, t)$ is the interest degree of user u_i in topics $t_k \in \mathcal{T}$ $(k = 1, \ldots, p)$, X may be Sum, Max, Cor as defined in Formulas (7), (8), (9). The definition of vectors with interest degrees is utilized for constructing the similarity of users which is considered in the next section.

3 Refined Experience Topic-aware Trust

This section is devoted to investigating the refinement of representation of the experience topic trust which has been proposed by ourselves (refer to [5] [6] [7] for more detail). We concentrate first on constructing formulas for representing the degrees of familiarity, common interests and responds among users. Then by means of the representation, we reformulate the estimation of experience topic trust.

3.1 Familiarity and Common interests

Definition 1. *Let $I_{i\rightarrow} = \{u_j \| \text{There is an interaction from } u_i \text{ to } u_j\}$. The degree of familiarity of two peers u_i and u_j is defined as follows:*

$$famil(u_i, u_j) = \frac{\|I_{i\rightarrow} \cap I_{j\rightarrow}\|}{\|I_{i\rightarrow} \cup I_{j\rightarrow}\|} \tag{11}$$

Definition 2. *Let $T_i^\theta = \{t \| t \in \mathcal{T}, intX(u_i, t) \geq \theta\}$, where $\theta > 0$ is a given threshold. The degree of common interests of u_i and u_j is defined as follows*

$$comInt(u_i, u_j) = \frac{\|T_i^\theta \cap T_j^\theta\|}{\|T_i^\theta \cup T_j^\theta\|} \tag{12}$$

Definition 3. *Given $I_{i \leftarrow j}^{resp}$ be a set of all responds from u_j to u_i, where a respond is a feedback from u_j when receiving a message dispatched from u_i. The degree of responds of u_j to u_i is defined as follows*

$$respond(u_i, u_j) = \frac{\|I_{i \leftarrow j}^{resp}\|}{\|\bigcup_k I_{k \leftarrow j}^{resp}\|} \tag{13}$$

3.2 Refined Topic-aware Experience Trust

Definition 4. *A function $trust_{topic} : \mathcal{U} \times \mathcal{U} \times \mathcal{T} \rightarrow [0, 1]$ is called a topic trust measure, in which $[0, 1]$ is an unit interval of the real numbers, if and only if it satisfies the following condition:*

$$int^X(u_j, t_1) \geq int^X(u_j, t_2) \Rightarrow trust_{topic}(u_i, u_j, t_1) \geq trust_{topic}(u_i, u_j, t_2) \tag{14}$$

Then, given a source peer u_i, a sink peer u_j and a topic t, the value $trust_{topic}(i, j, t) = u_{ij}^t$ means that u_i (truster) trusts u_j (trustee) of topic t w.r.t. the degree u_{ij}^t.

Definition 5. *Refined experience trust of user u_i on user u_j, denoted $trust^{Rexp}(i, j)$, is defined by the formula*

$$trust^{Rexp}(i, j) = \alpha \times famil(i, j) + \beta \times comInt(i, j) + \gamma \times respond(i, j) \tag{15}$$

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

Definition 6. *Suppose that $trust^{Rexp}(i, j)$ is the refined experience trust of u_i on u_j, $intX(j, t)$ is the interest degree of u_j on the topic t. Then the refined experience topic-aware trust of u_i on u_j of topic t is defined by the formula:*

$$trust_{topic}^{Rexp}(i, j, t) = \lambda \times trust^{Rexp}(i, j) + \mu \times intX(j, t) \tag{16}$$

where $\lambda, \mu \geq 0,\ \lambda + \mu = 1$.

Proposition 1. *The refined experience topic-aware trust $trust_{topic}^{Rexp}(i, j, t)$ of u_i on u_j of topic t, which is defined by the formula (16), is a topic trust measure.*

4 Conclusions

In this paper, we have introduced a novel method of experience trust estimation which is constructed from degrees of interaction of peers. Being evolved from our previous work, the degree of interaction is identified by means of three factors: common interests, familiarity and respond. We are also currently performing experimental evaluation and comparing with other models of trust computation in social network. The research results will be presented in our future work.

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