SIMILARITY MEASURE AND PATH ALGEBRA FOR TOPIC-AWARE REPUTATION TRUST IN SOCIAL NETWORKS

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***Tóm tắt*—Computational trust more and more plays an important role in interaction process of users or peers in distributed systems. Most current trust models are constructed based on interaction experience and reputation. Interaction trust is estimated from interaction experience among users, whereas reputation trust is inferred from some commmunity evaluation via propagation mechanisms. However, these reputation models either lack a clear foundation for computation or have no rules for determining community. And these issues deduce to difficulty in the trust implementation and design. Our purpose of this paper is to present a trust model of reputation, which estimates trustworthiness degrees based on similairity and path algebra from community. The similarity measure is resulted from the interest degrees that are formulated by means of analyzing entries data dispatched by users and topics. The path algebra is built from two operators concatenation and aggregation for integrating respectively scores along a path and from various paths. We perform experiments to determine how the path algebra and similarity impact on trust estimation. Our experimental results show that the similarity-based estimation outperforms the path algebra computation.**

***Từ khóa*—social networks, computational trust, reputation, direct trust, inference trust, similarity, path algebra.**

I. INTRODUCTION

In the social networks, the establishment of trust among users holds paramount importance in ensuring the efficacy and security of interactions. Trust serves as a pivotal catalyst, facilitating the seamless exchange of information, collaborative endeavors, and informed decision-making processes. Consequently, the development of precise and dependable methods for estimating trust has garnered substantial attention within the domain of social network analysis.

This notion of trust encapsulates the reliability that a user (referred to as the truster) places upon their counterparts (referred to as trustees) within the ambit of their interaction processes. Notably, the exploration of trust has traversed diverse academic disciplines, including sociology, psychology, economics, and computer science, as evidenced by studies such as [1] and [2]. In modern contexts, trust assumes a pivotal role in activities like knowledge sharing, coordinated actions, and decision-making mechanisms. Noteworthy applications span from recommender and decision-making systems to search engines, exemplified by works like [3] and [4]. Its relevance extends even to the burgeoning domain of Social Internet of Things (IoT) wherein trust facilitates service discovery and selection, as alluded to in [5].

Within the realm of computer science and social computing, many trust computation models have been developed, encompassing variables such as interactions, peer relationships, propagation dynamics, and contextual influences [1], [6], [7], [8], [9], [10], [11], [12]. Notable validation efforts have been undertaken, with data collection from prominent social media platforms like Facebook and Twitter, as evidenced in [13] and [14].

This academic paper explores the establishment and management of trust within social networks. Drawing from the unique attributes of Online Social Networks (OSNs), we introduce innovative models to assess trust, encompassing two dimensions: (i) Direct trust, capturing confidence between two users, and (ii) Inference trust, reflecting reputation-based trust via intermediaries.

Direct trust measures reliance between directly connected users [15], [16]. Existing methods include [17], [18], [15], [16], and [19], introducing SWTrust and TidalTrust [20]. Many studies overlook subsequent confidence determination, treating levels as predetermined or adopting random values. Hamdi [17] explores direct trust based on shared interests, limited by predefined thresholds. Indirect (Inference) trust gauges trust between users without direct interaction, relying on the

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wider user community [21][22]. We combine network structure and inference [21], [22], [17], [20], [19], [23]. Notably, Tidal Trust, by Golbeck, uses a breadth-first search (BFS) variable to find the shortest trust path between users. Yet, it prioritizes the nearest neighbor's trust value to the destination node, impacting evaluation, especially in sole pathways. Hamdi [17] advances this by outlining confidence pathway determination based on pathway potency.ư

Reputation trust, as defined by [24] [25] [26] [27], pertains to the reliability of one peer (user) with respect to another, which is drawn from a specific community or group of peers. Several research efforts have leveraged the propagation of trust through the graph structure of networks to formulate reputation trust models, exemplified by TidalTrust [20], SWTrust [19], and TrustWalker [28]. These models adopt an approach where specific paths are selected for computation, with a particular emphasis on mitigating computational complexity. For instance, they often opt for the shortest path that connects the truster and the trustee. However, a critical limitation of this approach is the absence of foundational principles underpinning such computational choices.

This paper aims to address this limitation by introducing techniques for estimating trustworthiness from a community context. These techniques rely on similarity measures or operators within the framework of path algebra.

A further dimension of our inquiry involves a meticulous comparative analysis between our proposed similarity calculation and the approach advanced by Hamdi[17]. The crux of Hamdi's approach hinges upon the enumeration of common interest topics between users, with the threshold of interest serving as a determinant of user engagement. This exploration encompasses a triad of distinct threshold values: 0.25, 0.5, and 0.75, each characterizing the spectrum of user interest in a given topic. We formulate six discrete models, affording a comprehensive evaluation of both our proposed approach and Hamdi's method across varying threshold regimes.

The implications of our research findings reverberate significantly within the domain of trust estimation models and similarity calculations within social networks. By illuminating the efficacies and idiosyncrasies of distinct user reliability measures and their intricate interplay with similarity calculations, our work extends a valuable compass for augmenting trust assessment within the dynamic milieu of online communities.

This paper is organized as follows: In Section 2, we establish the foundational representation of social media networks and define user interest, setting the stage for subsequent discussions. Section 3 introduces novel similarity measurements between users within social media networks. Sections 4 and 5 delve into the formulation and elaboration of topic-aware trust estimation, providing a detailed formula. Moving forward, Section 6 empirically validates our proposed method and conducts a comparative analysis against a conventional approach within a social media group, demonstrating the superiority of our method. Finally, the conclusion encapsulates our findings and contributions, reflecting on the implications of our research in the realm of trust estimation in social media networks.

II. PRELIMINARIES

This section presents the necessary knowledge of experience trust for building reputation trust, which previously has appeared in our previous work [29], [30], [31].

A. Social Network Representation

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, $\mathcal{I}$ is a set of all interactions, $\mathcal{E} = \{E_1, \ldots, E_n\}$ is a set of entries dispatched by users u_i, $\mathcal{T} = \{t_1, \ldots, t_p\}$ is a collection of topics. For each user u_i, we denote the hierarchy structure of users, $L_i^0 = \{u_i\}$, $u_j \in L_i^1$ is a set of all users connecting directly with u_i, $L_i^k,\ k \geq 2$ is the set of all users who have direct interaction with $u_j \in L_i^{k-1}$ but without $u_j \in L_i^{k-2}$.

In this paper, we merely concern with building a model for computing trust

B. User Interests

In order to build the interest measure, we collect and analyse entries and topics and utilize the technique of word frequency $tf - idf$ to represent vectors of entries and topics (refer to [30] for more detail). To define the correlation $\mathrm{cor}(\mathbf{e_{ij}^t}, \mathbf{t_k})$ among entries e_{ij} given by u_i w.r.t. topics t_k, we utilize the Pearson measure:

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

where $\bar{u} = \frac{1}{n}(\sum_{i=1}^n u_i)$ and $\bar{v} = \frac{1}{n}(\sum_{i=1}^n v_i)$.

Suppose $\|E_i\|$ is the number of elements in E_i and n_i^t is the number of θ-entries concerned with the topic t given by u_i. It is stated that *θ-entry* w.r.t. topic t_k if $\mathrm{cor}(\mathbf{e_{ij}^t}, \mathbf{t_k}) \geq \theta$, where $0 < \theta \leq 1$ is a given threshold. We are able to define the degree of interest of user u_i in topic t as follows [29]:

- Based on the maximum value of the correlations observed between entries w.r.t. some topic

$$\mathrm{intMax}(u_i, t) = \max_j(\mathrm{cor}(\mathbf{e_{ij}^t}, \mathbf{t})), \quad (2)$$

- Based on the average of the correlations observed between entries w.r.t. some topic.

$$\text{intCor}(u_i, t) = \frac{\sum_j \text{cor}(\mathbf{e^t_{ij}}, \mathbf{t})}{\|E_i\|}, \quad (3)$$

- Based on the number of entries that exhibit a correlation with the topic above the threshold θ.

$$\text{intSum}(u_i, t) = \frac{1}{2}\left(\frac{n_i^t}{\sum_{l\in\mathcal{T}} n_i^l} + \frac{n_i^t}{\sum_{u_k\in\mathcal{U}, l\in\mathcal{T}} n_k^l}\right). \quad (4)$$

For easy presentation, we denote $\text{intX}(u_i, t)$ to be one of the above formulas, in which X may be $\text{Sum}, \text{Cor}, \text{Max}$.

III. Similarity and Path Algebra

A. Similarity Measure

Similarity measure has been used widely to construct recommendation of items, and services in the recommender system [20], social network [32][33][10]. Golbeck [32] states that there is a strong and significant correlation between trust and user similarity: the more similar two people were, the greater the trust between them. However, in contrast to her similarity inferred from ratings on films, in this paper we utilize the degree of user's interest for bulding the similarity. Similar to our previous paper [34], we formalize the definition of similarity based on the usual metric measure as follows.

Definition 1. *Given a vector space V. A function $sim : V \times V \to [0, 1]$ is a similarity measure if it satisfies the following conditions:*

(i) $sim(u, u) = 1$, *for all* $u \in V$
(ii) $sim(u, v) = sim(v, u)$ *for all* $u, v \in V$
(iii) $sim(u, w) + sim(w, v) - sim(u, v) \leq 1$ *for all* $u, v, w \in V$

We have the following proposition.

Proposition 1. *The measure defined by the following formula is the similarity measure of two peers u_i and u_j in topic t*

$$sim_t^X(i, j) = 1 - \|intX(i, t) - intX(j, t)\| \quad (5)$$

where $intX(k, j)$ is the user's interest as defined in Section II-B.

B. Path algebra

This subsection presents briefly the operators of path algebra [35] which has been applied in trust computation [36] [23] [37] [38] [39]. We reformalize the necessary formulas for the purpose of our paper.

Definition 2 ([35]). *Given a set of natural numbers $\mathbb{N}$. A mapping $op : \cup_{n\in\mathbb{N}}[0, 1]^n \to [0, 1]$ is called an aggregation operator if it fulfills the following conditions:*

(i) $op(0, \ldots, 0) = 0$ *and* $op(1, \ldots, 1) = 1$
(ii) *For all* k, $x_1 \leq y_1 \ldots x_n \leq y_n \Rightarrow op(x_1, \ldots, x_n) \leq op(y_1, \ldots y_n)$

It is easy to prove the following proposition.

Proposition 2. *Mappings $op : [0, 1]^n \to [0, 1]$, which are defined by the following formulas, are aggregation operators:*

(i) $op(x_1, \ldots, x_n) = \max(x_1, \ldots, x_n)$
(ii) $op(x_1, \ldots, x_n) = \min(x_1, \ldots, x_n)$
(iii) $op(x_1, \ldots, x_n) = \Pi_{i=1}^n x_i$
(iv) $op(x_1, \ldots, x_n) = \frac{(x_1, \ldots, x_n)}{n}$

IV. Topic-aware Experience Trust

This section presents briefly the experience trust model which is determined by means of aggregation function of three forms of interaction and degrees of user's interests as follows (refer to [40] for more detail).

- Familiarity $\text{famil}(i, j) == \frac{\|I_{i\to} \cap I_{j\to}\|}{\|I_{i\to} \cup I_{j\to}\|}$ is a measure of the degree of common neighbors of two peers;
- Responsibility $\text{response}(i, j) = \frac{\|I^{\text{resp}}_{i\leftarrow j}\|}{\|\bigcup_k I^{\text{resp}}_{k\leftarrow j}\|}$ is a measure of degree of feedback among a sender u_i (truster) and a receiver u_j (trustee);
- Dispatching $\text{dispatch}(i, j) = \frac{\|I_{ij}\|}{\sum_{k=1}^n \|I_{ik}\|}$ is a measure of the degree of messages a truster sends to a trustee.

Interaction experience trust $\text{trust}^{\text{exp}}(i, j)$ of user u_i on user u_j is defined by the formula

$$\text{trust}^{\text{exp}}(i, j) = w_1 \times \text{famil}(i, j) + \\ + w_2 \times \text{respond}(i, j) + w_3 \times \text{dispatch}(i, j) \quad (6)$$

where $w_1, w_2, w_3 \geq 0,\ w_1 + w_2 + w_3 = 1$.

Definition 3. *Suppose that $\text{trust}^{\text{exp}}(i, j)$ is the experience trust of u_i on u_j, $\text{intX}(j, t)$ is the interest degree of u_j on the topic t. Then the topic-aware experience trust of u_i on u_j of topic t is defined by the formula:*

$$\text{trust}^{\text{exp}}_{\text{topic}}(i, j, t) = \lambda \times \text{trust}^{\text{exp}}(i, j) + \mu \times \text{intX}(j, t) \quad (7)$$

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

V. Topic-aware Reputation Trust

A. Path Algebra based Reputation Trust

Suppose that $\Phi(i, j)$ is the set of paths $p(i, j)$ connecting u_i and u_j via nodes $u_i = u_0, u_1, \ldots, u_p = u_j$. According to the formula (7), it is able to compute $trust^{exp}_{topic}(k, l, t)$ w.r.t. each couple $u_k, u_l,\ k = 0, \ldots, p-1, l = 1, \ldots, p = j$ We use two operators

$\otimes$ and $\oplus$ repectively to represent the aggregation of trustworthiness along paths and various paths.

Definition 4. *The path based topic-aware reputation trust of u_i on u_j of t is defined by the following formula:*

$$trust_{topic}^{path}(i,j,t) = \oplus_{p(i,j)\in\Phi(i,j)}(\otimes_{k,l} trust_{topic}^{exp}(k,l,t)) \tag{8}$$

where $\otimes$ and $\oplus$ are concatenation and aggregation operators, respectively.

Definition 5. *Given a source peer u_i and L_{ij}^1 is the 1-neighbors of both u_i and u_j. The topic-aware reputation trust of u_i on u_j with repmaX is defined by the formula:*

$$trust_{topic}^{repmaX}(i,j,t) = \max_{v\in L_{ij}^1}(trust_{topic}^{exp}(i,v,t) \times trust_{topic}^{exp}(v,j,t)) \tag{9}$$

in which $trust_{topic}^{exp}()$ is the topic-aware experience trust given in formula (7).

Definition 6. *Given a source peer u_i and L_{ij}^1 is the 1-neighbors of both u_i and u_j. The topic-aware reputation trust of u_i on u_j with repaP is defined by the formula:*

$$trust_{topic}^{repaP}(i,j,t) = \frac{\sum_{v\in L_{ij}^1}(trust_{topic}^{exp}(i,v,t) \times trust_{topic}^{exp}(v,j,t))}{\sum_{v\in L_{ij}^1} trust_{topic}^{exp}(v,j,t)} \tag{10}$$

in which $trust_{topic}^{exp}()$ is the topic-aware experience trust given in formula (7).

B. Similarity based Reputation

Definition 7. *Given a source peer u_i and L_{ij}^1 is the 1-neighbors of u_i and u_j. The topic-aware reputation trust of u_i on u_j with trustee similarity (repeeS) is defined by the formulas:*

$$trust_{topic}^{repeeS}(i,j,t) = \frac{\sum_{v\in L_{ij}^1} trust_{topic}^{exp}(i,v,t) \times sim(v,j)}{\sum_{v\in L_{ij}^1} sim(v,j)} \tag{11}$$

in which $sim(v,j)$ is the similarity measure of v on u_j being defined by the formula (5).

Definition 8. *Given a source peer u_i and L_{ij}^1 is the $1-level$ neighbors of u_i and u_j. The topic-aware reputation trust of u_i on u_j with truster similarity (repeS) is defined by the formulas:*

$$trust_{topic}^{repeS}(i,j,t) = \frac{\sum_{v\in L_{ij}^1} trust_{topic}^{exp}(v,j,t) \times sim(i,v)}{\sum_{v\in L_{ij}^1} sim(i,v)} \tag{12}$$

in which $sim(i,v)$ is the similarity measure of v on u_i being defined in the formula (5).

Definition 9. *Suppose that $trust_{topic}^{exp}(i,j,t)$ and $trust_{topic}^{rep}(i,j,t)$ are the experience and reputation trust degrees of u_i on u_j, respectively. The unified topic-aware trust of u_i on u_j of topic t is defined by the formula:*

$$trust_{topic}(i,j,t) = \gamma \times trust_{topic}^{exp}(i,j,t) + \delta \times trust_{topic}^{repY}(i,j,t) \tag{13}$$

where $repY$ may be $repmaX$, $repaP$, $repeS$ or $repeeS$ and $\gamma, \delta \geq 0$, $\gamma + \delta = 1$.

VI. Experimental Evaluation

A. Problem Statement

- Evaluate the influence of User Similarity on trust: This study aims to assess the influence of user similarity on trust measures. Specifically, we compare two approaches for determining trust: one based on user similarity (utilizing repeeS and repeS formulas) and another without considering similarity (employing repmaX and repaP formulas). The objective is to investigate the effect of incorporating user similarity measures on trust determination.
- A Comparative Evaluation of User Similarity Measures: Additionally, we seek to compare and evaluate the outcomes obtained from our proposed method of determining user similarity with the similarity determination approach presented in the thesis by Hamdi [17].

B. Evaluation Methods

We designed a comprehensive test scenario to address the aforementioned research questions.

In the context of a large social network group with continuous article postings, tracking all the posts, especially those of interest, becomes challenging. Thus, the fundamental problem we aim to address is whether we can suggest articles to a specific member (denoted as 'x') in the group that align with their preferences and interests.

To achieve this, we explore the following aspects:

1. Analysis of User Interests and Interactions: Based on the available group data, we investigate the feasibility of analyzing a user's content preferences and their historical interactions with other members.

2. Importance of Post Content in Predicting User Interest: We examine whether the content of a post, reflecting specific topics, plays a significant role in predicting a member's interest in that article.

3. Trustworthiness of the Article Poster: Considering that an article also contains information about

its poster, we explore how the historical interaction data helps ascertain the level of trustworthiness a user places in the poster. This, in turn, influences the user's motivation to receive information from that article.

To address the above aspects, we propose methods for calculating the level of user interest in a topic ($intX$), determining the similarity between two users on a topic ($sim(i, j, t)$), and establishing the trust between two users ($repmaX, repaP, repeeS$, and $repeS$). These parameters serve as input factors influencing the output of the scenario described.

In the literature, the definition of similarity lacks clarity. However, Hamdi's thesis proposes a method to determine similarity between two users based on their shared interests in various topics, as shown in the formula below:

$$st_{v \to v'} = \frac{|domains_v \cap domains_{v'}|}{|domains_v \cup domains_{v'}|} \quad (14)$$

Here, $N = domains_v$ and $N = domains'_v$ refers to the number of topics that user v and v' are interested in. This formula quantifies the degree of similarity between two users by calculating the proportion of their shared interests to the total number of interest.

In our investigation, we adopt a classification-based feature extraction approach, utilizing various formulaic techniques as input models. Additionally, we employ traditional performance measures such as recall, precision, and F1-score for evaluation purposes. Precision is computed as follows:

$$Precision = \frac{TruePositives}{TruePositives + TrueNegatives} \quad (15)$$

The recall is calculated as follows:

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives} \quad (16)$$

F_1-score is determined by means of precison and recall as follows:

$$F_1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (17)$$

C. Experimental Data

We utilized a dataset obtained from Kaggle, specifically sourced from a Facebook group known as "Cheltenham's Facebook Groups" (https://www.kaggle.com/datasets/mchirico/cheltenham-s-facebook-group), which we will refer to as CG. The discussions within this group are conducted in the English language and encompass various topics related to the daily challenges faced by Cheltenham, Pennsylvania, USA residents. These topics range from issues concerning traffic problems, sewer concerns, and pet-related matters (dogs, cats), to more significant subjects like Bill Cosby's lawsuit. For detailed statistics of the dataset, please refer to Table I. With this dataset, we conducted the testing process as follows:

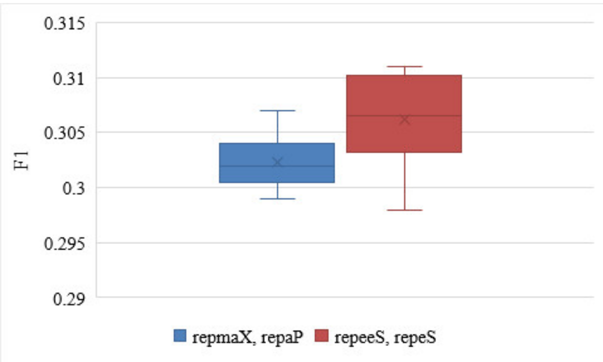
Bảng I: Statistics of data collected from CG

Collected Data	CG
Number of members	22491
Number of members actively posting	2846
Number of posts	221001
Number of comments (N-Comment)	140856
N-Comment6.707 (mean)	15536
N-Comment $\leq$ 0 (min)	8127
N-Comment $\leq$ 0 (25%)	8127
N-Comment $\leq$ 2 (50%)	12076
N-Comment $\leq$ 7 (75%)	16077
N-Comment $\leq$ 412 (max)	21001

The test data, with $K = 7$, is provided in Table II. The experimental evaluation of the models was performed and will be presented in the subsequent subsection, providing comprehensive insights into the results obtained.

D. Experimental Result

In this evaluation, we investigated the impact of user trust measures on trust. We considered two approaches for determining trust based on linear algebra, namely repaP and repmaX, which do not take user similarity into account. We compared these approaches with repeeS and repeS, which incorporate user similarity. The F1 measure was used to assess the performance of each model. The results are presented in Table III and Figure 1 and Figure 2.



Hình 1: Effect of Similarity Measure on trust

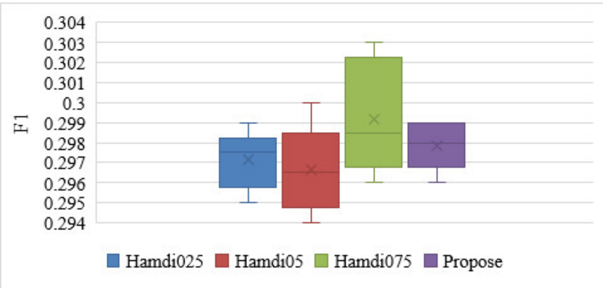
The tested models were dependent on various input parameters. In Table III, we observed that when calculating trust based on interactions, combining all three types of interactions (respond, dispatch, and familiarity) led to the empirical trust calculation. Combining interaction-based trust with one of three functions of interest (intMax, intSum, and intCor), we have 3 options, and, determining trust in a community-based

Bảng II: Parameters of two datasets DAR and CG

Datasets	Total Posts	Total members	Active members	Train Data	Test Data	Observation	Labeled Data
CG	4049	2000	1035	3470	579	4049 x1035 = 4,190,715	16601

Bảng III: F1 Measure Values in Two Cases: Trust Based on Path Algebra and Trust Based on Similarity

model	res	dis	fam	intMax	intSum	intCor	repmaX	repaP	repeeS	repeS	F1
1	x	x	x	x			x				0.303
2	x	x	x		x		x				0.299
3	x	x	x			x	x				0.301
4	x	x	x	x				x			0.307
5	x	x	x		x			x			0.301
6	x	x	x			x		x			0.303
7	x	x	x	x					x		0.31
8	x	x	x		x				x		0.305
9	x	x	x			x			x		0.311
10	x	x	x	x						x	0.305
11	x	x	x		x					x	0.308
12	x	x	x			x				x	0.298



Hình 2: F1 Comparision between Hamdi and proposed model

manner, we obtained four options: repmaX, repaP, repeeS, and repeS. Thus, there were a total of 12 models, and the results are shown in the table.

As a second evaluation, we compared the similarity calculation between two users proposed by our model and the similarity calculation suggested by Hamdi. Hamdi's approach determines the similarity between two users based on the number of common interests they share. It involves determining the user's interest in a topic above a threshold value. However, we identified a limitation in Hamdi's proposal related to threshold selection. In this section, we experimented with three different thresholds: 0.25, 0.5, and 0.75. A user was considered interested in a topic if their interest level surpassed these respective threshold values.

We calculated the similarity between two users using repeeS and repS formulas, and the obtained trusts were used as input parameters for the model. Consequently, we had a total of six models, and the F1 measurement results are presented in Table 2.

In the table, $F1_{Propose}$ represents the F1 measure for our proposed model, while $F1_{Hamdi025}$, $F1_{Hamdi05}$, and $F1_{Hamdi075}$ denote the F1 measure values for Hamdi's model with thresholds of 0.25, 0.5, and 0.75, respectively.

Furthermore, figure 2 illustrates the comparison of thresholds. We observed that when using a threshold of 0.25, Hamdi's formula yielded lower F1 results compared to our proposal (Figure 2). Similarly, for the 0.5 threshold, the F1 results remained lower and exhibited larger fluctuations compared to our proposed model. When setting the threshold to 0.75, corresponding to a substantial user interest in a topic, Hamdi's formula produced slightly higher F1 results than our proposed model, but the variability in F1 values remained significant. We highlighted the drawback of Hamdi's proposal, which depends on threshold selection for determining user similarity.

In this section, we present the corresponding experimental results which are concerned with our model:

- The measure of user's interests is defined by one of three functions which are shown in Proposition 2: Max, Cor, and Sum. The question is how those measures affect user interest in a topic. We utilize the mean deviation to investigate the effects of Max, Cor, Sum on user similarity.
- The formula (13) represents a computational function of trust estimation of a truster u_i on a trustee u_j by means of refined experience trust and degree of trustee's interests. Our question is which factor affects more trustworthiness computation. We utilize the mean deviation to define the effects of parameters λ, μ on the estimation.

VII. Conclusions

In this paper, we introduced a novel model of topic-aware reputation trust which is infered some community evaluation. We considered two techniques for construsting trustworthiness estimation: similairty

Bảng IV: F1 Measure Values for User Similarity Comparison

model	res	dis	fam	intMax	intSum	intCor	repeeS	repeS	$F1_{Propose}$	$F1_{Hamdi025}$	$F1_{Hamdi05}$	$F1_{Hamdi075}$
1	x	x	x	x			x		0.299	0.296	0.3	0.303
2	x	x	x		x		x		0.297	0.298	0.297	0.298
3	x	x	x			x	x		0.299	0.295	0.295	0.297
4	x	x	x	x				x	0.296	0.298	0.296	0.302
5	x	x	x		x			x	0299	0.297	0.298	0.299
6	x	x	x			x		x	0.297	0.299	0.294	0.296

and path algebra. We utilize operators concatenation and aggregation for fusing evaluation from community according to paths from truster to trustee. We consider a similarity measure on a topic for user's interests and investigate similar degrees w.r.t. truster or trustees. Upon the determination, we obtain trustworthiness degrees repective trust repeS and repeeS. We also propose a refined formula for integrating esperience and reutation trust. We conduct the experimental evaluation for our novel model. The results indicate that the community evaluation based on similarity outperforms path algebra. Our model has some limitations. The estimation formulas in the paper is to devote trustees which have direct interaction with truster. Trustees belonging to layers k-neighbors ($k \geq 2$) have been not yet considered fully. We are currently investigating an application of combining similarity and path algebra among peers to the case of estimating the trust degree of trustees via community in various layers L_i^k where $k \geq 2$. The research results will be presented in our future work.

TÀI LIỆU THAM KHẢO

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ĐỘ ĐO TIN CẬY VÀ ĐẠI SỐ ĐƯỜNG CHO TÍNH TOÁN TIN CẬY CỘNG ĐỒNG THEO CHỦ ĐỀ TRONG MẠNG XÃ HỘI

***Tóm tắt*—Tính toán tin cậy càng ngày càng đóng vai trò quan trọng trong quá trình tương tác của người sử dụng trong các hệ phân tán. Đa phần các mô hình tin cậy hiện thời được xây dựng dựa trên kinh nghiệm tương tác và đánh giá cộng đồng. Trong khi tin cậy tương tác được ước lượng từ kinh nghiệm tương tác giữa những người sử dụng, tin cậy cộng đồng được rút ra đánh giá cộng đồng thông qua cơ chế lan truyền nào đó. Tuy nhiên, những mô hình tin cậy cộng đồng hoặc thiếu cơ sở tính toán hoặc thiếu quy tắc để xác định cộng đồng. Những hạn chế này dẫn đến khó khăn cho cài đặt và thiết kế tin cậy. Mục đích của bài báo này nhằm trình bày mô hình tin cậy cộng đồng dựa trên độ tương tự và đại số đường. Độ tương tự được xây dựng từ độ quan tâm hình thành từ phân tích các phát biểu bởi người dùng và các chủ đề. Đại số đường được xây dựng từ hai toán tử tích hợp và tổng hợp tương ứng các đánh giá dọc theo đương và các đường khác nhau. Chúng tôi tiến hành đánh giá thử nghiệm để xác định ảnh hưởng của đại số đường và tương tự đối với ước lượng tin cậy. Kết quả thử nghiệm đã chỉ ra rằng ước lượng tin cậy dựa trên tương tự cho kết quả tốt hơn đại số đường.**

***Từ khóa*—mạng xã hội, tính toán tin cậy, cộng đồng, tin cậy trực tiếp, tin cậy gián tiếp, tương tự, đại số đường.**

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