MedTrust: Towards Trust-assured Social Networking for Healthcare

Juan Li[1], Nazia Zanman[1], Yan Bai[2]

[1]Department of Computer Science, North Dakota State University, Fargo, USA
{j.li@ndsu.edu, nazia.zaman@my.ndsu.edu}

[2]Institute of Technology, University of Washington Tacoma, Tacoma, USA
yanb@uw.edu

Abstract. Online social networks have enabled communication, collaboration and information sharing in the healthcare domain. Despite the benefits offered by new healthcare social networking applications, there are many challenges. The unique trust and privacy requirements of healthcare make trust management an utmost important issue. In this paper, we propose a personalized self-managed trust model, MedTrust, to establish trust relationships among participating healthcare social network users. The model identifies key trust factors in a healthcare social networking environment, and uses fuzzy logic to represent and evaluate trust. Experiments were conducted and demonstrated that our approach can generate accurate and realistic outcomes in assessing trust and predicting the scope and impact of different trust factors.

Keywords: trust, security, privacy, social networking, healthcare, fuzzy

1. Introduction

Social networking has moved from niche phenomenon to mass adoption. It empowers non tech-savvy users to manifest their creativity, engage in social interaction, contribute their expertise, share content, collectively build new tools, disseminate information and propaganda, and assimilate collective bargaining power [1]. Similar to the growing importance in other domains such as entertainment and education, social networks are playing an increasingly prominent role in healthcare. To date, online social networks have enabled communication, collaboration and information sharing in the healthcare domain. According to a recent survey, approximately one-third of Americans who go online to research their health problems are using social networks to find fellow patients and discuss their conditions [2, 3]. Thirty-six percent of social network users evaluate and leverage other consumers' knowledge before making healthcare decisions [4]. Meanwhile, healthcare professionals, hospitals and academic medical centers are diving into social networks: sixty percent of surveyed physicians are interested in using social networks for professional studies [5]; approximately one out of every six U.S. physicians are members of Sermo, an online physicians network [6]; and sixty-five percent of surveyed nurses indicate they are planning to use social networks for their work [7, 8].

Presently, many new networks and tools are being developed to enable social networking for healthcare. For example, an online social networking site called PatientsLikeMe provides users with tools to track disease progress, and access disease information. Users can also learn from other patients' experience on similar medical conditions, and share their findings with fellow patients, healthcare professionals and industry organizations. Another consumer-directed social site is MedHelp which offers a number of tracking tools for pain, weight and other chronic conditions. CureTogether is another site that helps people anonymously track and compare health data to better understand their health, make more informed treatment decisions and contribute data to research. DailyStrength is also a social networking website centered on support groups, where users provide one another with emotional support by discussing their struggles and successes with each other. The site contains online communities that deal with different medical conditions or life challenges. Medical professionals are also available to contact and treatments for a variety of illnesses and problems. Moreover, the site Inspire hosts different communities, some of which are co-sponsored by non-profit foundations, to educate and offer support. FacetoFace Health is a social network that uses a proprietary algorithm to match people with similar diagnoses. Meddik is a new online platform empowering patients to easily search for health information and learn from the collective experience of others. The medical profession could be one of the most socially interdependent networks, with which physicians depending on their colleagues for face-to-face training, consultation, and advice. Doximity is a professional network for doctors and medical students, which provides a way to extend the interactions and relationships between professionals to a consolidated, secure and easily accessible online space.

Despite the benefits offered, there are many risks that accompanied with online healthcare social networking. Personal health information belongs to the most valuable and closely guarded information pertaining to individuals. The disclosure of this type of data to untrusted parties can result in serious consequences for an individual, ranging from social embarrassment and dissolution of relationships to the termination of insurance and employment contracts. It could be more dangerous to place trust on false information. There is nothing that can destroy the value of a peer to peer support group faster than harmful information, exploitive behavior, and disrespectful interactions [9]. Negative information can either be inaccurate medical information or therapy recommendations that are inappropriate. Because of the prevalence of motivated reasoning and emotional information processing in these domains, information cascades can develop frequently and spread rapidly if they are not actively contravened. Therefore, trust is one critical issue as it highly impacts person's decision on whether go on-line, what kind of on-line activities to conduct, and with whom they will communicate.

Healthcare social networking brings trust new opportunities and challenges. On one hand, the user is able to acquire more information on the trust evaluation. In traditional healthcare collaborations, an agent's trust is based on its own experience and the word-of-mouth experience provided by limited number of acquaintances. The information may be far from enough to reveal the real quality of the target agent, let alone the situations under which no information is available. By connecting with many different people and professionals, healthcare social network enables more efficient collections and exchanges of the information required by the user's trust evaluation. On the other hand, the healthcare social network lays the user's trust evaluation in a more dynamic and uncertainty environment. A large number of users are involved in the healthcare system. Compared with the traditional healthcare, a user has more chances to collaborate with unknown people. This makes the trust evaluation more difficult. The unique trust and privacy requirements of healthcare make it one of the first "verticals" in need of specialized networks for both doctors and patients alike [10].

Given the new opportunities and challenges, we propose an effective mechanism to evaluate the relative truth or reliability of online healthcare information sources. In particular, we propose a fully decentralized and self-managed trust model to establish trust relationships among participating healthcare social network users.

In this model, we use semantic web technology to identify the semantic relationship and proximity between entities in the healthcare social network, and apply fuzzy logic to represent and evaluate trust. Trust evaluation is an "assessment" of something hypothetical defined as "trust" , which must then be interpreted as "high", or "medium", or "low". Such assessment, whether qualitative or quantified, requires analyst's judgment, expert human knowledge and experience. Quantification of trust in scalar values is subject to uncertainties for many reasons including difficulties in defining the likelihood and consequence severity and the mathematics of combining them. In contrast, fuzzy logic techniques allow the use of degrees of truth to calculate the results. It is tolerant of imprecisely defined data; it can model non-linear functions of arbitrary complexity; and it is able to build on top of the experience of experts. In addition to vagueness, intuitive and experiences in modeling trust assessment in a healthcare system must be accommodated because human observation forms the basis of any trust assessment [11]. Fuzzy logic ensures that we do not neglect human common sense, intuition, and experiences. Fuzzy logic and fuzzy set operations enable characterization of vaguely defined (or fuzzy) sets of likelihood and consequence severity and the mathematics to combine them using expert knowledge.

The rest of the paper is organized as follows. In Section 2, we survey the existing work on enhancing security and trust in healthcare social networks. Section 3 describes our fuzzy-based model of trust assessment, MedTrust. Section 4 discusses the use of MedTrust for trust management in healthcare social networks. We conclude our paper with future work in Section 5.

2. Related Work

In this section, we survey the work that has been done on enhancing trust of healthcare social networking and social networking in general. While some problems have been addressed, it is clear that there is room for further improvement.

Trust has its roots in authentication and authorization [12]. Authentication will prove that the person presenting them is indeed the person to which credentials were originally issued. Authorization is the process by which an entity such as a user or a server gets permission to perform a restricted operation. In the context of authentication, trust is established by means such as digital certificates. These certificates are proof of either identity directly or membership in a group of good reputation. In [13, 14], a few such authentication-related trust mechanisms are discussed. Policy languages are used to automatically determine whether certain credentials are sufficient for performing a certain action, i.e., to authorize the trustee [15, 16, 17].

Healthcare social networking systems have used authentication and authorization to enhance trust. For example, trust is bred through transparent and verified data on Doximity. Unlike traditional social networks, physicians and medical students use their real names and real identities for authentication–meaning that the system validates legitimate users, and brings a whole new level of credibility and confidence to communication across the network. Doctors communicate in a safe and authenticated environment. They know whom they are talking to; indeed, they are reaching out to specific colleagues or even medical school classmates. Rigorous verification of users prevents patients, companies, or drug representatives from being involved in the conversation, thus allowing Doximity members to pinpoint and communicate with other experts, which is the key for trust and security. In Doximity, trust and recommendation are enabled with authenticated member specialties, such as family medicine, internal medicine, pediatrics, obstetrics & gynecology, and surgery.

Sermo is another network that establishes trust relationships also based on authentication. This network is exclusive to physicians. Sermo requires that a member submit professional and personal information in order to confirm that she is in fact a physician when she sign up to join the network.

Another example is to use authentication and authorization to identify the roles and attributes of the users, which in turn, assist users establishing appropriate trust relationship. For instance, in DailyStrength, a healthcare social networking site, people tend to trust information from the forum of "Expert Answers". This is because the answers are from authenticated doctors.

To make trust more dynamic, the behavior of the trustee should be considered as well [12]. Behavior history collection has been included in one form or another in numerous trust models. Behavior information can be gathered locally [18, 19], or received as third-party observations through a reputation system [20]. Reputation system can monitor, address, and mitigate what is said about people or service. Comments from dissatisfied patients posted to blogs, or websites, such as HealthGrades.com, can directly affect the public's trust of the physician and the practice. From the perspective of trust, peer-to-peer recommendations carry far more weight than any traditional media campaigns [21].

In the context of general social networks, much work has also gone to identifying factors which either are considered to affect trust directly or which are used together on making trust decisions. Example factors include: ability to recommend [24], similarity of users [22], reputation [25], distrust [26], context [27], and so on. However, none of these factors and computations was defined specially for a healthcare system. Many trust models have been proposed [23, 28, 29]. However, a general trust evaluation test bed does not exist. Based on the representation of trust value, trust model can be divided into four classes, namely discrete model, probabilistic model, belief model, and fuzzy model [30]. Discrete trust model [23] expresses trust in a scale of discrete data. Probabilistic trust model [31, 32] represents trust value with probabilities. In belief models [26, 33], trust is modeled with a triple interpreted as the weights of belief, disbelief, and uncertainty, respectively. Fuzzy models use fuzzy logic to represent and evaluate trust. In this model, trust is often expressed by linguistic terms rather than numerical value. Example fuzzy model include [34, 35, 36, 37, 38].

3. MedTrust

The main focus of this paper is the design and development of MedTrust—a semantics-enhanced fuzzy-based trust model for quantifying and assessing the trustworthiness of entities in online healthcare communities. MedTrust is a personalized and self-managed trust model to establish trust relationships among participating healthcare social network users. It uses fuzzy logic to model and evaluate trust. In this model, trust is expressed by linguistic terms rather than numerical values. Fuzzy logic is suitable for trust evaluation as it takes into account the uncertainties of the data (for example, human relationships). People naturally use linguistic expressions when they are asked to state their trust to others. Fuzzy inference copes with imprecise inputs, such as assessments of quality or relevance, and allows inference rules to be specified using imprecise linguistic terms, such as "very knowledgeable" or "not useful". More importantly, as shown in [39], fuzzy-based modeling performs better in combining contradictory information. Trust has a certain degree of vagueness and involves truth degrees that one requires to present and reason about. The fuzzy model will be used to collectively analyze and interpret these uncertain values.

Existing models have successfully used fuzzy logic to represent trust [40, 41, 42]. However, they use trust as a means of establishing reputation, rather than focusing on individual trust decisions. In this paper we describe a method that uses fuzzy logic to make assessments about various aspects of trust, and allows peers to make decisions based on trust. In the following sections, we describe our trust model in details.

3.1 Trust factors for healthcare social networking

Our trust model identifies three important factors for evaluating the trustworthiness of a user in an online health community: roles, reputation and similarity.

Roles: One major difference between mainstream social networking applications and those used in healthcare is that the latter often groups users based on their roles [43]. For instance, patients are users who seek to manage and improve their health, while providers are registered and trained healthcare practitioners such as physicians, nurses and occupational therapists. Due to the regulated nature of these professions, healthcare providers may receive guidance from their professional associations concerning participation in healthcare social networks. In contrast, caregivers are non-registered healthcare providers, free from oversight by regulatory bodies. Healthcare support staff may perform operational functions on behalf of healthcare providers. Family members may also have legitimate interests in accessing health information about an individual, even if they do not manage their own information on the same site. Lastly, substitute decision makers are persons entrusted with the ability to make decisions about an individual's health, typically on the basis of a legal or administrative power. People normally give different trust levels, and consequently reveal different personal information to different users with different roles in a healthcare social network. Based on a recent survey [44], 61% of patients trust information posted by physicians on social media. This was well above the percentage of patients who said they are likely to trust drug companies (37%). Based on the aforementioned reasons, our trust model provides users with the ability to determine who can be trusted according to their respective roles.

Reputation: Reputation is another important factor affecting the user's trust of others. This is especially true in healthcare communities, in which people tend to trust information sources with a good reputation [45]. Reputation is the opinion or a social evaluation of the public towards an entity based on their past experiences. A user's reputation reflects a global degree of trustworthiness in an environment. It is a collective measure of trustworthiness based on the recommendations from other agents. The higher a reputation a person has, the more reliable she/he is. Reputation is closely related to trust, but there are still distinct differences. Trust reflects the trustor's subjective view on the trustee's trustworthiness, whereas reputation is a global score of the trustee's trustworthiness which can be seen by all agents.

There are many existing approaches of managing reputations in a social network, such as the centralized approaches [46, 47, 48], in which a central server store and manage the reviews comments and reputation for each individual, and decentralized reputation management such as [49, 50, 51, 52], in which reputation is collected on-demand using a peer-to-peer manner. We therefore, can use these approaches to get the reputation information of a particular user.

Similarity: In an online health social network, one of the striking benefits is the emphasis on common experience among participants [53]. Studies have suggested that perceived similarity is associated with increased levels of affect and trust [57]. In healthcare social networking, people with similar health issues may find it easier to connect with each other, and be more comfortable in sharing factual information and emotional feelings [54]. Moreover, people with similar health conditions would be viewed more capable and honest in terms of sharing their experience. Doctors and other healthcare providers would also trust more on peers with similar expertise and experiences.

Messages in online health communities are often narrative and story-telling, creating multidimensional user profiles, such as personal information and users' opinions and ratings of online information. To measure the similarity between different users, we compare their profiles. In particular, we adopted our previous semantics-based profile similarity metric [58] to measure the similarity between patients and between patients and doctor's expertise, and compute how much one should trust another.

3.2 Our fuzzy-based trust model

To construct our fuzzy model, MedTrust, four major steps are involved. Step 1 specifies key trust indicators and defines linguistic variables. In MedTrust, three key trust indicators are defined as input: (1) l - the role of a trustee in a healthcare social network, (2) r - the reputation of the trustee, and (3) s - the similarity between trustor and trustee. The output is the trust, t. The inputs and the output constitute vague estimates rather than crisp values; such vague estimates defined general categories, as opposed to rigid, fixed collections. Valid ranges of the inputs are considered and divided into classes, or fuzzy sets. These categories have more flexible membership requirements that allow for partial membership to a category. The degree to which a value is a member of a category can be any value between 0 and 1. In fuzzy logic, these categories are called fuzzy sets. We cannot specify clear boundaries between classes. The degree of belongingness of the values of the variables to any selected classes is called the degree of membership [55]. Table 1 lists the input and output variables and their ranges.

Table 1. Input and Output Variables and Their Ranges

Variables	Value	Notation	Normalized Range
l **-** role of a trustee	Ordinary	O	[0 0.4]
	Professional	P	[0.23 0.77]
	Expert	E	[0.61 1]
r **-** reputation of a trustee	Bad	B	[0 0.3]
	Unsatisfactory	U	[0.21 0.49]
	Average	A	[0.34 0.64]
	Good	G	[0.57 0.9]
	Excellent	E	[0.69 1]
s **-** similarity between trustor and trustee	Very Low	VL	[0.001 0.33]
	Low	L	[0.19 0.49]
	Moderate	M	[0.39 0.72]
	High	H	[0.51 0.81]
	Very High	VH	[0.67 0.1]
t **-** trust	Very Low	VL	[0 0.3]
	Low	L	[0.15 0.42]
	Moderate	M	[0.35 0.62]
	High	H	[0.51 0.82]
	Very High	VH	[0.69 1]

Step 2 determines fuzzy sets. Each fuzzy set has a corresponding membership function that returns the degree of membership for a given value within a fuzzy set. We choose Gaussian as our membership function. Figures 1-4 show how we can represent the inputs and outputs by means of membership functions.

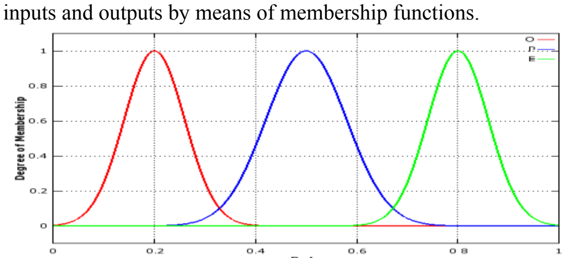

Fig. 1. Fuzzy Sets of Role

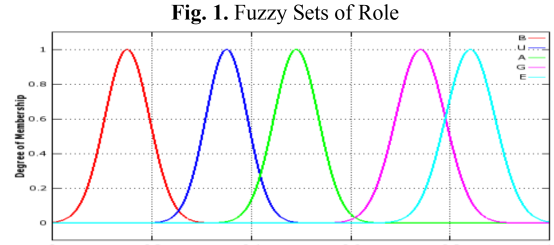

Fig. 2. Fuzzy Sets of Reputation

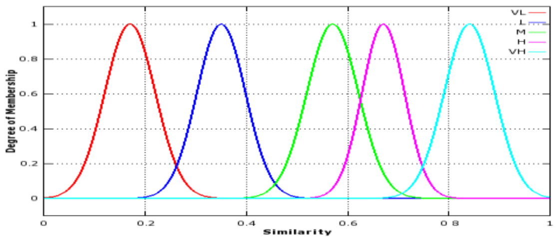

Fig. 3. Fuzzy Sets of Similarity

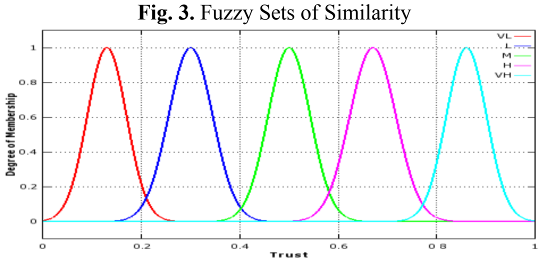

Fig. 4. Fuzzy Sets of Trust

Step 3 specifies fuzzy rules. Having specified the trust and its indicators, next step is to specify how trust varies as a function of the factors. Experts provide fuzzy rules that relate trust to various levels of indicators based on their knowledge and experience. To define the rules, we first make use of the most fundamental relations. For example,

1) If (*l* is *E* and *r* is *E* and *s* VH) then (t is *VH*)
2) If (*l* is *P* and *r* is *A* and *s* VH) then (t is *M*)
3) If (*l* is *O* and *r* is *B* and *s* is M) then (t is *VL*)

Meanwhile, a detailed analysis of the system may enable us to derive 75 rules that represent complex relationships between all variable used in the system. For a three-by-one system (three inputs and one output), the representation of the rule metrics takes the shape of a 3*5*5 cube called FAM (fuzzy associative memory).

Lastly, we encode the fuzzy model and tune the system. This could be the most laborious step to evaluate and tune the system to let it meet the requirements specified at the beginning. To build our fuzzy expert system, we use Octave Fuzzy Logic Toolkit [56], a mostly MATLAB-compatible fuzzy logic toolkit for Octave. It provides a systematic framework for computing with fuzzy rules and graphical user interfaces. The fuzzy Logic Toolbox can generate surface to help us analyze the system's performance. We can generate a three-dimensional output surface by varying any two of the inputs and keeping other inputs constant, and observe the performance of our three-input one-output system on three three-dimensional plots. Figs 5-7 represent the three-dimensional plots of the system.

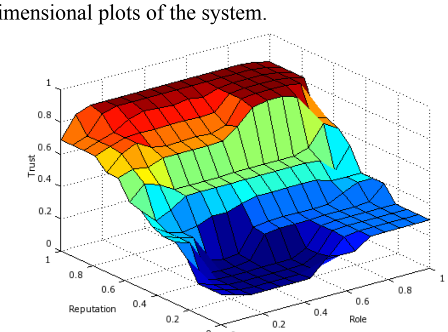

Fig. 5. Three-dimensional Plots of Inference Rules in Terms of Role and Reputation

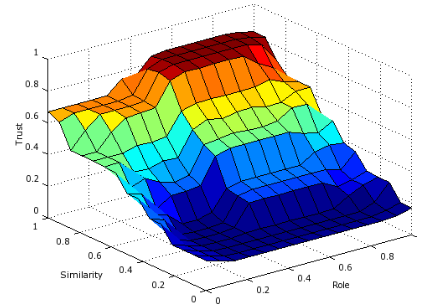

Fig. 6. Three-dimensional Plots of Inference Rules in Terms of Role and Similarity

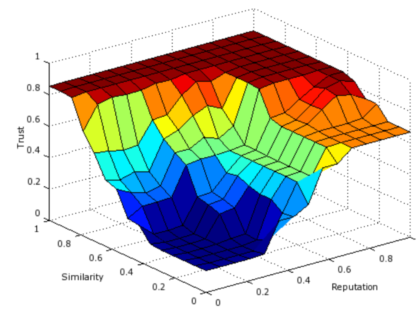

Fig. 7. Three-dimensional Plots of Inference Rules in Terms of Reputation and Similarity

4. Using MedTrust to evaluate trust

The use of fuzzy model, MedTrust, developed in Section 3 to determine trust in a healthcare social network consists of four main steps: Fuzzification, Rule Evaluation, Aggregation, and Defuzzification. In the following, we use an example to illustrate how to use MedTrust to evaluate trust. Suppose a patient is reading a piece of health news related to diabetes on a healthcare social website. Related to this action, there are three input variable values: the role of the poster, assuming who is a nurse l_1 (0.67), the reputation of the poster is r_1 (0.82) and the similarity between the user (patient) and the poster is s_1 (0.78).

Step 1: Fuzzification: The first step is to take the crisp input, l_1, r_1, s_1, and determine the degree to which these inputs belong to each of the appropriate fuzzy set. For example, the crisp input l_1 (role of the user, rated as 67%) corresponds to the membership functions L_1 and L_2 (*expert*, *professional*) to the degrees of 0.1 and 0.12 respectively, the crisp input r_1 (reputation, rated as 82%) maps the membership functions R_1 and R_2 (*good, excellent*) to the degree of 0.23 and 0.91 respectively and the crisp input s_1 (similarity, rated as 78%) maps the membership functions S_1 and S_2 of degree 0.05 and 0.43 (*high*, *very high*). In this manner, each input is fuzzified over all the membership functions used by the fuzzy rules.

Step 2: Rule evaluation: The second step is to take the fuzzified input *u* (l=L_1, L_2) = expert, professional, *u* (r=R_1, R_2) = excellent, good, *u* (s=S_1, S_2, S_3) = very high, high, and medium and apply them to the fuzzy rules described in the following.

- Rule 1: If *l* is *expert* and *r* is *excellent* and *s* is *very high* then *trust* is *very high*.
- Rule 2: If *l* is *expert* and *r* is *excellent* and *s* is *high* then *trust* is *very high*.
- Rule 3: If *l* is *expert* and *r* is *good* and *s* is *very high* then *trust* is *very high*.
- Rule 4: If *l* is *expert* and *r* is *good* and *s* is *high* then *trust* is *high*.

- Rule 5: If *l* is *professional* and *r* is *excellent* and *s* is *very high* then *trust* is *very high*.
- Rule 6: If *l* is *professional* and *r* is *excellent* and *s* is *high* then *trust* is *high*.
- Rule 7: If *l* is *professional* and *r* is *good* and *s* is *very high* then *trust* is *high*.
- Rule 8: If *l* is *professional* and *r* is *good* and *s* is *high* then *trust* is *medium*.

Step 3: Aggregation of the rule outputs: Aggregation is the process of unification of the outputs of all rules. In other words, we take the membership functions of all rule consequents previously clipped or scaled and combine them into a single fuzzy set. Thus, the input of the aggregation process is the list of clipped or scaled consequent membership functions, and the output is one fuzzy set for each output variable. If we aggregate the output of the 8 rules mentioned above we will have an aggregated fuzzy output as shown in Fig. 8.

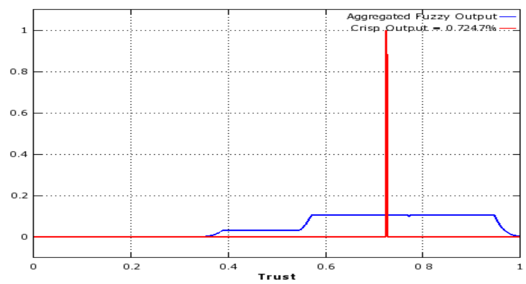

Fig. 8. Aggregated Fuzzy output and Crisp output (considering role and similarity)

Step 4: Defuzzification: The final output of a fuzzy system has to be a crisp number. The input for the defuzzification process is the aggregate output fuzzy set and the output is a single number. We adopted the most popular method, centroid technique to defuzzifize the output. For example, crisp output z is 0.7247. It means for instance, that the trust involved in our system is 72.47 percent, which is high.

Through extensive examinations by human experts, the proposed fuzzy approach has demonstrated good performance in generating accurate and realistic outcomes in assessing trust and forecasting the scope and impact of different trust factors.

5. Conclusions

We propose a semantic-enhanced fuzzy-based model, MedTrust, to evaluate the trustworthiness of entities in online health communities. It consists of three important factors affecting trust in healthcare social networking environments: role, reputation and similarity. Fuzzy logic is used in MedTrust since it is tolerant of imprecisely defined data and can model non-linear functions of arbitrary complexity. More importantly, human observation forms the basis of trust assessments, and fuzzy logic can accommodate vagueness, intuition and experiences in modeling trust in a healthcare system. Semantics-based profile similarity metrics are adopted to measure the similarity. Experiments have demonstrated the effectiveness of the proposed system.

References

[1] M. Parameswaranand A.B. Whinston, "Social Computing: An Overview", Communications of the Association for Information Systems: Vol. 19, Article 37, 2007. http://aisel.aisnet.org/cais/vol19/iss1/37, accessed on March 4, 2015.

[2] Manhattan Research's Cybercitizen Health, "HEALTH 2.0 ON THE RISE – 35% OF U.S. ADULTS USE SOCIAL MEDIA FOR MEDICAL INFORMATION", http://manhattanresearch.com/News-and-Events/Press-Releases/health-2-0-social-media-on-the-rise, accessed on March 4, 2015.

[3]N. Elkin, "How America Searches: Health and Wellness," iCrossing, January 2008, http://www.icrossing.com/sites/default/files/how-america-searches-health-and-wellness.pdf, accessed on March 4, 2015.

[4] M. Levy, "Online Health: Assessing the Risks and Opportunity of Social and One-to-one Media, 2007", in Jupiter Research, Vol. 2, 2007.

[5] Manhattan Research, Taking the Pulse, http://manhattanresearch.com/Products-and-Services/Physician/Taking-the-Pulse-U-S, accessed on March 4, 2015.

[6] Sermo, http://www.sermo.com/what-is-sermo/overview, accessed on March 4, 2015.

[7] Nicholson Kovac Inc, New Media Usage Study: Healthcare professionals, February 2010.

[8] Paul H. Keckley, and Michelle Hoffmann. Social Networks in Health Care: Communication, collaboration and insights, Deloitte Development LLC.

[9] M. Resnick, "Social Networking in Health Care", http://www.worldusabilityday.org/social-networking-health-care-part-ii-managing-trust-peer-peer-support-groups-social-networks, accessed on March 4, 2015.

[10]Tim Soo, Changing the Tides of Healthcare Communication with Social Media, 2012, http://www.physiciansnews.com/2012/09/20/changing-the-tides-of-healthcare-communication-with-social-media/, accessed on March 4, 2015.

[11] S. Kim, and S. Han, "The Method of Inferring Trust in Web-based Social Network using Fuzzy Logic", International Workshop on Machine Intelligence Research, Nagpur, India, Jan. 2009, pp. 140-144.

[12] S. Ruohomaa, L. Kutvonen, "Trust Management Survey", in Proceedings of Trust 2005, Lecture Notes in Computer Science, Springer, 2005, pp. 77–92.

[13] W.H. Winsborough, K.E Seamons, and V.E. Jones, "Automated Trust Negotiation", DARPA Information Survivability Conference and Exposition, 2000. Volume 1, pp.88–102.

[14]I. Djordjevic, T.Dimitrakos,"Towards Dynamic Security Perimeters for Virtual Collaborative Networks", Second International Conference on Trust Management,, iTrust 2004, Oxford, UK, March/April 1, 2004. Volume LNCS 2995/2004, pp.191–205.

[15]Y.H., Chu, J. Feigenbaum, B.LaMacchia, P. Resnick, and M.Strauss, "REFEREE: Trust Management for Web Applications", Computer Networks and ISDN Systems 29 (1997) pp.953–964.

[16] M. Blaze, J. Feigenbaum, J. Lacy,"Decentralized Ttrust Management", In Proceedings of the 1996 IEEE Symposium on Security and Privacy, 1996,pp.164-173.

[17]M. Blaze, J. Feigenbaum, A.D. Keromytis, "KeyNote: Trust Management for Public-key infrastructures", , the6th International Workshop on Security Protocols,, Cambridge, UK, April 1998. Volume LNCS 1550/1998., Springer-Verlag (1998), pp. 59–63.

[18]W. Wagealla, M. Carbone, C.English, S. Terzis, P. Nixon, "A Formal Model on Trust Lifecycle Management", Workshop on Formal Aspects of Security and Trust (FAST2003) at FM2003. Volume IIT TR-10/2003. IIT-CNR, Italy (2003),pp. 184–195.

[19]A. Jøsang,.S.L.Presti,"Analysing the Relationship between Risk and Trust", " Second International Conference on Trust Management: iTrust 2004, Oxford, UK, March/2004. Volume LNCS 2995/2004, pp.135–145.

[20]P. Resnick, R. Zeckhauser, E. Friedman, K. Kuwabara,"Reputation Systems", Communications of the ACM 43 (2000),pp. 45–48.

[21] Social Media in Healthcare. A Primer for Orthopaedic Surgeons. AAOS Practice Management Committee. Adam Soyer, DO, Editor. February 2012.
[22] J. Golbeck, "Trust and nuanced profile similarity in online social networks", ACM Trans. Web, Vol. 3, No. 4. (2009), pp. 1-33.
[23] J. Golbeck, "Computing and Applying Trust in Web-based Social Networks", PhD thesis, University of Maryland, College Park, 2005.
[24] D. Quercia, S. Hailes, and L. Capra,"Lightweight distributed trust propagation", IEEE International Conference on Data Mining, 2007,pp.282–291.
[25] J. Patel, W. L. Teacy, N. R. Jennings, and M. Luck,"A Probabilistic Trust Model for Handling Inaccurate Reputation Sources", In Proceedings of Third International Conference on Trust Management (iTrust 2005):, volume 3477 of LNCS, Springer-Verlag, Apr. 2005,pp. 193–209.
[26] R. Guha, Ravi Kumar, Prabhakar Raghavan, and Andrew Tomkins. Propagation of trust and distrust. In WWW '04: Proceedings of the 13th international conference on World Wide Web, pages 403– 412, New York, NY, USA, 2004. ACM.
[27] S. Bistarelli, F. Martinelli, F. Santini, "A Semantic Foundation for Trust Management Languages with Weights: An Application to the RT Family", In: ATC '08, Springer (2008), pp. 481–495.
[28]C. Dwyer, S. R. Hiltz & K. Passerini,"Trust and Privacy Concern Within Social Networking Sites: A Comparison of Facebook and MySpace", Proceedings of AMCIS 2007.
[29] J. Li, Z. Zhang,W. Zhang, "MobiTrust: Trust Management System in Mobile Social Computing", the Third IEEE International Symposium on Trust, Security and Privacy for Emerging Applications (TSP-10), 2010, UK.
[30]T. Abdessalem, B. Cautis and A. Souhli, "Trust Management in Social Networks", ISICIL Project ANR-08-CORD-011-05, 2010.
[31]C.W. Hang, Y. Wang, and M. P. Singh, "Operators for Propagating Trust and their Evaluation in Social Networks", In Proceedings of the 8th International Conference on Autonomous Agents and Multiagent Systems (AAMAS), Budapest, Hungary, 2009, volume 2, pp.1025–1032.
[32]C. W. Hang, "Probabilistic Trust Models for Social and Service Networks" PhD Dissertation, North Carolina State University, April 2011.
[33]A. Jøsang, "A Logic for Uncertain Probabilities", International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 9(3):279–212, 2001.
[34]S. Kim, and S. Han, "The Method of Inferring Trust in Web-based Social Network using Fuzzy Logic", In International Workshop on Machine Intelligence Research(2009), pp 140-144.
[35]K. Aberer, Z. Despotovic, W. Galuba, and W. Kellerer. The Complex Facets of Reputation and Trust. In the 9th Fuzzy Days, International Conference on Computational Intelligence Fuzzy Logic Neural Networks Evolutionary Algorithms2006, pp.283–294.
[36]S. Schmidt, R. Steele, T.S. Dillon, E. Chang, " Fuzzy Trust Evaluation and Credibility Development in Multi-agent Systems", Applied Soft Computing Journal, 2007, 7(2):492-505.
[37]G. Chen, Z. Li, Z. Cheng, Z. Zhao, and H. Yan, "A Fuzzy trust Model for Multi-agent System", In ICNC (3), 2005, pp. 444–448.
[38] S. Nefti, F. Meziane, and M.K. Kasiran, "A fuzzy Trust Model for e-commerce", In CEC, 2005,pp.401–404.
[39] M. A. A. Leite and I. L. M. Ricarte, "Fuzzy Information Retrieval Model based on Multiple Related Ontologies," in Proceedings of The 20th IEEE International Conference on Tools with Artificial Intelligence (ICTAI '08), November 2008, pp. 309–316,
[40] D. W. Manchala, "E-commerce Trust Metrics and Models", IEEE Internet Computing, 4(2):36–44, 2000.
[41]S. D. Ramchurn, C. Sierra, L. Godo, and N. R. Jennings, "Devising a Trust Model for Multi-agent Interactions using Confidence and Reputation",Artificial Intelligence, 18(9–10):833–852, 2004.
[42]S. Song, K. Hwang, R. Zhou, and Y.-K. Kwok, "Trusted P2P Transactions with Fuzzy Reputation Aggregation", IEEE Internet Computing, 9(6):24–34, 2005.
[43]J. Williams,"Social Networking Applications in Health Care: Threats to the Privacy and Security of Health Information", of the 2nd Intl. ICSE Workshop on Software Engineering in Health Care (SEHC). ACM, New York (2010).
[44]PwC Health Research Institute survey: http://www.ama-assn.org/amednews/2012/04/30/bisa0430.htm, accessed on March 4, 2015.
[45] W. Ebner, J.M. Leimeister, and H. Krcmar. "Trust in Virtual Healthcare Communities: Design and Implementation of Trust-enabling Functionalities", the Thirty-Seventh Hawaii International Conference on System Sciences. Los Alamitos, CA, 2004.
[46]Z. Xu, Y. He, and L. Deng, "A Multilevel Reputation System for Peer-to-Peer Networks," Proc. Sixth Int'l Conf. Grid and Cooperative Computing (GCC '07), 2007, pp. 67-74.
[47]M. Gupta, P. Judge, and M. Ammar, "A Reputation System for Peer-to-Peer Networks", the13th Int'l Workshop Network and Operating Systems Support for Digital Audio and Video (NOSSDAV), 2003.
[48]M. Piatek, T. Isdal, A. Krishnamurthy, and T. Anderson, "One Hop Reputations for Peer to Peer File Sharing Workloads," Proc. Fifth USENIX Symp. Networked Systems Design and Implementation (NSDI '08), 2008, pp. 1-14.
[49]E. Damiani, S.D.C. di Vimercati, S. Paraboschi, and P. Samarati, "Managing and Sharing Servents' Reputations in p2p Systems," IEEE Trans. Knowledge and Data Eng., vol. 15, no. 4, pp. 840-854, July 2003.
[50]B.C. Ooi, C.Y. Kiau, and K. Tan, "Managing Trust in Peer-to-Peer Systems Using Reputation-Based Techniques," theFourth Int'l Conf. Web Age Information Management, Aug. 2003.
[51]L. Liu, S. Zhang, K.D. Ryu, and P. Dasgupta, "R-Chain: A SelfMaintained Reputation Management System in p2p Networks," Proc. 17th Int'l Conf. Parallel and Distributed Computing Systems (PDCS), Nov. 2004.
[52]R. Zhou, K. Hwang, and M. Cai, "Gossiptrust for Fast Reputation Aggregation in Peer-to-Peer Networks," IEEE Trans. Knowledge and Data Eng., Aug. 2008,vol. 20, no. 9, pp. 1282-1295,
[53]Hanmei Fan, "Why People Trust in Online Health Communities: An Integrated Approach", http://aisel.aisnet.org/acis2010/20/, accessed on March 4, 2015.
[54]M.D. Slater, D.B. Buller, E. Waters, M. Archebeque, and M. Leblanc, M. "A Test of Conversational and Testimonial Messages versus Didactic Presentations of Nutrition Information," Journal of Nutrition Education and Behavior (35:5) 2003, pp 255-259.
[55]W.-H. Au and K.C.C. Chan, "Classification with Degree of Membership: A Fuzzy Approach", in: Proc. of the 1st IEEE Int'l Conf. on Data Mining, San Jose, CA, 2001, pp. 35–42.
[56]Octave Fuzzy Logic Toolkit: http://sourceforge.net/projects/octave-fuzzy.
[57]Ziegler, C., and Golbeck, J. "Investigating Interactions of Trust and Interest Similarity", Decision Support Systems (43:2) 2007, pp 460-475.
[58]J. Li, H. Wang, and S. U. Khan, "A Semantics-Based Approach to Large-Scale Mobile Social Networking" ACM/Springer Mobile Networks and Applications.Volume 17, Issue 2 (2012), pp. 192-205.