A NEW APPROACH FOR THE TRUST CALCULATION IN SOCIAL NETWORKS

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Abstract: This paper aims at the trust calculation in social networks by addressing some major issues: Firstly, the paper evaluates a specific trust function and its behaviors, and then it focuses on the modification of that trust function by considering diverse scenarios. After that, the paper proposes a new approach with a specific functionality. The main goals are to support good agents strongly, block bad ones and create opportunities for newcomers or agents who want to show their merit in our society although we can not judge them. Finally, a mathematical discussion by a new trust function is provided with ultimate results.

1 INTRODUCTION

One of the major challenges for electronic commerce is how to establish a relationship of trust between different parties and how to form a reputation scheme as a global vision. In many cases, the parties involved may not ever have interacted before. It is important for participants such as buyers, sellers and partners to estimate each other's trustworthiness before initiating any commercial transactions.

According to (Mui, 2002), *"Trust"* is a personal expectation an agent has about another's future behavior, it is an *individual quantity* calculated based on the two agents concerned in a present or future dyadic encounter while "*Reputation" is* perception that an agent has of another's intentions, it is a *social quantity* calculated based on actions by a given agent and observations made by others in a social network. From the cognitive point of view (Castelfranchi and Falcone, 1998), trust is made up of underlying beliefs and it is a function of the value of these beliefs. Therefore, reputation is more a social notion of trust. In our lives, we each maintain a set of reputations for people we know. When we have to work with a new person, we can ask people with whom we already have relationships for information about that person. Based on the information we gather, we form an opinion about the reputation of the new person.

To form a pattern for agents, we should consider a "*social network"* which is a social structure made of nodes and ties. Nodes are individual actors within the networks, and ties are relationships between the actors. In E-commerce, social network refers to an electronic community which consists of interacting parties such as people or businesses.

Another concept is "*reputation systems"* which collect, distribute and aggregate feedback about participants' past behavior. They seek to address the development of trust by recording the reputations of different parties. The model of reputation will be constructed from a buying agent's positive and negative past experiences with the aim of predicting how satisfied the buying agent will be with the results of future interactions with a selling agent. OnSale exchange and eBay are practical examples of reputation management. OnSale allows users to rate and submit textual comments about sellers. The overall reputation of a seller is the average of the ratings obtained from his customers. In eBay, sellers receive feedback (-1, 0, +1) for their reliability in each auction and their reputation calculated as the sum of those ratings over the last six months. The major goal of reputation systems is to help people decide whom to trust and deter the contribution of dishonest parties. Most existing online reputation systems are *centralized* and have been designed to foster trust among strangers in e-commerce (Resnick et al, 2000).

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To extend reputation systems, a *"social reputation system"* can be applied in which a buying agent can choose to query other buying agents for information about sellers for which the original buying agent has no information. This system allows for a *decentralized* approach whose strengths and weaknesses lie between the personal and public reputation system.

For creating a *"reputation model"*, researchers apply various approaches. For example in (Yu and Singh, 2002), an agent maintains a model of each acquaintance. This model includes the agent's abilities to act in a trustworthy manner and to refer to other trustworthy agents. The first ability is *"expertise: ability to produce correct answers"* and the second one is *"sociability: ability to produce accurate referrals"*. The quality of the network is maximized when both abilities are considered.

The other essential factor is *"social behavior"*. This refers to the way that agents communicate and cooperate with each others. Usually, in reputation systems good players are rewarded whereas bad players are penalized by the society. For instance, if A_1 encounters a bad partner (A_2) during some exchange, A_1 will penalize A_2 by decreasing its rating and informing its neighbors. In a sample proposed approach (Yu and Singh, 2000), A_1 assigns a rating to A_2 based on:

1. Its direct observations of A_2
2. The rating of A_2 as given by his neighbors
3. A_1's rating of those neighbors (witnesses)

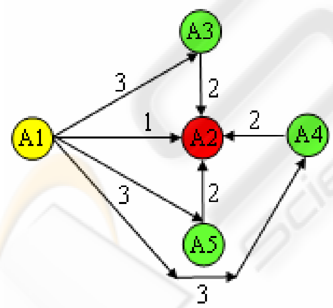

Figure 1: A sample rating assignment.

As you can see, this approach seeks to create trust based on local or social evidence; "*local trust*" is built through direct observations while *"social trust"* is built through information from others.

The purpose of this paper and our major motivations are to evaluate the behavior of a specific trust function and propose a new approach for the modification of the trust calculation. The rest of this paper is organized as follows. Section 2 reviews the existing literature on the trust and reputation systems. Section 3, illustrates the behavior of a specific trust function and its modification by proposing a new approach. Section 4, presents a new trust function and shows the final results. Finally in section 5, some concluding remarks are provided.

2 LITERATURE REVIEW

In this section, we review many interesting approaches in various research projects in order to form a clear vision of trust and reputation systems.

Trust is one of the most important parameters in electronic commerce technology. According to (Brainov and Sandholm, 1999), if you want to maximize the amount of trade and of agents' utility functions, the seller's trust should be equal to the buyer's trustworthiness; this shows the impact of trust in E-commerce. Mui et al. (2002) summarize existing works on rating and reputation across diverse disciplines, i.e., distributed artificial intelligence, economics, and evolutionary biology. They discuss the relative strength of the different notions of reputation using a simple simulation based on "*Evolutionary Game Theory"*. They focus on the strategies of each agent and do not consider gathering reputation information from other parties.

A "*Social Mechanism"* of reputation management was implemented in Kasbah (Chavez and Maes, 1996). This mechanism requires that users give a rating for themselves and either have a central agency (direct ratings) or other trusted users (collaborative ratings).Yu and Singh (2003) present an approach which understands referrals as arising in and influencing *"Dynamic Social Networks"* where the agents act autonomously based on local knowledge. They model both expertise and sociability in their system and consider a weighted referral graph. Sabater and Sierra (2002) show how social network analysis can be used as part of the *"Regret Reputation System"* which considers the social dimension of reputation. Pujol et al. (2002) propose an approach to establish reputation based on the *position of each member* within the corresponding social networks. They seek to reconstruct the social networks using available information in the community.

Yolum and Singh (2004) develop a "*Graph Based Representation"* which takes a strong stance for both local and social aspects. In their approach, the agents track each other's trustworthiness locally and can give and receive referrals to others. This approach naturally accommodates the above conceptualizations of trust: social because the agents give and receive referrals to other agents, and local because the agents maintain rich representations of each other and can reason about them to determine their trustworthiness. Further, the agents evaluate each other's ability to give referrals. Lastly, although this approach does not require centralized authorities, it can help agents evaluate the trustworthiness of such authorities too.

To facilitate trust in commercial transactions *"Trusted Third Parties"* (Rea and Skevington, 1998) are often employed. Typical TTP services for electronic commerce include certification, time stamping, and notarization. TTPs act as a bridge between buyers and sellers in electronic marketplaces. However, they are most appropriate for closed marketplaces. Another method is from "*Social Interaction Framework (SIF)"* (Schillo et al., 2000). In SIF, an agent evaluates the reputation of another agent based on direct observations as well through other witnesses.

Breban and Vassileva (2001) present a *"Coalition Formation Mechanism"* based on trust relationships. Their approach extends existing transaction-oriented coalitions, and might be an interesting direction for distributed reputation management for electronic commerce. Tan and Thoen (2000) discuss *the trust that is needed to engage in a transaction.* In their model, a party engages in a transaction only if its level of trust exceeds its personal threshold. The threshold depends on the type of the transaction and the other parties involved in the transaction.

In (Yu et al., 2004) an agent maintains a model of each acquaintance. This model includes the acquaintance's *reliability* to provide high-quality services and *credibility* to provide trustworthy ratings to other agents. Marti and Garcia-Molina (2004) discuss the effect of reputation information sharing on the *efficiency and load distribution of a P2P system*, in which peers only have limited or no information sharing. In their approach, each node records ratings of any other nodes in a reputation vector. Their approach does not distinguish the ratings for service (reliability) and ratings for voting (credibility) and does not consider how to adjust the weight for voting.

Aberer and Despotovic (2001) use a model to manage trust in a P2P network where no central database is available. Their model is based on *"Binary Trust"*. For instance, an agent is either trustworthy or not. In case a dishonest transaction is detected, the agents can forward their complaints to other agents. Recently, a new P2P reputation system is presented in (Song et al., 2005) based on *"Fuzzy Logic Inferences"* which can better handle uncertainty, fuzziness, and incomplete information in peer trust reports. They demonstrate the efficacy and robustness of two P2P reputation systems (*FuzzyTrust* and *EigenTrust*) at establishing trust among the peers.

In the next section, we evaluate the behavior of the proposed trust function in (Yu and Singh, 2000) and offer a new approach for the trust calculation.

3 TRUST FUNCTION

In this section, we evaluate a specific trust function by Yu and Singh (2000) and assess its behavior. In the proposed scheme, after an interaction the updated trust rating T_{t+1} is given by the following formulas (Table 1) and depends on the previous trust rating where:

$\alpha >= 0$, $\beta <= 0$

Table 1: Trust function from (Yu and Singh, 2000).

T_t	**Cooperation**
> 0	$T_t+\alpha\,(1-T_t)$
< 0	$(T_t+\alpha)/(1-\min\{\lvert T_t\rvert,\lvert\alpha\rvert\})$
= 0	α
T_t	**Defection**
> 0	$(T_t+\beta)/(1-\min\{\lvert T_t\rvert,\lvert\beta\rvert\})$
< 0	$T_t+\beta\,(1+T_t)$
= 0	β

The following diagram (Figure 2) shows the behavior of the Yu trust function, it is convergent at points (+1, +1) and (-1, -1). The above curve is for the cooperation and the other one is for the defection. This function also crosses axis Y at the following points: α=0.1 and β=-0.2 where T_t is equal to zero.

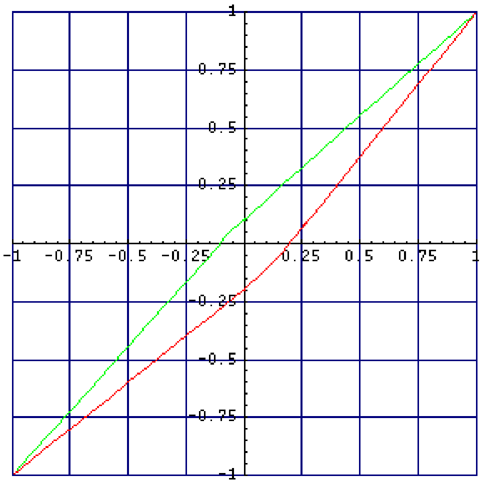

Figure 2: Yu trust function diagram (α =0.1 & β=-0.2).

3.1 Evaluation of the Yu Trust Function

To see the exact properties of the Yu trust function, refer to the Table 2, which shows T_t and its corresponding value (T_{t+1}) in the interval [-1, +1].

Table 2: Trust function's behavior, α =0.1 & β=-0.2.

T_t	Plus	T_{t+1}	T_t	Minus	T_{t+1}
1	0	1	1	0	1
0.9	0.01	0.91	0.9	-0.03	0.87
0.8	0.02	0.82	0.8	-0.05	0.75
0.7	0.03	0.73	0.7	-0.08	0.62
0.6	0.04	0.64	0.6	-0.1	0.5
0.5	0.05	0.55	0.5	-0.13	0.37
0.4	0.06	0.46	0.4	-0.15	0.25
0.3	0.07	0.37	0.3	-0.18	0.12
0.2	0.08	0.28	0.2	-0.2	0
0.1	0.09	0.19			
			0.16	-0.21	-0.06
0	0.1	0.1	0.12	-0.21	-0.09
			0.08	-0.21	-0.13
-0.02	0.1	0.08	0.04	-0.21	-0.17
-0.05	0.1	0.05			
-0.08	0.1	0.02	0	-0.2	-0.2
-0.1	0.1	0	-0.1	-0.18	-0.28
-0.2	0.09	-0.11	-0.2	-0.16	-0.36
-0.3	0.08	-0.22	-0.3	-0.14	-0.44
-0.4	0.07	-0.33	-0.4	-0.12	-0.52
-0.5	0.06	-0.44	-0.5	-0.1	-0.6
-0.6	0.04	-0.56	-0.6	-0.08	-0.68
-0.7	0.03	-0.67	-0.7	-0.06	-0.76
-0.8	0.02	-0.78	-0.8	-0.04	-0.84
-0.9	0.01	-0.89	-0.9	-0.02	-0.92
-1	0	-1	-1	0	-1

Figure 3 illustrates the behavior of the proposed trust function in cooperation situations. It shows the reward values in the interval [-1, +1]. The main critique here is for cooperation in the interval (0, +1] but the behavior of the function in the interval [-1, 0) is fine. Consider the two following scenarios for cooperation:

a) If the participant is a trustworthy agent (e.g. T=0.8) and shows more cooperation, the function increases the trust value a little bit (0.02), but if it is not very trustworthy (e.g. T=0.2) and shows cooperation, the function enhances the trust value a lot (0.08). These are not good properties.

b) If the participant is a corrupt agent (e.g. T=-0.8) and shows cooperation, the function increases the trust value a little bit (0.02) and if agent's trust value is e.g. T=-0.2 and shows cooperation, the function enhances the trust value more (0.09) in comparison to the previous situation. These are good properties.

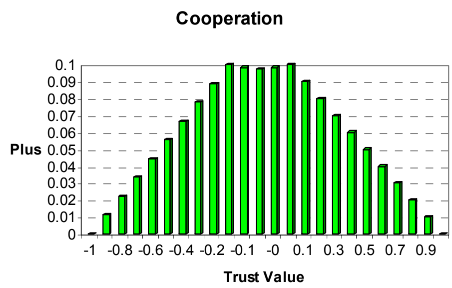

Figure 3: Yu trust function's behavior in cooperation.

Figure 4 demonstrates the behavior of the proposed trust function in defection situations. It shows the penalty values in the interval [-1, +1]. The main critique here is for defection in the interval [-1, 0) but the behavior of the function in the interval (0, +1] is fine. Consider the two following scenarios for defection:

c) If the participant is a trustworthy agent (e.g. T=0.8) and shows defection, the function decreases the trust value a little bit (-0.05), but if it is not very trustworthy (e.g. T= 0.2) and shows defection, the function decreases the trust value a lot (-0.2) which are good properties to some extend.

d) If the participant is a corrupt agent (e.g. T=-0.8) and shows more defection, the function decreases the trust value a little bit (-0.04) and if agent's trust value is e.g. T=-0.2 and shows defection, the function decreases the trust value more (-0.16) in compare to the previous state. These are not good properties.

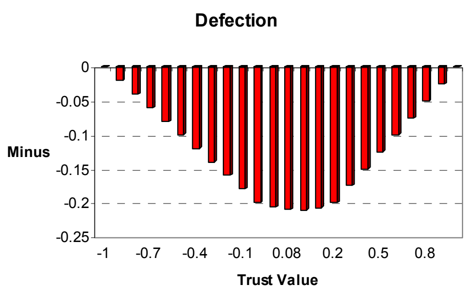

Figure 4: Yu trust function's behavior in defection.

Therefore, this paper's major critique is for cooperation in scenario "a" and defection in scenario "d". They show bad behaviors of the trust function. In the next section, a sample improved function is provided to modify the trust calculation for the social networks.

3.2 Modification of the Trust Function

To modify the trust function in (Yu and Singh, 2000), we consider six possible situations (Table 3). If trust value is less than β then the agent is a *bad* participant, if it is greater than α then the agent is a *good* member of the society, otherwise ([β , α]) we can not judge the agent. We just suppose it is a member who is looking for some opportunities. By considering both cooperation and defection factors, we have the following rules:

(1) If a bad agent cooperates, then we *encourage* it a little bit, e.g. by the factor $X_E \in (0.01, 0.05)$

(2) If we encounter with an agent who is looking for a chance by cooperating, then we *give it some opportunities* by the factor $X_{Give} = 0.05$

(3) If a good agent cooperates, then we *reward* it more than the encouragement factor: $X_R \in (0.05, 0.09) > X_E \in (0.01, 0.05)$

(4) If a good agent defects, then we *discourage* it a little bit, e.g. by the factor $X_D \in (-0.05, -0.01)$

(5) If we encounter with an agent that we can not judge it while it is defecting, then we *deduct its credit value* by the factor $X_{Take} = -0.05$

(6) If a bad agent defects, then we *penalize* it more than the discouragement factor: $|X_P| \in |(-0.09, -0.05)| > |X_D| \in |(-0.05, -0.01)|$

If the agent has an excellent trust value (e.g. 0.99) and shows more cooperation, we increase the trust value in a way that it would be convergent to 1. On the other side, if the agent has a poor trust value (e.g. -0.99) and shows more defection, we decrease the trust value in a way that it would be convergent to -1. Therefore, the new trust function is also in interval [-1, +1]. This function covers all the above proposed rules, more detailed behaviors are provided in Table 4.

Table 3: Six possible situations for interaction.

Trust Value	Cooperation	Defection
$T_{\text{Bad Agent}} \in [-1, \beta)$	***Encourage***	***Penalize***
No Judgment: $[\beta, \alpha]$	***Give/Take***	***Opportunities***
$T_{\text{Good Agent}} \in (\alpha, +1]$	***Reward***	***Discourage***

Table 4: Modified trust function, α =0.1 & β=-0.1.

T_t	Plus	T_{t+1}	T_t	Minus	T_{t+1}
-1	0.005	-0.995	**-1**	**0**	**-1**
-0.9	0.01	-0.89	**-0.975**	**-0.024**	**-0.999**
-0.8	0.015	-0.785	**-0.95**	**-0.047**	**-0.997**
-0.7	0.02	-0.68	**-0.925**	**-0.07**	**-0.995**
-0.6	0.025	-0.575	-0.9	-0.09	-0.99
-0.5	0.03	-0.47	-0.8	-0.085	-0.885
-0.4	0.035	-0.365	-0.7	-0.08	-0.78
-0.3	0.04	-0.26	-0.6	-0.075	-0.675

-0.2	0.045	-0.155	-0.5	-0.07	-0.57
-0.1	0.05	-0.05	-0.4	-0.065	-0.465
-0.05	0.05	0	-0.3	-0.06	-0.36
0	0.05	0.05	-0.2	-0.055	-0.255
0.05	0.05	0.1	-0.1	-0.05	-0.15
0.1	0.05	0.15	-0.05	-0.05	-0.1
0.2	0.055	0.255	0	-0.05	-0.05
0.3	0.06	0.36	0.05	-0.05	0
0.4	0.065	0.465	0.1	-0.05	0.05
0.5	0.07	0.57	0.2	-0.045	0.155
0.6	0.075	0.675	0.3	-0.04	0.26
0.7	0.08	0.78	0.4	-0.035	0.365
0.8	0.085	0.885	0.5	-0.03	0.47
0.9	0.09	0.99	0.6	-0.025	0.575
0.925	**0.07**	**0.995**	0.7	-0.02	0.68
0.95	**0.047**	**0.997**	0.8	-0.015	0.785
0.975	**0.024**	**0.999**	0.9	-0.01	0.89
1	**0**	**1**	1	-0.005	0.995

In the next section, the result of the new trust function in different intervals with various scenarios is illustrated; moreover, a quadratic regression is provided in order to find a simpler approximating formula for the new trust function.

4 RESULTS

In this part, a detailed evaluation of the new trust function with its regression is presented. First of all look at the Figure 5. It illustrates the behavior of the new function in cooperation situations. This diagram shows the value that trust function adds to the trust value each time according to the following scheme:

[-1, β) → *Encourage*
[β, α] → *Give Opportunities*
(α, +1] → *Reward*

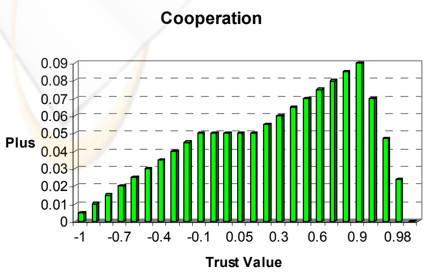

Figure 5: New function's behavior in cooperation.

Figure 6 also illustrates the behavior of the new function in defection situations. This diagram shows the value that trust function deducts from the trust value each time according to the following scheme:

[-1, β) → *Penalize*
[β, α] → *Take Opportunities*
(α, +1] → *Discourage*

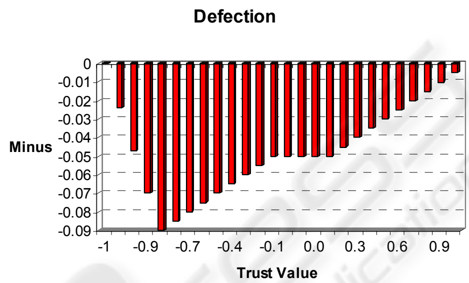

Figure 6: New function's behavior in defection.

The last two diagrams show important properties. They complete behaviors of each other.

In interval [β, α] they neutralize each other (if $\beta = \alpha$) to provide opportunity for new agents that their past behaviors are not available (newcomers) and also agents who want to pass the border between bad players and good ones. They must prove their merit in this area; otherwise they will be stuck in this region, because we add or deduct the trust value with the same rate, for instance |0.05| (we can play with α and β to change the interval, e.g. [-0.2, +0.1]).

In interval [-1, β), we penalize bad agents more than the rate that we encourage them. This means that we try to avoid and block bad participants in our business, at the same time we provide a chance by interval [β, α] for the agents who want to show their merit, if they reach this area then we behave more benevolently.

In interval (α, +1], we reward good agents more than the rate that we discourage them. This means that we try to support good players in our business and keep them in our trustee list as much as we can and as long as they cooperate, although they will be guided to the interval [β, α] if they show bad behaviors continuously.

The other important scenario is related to the value of the transactions, suppose a good agent cooperates for a long time in cheap transactions (e.g. $100) to gain a good trust value and after that he tries to defect for some expensive transactions (e.g. $1000). The solution is that we can consider a coefficient (λ) for the value of a transaction and then increase or decrease the trust value according to the λ. For example, if the transaction value is $100 then: λ=1 and if it is $1000 then: λ=10; therefore, if an agent cooperates for 5 times on the cheap transactions (λ=1) then we add his trust value 5 times. If he defects after that on an expensive transaction (λ=10) then we deduct his trust value 10 times continuously. So, by this approach we have a more reliable trust function which depends on the transaction value.

In Figure 7, you can see a quadratic regression that approximates the new trust function (Table 4) with 99.9% accuracy.

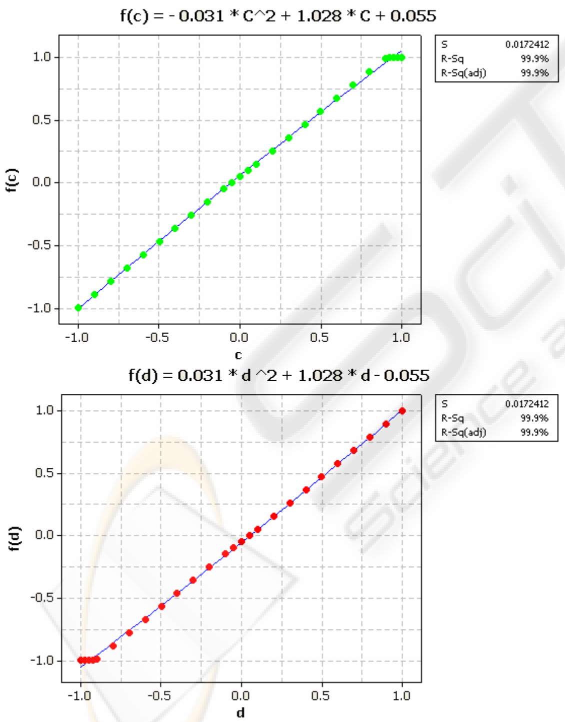

Figure 7: Quadratic regression for the new function.

The quadratic approximation to the trust function is as follows and you can see its diagram in Figure 8:

$$
\begin{cases}
T_{t+1} = \omega * T_t^{\,2} + \theta * T_t + \sigma \\
Cooperation: \omega = -0.031, \theta = 1.028, \sigma = 0.055 \\
Defection: \omega = 0.031, \theta = 1.028, \sigma = -0.055
\end{cases}
$$

Where:

$T_t \in [-1,+1]$
α =0.1 & β=-0.1
$X_E \in (0.01, 0.05)$
$X_{Give} = 0.05$
$X_R \in (0.05, 0.09) > X_E \in (0.01, 0.05)$
$X_D \in (-0.05, -0.01)$
$X_{Take} = -0.05$
$|X_P| \in |(-0.09, -0.05)| > |X_D| \in |(-0.05, -0.01)|$

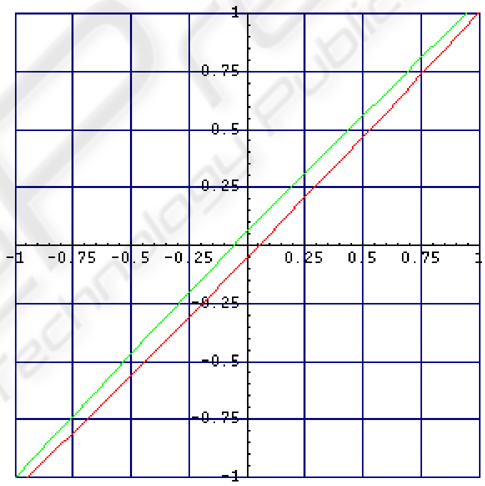

Figure 8: New proposed trust function.

Above function is simpler and has better behavior in comparison to the trust function in (Yu and Singh, 2000), which is more complex with some irrational behaviors. On the other hand, this function satisfies the proposed approach in this paper, although we can use the cubic regression with more sample points to achieve better accuracy. In the next section, some discussion and concluding remarks are provided.

5 CONCLUSION

In this paper, we evaluated a specific trust function for social networks. The paper showed the behavior of that function and proposed a new mathematical approach to modify a previously published trust formula (Yu and Singh, 2000). A mathematical discussion with various scenarios was provided to demonstrate the behavior of the new trust function. The paper used a bottom-up approach to create a new trust function; and it provided sample points according to the function's behavior for certain values of 8 constants used to parameterize our approach. We also provided a quadratic approximation to simplify calculation of the function, with only minor cost in accuracy. Alternative approximations would be needed if any of the eight constants were changed.

Another important factor is to consider both *expertise* (ability to produce correct answers) and *sociability* (ability to produce accurate referrals) in social networks. Usually, the goal of a trust function is to calculate expertise, but we should also consider another function for the calculation of sociability. If we do so, then we can evaluate our social networks by those two functions. As a future work, we would like to work on the computation of sociability. Our purpose is to evaluate social behaviors of agents by considering both functions at the same time and apply a two dimensional function for this assessment.

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