A Generalized Function for Reputation Estimation

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Abstract: - Some form of measure of *reputation* seems to be at the heart of all online transactional activities that require trust. However, most of the first generation *reputation management systems* (RMS) used are yet very basic and often vulnerable to various attacks. In this research, we take a holistic approach to the problem of RMS design. We propose a generalized set-theoretic reputation function construct where its specific components can be customized to meet the reputation assessment requirements in wide variety of scenarios encountered in today's online activities. We also show the construction of several canonical classes of reputation functions built on this construct.

Key-Words: - **reputation management system, opinion, reputation.**

1 Introduction

Reputation is a socio-cognitive mechanism [1] that has been shown to strengthen various collective actions and to promote order in social systems. Trust and reputation are believed to be essential conditions for reciprocity, and consequently for co-operation and collective action [2]. Social scientists have long observed it to be especially important in explaining co-operation in social settings where institutions, social monitoring and control are distributed.

Internet today is also seeing the emergence of distributed virtual communities. Almost all the online communities- ranging from buyers, sellers, or auctioneers of e-commerce-sites, millions of peer-to-peer file sharers, to the brigade of editors in wiki-sites- all need a reputation function and a reputation management system. In the real world, we notice that trust and reputation [2] are related to each other. Normally a person tends to trust another person if that person has a good reputation in the community. In a real society reputation plays a major roll in the commitment of joint activity.

Unfortunately, in the general virtual environment, all peers are equal and there is generally no centralized entity to serve as intermediaries for establishing trust between participants. Reputation management systems provide a way to overcome this problem in a distributed environment. Out of practical need designers of various virtual communities have used various schemes. Many [3, 4, 5, 6] have been specifically designed for peer-to-peer systems. As an interacting element of the society, we probably also estimate some form of reputation. However, there are several interesting questions. Can there be a better reputation function? Is there different functions are in use in different scenarios? What type of computation do we perform to thwart various threats posed by malicious peer conspiring to stage a coordinated attack on the reputation estimation? Can there be a generic function applicable to the spectrum of distributed virtual community scenarios?

In this context, we have recently investigated an interesting generic framework for quantifying the reputation of a peer in a community-like environment. Our main goal is to have a generic system, which is dynamic and customizable. In this paper, we present the proposed generic reputation management system (RMS) framework.

The paper is organized in the following way. First section-2 presents the set-theoretic function model and identifies various factors that might get accounted in a real-life reputation model. Sections-3 then presents the case specific forms and shows canonical cases of the functions. Finally, section 4 presents experimental evaluation that how well some of these proposed functions may withstand various attacks.

2 Reputation Model

In this section, we present a social-transactional model of a generalized reputation management system framework. Our goal is to develop a reputation estimation function, which is generic and at the same time customizable so that it can mimic various models of reputation estimation that are encountered in real life. This is followed by a discussion of the various factors that influence the reputation of a peer and towards the end we present a mathematical formulation for quantifying reputation.

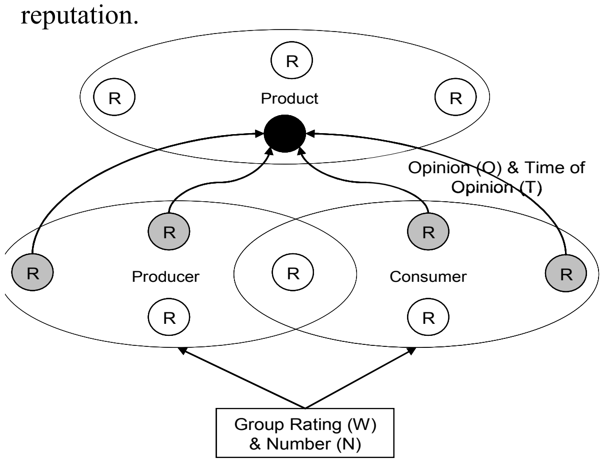

Figure 1 Set Based Model Of Any Environment

Reputation is estimated in a social setup. However, various social transactions are the basis for this evaluation process. Any transaction involves three parties: producer, product, and consumer. Each of the transactions occurs in a communal context. A particular product is sold repeatedly- but perhaps to different consumers, perhaps by different producers. Similarly, a consumer buys various products. Thus, there is a set of consumers, a set of producers and set of products. Thus, these transactions collectively build up a memory about a target individual and this is estimated in target's reputation function. The value is useful to establish trust in a later transaction involving the target in these communities.

Figure 1 illustrates one such transaction. The producer and the consumer sets are expressing their opinions about a product in the product set. Generally, the reputation of a peer indicates the level of trust his community has in him. The interacting peers express their satisfaction or dissatisfaction by providing an opinion about the transaction. In our research, we have identified several important factors those seem to be in use to define the reputation of a member of any group. (1) The opinion in terms of amount of satisfaction a peer receives from another peer, (2) the total number of transactions/interactions a peer has performed, (3) the reputation of the opinion provider reflecting his credibility, (4) temporal adaptability of opinion factor, and (5) the community context factor.

2.1 Opinion about a Transaction (O)

Generally, each transaction creates an evaluation about the goodness of a peer. Reputation relies on these individual feedbacks or *opinions* to evaluate a stable measure about the goodness of a peer. In many online RMS the reputation of a peer is simply, an average or summation of the feedbacks it receives Equation 1 gives a summation and averaging function, which is being used by many pioneering systems such as eBay.

$$R_A = \sum_{j=1}^{N} O_j \tag{1}$$

In such a system the buyer can leave a positive (+1), a negative (-1) or a neutral (0) feedback. The reputation of the peer is evaluated as the sum of these feedbacks. Using this equation the reputation of a person who has performed 20 good transactions (reputation = 20) is same as the one who has performed 21 good transactions and 1 bad transaction (reputation = 21 + (-1) = 20). Semantics of some transaction may consider the negative to be weighted heavily, while in some other case it might be perfect to just compute a sum.

2.2 Reputation of Opinion Provider (R)

Whenever a peer expresses an opinion, many social scenarios seem to take into account as to who exactly is providing this opinion. These make distinction between the opinion providers. The opinion from those with higher reputation is often weighted more heavily than those with lower reputation. While some systems - such as most voting systems do not distinguished between individual opinions providers.

2.3 Age of the Opinion (T)

In many scenarios, it seems the age of opinion is often considered an important factor in calculating reputation. By age what we mean is that the freshness of the opinion. By incorporating temporal adaptivity some social systems tends to encourage honest and good peers to remain honest. Due to the aging factor in our system a peer cannot sit on his past laurels and start misbehaving ,because his recent opinions would be the ones which impact his reputation the most rather than the older ones.

2.4 Number of Transactions (N)

As we have mentioned earlier the summation equation is not a reliable indicator of the overall reputation of a peer. In this system, a peer can hide his misbehavior by simple increasing the volume or number of transactions he indulges in. Thus, the total number of transactions is an important factor in determining the reputation of different peers irrespective of the volume of transaction they undertake. A modification to the summation equation (equation 1) can be defined as the ratio of the summation of the different feedback and the total number of transactions.

2.4 Group Reputation (W)

A peer with a high individual reputation will usually be associated with a group whose members are also highly reputed. However, in cases where a highly reputed peer becomes a member of a group whose members are know to misbehave; group reputation becomes an important factor. In our model, the group reputation, which is an average of the reputation of all the members of a group, would be an indictor of the credibility of the opinion provider. Since the lower group reputation is affecting the good peer, he would have an incentive in encouraging the other members to indulge in honest transactions

2.6 Impact Parameters

We introduce two types of impact parameters the Impact Variable (X) and the Impact Weight (α). These variables are used to control the direction of influence and the amount of influence the above-mentioned variables would have on the overall reputation of the peer. Table 1 gives the notations for the various impact parameters. Finally, we bring all the variables together to form a generic reputation function (equation 2)

$$R_A(t)=\sum_{k=1}^{m} W_k \left[\frac{\sum_{j=1}^{N} R_j^{\alpha^R \times X^R} \times O_j^{\alpha^O \times X^O} \times e^{(-\lambda Tj)\alpha^T \times X^T}}{N^{\alpha^N \times X^N} + \sum_{j=1}^{m} W^{\alpha^W \times X^W}} \right] + \Phi e^{-\lambda / T_n} \qquad (2)$$

Variable	Impact Variable	Impact Weight
Opinion	X^O	α^O
Rating	X^R	α^R
Time	X^T	α^T
Count	X^N	α^N
Time Span	X^S	α^S
Group Rating	X^W	α^w

Table 1: Notations for Impact Parameters

2.7 Generic Reputation Function

How does the generic reputation function (equation. 2) address the general concerns faced by present day reputation functions? The summation equation (equation 1) is replaced by an averaging function that calculates the reputation of an individual over a period. The opinion credibility issue is taken care off by involving the individual reputation (R) of the opinion provider. The decay of opinions with time is addressed by the exponential part of equation 2 where *"λ"* is used to define the rate at which the opinions would get older.

In our system the individual starts of with some initial reputation instead of zero. The variable *"Φ"* is used to assign the initial reputation value and it serves the dual purpose of stabilization.

2.8 Recursive Implementation

$$R_n = \frac{\left(R_n^{\alpha^R \times X^R} \times O_n^{\alpha^O \times X^O} \times W_n^{\alpha^W \times X^W} \right) + \left(e^{(-\lambda Tj)} \times R_{n-1} \right)}{1 + e^{-\lambda Tj}} \qquad (3)$$

Where : $T_j = (T_n - T_{n-1})$

Equation 3 shows a scheme of estimating the reputation function incrementally.

3 Canonical Classes of the Function

One of the key features of the generic RMS is that it is customizable and dynamic. Depending upon the deployment environment, certain variables would impact the reputation where as others wont' be part of the determination process. There are four primary customizable variables viz. R, T, N and W, thus there are sixteen possible ways to customize them. However, we have found real life correspondence at least of five cases. Table 2 shows the various applications we have found that could use the RMS.

3.1 A Fading Memory Averaging Function

$$R_A(t) = \left[\frac{\sum_{j=1}^{N} R_j^{\alpha^{R} \times X^{R}} \times O_j^{\alpha^{O} \times X^{O}} \times e^{(-\lambda Tj)\alpha^{T} \times X^{T}} \times W^{\alpha^{W} \times X^{W}}}{\sum_{j=1}^{N} e^{(-\lambda Tj)}} \right] + \Phi e^{-\lambda / T_n} \quad (4)$$

In equation 4, $R_A(t)$ denotes the reputation of peer *"A"* at time *"t"*. R_j is the individual reputation of the peer providing the opinion O_j and T_j is the age of the opinion. The value $\Phi e^{-\lambda / T_n}$ is the normalizing factor for stabilizing the value of the reputation. α and X are the impact variables and "λ" is the decay factor. The formula consists of two parts. The first part is the average amount of reputation a peer receives for its transactions.

The second part is to take care that the reputation of the peer does not decay down to zero with time. If a peer does not indulge in any kind of transactions for a long period, there are no fresh opinions coming in. Hence, due to the decay factor the value would eventually reach zero. In order to protect the reputation function from this situation the reputation value stabilizes itself to "Φ".The function remembers the most recent opinion and exponentially forgets the older ones. Example: Readers expressing opinions about a book. The individual reputation of the reader matters since we want to weight the opinion expressed by a professor more than the opinion of a casual reader.

The time of the opinion matters since a potential buyer would like to know the current reputation of the book as oppose to the past reputation. The number of opinions helps in calculating the average reputation of the book and finally the group reputation matters because of the same arguments put forth in section 2.5.

3.2 A Memory Less Summation Function

$$R_A(t) = \sum_{j=1}^{N} R_j^{\alpha^{R} \times X^{R}} \times O_j^{\alpha^{O} \times X^{O}} \times W^{\alpha^{W} \times X^{W}} \quad (5)$$

In this scenario, the target is the product but the evaluator is the producer. This is a memory less summation function because in this scenario the producers express their opinions once. This function evaluates the reputation of a product based on the producer/producers reputation, his/their opinion about the product and if applicable the group reputation of the producers. Example: Authors expressing opinion about their book .Single or multiple authors can be associated with writing a book. These authors in turn might express an opinion about their book. This is always a one-time process. One does not find situations where the authors keep on changing their opinion about their book. Hence, the reputation of the book is simply a summation of the product of author reputation, author opinion and author group reputation.

Target ~ Evaluator	R	T	N	W
Book ~ Reader	1	1	1	1
Book ~ Author	1	0	0	1
Movie ~ Viewers	0	1	1	1
Movie ~ Critics	1	1	1	0
Article ~ Reviewer	1	1	1	0
Article ~ Writer	1	0	0	1
Article ~ Journal	1	0	1	0
Article ~ Reader	1	1	1	1
Course Material ~ Student	0	1	1	1
Course Material ~ Preparing Teachers	1	0	0	1
Course Material ~ Other Teachers	1	1	1	1
Protocol ~ Companies	1	1	1	1
Protocol ~ Users	0	1	1	1
Satellite ~ Space Agency	1	0	1	0
Satellite ~ Satellite Service User	0	1	1	1
Automobile ~ Manufacturer	1	0	0	1
Automobile ~ Mechanic	1	1	1	1
Automobile ~ Buyer	0	1	1	1
University ~ Faculty	1	0	1	0
University ~ Students	0	1	1	1

Table 2: Example Environments

3.3 A Fading Memory Averaging Function Without Opinion Credibility

$$R_A(t) = \left[\frac{\sum_{j=1}^{N} R_j^{\alpha^{R} \times 0} \times O_j^{\alpha^{O} \times X^{O}} \times e^{(-\lambda Tj)\alpha^{T} \times X^{T}} \times W^{\alpha^{W} \times X^{W}}}{\sum_{j=1}^{N} e^{(-\lambda Tj)}} \right] + \Phi e^{-\lambda / T_n} \quad (6)$$

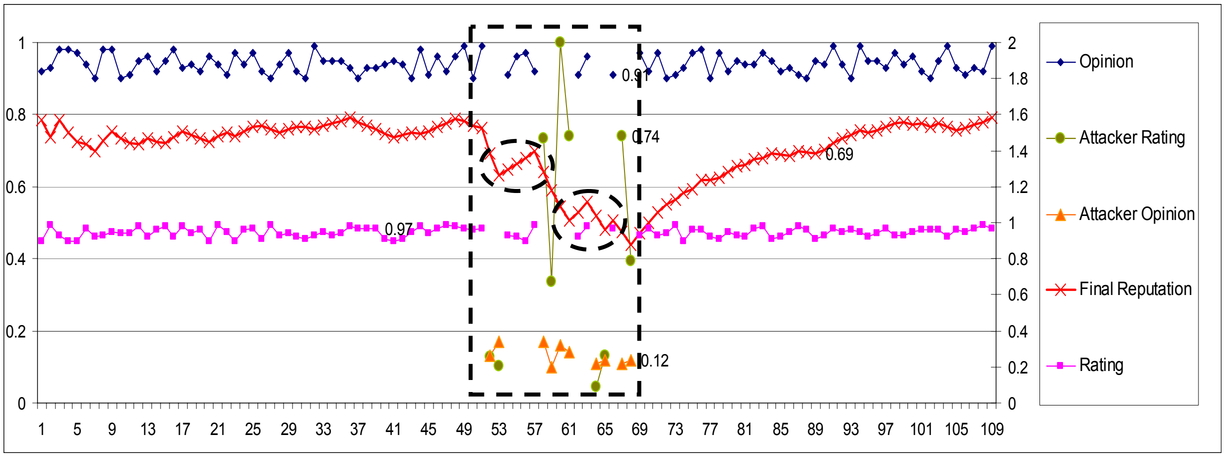

Figure 3: Behavior of the reputation function the attacking group's members have random personal reputations.

This is again a fading memory averaging function but here only the opinion matters where as the reputation of the opinion provider does not matter. The reputation of the opinion provider is dropped since this function is deployed in scenarios where the opinion providers fairly have the same reputation. Thus, we set the value of X^R to zero.

If at some point we want to differentiate between the opinions, we can use the $\boldsymbol{\alpha}^{\mathbf{O}}$ parameter to vary the impact weight of the opinions. Example: The Movie ~ Viewer example captures this scenario where the individual reputation of the viewers does not have any impact on the reputation of the movie. Since there are so many viewers and they are almost on the same level as far as reputation goes.

3.4 A Fading Memory Averaging Function Without Community Context Factor

$$R_A(t)=\left[\frac{\sum_{j=1}^{N} R_j^{\alpha^{R}\times X^{R}} \times O_j^{\alpha^{O}\times X^{O}} \times e^{(-\lambda T_j)\alpha^{T}\times X^{T}} \times W^{\alpha^{W}\times 0}}{\sum_{j=1}^{N} e^{(-\lambda T_j)}}\right]+\Phi e^{-\lambda/T_n} \quad (7)$$

Here we do not include group reputation in the computation of reputation. This is due to two reasons. Firstly, the evaluators cannot be further divided into distinct groups. Secondly, they represent a part of the society that is best in their field. Example: The example to critics providing opinion about a movie exposes this scenario where the critics cannot be distinguished from each other by grouping them. Thus, since we are not able to form independent groups the community reputation variable does not come into picture.

3.5 A Memory Less Averaging Function

$$R_A(t)=\left[\frac{\sum_{j=1}^{N} R_j^{\alpha^{R}\times X^{R}} \times O_j^{\alpha^{O}\times X^{O}} \times W^{\alpha^{W}\times 0}}{N}\right] \quad (8)$$

In this case, the target is the product and the evaluators are the producers. Here we do not take the group reputation and the time of opinion while computing the reputation of the target. The reason for not including group reputation is the same as that for equation 7 and that for not including time of opinion is same as for equation 5.

4 Experimental Evaluation

We performed an experiment to evaluate the resilience of the reputation function.

In this experiment, we considered a common form of attack scenario where a group of attackers are turning hostile towards the target peer. During the attack, the attacking group continually expresses bad opinion about the target in a given span of time with the intension of pulling down the target's reputation. Since, the attack is deliberate we assume that during the attack period, the frequency at which the attacker group expresses its opinion is higher than that of the community's honest members. We have a single target and a group of attackers. The attackers are initially part of the evaluator group but abruptly turn evil.

We consider a larger than expected attack group to consider the worst case. The number of members of the attacker group is set to 10 % of the total number of evaluator peer. The graphs show the ordinary members *opinion* and *ratings* which stays stable. A small group of members than turns into attacker in the attack span. The *attacker ratings* are random but *attacker opinions* are deliberately low.

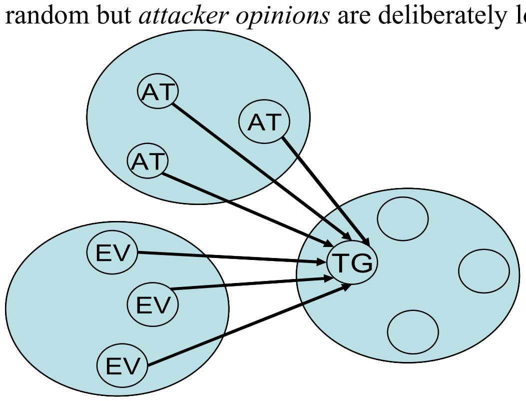

Figure 2. Damaging Gang Attack

The dynamic final reputation of the target is plotted. Figure 2 gives a graphical representation of the attack. The rectangular dotted region represents the attack periods. The top curve shows the general opinions and the bottom curve shows the attackers' given opinions.

In figure 3, we see a saw tooth like behavior because the honest group frequency is only a few times lower than the attacker frequency and the attackers have random personal reputation. Hence, there are recoveries at regular intervals but eventually the reputation goes down.

In figures 3, we observe that though the attackers manage to bring down the reputation of the target during the attack period, they are not able to inflict permanent damage. The function recovers itself to the original value through the honest opinion expressed by evaluators with high reputation and the age of the opinion variable.

5 Conclusions

We have presented a generalized reputation function construct which can be customized and used in various environments. We have identified the core factors that can affect the reputation of an individual. In most of the other reputation functions, the core factors are static whereas in the proposed function they can be changed according to the demands of the environment. However, it is quite possible to frame other reputation functions.

As interacting elements of a society, we all probably also estimate some form of reputation. It will be an interesting pursuit to study how individuals formulate the notion. It is quite possible that perhaps various individuals use alternate schemes, which probably play a role in success or failure of trust dependant social activities. Very little previous work can be traced on it.

Also, in this paper we have shed light towards plausible design objectives. We have demonstrated the robustness of the reputation system under limited kind of attack. We are currently studying robustness with respect to other forms of attacks on the reputation management.

On the basis of estimated robust reputation various forms of complex social applications are feasible. In [7] we present a related research on various forms of reputation based social computing.

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