A System for Centralizing Online Reputation

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***Abstract* - Online reputation systems have emerged as some of the most promising tools for fostering trust in online business and interpersonal interactions. These systems collect, aggregate, and distribute feedback about participants' past behaviour. Although successfully used, current online reputation systems lack an important feature which is globality. Participants build a reputation within one community, and sometimes several reputations within several communities, but each reputation is bound to the corresponding community. Moreover, such reputation is usually computed using algorithms over which the inquiring agent has no control. This paper proposes one way of dealing with this problem. We introduce an online reputation centralizer that collects raw reputation data about users from several online communities and allows for it to be aggregated according to the inquiring agent's requirements, using a stochastic trust model, and taking into account factors that qualify a user's reputation.**

***Index Terms* - Reputation System, Online Trust, Portability, Stochastic Model**

I. Introduction

The Internet has enabled the proliferation of online interpersonal and business interactions between individuals who have never interacted before. These interactions are usually completed with some concern given that private information and the exchange of money and goods are involved. A mechanism is therefore needed to build trust among strangers who interact online. Trust can be divided into direct and recommender trust. While direct trust comes from direct experience, recommender trust is derived from word-of-mouth recommendations [1]. Trust is dynamic and can be developed over time as "the outcome of observations leading to the belief that the actions of another may be relied upon" [3].

One way to foster trust in online interactions is through collecting and managing information about the past behaviour of interacting parties. This information is then aggregated into an entity called reputation. Reputation is defined as a collective measure of trustworthiness based on the ratings of community members [2] which might affect the interacting party's future payoffs [4].

Online reputation systems are community tools that "collect, distribute, and aggregate feedback about participants' past behaviour" [5]. A negative reputation system gathers and distributes feedback on untrustworthy participants to discourage their behaviour; while a positive reputation system encourages participants with a history of honest behaviour [6]. In a hybrid reputation system, both positive and negative behaviours are taken into account. In such a case, participants start with neutral reputation values, and then points are taken away as a punishment for bad behaviour or added as a reward for good behaviour [7]. EBay's feedback forum (ebay.com) is an example of a hybrid reputation system. It allows participants to rate each other with +1 for positive, 0 for neutral, and -1 for negative feedback. All the feedback values are then aggregated into one reputation value to be made available to members of the eBay community [2].

Three entities are usually involved in trust models for online reputation systems: (1) the ***querying agent*** is the user who wants to know whether a given user (the ratee) can be trusted; (2) the ***ratee*** is rated by others on his/her past behaviour; and (3) the ***rater***, also called recommender, is the user providing information about (i.e., rating) the ratee, usually after having interacted with him/her.

Online reputation systems raise numerous challenging research questions [4]. In this paper we address one of them: the lack of globality (also referred to as "portability"). It is indeed difficult to exchange reputation data between different online reputation systems [5]. A member of the eBay community, for instance, cannot use his/her reputation outside the eBay community - hence the name "local reputation". It is desirable that a user who has built a good reputation within a given community could take advantage of that reputation within other communities - hence the name "global reputation" (or "portable reputation").

As a step towards globality, we suggest the aggregation of reputation data from different online communities. A major difficulty in doing so is that each community calculates reputation differently. For instance, a rating value on eBay is between -1 and 1 while other online communities use ratings between 0 and 5 and may include textual comments as well. In order to aggregate reputation data from various communities, we propose a common reputation model into which the data can be translated.

Within our "global view" of online reputation, a ratee grants permission (with the possibility of opting out at

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any moment) to the communities where he/she has developed a reputation to share his/her data with a global aggregation service. We envision such a service to be offered by a third party who partners with online communities. The business, privacy, and security implications of an aggregation service are undoubtedly important but they are beyond the scope of this paper. Before interacting with the ratee, a user (the querying agent) logs into the aggregation service, looks up the ratee, gets access to his/her raw reputation data from partnering online communities, and configures the aggregation process. This configuration process involves parameters such as: weights assigned to online communities (perhaps giving more weight to the more established communities), transaction dates (perhaps giving more weight to the more recent recommendations), transaction values/volumes (perhaps giving more weight to recommendations regarding high value transactions), etc. Instead of providing a “dead” reputation score (as most of today’s online reputation systems - e.g., eBay’s feedback forum), the querying agent is given the opportunity to be involved by configuring the aggregation process and thus will find the aggregated feedback more useful.

The rest of the paper is organized as follows. Section 2 defines and classifies online reputation systems and identifies the research challenges they raise, including the lack of globality. Section 3 details our proposed trust model, starting with an introduction of discrete trust computation models. An example is used to illustrate how our model works. Section 4 reports on an implementation of our model. Section 5 reviews related work and contrasts it with our solution. Section 6 concludes the paper.

II. Online Reputation Systems

1. Definition and Classification

When interacting online, individuals usually find themselves in situations where they need to trust complete strangers in order to conclude a deal. The deal can be commercial or interpersonal, and the stranger can be an organization or another individual. Buying a product or service from an online retailer or from an individual you meet in an online marketplace, asking for and obtaining financial advice from an expert on the web, or simply getting your news of the day from an online news source or a blogger are examples of such situations.

Efforts are being undertaken by businesses that rely on their consumers’ trust for the viability of their business model to develop innovative ways to diminish or eliminate the fear that these consumers experience when interacting with them or through them. Online reputation systems have emerged as a technology for building trust and fostering communication in online communities such as eBay, Amazon’s zShops (amazon.com), Epinions (epinions.com), BizRate (bizrate.com), ExpertCentral (expertcentral.com), and OpenRatings (openratings.com), just to name a few. Such systems are believed to have a wide impact on consumer behaviour and public opinion formation [4].

A reputation system is an information system that aggregates and presents second-party opinions. Typically, it uses a mechanism for rating products, services, or individuals’ past behaviour and performances on various aspects and computing an overall value, such as a reputation score, based on the feedback ratings from different peers in a community. Those values and ratings are made publicly visible so that other peers can use them as a prediction of a given party’s future performance. The most popular applications of reputation systems are those used in online marketplaces. For instance, eBay, as was mentioned in Section 1, uses a mechanism to allow transaction partners (usually a seller and a buyer) to rate each other (using the values 1, 0 or -1) based on their performance in a given transaction. Amazon’s zShop users are provided with a rating scale (1 to 5) and a set of measures such as “fairness”, “product quality”, etc. Other mechanisms exist but they are usually similar to the ones we just mentioned.

As reported in [18], the main advantages of online reputation systems include:

- *Community building*: Reputation systems help responsible members share ethical values and a sense of building a better and safe future for their online community.
- *Reduction in the perception of risk*: Viewing user feedback diminishes potential customers’ perception of risk by helping them comprehend the past performance history of their potential transaction partners.
- *Positive reinforcement*: Reputation systems encourage the consistency of honest behaviour. Once a participant has built a positive reputation, there is great incentive to maintain and improve on it.
- *Rich format*: Reputation systems often depend on unstructured free text comments as well as quantitative summary measures, which adds to the richness and utility of the feedback.
- *Dynamism*: Reputation systems are highly dynamic as their feedback components capture comments and ratings over a large number of participants and over time. This dynamic nature is particularly important in supporting the principle that trust is time dependent.

From an economic point of view, reputation systems are believed to decrease the cost that businesses dedicate to building consumer trust online. For example, trusted third-party services such as trust seals and Escrow services are popular and play a big role in establishing trust online, but those services are usually costly. The appeal of reputation systems is that, when functioning well, they establish trust and facilitate cooperation without the requirement for those expensive services. The success of eBay is believed to be, in part, due to its feedback forum.

Beyond online marketplaces, reputation systems are being deployed to support different business models that provide different services. We classified online reputation systems into the following categories based on the position they occupy within the business model of the online entity that deploys them [22].

- *Online Market Makers*: these online businesses provide participants with a reputation system to rate each other. Good reputation builds trust between market participants; therefore more transactions take place which translates into more profit for the market maker. Online auction sites such as eBay and Yahoo! Auctions (auctions.yahoo.com) fall within this category.
- *Complaint Clearinghouses*: these online entities provide a platform for consumers to post complaints about businesses. The model used by BBBOnline (bbbonline.com), for instance, makes revenue by certifying participating businesses and by selling its approval seal. The business model of BadBusinessBureau (badbusinessbureau.com) makes money through donations from registered consumers and online advertising. The former model is obviously difficult to maintain financially since it presents itself as a public service that needs donations to survive.
- *Product or Vendor Reviews*: many online businesses provide a platform for consumers to review products and services. Epinions, for instance, generates profits through online advertising by offering access to its content (providing XML feeds to its partners) and licensing its technology. BizRate sells market research and advertises online. Its vendors pay in order to be ranked higher. Amazon (amazon.com) provides an online book review system to help buyers make informed decisions, hopefully generating more sales for Amazon and more customer satisfaction and loyalty.
- *Reputation Software*: this category includes enterprise software usually classified as business intelligence (BI) applications, used to mine the web (as well as internal and external databases) for reputation related information on a company or its competitors. A typical example is the Biz360 (biz360.com) market intelligence software which, according to its vendor, aggregates, analyzes, and measures corporate reputation across the broadest array of print, online and broadcast sources.

2. Research Challenges

Despite their widespread use, reputation systems face several challenges related to gathering, distributing, aggregating and displaying feedback. These challenges include but are not limited to the following [5, 4, 9, 17]:

- After completing interactions, people have little incentive to, or may not bother to leave feedback on their transaction partner.
- It is common that people choose not to provide negative feedback as they tend to avoid retaliatory negative feedback or unpleasant potential transactions.
- It is usually difficult to assure the honesty of feedback. Some users might use negative feedback as a way to harm other users' reputation or use positive feedback to reward an undeserving accomplice.
- Online identity (i.e., username, pseudonym) change is a major problem in distributing feedback. Users who accumulate negative feedback can always register to a service with a new pseudonym and benefit from a fresh start.
- The dynamic personality of peers gives way to users oscillating between building and milking (i.e., taking advantage of) their reputation.
- Different online communities have different rating systems to aggregate and display feedback. EBay for instance operates a mechanism displaying the net feedback (positive minus negative ratings) while others like Amazon display an average. These simple numeric ratings fail to reflect important subtle details of online transactions such as whether the feedback comes from low value transactions or whether it is provided by reputable raters.

These and other issues are being addressed by the research community with the aim of understanding, designing, developing, and deploying robust and useful online reputation systems. Yet there is one characteristic of online reputation systems which is rarely addressed: globality [5, 17, 19].

Globality is a feature that allows users to take their online reputation with them anywhere they go in the online environment. It takes time and effort for a user to build a reputation within an online system or community, but a user receives no reward for that time and effort outside that system or community [17].

Global (i.e., portable) reputation systems aim to solve this problem by making a user's reputation information accessible to any online entities s/he wishes to interact with. Not only can these systems save the time and effort that people spend on building reputation in different online communities, they also increase the rate of successful interactions as a result of providing more information about transaction partners' past behaviour and performances. They can therefore be more effective than current reputation systems.

In addition to benefiting individuals, the globality (i.e., portability) of online reputation plays an important role in helping businesses. Most successful reputation systems are maintained by such dominant businesses as eBay, Amazon, and Yahoo, thus it is not easy for a small online business to compete. A global online reputation system can help small online businesses build their brands and promote their products and services through the sharing of reputation information. Besides, there is no reason for users not to adopt global reputation systems for they are supposed to reveal more reputation information about specific individuals who might be potential transaction partners.

III. Proposed Trust Model

1. Discrete Trust Computation Models

Computation models for online trust can be classified into summation, weighted average, fuzzy, flow, Bayesian, belief, and discrete models [2]. We only discuss discrete models here.

Using a discrete model such as the one in [13], a rater evaluates his/her interaction with the ratee as “excellent”, “good”, “normal”, “bad” or “worst”. One shortcoming of discrete models is that they are not precise since “heuristics mechanisms like lookup tables must be used” [2] to convert feedback values into their numeric equivalent.

In [14] discrete feedback is used in conjunction with a statistical model to compute trust based on self-experience and recommendations from raters. It is assumed that the space of possible outcomes of transactions is finite (e.g., “excellent”, “very good”, “good” and “bad”) and that N transactions have been observed for the same ratee by the querying agent or other raters. Assuming that ratee b will perform in a similar manner in the future, one can predict the probability of the different outcomes for future transactions using the formula:

$$T_b(o) = (\text{number of times the observed outcome was equal to } o) \,/\, N.$$

$T_b(o)$ is the probability that a future transaction with ratee b will lead to an outcome o. The sum of the values $T_b(o)$ over all values of o yields the value one. $T_b(o)$ is also called the “trust that ratee b will provide an outcome o”. Instead of keeping all previous transaction outcomes in memory, an incremental trust update formula is used [14]. The current trust $T_b(o)$ (for each value of o) and the number of observations to date are kept in memory, and after a new transaction yielding outcome o is observed, the trust values and N will be updated as follows:

$$T_b(o) = (T_b(o)*N +1)/ (N+1).$$
$$T_b(o') = (T_b(o')*N)/ (N+1) \text{ for } o' \text{ different from } o.$$
$$N=N+1.$$

Note that a multidimensional reputation model can be considered in the context of discrete reputation. For instance, a seller’s reputation can be evaluated according to two dimensions: quality of good and service. For both dimensions, one may set up discrete values for the possible outcomes, such as “excellent”, “good”, etc.

2. Model for Global Online Reputation

Our approach first aggregates a ratee’s ***local*** reputations (assuming there are many) then combines them into a ***global*** one.

A ratee’s ***local reputation*** is linked to a single community (e.g., a seller’s reputation on eBay is considered local to the eBay community). If a community maintains an online reputation system, then the ratee is rated every time he/she transacts within that community. Note that we are not interested in the aggregated reputation value as provided by the community’s reputation system but rather in the raw data.

Let us assume that the raw data is comprised of the following elements.

- *Feedback value*: this is an essential parameter in reputation models (also called rating or recommendation). This value is typically given by a rater as feedback on a single transaction with the ratee. Reputation systems differ in their feedback representation formats, which could be discrete or continuous; numerical or textual or both. Some systems use feedback values alone to aggregate a user’s reputation without considering other attributes (e.g., eBay only sums up the feedback values).

- *Information on rater credibility*: the quality of recommendations in trust systems is not guaranteed since nothing prevents malicious raters from providing unfair recommendations. As stated in [8, 9, 10, 16], feedback from raters with higher credibility should be weighted more than feedback from those with lower credibility since these are more likely to submit dishonest feedback. However determining rater credibility is a challenge. Shi et al. [15] for instance use data analysis and machine learning techniques to detect unfair recommendations. The querying agent may also compare the recommendation with his own experience. If the querying agent decides to interact with a ratee based on a recommendation from a rater, the difference between the rater’s and the querying agent’s perceptions, called semantic distance [1], can be used to adjust future recommendations from the same rater. In [9], raters’ credibility is a function of their reputation within the community, hence reputable raters are considered more credible, and therefore their ratings weigh more.

- *Context factor*: various transaction parameters such as the size and time of a transaction can be considered, for instance the feedback for larger and more recent transactions may be assigned more weight. More recent transactions are likely to better reflect the current behaviour of the ratee [12, 16]. The size of the transaction [16] is considered in order to avoid the situation where a user behaves honestly for small transactions and dishonestly for larger ones.

- *Number of transactions*: the number of transactions is useful because the total feedback divided by the number of transactions reflects a ratee’s reputation better than the total feedback alone.

It is important to note that other elements can be part of the raw reputation data hence it should not be limited to the elements mentioned above. Some reputation models, for instance, consider that the longer a rater has been part of a community, the more weight should be given to his/her feedback on other members. Others value the feedback of raters with the most transactions (regardless of how long they have been in the community). For more on this topic, the reader is referred to [4].

We assume discrete feedback is used. For instance eBay uses the discrete values “1”, “0” and “-1’ to stand for “Positive”, “Neutral”, and “Negative”. Discrete feedback needs to be normalized, so normalizing the three eBay discrete values within the range [0, 1] would yield the numerical values 1, 0.5 and 0. Unfortunately, normalization could lead to unrealistic results. For instance, one ratee may have five “Positive” (1), and five “Negative” (0) transactions, while another may have ten “Neutral” (0.5) transactions. If every feedback is equally weighted, these two ratees would end up with the same reputation value (namely 0.5), which does not reflect the reality.

For that reason, we decided to follow a different approach inspired by Shi et al. [14]. In order to represent discrete reputation better, we propose a ***stochastic trust model*** based on the assumption that the ratee behaves like a stochastic process, and the reputation value represents the expectation that the ratee will act accordingly in the future. We calculate (Formulas 1, 2, 3) the estimated probability of each possible distinct outcome ("Positive", "Neutral", or "Negative") for the action of the ratee taking into account the different rating attributes introduced earlier. We then sum up these values together with the corresponding numerical value (representing that outcome) (Formula 4). The aggregated reputation of ratee i denoted by R_i is calculated using the following formulas:

$$P_i(o) = \sum_{k=1, f_{ik}=o}^{I(i)} \frac{W_{ik}}{\sum_{m=1}^{I(i)} W_{im}} \quad (1)$$

$$W_{ik} = CR_{ik} * CF_{ik} \quad (2)$$

$$CF_{ik} = a * T_{ik} + b * S_{ik} + c\ .\ a,b,c \in [0,1] \,\&\, a+b+c=1 \quad (3)$$

$$R_i = \sum_{o \in O} P_i(o) * NumVal(o) \quad (4)$$

Here:
$P_i(o)$ = the estimated probability that ratee i will provide the outcome o in the future; O = the set of possible outcomes, such as "excellent", "good", "average", "bad", and "very bad";
$I(i)$ = the total number of transactions;
f_{ik} = ratee i's feedback value for transaction k;
W_{ik} = the aggregation weight for ratee i's feedback value for transaction k;
CR_{ik} = the credibility of the rater who rated ratee i for transaction k (note that ratee i can be rated many times by the same rater, but we only consider the rater's reputation at the moment transaction k is performed);
CF_{ik} = the context factor for ratee i's feedback value for transaction k;
T_{ik} = the time context factor for ratee i's feedback value for transaction k;
S_{ik} = the size context factor for ratee i's feedback value for transaction k;
$NumVal(o)$ = the numerical value corresponding to the outcome o (using a lookup table).

For an illustration, consider the example of a ratee i within a community X who has been rated 10 times (i.e., I(i) = 10) possibly more than once by the same rater. Table 1 shows the 10 feedback values as well as their corresponding f_{ik}, and the aggregation weights W_{ik} for each feedback value. Table 2 shows the mapping of discrete values into numerical values.

TABLE I.
FEEDBACK VALUES, THEIR CORRESPONDING F_{IK} AND AGGREGATION WEIGHTS

K	f_{ik}	W_{ik}
1	"Positive"	1
2	"Neutral"	0.5
3	"Negative"	0.5
4	"Positive"	1
5	"Neutral"	1
6	"Negative"	1
7	"Positive"	1
8	"Positive"	0.7
9	"Neutral"	1
10	"Positive"	0.3

TABLE II.
LOOKUP TABLE

Discrete	*Numerical*
"Positive"	1
"Neutral"	0.5
"Negative"	0

The estimated probability of ratee i being "Positive", "Neutral" or "Negative" in future transactions can be calculated as follows:

$$P_i(Positive) = \sum_{k=1, f_{ik}=Positive}^{10} \frac{W_{ik}}{\sum_{m=1}^{10} W_{im}} = \frac{1+1+1+0.7+0.3}{8} = \frac{1}{2}$$

$$P_i(Neutral) = \sum_{k=1, f_{ik}=Neutral}^{10} \frac{W_{ik}}{\sum_{m=1}^{10} W_{im}} = \frac{0.5+1+1}{8} = \frac{5}{16}$$

$$P_i(Negative) = \sum_{k=1, f_{ik}=Negative}^{10} \frac{W_{ik}}{\sum_{m=1}^{10} W_{im}} = \frac{0.5+1}{8} = \frac{3}{16}$$

The local reputation of ratee i within community X has a value of 0.65625 as estimated below.

$$R_i = \sum_{o \in O} P_i(o) * NumVal(o) = \frac{1}{2} * 1 + \frac{5}{16} * 0.5 + \frac{3}{16} * 0 = \frac{21}{32} = 0.65625$$

In order to apply the computation model, the attributes that serve in the aggregation need to be normalized. Reputation systems maintained by different online communities use different formats to represent these attributes. Before aggregating them, it is necessary to normalize them into numerical values using mapping tables or conversion formulas as proposed in [11].

After the local reputations for every online community have been calculated they are aggregated into a ***global reputation***. The global reputation (GR_i) is calculated as follows:

$$GR_i = \sum_{j=1}^{I(j)} R_{ij} * \frac{W_j}{\sum_{m=1}^{I(j)} W_m}$$

Here: R_{ij} = local reputation for ratee i within community j; W_j = the aggregation weight for community j; $I(j)$ = the number of communities considered. Note that assigning a weight of zero to a community discards it from the global reputation aggregation.

We assume here that a ratee can be globally identified throughout all communities. However, the raters only need to be indentified within their community where their credibility is supposed to be known. The same rater may occur in different communities with different identifiers and different local credibility values.

IV. Implementation

We implemented, deployed, and tested the reputation model described above in the form of an Online Reputation Aggregation System (ORAS).

The system is composed of the following components (see Figure 1 for the architecture): User Interface, Administrator Interface, Aggregation Module, Mapping Module and Lookup Tables.

The *User Interface* can be used by querying agents to register, enter the identity of the ratee to be looked up, select the rating attributes, their weights, etc. Through the User Interface, the querying agent can select the configuration parameters for the aggregation process, such as the values of *a* (importance of time context factor) and *b* (the importance of the size context factor), and for each community j included in the aggregation, the weight W_j for the reputation in that community and the lookup table $NumVal_j$ containing the numerical values of the different outcomes considered in that community.

The Administrator Interface can be used to setup *Lookup Tables*, calculation algorithms, mapping schemes, conversion parameters, etc. The *Aggregation Module* implements the algorithms used to compute the local reputation for every community as well as the global reputation. The *Mapping Module* normalizes raw reputation data into a common format using Lookup Tables. Finally, participating *Online Communities* create and expose *Web Services* that give access to the raw *Reputation Data* of the ratees (and only those) who have granted them permission to do so.

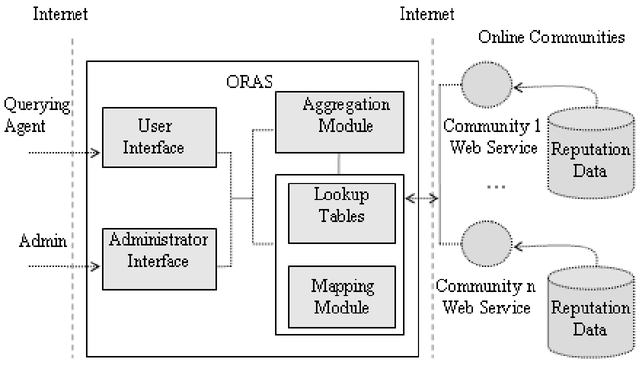

Figure 1. Conceptual Architecture of ORAS

Figure 2 shows how the user Hui@mail.com selects the communities (named X, Y, Z in this example) she wants to consider in her calculation. Remember that these communities are partnering with the aggregation service, and that the ratee in question (identified as Alex@mail.com in this example) has agreed to his data being shared with the aggregation service. In this example, the user assigns the highest weights to the communities believed to be the most accurate in reflecting the real reputation of the ratee.

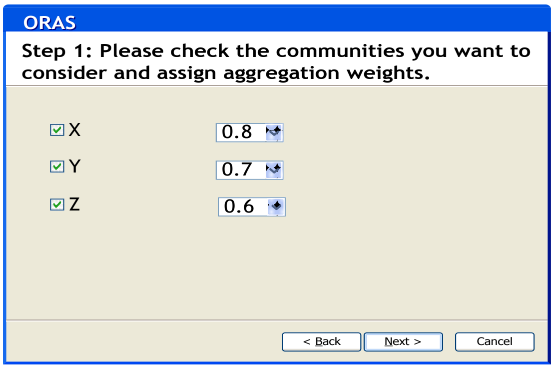

Figure 2. User Interface (Step 1)

In Step 2, the user chooses the rating attributes and sets their weights. In the current implementation of ORAS, the credibility of a rater is taken to be the value of his/her own reputation at the moment he/she provided the feedback. Other methods for computing rater credibility can be implemented.

Figure 3 shows the output screen after ORAS computes the local and global reputation values for ratee Alex@mail.com.

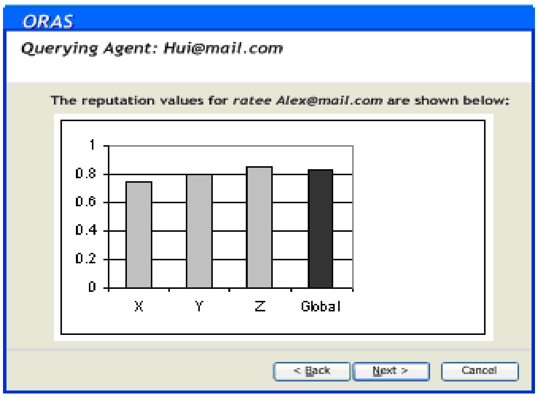

Figure 3. Local and global reputations are displayed

V. Related Work

In this section we contrast our model with three academic and two commercial initiatives.

EgoSphere [17] is a system aiming to integrate different reputation services by facilitating the transfer of reputation between them. It is composed of a web proxy, a reputation database and a reputation exchange. The web proxy runs on a user's computer monitoring all reputation-related activities. It fetches the webpage requested by the user from an EgoSphere-supported server, and analyzes the HTML code searching for reputation evidence. The reputation database receives and manages the reputation evidence from many web proxy sources. The reputation exchange uses such evidence to calculate how much reputation data should be transferred from one service to another. The basic idea is that the more similarity two services have, the more reputation evidence can be transferred from one to the other.

Our solution is different in that the sharing of reputation information is conditioned by the user's approval, and our system does not need to parse HTML code because it has access to the raw data from participating online communities.

Ismail et al. [20] proposed a design for reputation systems in which a collection center/certificate authority (CC/CA) module provides a reputation certificate that contains users' reputation information in past transactions. A user can use a certificate to promote his reputation anywhere he transacts. This mechanism represents the portability feature of the design. In order to obtain a certificate, the rater and the ratee need to register with the system through the Token Issue Module before doing transactions. The rater submits the feedback about a ratee to the CC/CA module where a reputation value will be calculated and a certificate for the ratee will be issued. Before the ratee shows his certificate to his trade partner in a transaction, the certificate will be sent to the Relying Party Module to be validated, helping users decide whether to proceed with a transaction or not.

Some of the differences between this approach and ours include the fact that our solution is transparent to the rater as well as the ratee, and the fact that the querying agent is able to configure the aggregation of the raw reputation data coming from various online communities.

Liau et al. [21] proposed a method to make peers' reputation portable in P2P networks. Their system is based on a reputation certificate which contains one peer's rating information collected from previous transactions with other peers. A peer first uses a resource discovery mechanism to find the service/product provider. All the peers that have the service/product will send this peer a response with their reputation certificates. The peer will make a decision after evaluating all the certificates, and then sends an acknowledgement with his digital signature to the chosen provider. After that, a time stamp will be sent from the provider to the peer consisting of the provider's digital signature and the time on the provider's computer. After verifying the signature and the time by using the public key of the provider, the peer will start the transaction with the provider. After the transaction, the peer will update the provider's reputation certificate by adding the ratings and the time stamp, and then a new certificate will be sent back to the provider to be displayed in the next transaction.

The main difference between this P2P approach and ours is the fact that ours is centralized. Also, our solution gives the querying agent the ability to configure the aggregation of the raw reputation data.

Some commercial applications have also been launched in an attempt to offer global reputation services.

The Authorati (authorati.com) rating service offers bloggers and online article authors a way to gain reputation and increase the visibility of their publishing. Users are allowed to list the URLs of their blogs/articles on their Authorati pages after registration. Readers can then rate the blogs/articles on Authorati. The rating consists of two parts: the authority rating (scale of 1-5) and the authorship rating (scale of 1-10). Each averaged rating will be shown below a blog or an article. Authorati allows readers to tag the contents of blogs/articles in fields such as arts, business, sports, technology, science, entertainment etc. In order to provide a portable rating service for blogs and online articles, Authorati offers its members a service for adding web widgets into their blogs or web pages to display the Authorati ratings. Members simply copy a piece of HTML code that generates the web widget and paste it on their blog, web page, or anywhere they want to show their Authorati ratings. Using a process that is more or less similar to Authorati, the iKarma (ikarma.com) online reputation service enables its members to rate other people and businesses. The idea is to provide a central location for managing reputation. In other words, when I interact with user U on website W, instead of rating him on website W, I go to a reputation centraliser (e.g., iKarma) and enter my ratings there. Typically, I can also click on user U's badge/widget (if displayed on website W) to see his current reputation.

What we propose in this paper is fundamentally different from what is currently offered by commercial services. Our solution (1) deals with raw reputation data; (2) offers the possibility to aggregate the local and global reputation according to the rater's specifications; (3) offers the possibility to select what communities (individual websites) to include in the aggregation process; and (4) provides a more configurable aggregation process for reputation.

The aim however remains the same: the portability, centralization, and globalization of online reputation.

V. Conclusion

This paper addressed the lack of globality in online reputation systems. Users who build a reputation in one community are unable to transfer it to another community. In view of the importance that reputation systems are gaining as a way of fostering trust in online business and interpersonal interactions, we believe globality to be an important feature. Our approach to achieve it is to gather raw reputation data about a ratee from various communities, aggregate the data from a given community into what we call a local reputation, then aggregate all local reputation values into a global reputation. The aggregation is based on options and weights which are selected by the inquiring agent according to his/her personal requirements. Our computation algorithm is based on a statistical model which takes into account several factors and parameters that qualify the reputation. A prototype based on the proposed model has been implemented and tested. The next step is to validate the model using real and/or simulated recommendation data.

Several extensions are envisaged for this work, among them: (1) considering reputation to be multidimensional where a ratee can be rated on more than one issue (product quality, service, etc.); (2) considering other factors in the aggregation of local reputation; and (3) investigating other ways to calculate the credibility of raters.

The novelty of our solution resides in the fact that it relies on raw reputation data from various online communities, relies on the ratee agreeing to (with the possibility of opting out) sharing his/her reputation data, involves the inquiring agent in the aggregation process for selecting various options, and uses a stochastic trust model in the aggregation process.

Finally, we note that several important aspects of global online reputation systems, such as business implications, privacy and security issues, and fraud prevention, are beyond the scope of this paper.

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