FOUNDATIONS OF COMPUTING AND DECISION SCIENCES
Vol. 40 (2015) No. 1

DE GRUYTER OPEN

DOI: 10.1515/fcds-2015-0003

ISSN 0867-6356

e-ISSN 2300-3405

HIDDEN AND INDIRECT (PROBABILISTICALLY ESTIMATED) REPUTATIONS - HIPER METHOD

Konrad LESZCZYŃSKI, Maciej ZAKRZEWICZ *

Abstract. It is a challenge to design a well balanced reputation system for an environment with millions of users. A reputation system must also represent user reputation as a value which is simple and easy to compare and will give users straightforward suggestions who to trust. Since reputation systems rely on feedbacks given by users, it is necessary to collect unbiased feedbacks.

In this paper we present a controversial, yet innovative reputation system. *Hidden and Indirect (Probabilistically Estimated) Reputations - HIPER Method* splits user reputation into two related values: *Hidden Reputation (HR)* is directly calculated from a set of feedbacks, *Indirect Reputation (IR)* is a probabilistically estimated projection of the hidden reputation and its value is public. Such indirect connection between received feedbacks and a visible reputation value allows users to provide unbiased feedbacks without fear of retaliation.

Keywords: trust management method, reputation system, e-commerce, online auctions

1. Introduction

In this paper we propose a novel approach to manage reputation of users. The method presented in this paper is fairly general and may by applied in a wide variety of e-commerce systems, online communities, social media, or even multi-agent system. The field that can take most advantage of HIPER is online trading. Therefore in this paper we will describe our method from the perspective of an online auction's reputation system and refer to truster as a buyer and trustee as a seller. With HIPER we want to solve wellknown problems of the eBay's reputation system (like *quality*

*Poznań University of Technology, Piotrowo 2, 60-965 Poznań, Poland, Email: {konrad.leszczynski, maciej.zakrzewicz}@cs.put.poznan.pl

variations over time). Also, we have realised that if buyers are to provide feedbacks without hesitation, they must be more anonymous.

Instead of providing another sophisticated formula to calculate reputation, our method replaces the single reputation value with two separate values – hidden and public reputation. *Hidden and Indirect (Probabilistically Estimated) Reputations - HIPER Method* splits seller's reputation into two related values: *1. Hidden Reputation (HR)* represents the direct, explicit value of seller's reputation. The system computes HR value using one of the standard algorithms but hides this value from the portal users, even the seller does not know his/her HR value. HR calculation is based on direct ratings from buyers and its value changes every time a new feedback rating is provided. *2. Indirect Reputation (IR)* is a periodically changing, public and randomised reputation value. IR is recalculated probabilistically according to the current HR value. IR value is a publicly visible reflection of the Hidden Reputation.

2. Motivations

Most of auction sites provide very simple participation counts for reputation rating. On eBay, Taobao or Allegro the highest reputation scores characterise users who participate in auctions most often, not necessarily those who provide the best quality of service and best-quality products. A reputation system must adapt to changes in the users' behavior. Thus ratings should be discounted over time so that the most recent feedbacks have more impact on the users's reputation value. A user who starts acting unfair must lose reputation quickly and old feedbacks will have little influence on the reputation value. This will minimize the *quality variations over time* problem (see survey [6] for details) or event prevent *playbooks attack* (see [5] for details).

Not every transaction is followed by feedbacks, which makes it difficult to asses reputations. One of the reason why users do not leave any feedback is the fear of a reciprocated negative feedback which probably appears as an answer to the publicly expressed dissatisfaction [8]. Analyses show that there are almost no negative feedbacks on online auction portals. In our previous work [11] we statistically analysed the structure of feedbacks on Allegro and found out that 99% of feedbacks were positive. Similar results are reported in [13]. Likewise on eBay: it was found by [16] that only 0.6% of all the feedbacks provided by buyers were negative. These results were confirmed by [3] and [9].

2.1. Why There Are Almost No Negative Feedbacks?

Of course it is great that most of the transactions are successful but studies suggest that buyers are sometimes hesitant to give negative feedbacks even when necessary. This phenomenon is called *"reporting bias"* or *"bias towards positive ratings"* and is among the most important problems of trust and reputation systems (see survey [6]). Many authors, example [2, 13] realised that a seller who receives a bad rating may retaliate unfairly. In [9] authors quote many eBay users to demonstrate fear of retaliation and conclude "positive feedbacks are likely to be given too often and negatives are likely to be given too seldom".

Fear of retaliation is a big problem also due to possible lawsuits against buyers who deliver negative feedbacks [14]. There are press reports about lawsuits against eBay users [21, 19, 22] and Allegro users [20]. Consequently in most auction sites there are almost no negative feedbacks therefore it is very difficult to spot suspicious sellers and fraudsters. Lack of negative feedbacks makes it virtually impossible to differentiate between sellers' reliability.

2.2. How to Overcome "Bias Towards Positive Ratings"?

Some authors suggest that both buyer and seller should reveal their rating simultaneously [15], or to make sellers rate first (however this will give a dishonest seller an opportunity to postpone or block the unwanted rating). Dellarocas and Wood [3] realised that the situation is potentially more complex. For example a buyer has no incentive to give a negative feedback but would rather try to negotiate. A buyer will not get his/her money back by giving negative feedback, but he/she can lose reputation because of the retaliatory negative feedback

One way to overcome this problem is to take into consideration transactions which did not get any feedback. When a buyer who usually provides feedbacks does not rate one particular transaction, this transaction probably was not successful. The reputation system may treat lack of any feedback from the buyer as a "partly-negative feedback", such system was proposed in [13]. Silent transactions (i.e., transactions for which no feedback was posted) should become a part of a trader's feedback profile [3].

Another option is to mine textual comments. For example, methods presented in [7] can be applied also to positive comments and search for words "but", "however", "almost", etc.

But these are half measures, to solve *bias towards positive rating problem* users' fear from retaliation – the psychological barrier must be broken. Anonymity would be a solution but complete anonymity is unacceptable because it allows any abuse without consequences.

2.3. Our Solution

Our idea is to hide the exact feedbacks. It is of course not enough to simply hide the username of the feedback provider because the seller may easily spot her/his reputation drops and find out who gives the negative feedback. Therefore feedbacks should not change the reputation value directly so users are not aware of who and when gave each feedback.

In *HIPER* method a provided feedback changes *Hidden Reputation(HR)* directly, whereas *Indirect Reputation (IR)* is changing asynchronously. IR is changing periodically but the changes (positive or negative) are probabilistically related to HR. The buyer is aware that his/her opinion will start to influence the seller's Indirect

Reputation as soon as the feedback changes the Hidden Reputation.

3. HIPER Model

Given is a seller S and a set of finalised auctions (transactions) in which this seller was involved $A = \{a_1, a_2, ..., a_n\}$. Given is a set of possible feedbacks' ratings from buyers R (in case of eBay-like online auctions $R = \{-1, 0, 1\}$ where each value represents the "negative", "neutral" and "positive" feedback respectively). A seller's auction is described by a rating and a transaction price $a_i = \langle r_i, p_i \rangle$. Let HR_i represents the seller's *Hidden Reputation* after i-th transaction (i-th feedback gained by this seller). Let IR_t represent the seller's *Indirect Reputation* in time t, where $t = 0, 1, ...$ are successive time instants spaced at uniform time intervals.

Hidden Reputation HR is changing after a feedback/rating is provided whereas Indirect Reputation IR is changing periodically once every time instance t. Although the remainder of this section presents many different ways of computing HR and IR, the main rule is fixed: for every time instant t, IR_t is probabilistically estimated according to the Hidden Reputation value at that time HR_t.

3.1. Calculation of Hidden Indirect Reputation

The Hidden Reputation HR value is the reputation calculated in a "standard" way. After a new feedback is given, HR is changed. There are unlimited ways of calculating the Hidden Reputation value, in this paper we propose a few that will be easy to implement in real world systems. Later, in the experiment section we will discuss which of them is the most suitable one.

3.1.1. Simple Statistics

For many cases a measure of location, or central tendency, such as the arithmetic mean may be sufficient to compute HR.

Mean: Probably the simplest way of calculating reputation is the mean value of ratings. Let HR_n be the value of the Hidden Reputation after n feedbacks/ratings obtained, then:

$$HR_n = \frac{\sum_{i=0}^{n} r_i}{n} \tag{1}$$

Rolling mean (moving average): Malicious sellers may cheat after having obtained a good reputation. This problem is called *quality variations over time* and is a common vulnerability of many reputation systems (see survey [6]). Therefore we must consider using rolling mean to calculate reputation. This solution will punish sellers who stop providing high quality services (the value of HR calculated from recent transactions' ratings will be low).

Normalization of ratings: Auction portals owners may want HR values to be always in the range of $[0, 1]$, therefore we may use *Min-Max normalization of ratings values*, and define HR value as *mean of normalized ratings.* For example in case of 5-star rating systems (using for example by Amazon):

$$R' = \frac{R - R_{min}}{R_{max} - R_{min}} = \frac{R - 1}{4} \tag{2}$$

so the normalized ratings will be $R' = \{0, 0.25, 0.5, 0.75, 1\}$. In case of eBay-like ratings systems (where $R = \{-1, 0, 1\}$ i.e. negative, neutral or positive):

$$R' = \frac{R - R_{min}}{R_{max} - R_{min}} = \frac{R + 1}{2} \tag{3}$$

so normalized ratings will be $R' = \{0, 0.5, 1\}$.

On one hand if $HR = [0, 1]$ then we can define HR value as probability that the IR Indirect Reputation will grow. On the other hand buyers may want to interpret a seller with half the feedbacks negative as completely untrustworthy and if seller's HR drops below 0 then the seller's IR will decrease certainly. In the experiment section we try both approaches, with and without the normalization of ratings.

3.1.2. Taking Price into Consideration

In case of auctions and e-commerce, price of a product/service is important, therefore it should be taken into account when reputation is being calculated. The straightforward method is to use *weighted mean:*

$$HR_n = \frac{\sum_{i=0}^{n} r_i p_i}{\sum_{i=0}^{n} p_i} \tag{4}$$

In particular, the value imbalance problem (also called "accumulation" fraud [12, 10]) may be used to exploit the reputation system. "Accumulation" fraud happens when a seller builds up the reputation by selling many unexpensive items for a while and then cheats selling expensive items. Therefore *weighted-rolling mean* may be the best method to calculate Hidden Reputation.

However it may be necessary to use more sophisticated methods to calculate the Hidden Reputation, for example the methods presented in [17, 18, 12, 1, 4]. Since we do not intend to provide literature review in this paper, we only demonstrate this using a sample algorithm – our own *Asymptotic Trust Algorithm (ATA)* [11].

Unlike many intricate algorithms, ATA keeps the simple way of interaction, i.e. buyers need only rate a transaction positive, negative, or neutral, therefore ATA can be implemented simultaneously with the systems currently used by eBay, Taobao or Allegro. ATA was designed in such a way that its resulting reputation is always in range $[0, 1)$ and therefore can by used as a rough probability estimator of sellers behaviour. Product price is taken into account and dramatic change of a seller's behaviour causes dramatic change of his/her reputation value.

ATA: Let $F(p)$ represent *the change function of price* – that function determines how much the reputation will change after a transaction. We also use a scaling factor α which is responsible for suddenness of reputation changes, the higher α the faster the reputation value will change. α is chosen arbitrarily from the range $(0, 1]$ and is constant for the reputation system. ATA is based on the following iterative equation:

$$HR_i = \begin{cases} HR_{i-1} + ((1 - HR_{i-1}) * F(p_i) * \alpha) & \text{for positive feedback} \\ HR_{i-1} & \text{for neutral feedback} \\ HR_{i-1} - (HR_{i-1} * F(p_i) * \alpha) & \text{for negative feedback} \end{cases} \tag{5}$$

In our implementation $F(p)$ is defined as:

$$F(p) = \tanh \frac{p}{\gamma} \tag{6}$$

γ parameter is a positive number chosen arbitrarily depending on what prices are considered expensive. A desirable property of hyperbolic tangent is the way it is changing its values – it allows us to "smoothly" differentiate products by their prices.

3.2. Calculation of Indirect Reputation

The Indirect Reputation IR is estimated probabilistically and publicly available for all users. IR is being recalculated in every time instance t for every seller in the system. The interval between time instances is defined arbitrarily (for example IR might be recalculated once a day – see experiments section). The value of Indirect Reputation will increase if the value of Hidden Reputation is high at the given time t and decrease otherwise. The rate of increase/decrease depends on the number of transactions, so the frequent sellers will build up reputation quickly. Let t_0 denote the time instance when the seller starts her/his activity in the system and let T denote the time when we want to evaluate her/his reputation. Let f_T be the frequency of the seller's interactions:

$$f_T = \frac{i}{T} \tag{7}$$

There are two basic ways of presenting the reputation value: as some kind of accumulation of ratings or as some kind of ratio of positive to negative ratings. For example eBay-like implementations accumulate ratings by summing them up (all positive feedbacks minus all negative ones), whereas Amazon shows the percentage of positive feedbacks over the recent year. On eBay and Allegro the reputation value is shown as colourful stars and there is no limit on the possible value of the reputation nor any method to decide how much reputation is enough. In many applications reputation needs to be normalized or at least to belong in a range. In this section we present both approaches to calculate IR.

3.2.1. Probabilistic Accumulation of Reputation

This approach allows us to keep the same order of magnitude of reputation values as eBay-like systems (this way we will not confuse the users). The idea is to increase the Indirect Reputation when the Hidden Reputation is high and decrease when HR is low. We accomplish this using the following iterative, probabilistic formula:

$$IR_t = \begin{cases} IR_{t-1} + f_t & \text{if } HR_t \geq u_t \\ IR_{t-1} - f_t & \text{if } HR_t < u_t \end{cases} \tag{8}$$

where u_t is uniformly distributed random variable $u_t \sim \mathcal{U}(0,1)$. Random values u_t are chosen for every time instance t, but they are global – equal for all the sellers in the system. $f_t = \frac{i}{t}$ is the frequency of the seller's interactions after a given time t.

The public reputation, the IR values will be of the same order of magnitude as the reputation values currently present on eBay-like auction sites. This is an advantage in case of introducing HIPER to an existing online auction system. On the other hand reputation on eBay is based on a participation count and it depends mostly on the number of transactions and not necessarily on the quality of service – we do not eliminate that problem here.

3.2.2. Indirect Reputation as Mean

If we want public reputation, the IR values to be independent on the number of the seller's finalised transactions, it must belong in a range, preferably unit range $[0,1]$. Also, in many cases reputation values need to be easily compared to each other. Furthermore, the public reputation can be represented as a percentage value (understandable for users).

To keep IR in the closed range $[0,1]$ we propose the following technique: let us define b_t as an indicator which describes whether at time t the Hidden Reputation HR_t is higher or equal to the uniformly distributed random value $u_t \sim \mathcal{U}(0,1)$.

$$b_t = \begin{cases} 1 & \text{if } HR_t \geq u_t \\ 0 & \text{if } HR_t < u_t \end{cases} \tag{9}$$

Our first method to keep IR in range $[0,1]$ is to calculate the weighted mean of these indicator values:

$$IR_T = \frac{\sum_{t=0}^{T} b_t f_t}{\sum_{t=0}^{T} f_t} \tag{10}$$

Again f_t is the frequency of the user's interactions in time t.

3.2.3. Indirect Reputation Iteratively

Another method to calculate IR is to use an iterative algorithm (based on a similar principles as ATA, see Formula 5). The iterative method relays on b_t values to decide whether the *IR* value should increase or decrease. When the HR value is low than the IR is decreased by a fraction of itself. When the HR value is high than the IR is increased by the fraction of its complement.

$$IR_t = \begin{cases} IR_{t-1} + ((1 - IR_{t-1}) * F(f_t) * \alpha) & \text{if } b_t = 1 \\ IR_{t-1} - (IR_{t-1} * F(f_t) * \alpha) & \text{if } b_t = 0 \end{cases} \tag{11}$$

where α is a scaling factor chosen arbitrarily from the range $(0, 1]$. The starting value of reputation IR_0 does not have to be set to 0. We discuss these parameters' values in the experiment Subsection 5.3. $F(f)$ is *the Change Function of Frequency*, and similar to the Change Function of Price (see Formula 6) it must keep the same mathematical properties. Therefore $F(f)$ is also defined as hyperbolic tangent:

$$F(f) = \tanh f \tag{12}$$

The above methods of calculating HR and IR have not exhausted all the possibilities. The main idea of HIPER is suitable for all kinds of calculation methods.

4. Demonstration of HIPER Principle

To demonstrate HIPER principle we present experiments conducted on a small dataset of synthetic data.

Let us consider a seller who gets feedbacks only at weekends. Every Saturday and every Sunday (for nine weeks) at 1PM the seller gets a feedback. This simple (though unusual) example allows us to demonstrate the way HIPER works. The seller gets 17 positive feedbacks and one negative feedback. On fifth Saturday (29th of January) the seller gets the negative feedback and this feedback is for a transaction 3 times more expensive than all the other transactions.

4.1. Hidden Reputation

Hidden Reputation HR is calculated in a "standard" way. Figure 1 demonstrates the Hidden Reputation values of the seller and compares different methods of calculating HR. For all calculation methods we can easily spot that the ninth feedback was negative, but the drop of the reputation differs. Charts on the left hand side of the Figure 1 show reputation changes when price is not taken into account. We see that for example the mean of normalized values produce gentle punishment for the negative feedback, whereas in case of rolling mean (in this experiment memory = 5) the change of reputation is sudden. Charts on the right hand side of the Figure 1 show methods that take price into account. We can see that the drop of reputation is larger for weighted mean than for mean on the left hand side. In case of Asymptotic Trust Algorithm the seller needs a few positive transactions to build up reputation, and a sudden change in behaviour result in the sudden drop in the reputation value[1].

[1] For this experiment the scaling factor $\alpha = 0.3$.

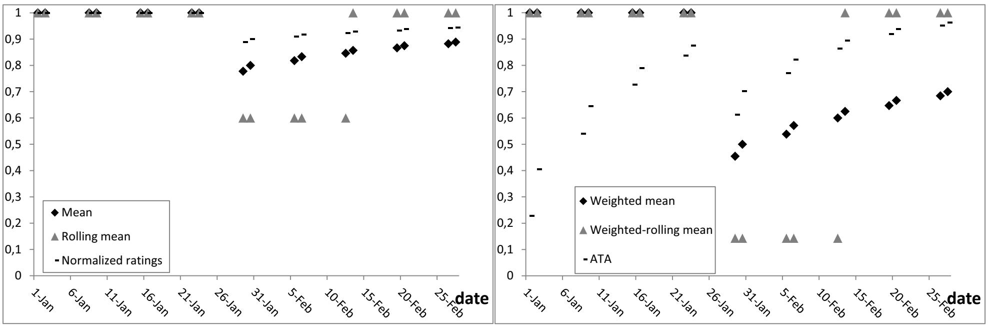

Figure 1: Different methods of calculating HR.

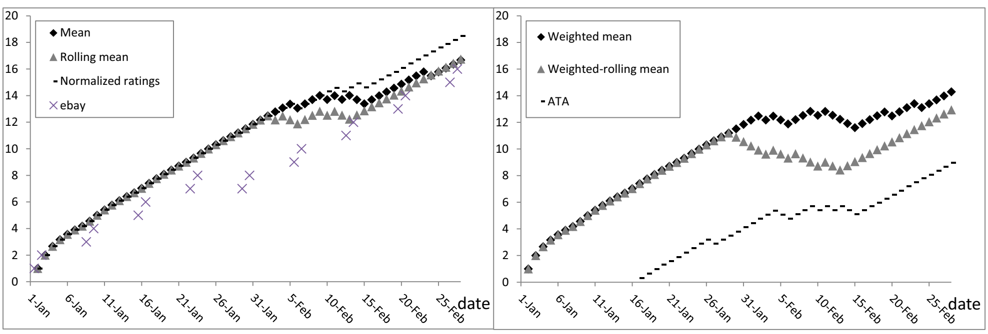

Figure 2: IR as probabilistic accumulation derived from different methods of calculating HR.

4.2. Indirect Reputation

In this section we present and compare methods of calculating Indirect Reputation. From each of the above Hidden Reputation data series we derive the Indirect Reputations. In the following experiments the time interval between IR calculations is set to one day. We draw a set of random values u_t once and than use the same set of random values in all the following experiments.

4.2.1. IR as Probabilistic Accumulation

Figure 2 presents Indirect Reputation calculated as *probabilistic accumulation* (see Section 3.2.1). To demonstrate how HR is reflected by IR, we compute IR values for each HR data series from Figure 1. For every calculation method of HR we see constant growth of IR until the negative feedback occurred. Note, however, that the timing of the slow-down of IR growth is not strictly corelated with the negative feedback occurrence. The negative feedback occurred on 29th of January, whereas

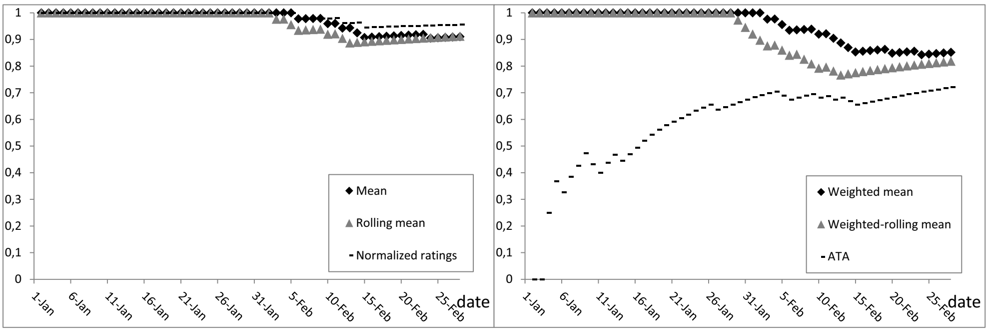

Figure 3: IR as mean and different methods of calculating HR.

Indirect Reputation stops growing constantly up a few days later.

The left hand side of the Figure 2 shows how Indirect Reputation of the seller would change if the Hidden Reputation is calculated without taking price into account. For comparison we added a chart of reputation that would be calculated using the standard eBay's algorithm (positive feedbacks minus negative feedbacks). In the previous section we observed that mean of normalized values results in "more gentle punishment for negative feedback" therefore IR derived from this HR dataset is the least affected by the negative feedback. In case of the rolling mean the HR drops suddenly and after 5 transactions (the size of memory) HR goes back to the highest value - this is reflected by the IR value: it stops growing for a while.

Right hand side of the Figure 2 shows what happens to the IR if we take price into account while calculating HR. Since the negative feedback is related to a transaction three times more expensive the change of HR value at the and of January is more drastic. Therefore the IR values in February are lower on the right hand side of the Figure 2. In case of ATA, HR is growing slowly, consequently resulting IR is below zero for several days. In a real life system this will make virtually impossible for a newcomer to gain trust.

As intended, probabilistic accumulation produces values similar (or at least in the same order of magnitude) to eBay's reputation algorithm. Unfortunately it also duplicate an essential problem of eBay's reputation algorithm – high reputation characterized experienced sellers not necessarily the honest ones.

4.2.2. IR as Mean

Figure 3 presents Indirect Reputation calculated as mean using Formula 10. To demonstrate how HR is reflected by IR, we compute IR values for each HR data series from Figure 1. As intended, IR is taking values between 0 and 1. The choice of the HR calculation method influences IR in the similar way as before: normalization of rating results in "gentle" reaction on negative feedback and the rolling mean makes the reputation drop more "sudden". Again if we take price into consideration the reputation drop after the negative feedback occurs is much greater. If HR is calculated

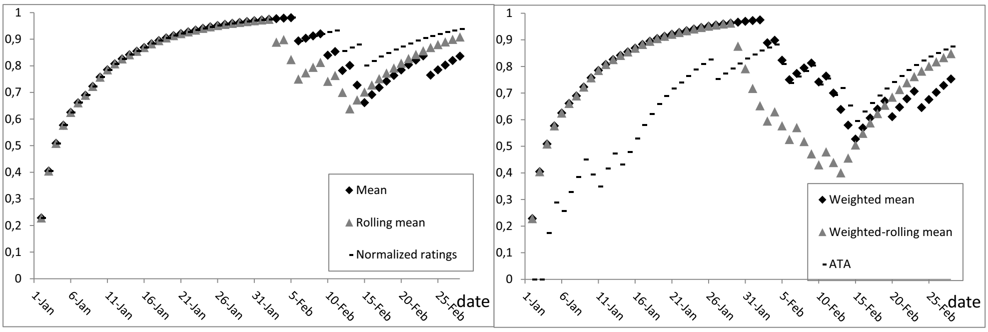

Figure 4: IR Iteratively and different methods of calculating HR.

using ATA it takes a while to build up reputation.

4.2.3. IR Iteratively

The iterative method defined by Formula 11 is based on one principle, i.e. at every time instance t IR increases or decreases depending on the current value of HR. Again, we take HR calculated in subsection 4.1 and compare how they influence Indirect Reputation[2]. In this calculation method reputation of a newcomer is low and the seller is building up reputation by getting positive feedbacks. This makes good reflection of the way humans trust each other – one needs to gradually gain trust of others.

The choice of the method of calculating HR has similar effect on iterative IR as before: the more ruthlessly HR is calculated, the more drastic is the Indirect Reputation loss after the negative feedback. If we compare charts on Figure 3 with the corresponding charts on Figure 4 we can observe that: Firstly, iterative IR reacts more distinctly on HR changes (in case of every HR method). Secondly, the randomness is more visible on charts with the iterative IR – even though there was only one negative feedback, we can see a few ups and downs.

5. Real Dataset Experiments

The experiments using synthetic datasets presented in the previous section were supposed to demonstrate the basic principle of HIPER. However, to choose the best calculation method for both HR and IR we need datasets from the real world. To address this we have obtained data about sellers' transactions from Allegro auction portal. Also, using this data we want to show that HIPER can be easily integrated

[2]For this experiment we chose the parameters: the scaling factor $\alpha = 0.3$ and the starting reputation value $IR_0 = 0$. However, later in the Subsection 5.3 we chose parameters more sufficient for bigger, real datasets.

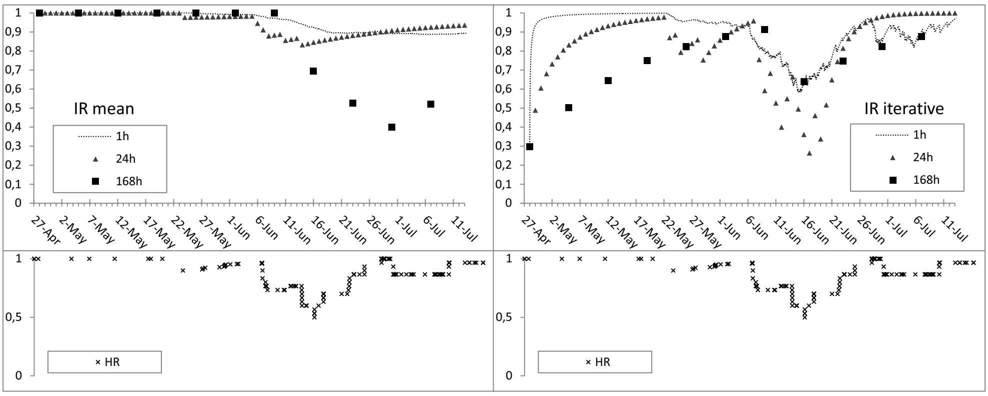

Figure 5: Different intervals of IR calculation.

into an existing system (without losing historical feedbacks).

5.1. Choosing Time Intervals of IR Calculation

In our previous experiments we intuitively chose day intervals between time instances. In this subsection we check whether other intervals product better results.

The Dataset: For this experiment we have chosen a seller who has a considerable number of neutral and negative feedbacks. Our dataset contains 151 feedbacks: 133 positive, 14 neutral and 4 negative. We have calculated HR using the rolling mean (with long memory: 30 feedbacks). Using the resulting HR data serries we have calculated IR values (by mean and interactive method) using different intervals between time instances t. Figure 5 compares the results. The left hand side of the figure shows the Indirect Reputation calculated using the mean method (Formula 10) and the right hand side shows IR calculated using the iterative method (Formula 11). Both methods ran three times using different intervals between IR calculations: 1 hour, 1 day and 1 week. The bottom of the Figure 5 shows the corresponding Hidden Reputation values (the same on both sides). In case of very long time intervals: one week (168 hours) – IR values are very random. In case of very short time intervals: one hour – IR values follow corresponding HR values very precisely (this is particularly visible on the right hand side of the figure where IR is calculated iteratively). Since one of the main purposes of HIPER is to obfuscate detailed feedbacks' history such close correlation is not intended. The interval of one day is the "happy medium": IR values follow HR values with slight and random delays.

5.2. Choosing Calculation Methods

Since online auction sites report many complaints about "accumulation" fraud (see [12]) for this experiment we have chosen a seller from Allegro who gained a lot of

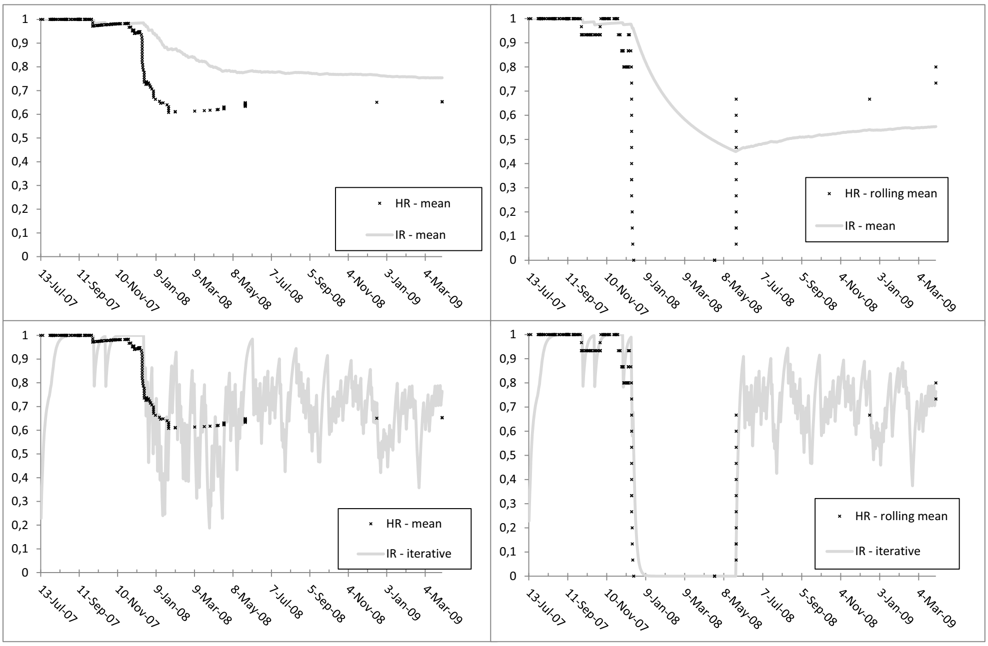

Figure 6: Comparison of calculation methods in case of a real seller.

positive feedbacks and then started acting dishonestly. The dataset contains 190 positive feedbacks, 2 neutral and 39 negative ones.

As we have concluded in the previous section (using synthetic datasets), if probabilistic accumulation is used to calculate IR, HIPER does not solve the main problems of the eBay's participation count algorithm. Therefore we consider only the mean and the iterative methods of IR calculation.

We choose two methods of computing HR: the mean (the charts on the left hand side of the Figure 6) and the rolling mean with long memory: 30 feedbacks (charts on the right hand side the figure). Indirect Reputation calculated as the mean is presented on the charts in the upper part of the Figure 6, whereas the iterative IR implementation is presented in the bottom part of the figure.

We can see how HR calculation method influences the IR. If the HR is calculated as the rolling mean, the public reputation IR is changing rapidly after the rapid change of seller's behavior, which was our intention. Note that in this experiment we would use the weighted-rolling mean to calculate HR but our dataset did not contain transaction prices.

Results of this experiment suggest that IR should be calculated as mean (with Formula 10) because it produces more "stable" reputation values. On the other hand, the iterative IR reacts quicker on the behaviour change. Random changes produced by the iterative IR calculations may be useful to obfuscate the exact feedbacks even more. This randomness is adjustable – see the next subsection.

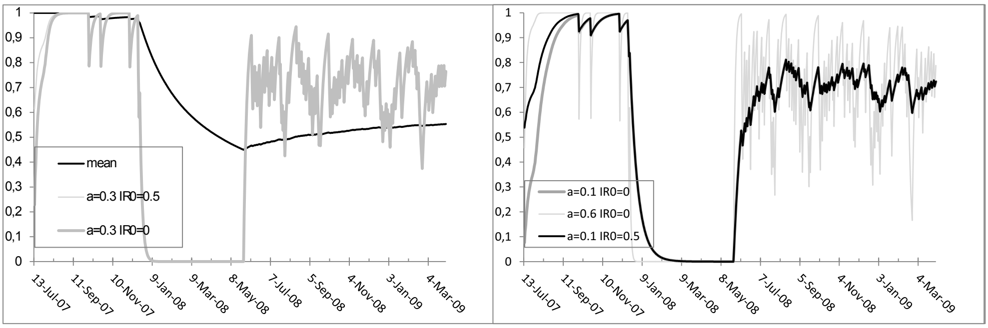

Figure 7: Fine-tuning of the iterative IR calculation.

5.3. Fine-tuning of Iterative Parameters

In all the previous experiments for the iterative IR we used the scaling factor $\alpha = 0.3$ and the starting value $IR_0 = 0$. These parameters allow us to demonstrate the idea behind the iterative method. However, these parameters may be used for adjustment and fine-tuning of the iterative method. In the previous experiment (Subsection 5.2) we saw how "chaotic" changes the iterative method may produce. In this subsection we present Indirect Reputation of the same seller[3] but calculated using different parameters: Figure 7. The charts on the left hand side of the Figure 7 compare the results from the previous experiment: IR calculated as the mean and iteratively (with the scaling factor $\alpha = 0.3$). As we concluded from the previous experiment, the iterative method reacts quicker on the behaviour change but in some cases it produces random changes in public reputation IR. The right hand chart of the Figure 7 shows the iterative calculation method using different scaling factors: $\alpha = 0.1$ and $\alpha = 0.6$. We can see how smaller α value reduces "randomness" of the IR data series. Unfortunately, a small value of α scaling factor makes the seller to wait very long and conduct many transactions to build up reputation. However, the starting value of IR does not need to be 0, newcomers may start from some level of reputation. To the charts in Figure 7 we have added IR data series with the starting value $IR_0 = 0.5$. As we can see in this case, the seller's reputation achieves high values quicker, but later (say from October 2007) the data series based on the same α value coincide.

5.4. Experiment Results

We want the reputation system to assess old feedbacks as less important. This will protect the reputation system from the *quality variations over time* problem (which was advocated by many, see for example classic SPORAS algorithm [17]). This demand is met when the Hidden Reputation is calculated using the rolling mean. Also to prevent the accumulation fraud, price must be taken into account, therefore the

[3] HR values are the same so for clarity we do not present HR data series here.

best method for HR calculation is the weighted-rolling mean.

IR calculated as the mean reflects changes in sellers behavior quite accurately. However, using the iterative method makes each seller build reputation gradually and IR drops faster if the seller stops acting honestly. Consequently we recommend IR to be calculated iteratively and HR to be calculated as the weighted-rolling mean in case of online auctions[4].

6. Conclusion

In this paper we have presented the HIPER – Hidden and Indirect (Probabilistically Estimated) Reputations method. The HIPER method instead of providing another intricate algorithm of computing reputation, provides an unconventional way to encourage buyers to give feedbacks without hesitation. Instead of a single reputation value, HIPER uses two values: Hidden Reputation HR and Indirect (public and probabilistically estimated) Reputation IR. No user (especially the seller himself/herself) knows the exact value of HR. Instead, the system shows IR which is periodically and slightly randomly changing according to the current value of HR. We have described HIPER in context of e-commerce and online auctions but our method is general enough to be applied elsewhere. Funny it may seem, this idea is very promising. HIPER will provide good estimation of reputation by applying higher weights to recent transactions (newer feedback are more important) and take price into account. Consequently, HIPER will prevent many types of common attack schemes. Even more important is the psychological aspect of HIPER: if buyers do not fear the retaliation they will provide unbiased feedbacks. Our experiments show that a seller will not know who and when gives him/her a negative feedback. Therefore buyers may feel free to provide unbiased feedbacks and at the same time the public value of reputation is a good reflection of sellers' trustworthiness.

In the paper we have shown only a few methods of computing Hidden and Indirect Reputation while HIPER is an "open solution", a framework that allows to use virtually any calculation methods. We will be happy to combine efforts with other researchers and implement or test their algorithms as a component of HIPER. For example we are considering taking into account the reputation of feedback provider in calculation of HR – therefore an additional system to asses buyers reputation is required.

HIPER is based on the same simple method of interaction currently used on eBay (users rating each transaction as positive, neutral or negative). Also other rating systems (for example 5-star eating system) can be easily adopted to work with HIPER. In the experiment section we also have shown that HIPER can be used as a data-mining technique on historical feedbacks. Therefore HIPER can be easily introduced to an existing e-commerce system.

[4]Note that to get this result we have performed dozens of experiments, but in this paper for clarity reasons we present only a few, those that demonstrate how we get to these conclusions.

References

[1] Bharadwaj, K.K., Al-Shamri, M.Y.H.: Fuzzy computational models for trust and reputation systems. Electron. Commer. Rec. Appl. 8(1), 37–47 (2009)

[2] Bhattacharjee, R.: Avoiding ballot stuffing in ebay-like reputation systems. third workshop on economics of peer-to-peer systems. In: In: P2PECON 05: Proceeding of the 2005 ACM SIGCOMM workshop on Economics of peer-to-peer systems. pp. 133–137. ACM Press (2005)

[3] Dellarocas, C., Wood, C.A.: The Sound of Silence in Online Feedback: Estimating Trading Risks in the Presence of Reporting Bias. Management Science 54, 460–476 (2008)

[4] Huynh, T.D., Jennings, N.R., Shadbolt, N.: FIRE: An Integrated Trust and Reputation Model for Open Multi-Agent Systems. In: 16th European Conference on Artificial Intelligence. pp. 18–22 (2004), event Dates: 2004

[5] Jøsang, A., Golbeck, J.: Challenges for robust trust and reputation systems. In: Proceedings of the 5th International Workshop on Security and Trust Management (SMT 2009), Saint Malo, France (2009)

[6] Jøsang, A., Ismail, R., Boyd, C.: A survey of trust and reputation systems for online service provision. Decision Support Systems 43(2), 618 – 644 (2007), http://www.sciencedirect.com/science/article/pii/S0167923605000849, emerging Issues in Collaborative Commerce

[7] Kaszuba, T., Hupa, A., Wierzbicki, A.: Advanced Feedback Management for Internet Auction Reputation Systems. IEEE Internet Computing 14, 31–37 (2010)

[8] Kaszuba, T., Turek, P., Wierzbicki, A., Nielek, R.: Prototrust: An environment for improved trust management in internet auctions. In: Local Proceedings of 13th East-European Conference, ADBIS 2009. pp. 385–398. JUMI Pubbbblishing House Ltd. (2009)

[9] Klein, T.J., Lambertz, C., Spagnolo, G., Stahl, K.O.: Last Minute Feedback. Discussion Paper Series of SFB/TR 15 Governance and the Efficiency of Economic Systems 62, Free University of Berlin, Humboldt University of Berlin, University of Bonn, University of Mannheim, University of Munich (Mar 2006), http://ideas.repec.org/p/trf/wpaper/62.html

[10] Kwan, M.Y.K., Overill, R.E., Chow, K.P., Silomon, J.A.M., Tse, H., Law, F.Y.W., Lai, P.K.Y.: Evaluation of Evidence in Internet Auction Fraud Investigations. In: IFIP Int. Conf. Digital Forensics. pp. 121–132 (2010)

[11] Leszczyński, K., Zakrzewicz, M.: Asymptotic Trust Algorithm: Extension for Reputation Systems in Online Auctions. Control and Cybernetics 40(3), 651–666 (2011)

[12] Morzy, M.: New Algorithms for Mining the Reputation of Participants of Online Auctions. In: WINE. pp. 112–121 (2005)

[13] Morzy, M., Wierzbicki, A.: The Sound of Silence: Mining Implicit Feedbacks to Compute Reputation. In: WINE. pp. 365–376 (2006)

[14] O'Donovan, J., Evrim, V., Smyth, B., McLeod, D., Nixon, P.: Personalizing Trust in Online Auctions. In: STAIRS. pp. 72–83 (2006)

[15] Reichling, F.: Effects of reputation mechanisms on fraud prevention in ebay auctions. Tech. rep., Working Paper, Stanford University (2004)

[16] Resnick, P., Zeckhauser, R.: Trust Among Strangers in Internet Transactions: Empirical Analysis of eBays Reputation System. The Economics of the Internet and E-Commerce 11(2), 23–25 (2002)

[17] Zacharia, G., Maes, P.: Trust management through reputation mechanisms. Applied Artificial Intelligence 14(7), 881–907 (2000)

[18] Zhang, H., Duan, H.X., Liu, W.: RRM: An incentive reputation model for promoting good behaviors in distributed systems. Science in China Series F: Information Sciences 51(11), 1871–1882 (2008)

[19] eBay buyer sued for defamation after leaving negative feedback on auction site. `http://www.dailymail.co.uk/news/article-1265490/eBay-buyer-sued-defamation-leaving-negative-feedback-auction-site.html`

[20] "Klamstwa nie podarujemy" - historia szantazu i negatywnych komentarzy na Allegro.
`http://technologie.gazeta.pl/internet/2029020,104530,10466941.html`

[21] Orange County man sued over negative eBay feedback. http://www.wftv.com/news/news/local/orange-county-man-sued-over-negative-ebay-feedback/nPCqn/

[22] Buyer sued for eBay feedback.
`http://news.cnet.com/8301-17852_3-10074157-71.html`,
http://www.geek.com/articles/news/ebay-negative-feedback-leads-to-lawsuit-20081027/

Received 26.04.2013, accepted 14.01.2015