

**Asymptotic trust algorithm:
extension for reputation systems in online auctions***

by

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Abstract: Online auctions have become a big business and the number of auction site users is growing rapidly. These virtual marketplaces give traders a lot of opportunities to find a contracting party. However, lack of physical contact between users decreases the degree of trust. Auction portals require an efficient mechanism for building trust between participants, whereas most of them provide simple participation counts for reputation rating. Moreover, a single opinion has virtually no effect on a big online store that already has many reputation points, so buyers are very hesitant to give negative feedback for fear of retaliation. Consequently, almost no negative feedback is provided¹.

In this paper we introduce a new trust system called Asymptotic Trust Algorithm (ATA) which prevents many fraud attempts and still is both simple and easy to understand for most users. Our new method can be applied in addition to the participation counts systems currently used by Allegro, eBay and most of other online auction sites because it does not require any additional information other than positive, negative or neutral feedback on transactions. Most importantly, ATA encourages users to submit unbiased comments, regardless of the number of previous transactions.

Keywords: online auction sites, reputation system, trust management, Web-mining.

1. Introduction

Portals like eBay and Allegro give a great opportunity to traders who can choose from a vast number of offers and meet millions of potential customers. Online transactions, however, are a bit more dangerous than traditional ones due to the anonymity of portal users. Furthermore, the majority of popular auction sites

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¹In appendix A we provide analysis of the number of feedbacks on Allegro auction site.

use the same very simple trust mechanism in which the credibility of a user is the number of positive feedbacks minus the number of negative ones. This is insufficient in many aspects and allows dishonest users to easily gain fake reputation. Moreover, such a simple feedback-based reputation system tends to favour users with a large volume of transactions instead of those with high quality of service. Users that make a lot of transactions have high reputation value even if they get a few negative feedbacks whereas those who always receive positive comments but make only few transactions have a low number of reputation points. Furthermore, fearing retaliation, traders with a low reputation value will probably not give negative feedback to a huge online store with thousands of reputation points. Only textual comments attached to feedback might provide information to form a trust opinion but it is very difficult for a buyer to read all comments on all potential sellers.

Let us consider a hypothetical user *Cut-Me-Own-Throat Dibbler* who has already gained high reputation value by selling 400 “*lucky amulets that bring good health*” for 3 euros each and then starts acting dishonestly. After selling every four or five cheap amulets he sells one mobile phone which is not exactly “*new and in good condition*” for 300 euros. In the existing system, *Dibbler* will constantly gain increasing reputation value as long as he gets positive feedback for more than half of transactions. Moreover, if a buyer who was cheated had only a few reputation points, he or she would hesitate before giving negative feedback because one negative comment has almost no influence on a user with hundreds of reputation points whereas retaliatory negative feedback will change the buyer’s reputation considerably. Fear of retaliation is so common also because buyers and sellers are treated equally. A buyer who sends money before getting the product takes a greater risk, yet he or she will lose the same value of reputation after getting negative feedback. On Allegro and eBay a negative feedback always decreases reputation by the value of one regardless of the user’s role in the transaction.

The reputation mechanism that we introduce in this paper addresses these problems. ATA allows a user to get high reputation after just a couple of successful transactions. The algorithm takes into account the fact that success of a transaction depends mostly on seller’s honesty. A change of reputation (i.e., a decrease of reputation value after an unsatisfying transaction and an increase after a successful one) is simply slower for the buyer. The price of the merchandise is also an important factor in our calculation of reputation change. Users like *Dibbler* from the above example could not feel safe because in ATA a rapid change of behavior will cause a rapid change of reputation value. A user who starts acting unfair will lose reputation quickly and old feedbacks will have little influence on the reputation value.

Our intention is to create a trust system that not only gives a better estimation of users’ credibility but also encourages users to give unbiased comments. We believe that users’ hesitation in submitting negative feedbacks is one of the main impediments to good credibility estimation.

2. Related work

It is common knowledge that trust management systems used in online auctions have many drawbacks. Malaga (2001) presented a detailed analysis of these drawbacks; also many others pointed out to flaws of the reputation algorithm invented by eBay, which is implemented by most of auction portals (see Xiong et al., 2003, and Houser et al., 2006).

There have been many attempts to solve these problems. SPORAS (see Zacharia et al., 2000) is an interesting example of a general reputation mechanism that takes into account many parameters and tries to model human behaviour in a “non-virtual” environment. Morzy and Jezierski (2006) suggested a cluster-based method to search for potential frauds. Another interesting model – PeerTrust, presented in Xiong and Liu (2003) is a peer-to-peer trust model, based on many parameters, ergo, it is also very complex. Some scientists suggest that the trust of a user cannot be presented as a single global value and depends on who is asking for the trust value (see DeFigueiredo et al., 2009). Instead of a single value trust may be presented as a graph – this approach is represented by HISTOS (see Zacharia and Maes 2000). Another interesting idea is to use a fuzzy computational model (see Bharadwaj and Al-Shamri 2009, and Carbo et al., 2003). Malik and Bouguettaya (2009) address another issue, i.e. how to choose the reputation value of a newcomer. Unfortunately, these solutions are difficult to introduce into existing auction systems.

It was realised by many authors that there are almost no negative feedbacks on auction portals. This issue is described in details in Resnick and Zeckhauser (2002), and O’Donovan et al. (2006). It is hard to believe that this results from the absolute honesty of traders and the best quality of their merchandise; therefore, our trust mechanism tries to encourage users not to hesitate to submit negative feedback from time to time.

3. Asymptotic Trust Algorithm (ATA)

Our intention was to create a mechanism that overcomes the problems of the existing systems without changing the way users interact. A great advantage of the trust system currently used by Allegro, eBay and other auction sites is its simplicity. Users are accustomed to just rating a finalised transaction as “negative”, “neutral” or “positive” and if we keep this simple feedback based method we will be able to use the new trust system simultaneously with the traditional one.

3.1. Desirable properties of the reputation system

We have designed a trust mechanism inspired by people’s behaviour in real life. ATA is based on the following principles:

- The reputation of a user who gets only positive feedbacks asymptotically approaches the value of 1 (maximum 100% reputation value).

- A dramatic change of reputation after a change of trader's behaviour. In a traditional system a user may stop acting honestly after earning high reputation and will retain most of his/her reputation. To overcome this drawback a reputation system must treat old feedback as less important.
- The value of reputation varies from 0 to 1. Reputation values are easy to compare and do not depend on the number of the user's finalised transactions. Furthermore, reputation can be represented as a percentage value (understandable for users), or even as a rough estimator of probability that the user will proceed honestly during future transactions.
- Merchandise price does matter. The reputation value will change more if the product is expensive. This prevents dishonest sellers from selling a lot of cheap things to gain reputation quickly.
- Newcomers can gain reputation fast. Not only very experienced users can have a high value of reputation, but one can gain high reputation after just several honest transactions.
- Buyers take greater risk, so a single transaction should affect the seller's reputation more than the buyer's reputation.
- The mechanism should be reasonably simple for users, we would like to avoid complex graph algorithms and intricate probabilistic methods to make our algorithm easy to understand and implement.
- The unchanged simple interaction mechanism – a user marks each transaction “negative”, “neutral” or “positive”.

3.2. Terms and definitions

We use R_i to denote the value of user's reputation after i -th transaction. Let $F(p)$ represent *the change function of price* – function determining how much reputation will change after a transaction. *The change function of price* depends on the merchandise price p and some arbitrary scaling factors (see below). The value of the change function of price should be higher for expensive products and it must remain between 0 and 1. We also introduce a scaling factor α , responsible for suddenness of reputation changes, the higher α the faster the reputation value will change. Buyers usually take greater risk, so we use different factors for sellers and buyers, α_s and α_b , respectively, with $\alpha_s \geq \alpha_b$. Both α_s and α_b are chosen arbitrarily from the range $(0, 1]$ and are constant for the reputation system.

To meet our requirements (see 3.1) we have designed the algorithm based on the following formulas.

$$R_i = \begin{cases} R_{i-1} + ((1 - R_{i-1}) * F(p_i) * \alpha) & \text{for positive feedback} \\ R_{i-1} & \text{for neutral feedback} \\ R_{i-1} - (R_{i-1} * F(p_i) * \alpha) & \text{for negative feedback} \end{cases} \quad (1)$$

The previous reputation value R_{i-1} is increased by a fraction $(F(p_i) * \alpha)$ of the complementary reputation $(1 - R_{i-1})$ in case of positive feedback, but in case of negative feedback it is decreased by $(F(p_i) * \alpha)$, where p_i denotes the merchandise price for i -th transaction. As mentioned before, $\alpha_s \geq \alpha_b$, so the reputation value of the seller will change more than the reputation value of the buyer.

Any continuous function which returns a value between 0 and 1 for any given price can serve as *the change function of price*. In our implementation $F(p)$ is defined as:

$$F(p) = \tanh \frac{p}{\gamma} \quad (2)$$

where γ is an arbitrary positive number depending on what prices are considered expensive. The value of hyperbolic tangent function for positive input is between 0 and 1, so $F(p)$ will always remain in range of $(0, 1)$. If the auction portal operates in one country, then γ can be correlated with gross domestic income or average salary in the country, whereas international portals must consider different currencies and use different γ parameters for each currency to make sure that the reputation change does not depend on the currency used in a transaction.

Notice that the hyperbolic tangent is a strictly increasing function. This is a very important property, since the higher the merchandise price the higher reputation change should be. Another desirable property of hyperbolic tangent is its variability, which allows us to “smoothly” differentiate products by their prices.

In our implementation the reputation value of a newcomer $R_0 = 0$, however, R_0 can be also greater than zero – it should only be reasonably low because a high value of initial reputation may encourage dishonest people to create new user accounts after a fraud.

3.3. Pseudocode

The Pseudocode 1 shows how ATA calculates a complete history of a user’s reputation. The `AsymptoticTrustAlgorithm()` function takes as a parameter a collection of *transaction structures* for a particular user. We assume that *transactions are sorted chronologically*. A transaction structure contains all information about a transaction, i.e.: `price` of the auctioned item, `rating` (positive, neutral, or negative opinion of transaction) and `role` (whether this user was a seller or a buyer in this transaction).

Before performing any transactions a user has the value of reputation of a newcomer R_0 (line 3). Next, the algorithm iterates over the collection of all user’s transactions (line 4). In each step it is checked whether this user was a buyer or a seller in the i -th transaction and the respective α value is chosen (lines 6–9). Then, formula 1 is calculated (lines 11–16).

Listing 1. Calculating reputation history for a particular user

```

1  function AsymptoticTrustAlgorithm(transactionsInfo[])
2  {
3    R[0] = newcomerReputation
4    for(i=1 to numberOfTransactions)
5    {
6      if(transactionsInfo[i].role == seller)
7         $\alpha = \alpha_s$ 
8      else if(transactionsInfo[i].role == buyer)
9         $\alpha = \alpha_b$ 
10
11     if(transactionsInfo[i].rating == positive)
12       R[i] = R[i-1] + ((1-R[i-1]) * F(transactionsInfo[i].price) *  $\alpha$ )
13     else if(transactionsInfo[i].rating == neutral)
14       R[i] = R[i-1]
15     else if(transactionsInfo[i].rating == negative)
16       R[i] = R[i-1] - (R[i-1] * F(transactionsInfo[i].price) *  $\alpha$ )
17   }
18   return R[ ]
19 }

```

The function returns the collection containing the user's reputation history (which can be used to draw reputation charts – see Fig. 6). The last value in this collection represents the current reputation of the user.

Time complexity of this algorithm is $O(n)$ (where n is the number of feedbacks received by the user).

4. Experimental evaluation

To verify if ATA meets our expectations (see 3.1) we performed a series of experiments using both synthetic and real datasets. We used synthetic datasets to examine how the reputation changes under certain conditions, wishing to observe how the reputation grows for honest users and how fast it drops in case of negative feedback. Gathering real data from Allegro auction site allowed us to check if ATA can be used “post factum” to compare potential traders.

4.1. Synthetic datasets: building reputation

Let us consider a system with the following parameters: $\alpha_s = 0.3$, $\alpha_b = 0.1$, $\gamma = 400\text{€}$ and $R_0 = 0$. The chosen value of α_s allows sellers to gain very high reputation after just several transactions (unless he/she sells very cheap items)

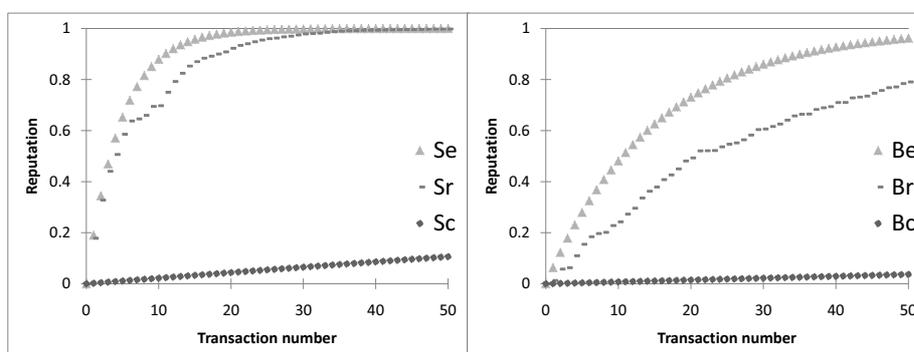


Figure 1. User reputation along transactions. The left chart shows the reputation of three sellers. S_e sells expensive products – mobile phones for 300€, seller S_c deals in cheap products – lucky amulets for 3€, and user S_r sells random products priced between 3 and 300€. Right chart shows the reputation of buyers, analogously, B_e buys products for 300€, B_c products for 3€ and B_r buys random products for 3 to 300€

whereas the value of α_b requires one to buy several dozen items to build high reputation. To see how reputation value grows let us consider an example where every transaction is marked as positive. This case is very common because most users want to make fair business on auction portals. Fig. 1 shows how reputation grows for different users.

As we intended, the reputation grows much faster for sellers, and an honest user can quickly gain reputation unless he/she trades worthless products. Also, the reputation of a user who gets only positive feedback will asymptotically approach the maximum value of 1.

4.2. Synthetic datasets: losing reputation

Fig. 2 shows the reputation of users who change their behaviour. In this experiment we used the same values of algorithm parameters, i.e.: $\alpha_s = 0.3$, $\alpha_b = 0.1$, $\gamma = 400\text{€}$ and $R_0 = 0$.

Our solution simplifies detection of user behaviour changes. Reputation dynamics also highly depends on merchandise price and most importantly, reputation is not earned forever, but one has to constantly look after it like in “real life” human relationships. Also, the *Dibbler* example shows that one cannot quickly build reputation by selling cheap products to cheat on expensive products.

4.3. Real datasets

To obtain information about real feedbacks on Allegro we have created a simple application that reads data directly from users’ information webpages. To assure the anonymity the application does not read usernames.

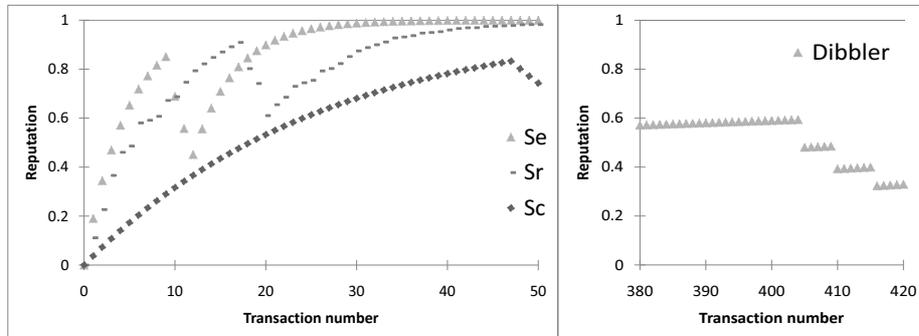


Figure 2. Reputation courses of users getting some negative feedbacks. S_e sells products for 300€. His 9-th, 10-th and 11-th transaction were marked negative. S_r sells random products and his transactions number 17, 18 and 19 got negative feedback. S_c sells products for 50€ and his transactions 47, 48, 49 were marked negative. The right chart shows the reputation of *Dibbler's* example (see Section 1) who gained reputation by selling “lucky amulets” for 3€ and after the 400th transaction started cheating on expensive products from time to time

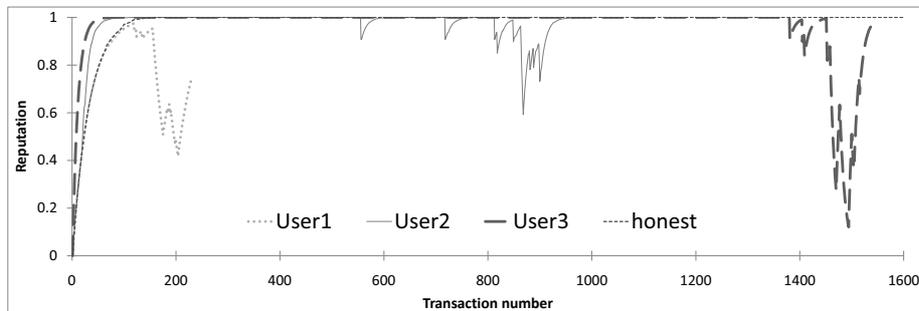


Figure 3. The history of reputation of four users. The honest user gets only positive feedbacks and his/her reputation asymptotically approaches 1. Users 1,2 and 3 stopped worrying much about new feedbacks once they had gained reputation. A simple participation counts system allows them to retain most of their reputation. ATA charts clearly show that the later behaviour of these users is suspicious

Among the users whose history we analysed there were some who did exactly what we wanted to prevent. Fig. 3 shows the history of three Allegro users who gained a lot of reputation points and then stopped bothering so much about new feedbacks. In contrast we added a user with positive feedbacks only – an “honest” user. All four users were selected from our dataset obtained from Allegro site².

This experiment showed that ATA can also be used to perform web-mining analysis without implementing it in an auction portal. One can easily parse trader’s feedbacks list from an auction site and produce a graphic representation of her/his reputation history. Obviously, if the algorithm is used post factum we lose the psychological factor because users are hesitant to submit negative feedbacks for fear of retaliation (the dataset obtained from Allegro contains almost no negative feedbacks – see appendix A for details). Nevertheless, ATA can provide additional information about potential traders.

5. Case of repeated interactions between the same traders

It is not uncommon that two users deal with each other many times. For example, buyers often buy several items at the same online store to get them in one package and save on shipping costs. Moreover, once a buyer has found a good online store he/she is likely to buy at this shop again. In the above scenarios a question arises, how multiple transaction with the same seller should impact the seller’s reputation?

Of course, the simplest approach to this problem is to let traders submit feedback to every single transaction independently. For example the eBay reputation management system lets users submit feedback to every transaction even between the same users as long as transactions were made in different weeks. Unfortunately, this may encourage frauds, two users may repeatably comment on each other positively even though no real transactions took place. On the other hand in the Allegro reputation management systems traders mark one another and not the transaction. Only the first positive or the first negative assessment from user A to user B is taken into account. It does not affect the reputation value whether user A gives user B one or several feedbacks of the same rating.

5.1. Solution based on a variant of ATA

We propose a modified solution: every *repeated opinion* becomes less important. A *repeated opinion* means that user **A** gives feedback to user **B** repeatedly with the same rating as in the previous interaction. Our reputation system counts how many times user **A** gave the same rating to user **B**. Let P_{AB} denote the number of positive feedbacks from user A to B in continual sequence of positive

²Allegro auction site provides full information about feedbacks so they can be easily obtained. Unfortunately, transaction details are available only for recent transactions and it was often impossible to get an item price, so prices in this experiment had to be estimated.

and neutral feedbacks only (if A gives negative feedback to B, P_{AB} is counted from 0). And let N_{AB} denote the number of negative feedbacks from user A to B uninterrupted by any positive feedback. P_{AB} and N_{AB} are calculated before calculating the reputation value according to the formula below:

$$\begin{cases} P_{AB} = P_{AB} + 1 \text{ and } N_{AB} = 0 & \text{for positive feedback} \\ P_{AB} \text{ and } N_{AB} \text{ not changed} & \text{for neutral feedback} \\ P_{AB} = 0 \text{ and } N_{AB} = N_{AB} + 1 & \text{for negative feedback.} \end{cases} \quad (3)$$

To decrease the importance of *repeated opinions*, α is raised to the power of P_{AB} (in case of positive feedback) or N_{AB} (in case of negative feedback). Formula (1) now takes the following form:

$$R_i = \begin{cases} R_{i-1} + ((1 - R_{i-1}) * F(p_i) * \alpha^{P_{AB}}) & \text{for positive feedback} \\ R_{i-1} & \text{for neutral feedback} \\ R_{i-1} - (R_{i-1} * F(p_i) * \alpha^{N_{AB}}) & \text{for negative feedback.} \end{cases} \quad (4)$$

This solution assures that two users will not conspire to raise the reputation of one another but also does not neglect feedback if some users happened to trade several times. It is important to take every feedback into account because on the ATA reputation chart (see Fig. 6) we want to show the whole reputation history.

5.2. Experimental evaluation

In order to illustrate how our modified algorithm works, let us consider a seller who sells expensive products for 300€ (we use the same values of algorithm parameters as in previous experiments, i.e.: $\alpha_s = 0.3$, $\alpha_b = 0.1$, $\gamma = 400€$ and $R_0 = 0$). Fig. 4 shows how the seller's reputation would differ if a buyer interacted with him/her many times.

In the first case all buyers are unique, so the parameters P_{AB} and N_{AB} do not influence the reputation change at all. In the second case user A interacted many times with the seller so in some transactions P_{AB} and N_{AB} caused smaller reputation changes. Transactions number 1, 2, 3, 9, 10 and 12 were made by user A, the reputation change after the second transaction is smaller (because α_s is raised to the power of $P_{AB} = 2$) and much smaller after the third transaction (it is the third positive transaction in a row with this buyer, so $P_{AB} = 3$). In the ninth transaction the same buyer, user A was not satisfied and gave negative feedback, so the opinion is not repeated ($N_{AB} = 1$ and $P_{AB} = 0$, like for a unique buyer). Transaction number 10 was also rated negatively by user A, so the reputation change is smaller (now $N_{AB} = 2$ and $P_{AB} = 0$). The transaction number 12 gets positive feedback, unlike the previous one with user A, the opinion is not repeated, so $P_{AB} = 1$ and $N_{AB} = 0$.

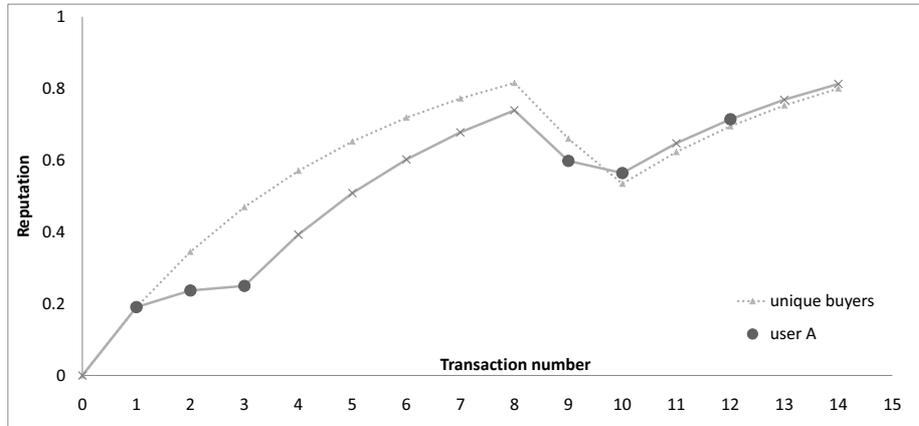


Figure 4. Reputation of a seller in two cases: when all buyers are unique and when the same buyer A deals several times. In both cases feedbacks to transactions 9 and 10 are negative, and other transactions get positive feedback

As we can see from the above example, the ATA modification that treats transactions with the same user differently is a good compromise between submitting feedbacks to the user and submitting feedbacks to transactions. On the one hand this solution prevents dishonest users from committing repeated fictional transactions in order to gain false reputation quickly, and on the other hand, if one wants to buy a few items at one online store then all the feedbacks will be presented on the reputation history chart.

5.3. Summary

Although there are millions of users on Allegro and eBay, it is not uncommon for two users to trade with each other many times. Buyers like to buy at shops which never disappoint them and often buy several items on one auction. If two users are in collusion and give each other positive feedbacks repeatedly without actual deals it is important for the reputation system to assure that they will not gain easily high reputation. This variant of ATA prevents an easy realisation of this kind of fraud. Repeated opinions of a single buyer are not multiplied, yet they are not ignored.

6. Detailed seller ratings

eBay and Allegro give buyers yet another opportunity to judge sellers. In addition to general transaction rating (negative, neutral, or positive feedback) a buyer can also leave *Detailed Seller Ratings* (DSRs) in four areas: *accuracy of item description*, *communication*, *delivery time and postage* & *packaging*

charges. The rating system is based on one to five star scale. Each of the four areas is assessed independently and none of them impacts the overall Feedback Score. Detailed Seller Ratings are anonymous and are only represented on the seller's Feedback Profile page with stars. The number of stars in each area is simply the average rating left for the seller³.

6.1. ATA adaptation to 5-star rating system

We have decided to adapt Asymptotic Trust Algorithm to work with this five star system. In basic ATA, feedback can take only three values (positive, neutral, negative), so the simplest way to extend the domain is to introduce "half positive" and "half negative" case. So the symmetrically extended ATA formula will be as follows:

$$R_i = \begin{cases} R_{i-1} + ((1 - R_{i-1}) * F(p_i) * \alpha) & \text{for positive feedback - 5 stars} \\ R_{i-1} + ((1 - R_{i-1}) * F(p_i) * \frac{1}{2}\alpha) & \text{for half positive feedback - 4 stars} \\ R_{i-1} & \text{for neutral feedback - 3 stars} \\ R_{i-1} - (R_{i-1} * F(p_i) * \frac{1}{2}\alpha) & \text{for half negative feedback - 2 stars} \\ R_{i-1} - (R_{i-1} * F(p_i) * \alpha) & \text{for negative feedback - 1 star.} \end{cases} \quad (5)$$

After analysing the Detailed Seller Ratings on eBay and Allegro we have realised that buyers left 5 stars feedback almost all the time, so we have concluded that only 5 stars really means positive feedback and everything below 4 stars has a negative meaning. Therefore, we have modified the ATA formula:

$$R_i = \begin{cases} R_{i-1} + ((1 - R_{i-1}) * F(p_i) * \alpha) & \text{for positive - 5 stars} \\ R_{i-1} & \text{for neutral - 4 stars} \\ R_{i-1} - (R_{i-1} * F(p_i) * \frac{1}{2}\alpha) & \text{for half negative - 3 stars} \\ R_{i-1} - (R_{i-1} * F(p_i) * \alpha) & \text{for negative - 2 stars} \\ R_{i-1} - (R_{i-1} * F(p_i) * 2\alpha) & \text{for double negative - 1 star.} \end{cases} \quad (6)$$

R_i denotes the seller's detailed reputation after i -th transaction in one particular area, so in fact to describe a seller we have to introduce four new, independent reputation values ($R_{AccuracyOfItemDescription}$, $R_{Communication}$, $R_{DeliveryTime}$, and $R_{Postage\&Packaging\Charges}$). None of these detailed reputation values affects the main, overall reputation that we have described in previous sections; p_i denotes the merchandise price for i -th transaction, $F(p)$ – the change function of price is defined as in (2). We use the same scaling factors γ and α as in basic ATA (in this case α for sellers because only sellers are assessed at this point). Note that in case of one star rating we multiply $F(p)$ by 2, therefore we have to add another constraint: $2\alpha \leq 1$ in order for the reputation value to remain between 0 and 1.

³The specific average value is not shown. eBay rounded the stars to the nearest half, whereas Allegro to one decimal place.

6.2. Experimental evaluation

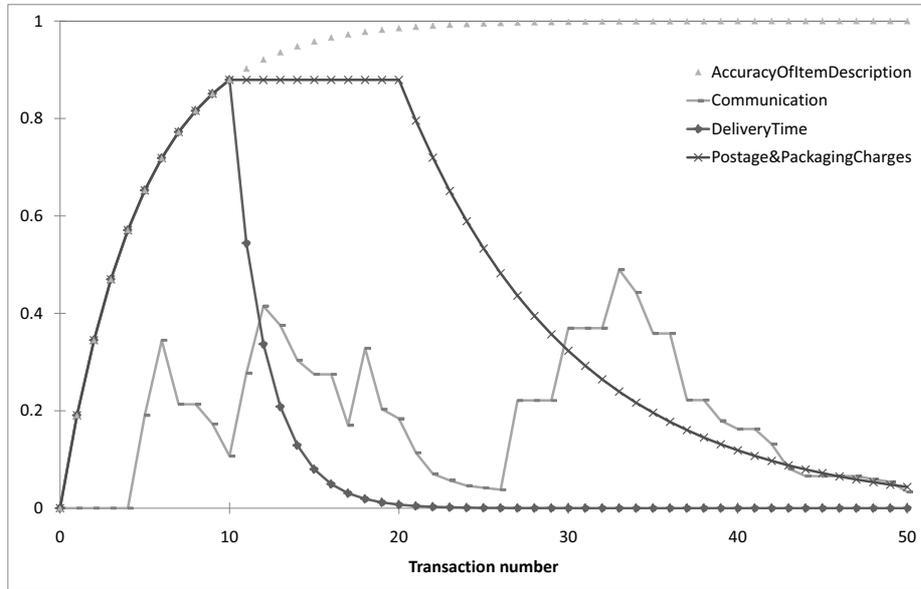


Figure 5. Detailed rating of a hypothetical seller, who sells expensive items for 300€ each, and always gets highest rating for *accuracy of item description*. For *communication* he/she gets random ratings (with uniform distribution). For *postage & packaging charges* the seller gets 5 stars for first 10 auctions and 1 star for every subsequent auction. For *delivery time* he/she received 5 stars rating for auctions 1 to 10, then 4 stars for auctions 11 to 20, and 3 stars for later auctions

To demonstrate how detailed reputation may change we performed experiments on synthetic data that represented one hypothetical seller. Fig. 5 shows detailed reputation of a user who sells expensive items (300€ each); the values of algorithm parameters were as in the previous experiments, i.e.: $\alpha_s = 0.3$, $\gamma = 400\text{€}$ and $R_0 = 0$. As intended, the value of *accuracy of item description* grows fast and asymptotically approaches the value of 1 because every rating in this area is 5. Between transactions 11 and 20, the value of *delivery time* does not change because 4 stars mark seems to be “not bad but not good either”. Here, we can compare value drops: the user gets “very negative” 1 star marks in *postage & packaging charges* and only a “little negative” 3 stars mark for *delivery time* after the 20-th transaction. The value of *communication* is always low because chances of getting a positive change are like 1 to 5.

6.3. Summary

This version of ATA can also be used in various portals where content is assessed on the 5 star scale. In case of detailed seller ratings we also intended not to change the way users interact. A chart like that of Fig. 5 can be displayed on a user profile page next to the stars currently provided by Allegro and eBay.

7. Conclusions

The Asymptotic Trust Algorithm is a novel trust system allowing traders to estimate the reputation of one another. This system can be implemented along with the commonly used trust system (see Fig. 6). Despite having a lot of drawbacks the trust mechanism used currently on Allegro and eBay is easy to use, hence it would be best not to replace it and not to change the way users interact by commenting on each finalised transaction. So, we suggest to combine our trust system with the existing one to provide users with more detailed information about potential traders.

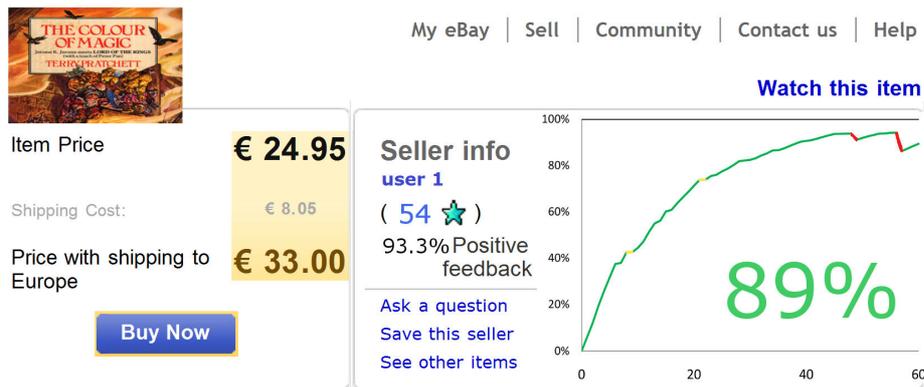


Figure 6. Sample screenshot of the main part of an item page on an auction portal. Traditional eBay user information (user credibility expressed as the number of positive feedbacks minus the number of negative ones – here 54) is enhanced by ATA reputation history chart with R_i value (here $R_i = 89\%$). To introduce ATA to existing auction portals, page layout needs to be changed only a little.

“A picture speaks a thousand words” – it is virtually impossible to describe the reputation with a single number and it is also very difficult for a user to search through comments to find out others’ opinions. Single negative feedback can be neglected by a big online store, so buyers are often hesitant to give it for fear of retaliation. The trust system we have presented allows for showing the whole history of a trader’s behaviour on a single chart (Fig. 6). The chart

shows transactions that were not satisfactory and it is easy to realise if this user earned reputation by many small transactions or few important deals.

In our future work we will consider different implementations and extensions of the algorithm. Work needs to be done also to find the best values for algorithm parameters (the scaling factor values) for particular systems. We will continue Allegro auctions web-mining to discover characteristics of transactions and traders. After this analysis we hope to be able to discover optimal parameter values, providing maximum diversity between honest and dishonest traders. We also consider using approach proposed by Malik and Bouguettaya (2009) to determine the value of R_0 .

A. Appendix: number of feedbacks analysis

We use web-mining techniques to study numbers of feedbacks from traders on Allegro. Here we present the conclusions from our analysis.

In this paper we claimed many times that there are almost no negative feedbacks on Allegro. To prove that point we gathered information about 109,720 randomly chosen users. Yet, many accounts had no feedbacks at all because they were blocked or not used. In our random sample only 48,236 users had any feedback (Fig. 8). Fig. 7 shows the distribution of feedbacks in the sample.

As expected, almost 99% of feedbacks were positive, and there were only 25% of active accounts with negative or neutral feedbacks⁴. These results were similar to those obtained in examination of the number of feedbacks on eBay (see Resnick and Zeckhauser, 2002, and O'Donovan et al., 2006).

Further analysis showed that more than half of the accounts were blocked or not used. Furthermore, almost 9,000 accounts in the random sample had only one single feedback and among the accounts in use there were only half with more than 10 feedbacks. Fig. 8 shows more details.

	buy		sell		sum	
positive	1 599 615	51.177%	1 494 494	47.814%	3 094 109	98.990%
neutral	2 057	0.066%	5 318	0.170%	7 375	0.236%
negative	14 643	0.468%	9 540	0.305%	24 183	0.774%
sum	1 616 315	51.711%	1 509 352	48.289%	3 125 667	100.000%

Figure 7. Number of feedbacks in the random sample, grouped according to the rating and trader's role (buyer or seller).

⁴In our random sample 48,236 accounts have been used at least once and only 12,341 have any negative or neutral feedback.

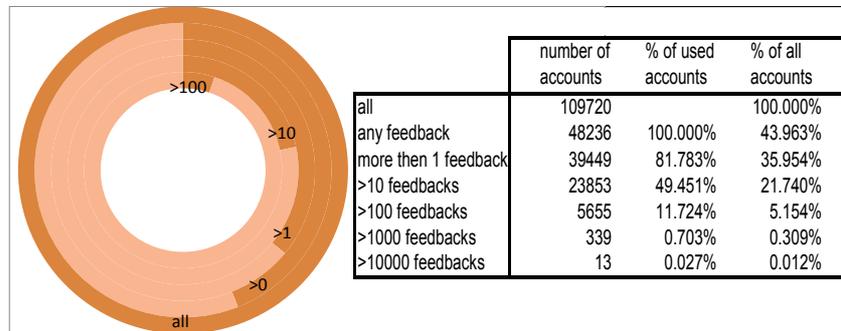


Figure 8. How many feedbacks have users got?

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