Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 7 / ISSUE 1 / APRIL 2012 / 34-50

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762012000100004

The Usage of Contextual Discounting and Opposition in Determining the Trustfulness of Users in Online Auctions

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Received 7 April 2010; received in revised form 7 December 2011; accepted 20 December 2011

Abstract

The communication within Internet auction systems proceeds as a rule under the situation in which users are not in physical contact nor they do not know anything of each other. They have therefore to rely on reputation mechanisms implemented within these online systems. Such mechanisms help to create a trustworthy environment on the basis of additional attributes associated with users and their roles. The trustworthy environment in online auction systems (trust of the system itself and trust among users of this virtual world) is the essential element for these systems functioning. This paper introduces a trust model based on reputation while it takes into account possible fraudulent behavior of users in online auctions as contextual information. The reputation is calculated from user's evaluations (feedback) following performed transactions. Information about possible fraudulent behavior is additional information determining the reliability of the user's reputation in our trust model. Reputation and fraudulent behavior are expressed in a form of belief functions and the resulting user's trustfulness is calculated. The case study shows that the proposed approach is valid and may be applicable in real online auctions.

Keywords: Reputation, Trust, Online auction, Belief functions, Contextual discounting, Belief discounting

1 Introduction

Currently, many users participate in auctions organized by different auction operators on the Internet infrastructure. Examples of such online auction systems are eBay (an American company with a turnover of 8.5 billion USD in 2008) or Aukro (a Czech auction company with a turnover of USD100 million and 1 million users in 2008). Successful Internet auction systems must perform many different activities. In addition to the creation, implementation and operation of their trading system (that is, login of users, displaying data about items being sold, including initial price and duration of auction, displaying of bids of buyers and other data) they must also solve problems with trust and trustfulness. This follows from the fact that transactions in the online auction mostly take place under the situation when users do not know each other. However if users want to do business among themselves they must decide whether they will trust each other. Online auction systems, such as eBay (Site 1), Aukro (Site 3) and others are successful primarily because they are able to create a trusted environment for users of online auctions.

Most of the mechanisms (reputation systems) which create a trusted environment use a variety of attributes associated with users and their roles. These attributes are designed on the basis of the past history of transactions. Buyers and sellers give feedback after performed transactions. They can give positive, negative or neutral comments expressing their satisfaction with a transaction. The potential buyer can always check the seller’s reputation which is quantified from feedback. The seller’s reputation is displayed on the online auction site together with the seller identifier. Reputation serves as a basis for taking decisions on intended transactions with this seller.

It is obvious that such reputation systems made it possible to prevent the majority of online auction fraud. However, some fraudulent behavior is not so easy to find, for example a shill behavior. A shill behavior is, according to the paper [3], the most prevalent form of fraud in online auctions. Shill behavior can be described as the submission of fictitious bids with the aim to artificially increase the price of auctioned items. Weak authentication enables the seller to create another false identity which then can be used for shilling.

In this article, a reputation model which employs all the appropriate information about user behavior in online auctions is described. The model is based on evaluation of feedback given by users after completion of transactions. This mechanism is supplemented by the monitoring of potential fraudulent user behavior. Reputation rate and the rate of possible fraudulent behavior are expressed as belief functions. The information about possible fraudulent behavior influences then the measure of reliability of reputation calculated from feedback. This influence is expressed by the means of contextual discounting and opposition. The proposed mechanism is innovative in the sense that it combines all available information regarding the behavior of users on online auctions to determine their trustfulness.

The remainder of this paper is organized as follows: Section 2 presents the basic principles of the Dempster-Shafer theory, including a description of a situation when there are some doubts about the reliability of an assignment. Section 3 summarizes some related work concerning the use of Dempster-Shafer in reputation systems and shill behavior modeling. Section 4 presents our approach. It outlines the key definitions of belief functions which represent the degree of reputation and the degree of potential fraudulent (shill) behavior. The resulting user’s trustfulness is then calculated on the basis of reputation value and information about the shill behavior. Contextual discounting is used here to express the influence of information about the shill behavior on a reputation score. Section 5 presents our experimental results and model verification. Section 6 describes some interesting conclusions and directions for further research.

2 Dempster-Shafer Theory

Information related to decision making about trust is often uncertain and incomplete. Therefore, it is of vital importance to find a feasible way to make decisions under this uncertainty. The desirable properties of trust representations in an Internet auction (and in all online systems) are:

1. Trust representation should integrate different types of uncertainty:
    - Uncertainty about the outcome of a transaction and uncertainty resulting from the fact of using a second-hand experiences.
2. Trust representation should allow for decision making and should have the following properties:
    - Possibility to rank alternatives;
    - Possibility to compare with own standards.

Our model is a particular application of the Dempster-Shafer theory. The Dempster-Shafer theory [24] is designed to deal with the uncertainty and incompleteness of available information. It is a powerful tool for combining evidence

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and changing prior knowledge in the presence of new evidence. The Dempster-Shafer theory can be considered as a generalization of the Bayesian theory of subjective probability. In this paper, we propose a unique trust model based on the Dempster-Shafer theory which combines evidence concerning reputation with evidence concerning possible illegal behavior on an Internet auction.

In the following paragraphs, we give a brief introduction to the basic notions of the Dempster-Shafer theory (frequently called theory of belief functions or theory of evidence).

2.1 Basic Notions

Considering a finite set referred to as *the frame of discernment* Ω, a *basic belief assignment (BBA)* is a function *m:* $2^{\Omega} \rightarrow [0,1]$ so that

$$\sum_{A \subseteq \Omega} m(A) = 1, \tag{1}$$

where $m(\emptyset) = 0$, see [24]. The subsets of 2^{Ω} which are associated with non-zero values of m are known as *focal elements* and the union of the focal elements is called *the core*. The value of *m(A)* expresses the proportion of all relevant and available evidence that supports the claim that a particular element of Ω belongs to the set *A* but not to a particular subset of *A*. This value pertains only to the set *A* and makes no additional claims about any subsets of *A*. We denote this value also as a *degree of belief* (or *basic belief mass* - *BBM*).

Shafer further defined the concepts of *belief* and *plausibility* [24] as two measures over the subsets of Ω as follows:

$$Bel(A) = \sum_{B \subseteq A} m(B), \tag{2}$$

$$Pl(A) = \sum_{B \cap A \neq \phi} m(B). \tag{3}$$

A *bba* can also be viewed as determining a set of probability distributions *P* over Ω so that $Bel(A) \leq P(A) \leq Pl(A)$. It can be easily seen that these two measures are related to each other as $Pl(A) = 1 - Bel(\neg A)$. *Moreover both of them are equivalent to m.* Thus one needs to know only one of the three functions *m*, *Bel*, or *Pl* to derive the other two. Hence we can speak about belief function using corresponding *bba*s in fact.

Dempster's rule of combination can be used for pooling evidence represented by two belief functions Bel_1 and Bel_2 over the same frame of discernment coming from independent sources of information. The Dempster's rule of combination for combining two belief functions Bel_1 and Bel_2 defined by (equivalent to) *bba*s m_1 and m_2 is defined as follows (the symbol $\oplus$ is used to denote this operation):

$$(m_1 \oplus m_2)(A) = \frac{1}{1-k} \sum_{B \cap C = A} m_1(B) \cdot m_2(C), \tag{4}$$

where

$$k = \sum_{B \cap C = \emptyset} m_1(B) \cdot m_2(C). \tag{5}$$

Here *k* is frequently considered to be a *conflict measure* between two belief functions m_1 and m_2 or a measure of conflict between m_1 and m_2 [24]. Unfortunately this interpretation of *k* is not correct, as it includes also internal conflict of individual belief functions m_1 and m_2 [11], [12]. Demspter's rule is not defined when $k = 1$, i.e. when cores of m_1 and m_2 are disjoint. This rule is commutative and associative; as the rule serves for the cumulation of beliefs, it is not idempotent.

When calculating contextual discounting we also use the un-normalized (conjunctive) combination rule established by Smets [26] in this form (we use the symbol $\otimes$ to denote this operation):

$$(m_1 \otimes m_2)(A) = \sum_{B \cap C = A} m_1(B) \cdot m_2(C). \tag{6}$$

2.2 Operations in Product Frames

In many applications, we need to express uncertain information about several variables taking values in different domains. Let *A* or *B* be two elements (hypotheses) belonging to frames of discernments Ω_A and Ω_B. We can then

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define the product frame $\Omega_{AB} = \Omega_A \times \Omega_B$. Mass function $m^{\Omega_A \times \Omega_B}$ on Ω_{AB} can be seen as an uncertain relation between elements A and B. The basic operations on product space are the following:

2.2.1 Marginalization

A mass function defined on a product space $\Omega\times\Theta$ may be marginalized in Ω by transferring each mass $m^{\Omega\times\Theta}(B)$ for $B \subseteq \Omega\times\Theta$ to its projection into Ω:

$$m^{\Omega\times\Theta\downarrow\Omega}(A) = \sum_{\substack{B\subseteq\Omega\times\Theta \\ Proj(B\downarrow\Omega)=A}} m^{\Omega\times\Theta}(B) \tag{7}$$

for all $A \subseteq \Omega$. Here $Proj(B\downarrow\Omega)$ denotes the projection of B into Ω.

2.2.2 Vacuous Extension on a Product Space

It is usually not possible to retrieve the original *bba* $m^{\Omega\times\Theta}$ from its marginal $m^{\Omega\times\Theta\downarrow\Omega}$ on Ω. However, the least committed, or least informative *bba* [25], such that its projection on Ω is $m^{\Omega\times\Theta\downarrow\Omega}$, may be computed. This defines the vacuous extension of m^{Ω} in the product space $\Omega\times\Theta$, noted $m^{\Omega\uparrow\Omega\times\Theta}$, and given by:

$$m^{\Omega\uparrow\Omega\times\Theta}(B) = \begin{cases} m^{\Omega}(A) & \text{if } B = A\times\Theta,\ \ A\subseteq\Omega \\ 0 & \text{otherwise} \end{cases}. \tag{8}$$

2.2.3 Conditioning on a Product Space

Conditional beliefs represent knowledge that is valid provided that a hypothesis is satisfied. Let m be a mass function and $B \subseteq \Omega$ a hypothesis (with $m(B) = 1$). The conditional belief function $m(A|B)$ is given by (we use the un-normalized conditioning here):

$$m(A\,|\,B) = \sum_{\{C|C\cap B=A\}} m(C)\,. \tag{9}$$

This equation is often written for practical reasons in the form: $m^{A}[B] = m \otimes m_B$.

Let $m^{\Omega\times\Theta}$ be defined on the product space $\Omega\times\Theta$, and θ_0 is an element of Θ, then the conditional *bba* $m^{\Omega}[\theta_0]$ is defined by combining $m^{\Omega\times\Theta}$ with $m_{\theta_0}^{\Theta\uparrow\Omega\times\Theta}$ (with $m_{\theta_0}^{\Theta}(\theta) = 1$), and marginalizing the result on Ω:

$$m^{\Omega}[\theta_0] = \left(m^{\Omega\times\Theta} \otimes m_{\theta_0}^{\Theta\uparrow\Omega\times\Theta}\right)^{\downarrow\Omega}. \tag{10}$$

2.2.4 De-conditioning on a Product Space (Ballooning Extension)

Assume now that $m^{\Omega}[\theta_0]$ represents beliefs conditional on θ_0, i.e., in a context where θ_0 holds. There are usually many *bba*s on $\Omega\times\Theta$, whose conditioning of θ_0 yields $m^{\Omega}[\theta_0]$. Among these, the least committed one is defined for all $A \subseteq \Omega$ by:

$$m^{\Omega}[\theta_0]^{\Uparrow\Omega\times\Theta}(A\times\theta_0 \cup \Omega\times\overline{\theta_0}) = m^{\Omega}[\theta_0](A)\,. \tag{11}$$

This operation is referred to as the de-conditioning or ballooning extension [20] of $m^{\Omega}[\theta_0]$ on $\Omega\times\Theta$.

2.3 Belief Function Correction

When receiving a piece of information represented by a belief function, some metaknowledge regarding the quality or reliability of the source that provides the information, can be available. In the following paragraphs, we describe briefly some possibilities how to correct the information according to this metaknowledge.

2.3.1 Contextual Discounting

To handle the lower reliability of information sources, a discounting scheme has been introduced by Shafer [24]. It is expressed by equations:

$$^{\alpha}m(A) = \begin{cases} (1-\alpha)\times m(A) & \text{if } A\subset\Omega \\ \alpha + (1-\alpha)\times m(\Omega) & \text{if } A=\Omega \end{cases} \tag{12}$$

where $\alpha\in[0,1]$ is a discounting factor and $^{\alpha}m(A)$ denotes the discounted mass of $m(A)$. The larger α is, the more masses are discounted from $A \subset \Omega$, while the more mass is assigned to the frame of discernment Ω.

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An extension of this classical approach is contextual discounting. It is described in detail in referenced papers [20], [21]. Contextual discounting is used if we know that the reliability of predictions for the assignment of individual elements of the framework differs.

We assume therefore that we have evidence concerning the reliability of each of $\theta_k \in \Omega$. We have therefore K conditional assignments $m^{\Re}[\{\theta_k\}]$, k = 1,...,K (instead of one unconditional assignment defined by (12)). We assume that they are defined as follows:

$$\begin{aligned} m^{\Re}[\{\theta_k\}](\{R\}) &= \beta_k \\ m^{\Re}[\{\theta_k\}](\{R, NR\}) &= \alpha_k \end{aligned} \tag{13}$$

Where α_k and β_k express the degree of evidence regarding the reliability of each $\theta_k \in \Omega$ (here $\beta_k = 1 - \alpha_k$).

$\Re = \{R, NR\}$, where R and NR stand respectively for “the source is reliable” and for “the source is not reliable”. Each of these assignments are subject to context θ_k, k = 1,…K. Their combination with m_S^{Ω} will define the contextual discounting $m_Y^{\Re}[\{\theta_k\}]$, k = 1,…K. Contextual discounting is denoted as ${}^{(\alpha)}m_Y^{\Omega}$ and it is defined by the vector (α_1,…α_K). We can assess contextual discounting in the following way [21]:

1. Compute the ballooning extension of $m^{\Omega}(\cdot|R)$ and $m^{\Re}(\cdot|\theta_k)$, k = 1,…K in $\Omega \times \Re$);

2. Combine the K + 1 mass function with the help of the conjunctional rule;

3. Marginalize the combined mass function on Ω.

The result of these procedures can also be expressed as [21]:

$$^{\alpha}m^{\Omega} = m_S^{\Omega} \circ m_1^{\Omega} \circ \ldots \circ m_K^{\Omega}, \tag{14}$$

with $m_k^{\Omega}(\theta_k) = \alpha_k$ and $m_k^{\Omega}(\emptyset) = 1 - \alpha_k$.

The $\circ$ operation was established by Smets[25]. It is called the disjunctive combination rule and is defined as:

$$m_1 \circ m_2(A) = \sum_{B \cup C = A} m_1(B) \cdot m_2(C). \tag{15}$$

2.3.2 Belief Function Opposition

The idea of discounting mechanism is a weakening of a given belief function (*BBA*). Thus, the principle of the discounting is transferring of parts of basic belief masses (*BBMS*) of all focal elements which are proper subsets of the frame of discernment to the entire frame. This process is the result of some additional information saying that the source is not entirely reliable. The transfer of *bbms* from a source to the framework reflects an increase of the degree of uncertainty regarding the data that the source produces.

However, we need in some special cases to transfer a part of the *bba* from one data source to another. For example, if we obtain information that the first source is less reliable than the other, and on the contrary, the same information says that the other is more reliable than we had anticipated at the beginning

The scenarios associated with this idea can often be found in the multi-evidence pooling systems, where decisions are made based on a set of existing pieces of evidence and the corresponding confidence in (or evaluation of) these pieces of evidence. Evidence and corresponding confidence may be elicited in different manners, e.g., drawn by different experts, or based on different viewpoints. The first reference of the possibility to correct the size of a belief function by increasing of its *bbms* is described in [35]. The authors introduced here a discounting factor α less than zero. This approach has its reason when we want to augment masses of $A \subset \Omega$ by taking mass from $m(\Omega)$ (if $m(\Omega) \neq 0$). This is the case when some additional information says to us that all information sources are more reliable then we supposed from the beginning. A disadvantage is that if α is greater then one we can not use the belief function framework to deal with this additional piece of information.

In this paper, we extend the above discounting scheme (12) by the possibility of totally opposing an existing evidence structure. We take the conventional discounting scheme presented by (12), namely that the masses of elements $A \subset \Omega$ (where $m(A) \neq 0$) are scaled down by a non-zero discounting factor and the deducted masses are added to that of Ω. Taking a similar strategy, we will construct for our special case of two-element frame of assignment the opposite process by scaling up the mass of $m(\overline{A})$ through taking the mass away from $m(A)$. We obtain the new evidence structure:

$$\begin{aligned} {}^{\alpha}m(A) &= (1-\alpha)\times m(A) \\ {}^{\alpha}m(\overline{A}) &= m(\overline{A}) + \alpha \times m(A) \\ {}^{\alpha}m(\Omega) &= m(\Omega) \end{aligned} \tag{16}$$

with $A \subset \Omega$, $\overline{A} = \Omega - A$, $\alpha \in [0,1]$.

Let's remind ourselves that the discounting scheme is originally based on a statistical point of view [24]. As a matter of fact, the determination of masses has been extended beyond the statistical scope, and they can be associated with any other confidence measures, e.g., human subjective judgements.

3 Related Work

In the first part of this section, we give a brief overview of the work dealing with reputation models and especially with applications of the Dempster-Shafer theory in these models. In the second section, we provide a brief overview of work dealing with the application of the Dempster-Shafer theory for detecting fraud in online auction systems.

3.1 Reputation Systems

The use of the theory of belief functions for online system trust management is described in [4], [16]-[18]. The authors [16] propose a metric of trust in online systems in the form $\omega_x^A = (b,d,u,a)$. This metric expresses the measure of confidence in the statements about the user trustfulness. This statement is marked as *x*. Additional parameters *b*, *d* and *u* represent here belief, doubt and ignorance. It is valid for them that b, d, u $\in$ [0, 1] and $b + d + u = 1$, see also [10]. Parameter a $\in$ [0, 1] is called relative atomicity. It represents a fundamental value of the probability in the absence of evidence (the evidence which would support the conviction concerning the statement *x*). It is used to calculate the probability of the expected value of a certain statement $E(\omega_x^A) = b + au$. That means that *a* specifies a level of uncertainty associated with $E(\omega_x^A)$.

The authors Yu et al. suggested in the referenced paper [32] the use of the Dempster-Shafer theory to represent the values of trust (reputation) in multiagent systems. They suggest two possible outcomes in their proposal. The first result is that the entity *A* is trustworthy (T_A). The second one is that an entity A is untrustworthy ($\neg T_A$). These two different beliefs about whether *A* is trustworthy or not (they are defined as belief function $m(T)$ or $m(\neg T)$) are stored in the system. Reputation score $\Gamma(A)$ of an entity *A* is defined as a difference between these belief functions:

$$\Gamma(A) = m(T_A) - m(\neg T_A), \tag{17}$$

where $m(T_A)$, $m(\neg T_A) \in [0,1]$ and $\Gamma(A) \in [-1,1]$

The evaluations undertaken by individual entities are determined as a function of the history and behavior of entity *A* within various transactions with other entities. Entities are then marked as trustworthy or untrustworthy (predefined thresholds are used here to determine what is trustworthy and untrustworthy behavior). Matt et al. [16] extended this work to include the game theoretical approach.

Also in other works [33], [34], Yu et al. have used the theory of belief functions of the Dempster-Shafer model for reputation systems. They focus themselves on the application of trust in multiagent systems.

3.2 Fraudulent Behavior

Shilling is a fraudulent behavior, which often occurs in online auctions. However, it is difficult to detect due to the pseudonymity of users [5] participating in the auction. Kauffman et al. [19] present the influence of shill behavior on the online auction. They analyze statistical data from a rare coin eBay auction and test empirically the course of the online auction and the final auction price which is influenced by the shill behavior. Trevathan et al [27] deal in their work with fraudulent behaviour in online auctions. He proposes in his paper an algorithm to detect shill behavior based on comparisons of patterns of behavior in online auctions. In the paper [28], Trevathan and Read extend their approach. They deal with a method for detecting colluding shill bidders. Rubin et al. [23] describe the reputation system which is based on statistical indicators of each seller in the course of the auction (the price of auctioned goods). Chau et al. [9] use the methods of data mining. He applies these methods on the user level and on the level of interaction among the users. He links these two levels and detects suspicious behavior patterns using Markov random field methods. Xu et al. introduces a dynamic auction model (DAM) for shill detection on real online auctions in [31] and uses formally specified shilling behaviors in different stages in linear temporal logic (LTL) to obtain verification of the shill behavior. The referenced authors [7], [29] suggest using Bayesian networks or decision trees (Hierarchical Clustering and Decision Trees) for the detection of fradulent behaviour on online Internet auctions.

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DOI: 10.4067/S0718-18762012000100004

The use of belief functions for shill behavior detection is presented in the work of Dong et al. [13]-[15]. The paper [15] describes some features of shill behavior which are then expressed by belief functions and combined with the aim to classify (and certify) users into categories of shill, suspect and trustworthy. The authors [13]-[15] indicate a conceptual design framework for calculating the belief functions. They demonstrate the correctness of their approach on eBay auctions case study.

4 Suggested Trust Model Based on Contextual Information

We chose the Dempster-Shafer theory for the mathematical representation of the reputation model. It allows the expression of uncertainty of a user at assessing the trustworthiness of another user within online auctions. If a user is not sure whether another user is rather trustworthy or untrustworthy, her response will be - I'm not sure. Our uncertainty (in the sense that we are not able to say that a user is trustworthy or untrustworthy) is therefore significant here and we need to express this uncertainty. For this reason, the Dempster-Shafer theory is particularly suitable for the application of the model to the problem of trust in online auctions.

The proposed trust model thus uses the belief function to represent the degree of trust arising from direct experience as a representation of the degree of reputability resulting from the evaluation (feedback) of other users and as a representation of the degree of prospective fraudulent behavior. The proposed model uses the Dempster combination rule for a systematic combination of all these belief functions expressing the user's trust or reputation and contextual discounting for calculating the resulting value of the user's trustfulness. If a user performs some unauthorized behavior (in particular acting as a shill), there will be a breach of the rules of online auctions. The integrity of that user is impeached. If a user behaves this way it is clear that they may commit another misconduct (such as the supply of low-quality goods or goods other than those listed in the auction description, etc.). Hence reputations should include information on whether the user has acted or not acted in accordance with the rules of online auctions.

The proposed model is innovative because it combines all available information relating to a specific user behavior to determine the trustfulness of this user.

4.1 Basics of Our Model

Our model consists of three steps:

Step 1. The determination of belief functions based on evaluations by other users (reputation)
The reputation of a given user is based on the rating by users who have completed a transaction with the given user and expresses the mean rating of the given user. We denote $\Omega = \{T, \neg T\}$ as a frame of discernment concerning the reputation; m_{Rp} is the mass function obtained from all entities which evaluate the quality of services (sold products) of a certain seller. The detailed procedure for calculation of mass m_{Rp} is presented in section 4.2

Step 2. Belief functions representing illegal behavior (shill behavior)
We have defined the following attributes of shill behavior: loyalty to the seller m_{Ve}, early timing of bids m_C, average timing of bids m_{Po} and small amount of won auctions m_{Mva}. The detailed procedures for calculation of mass m_{Ve}, m_C, m_{Po} and m_{Mva} are presented in Section 4.3.

Step 3. The assesment of the influence of evidence about shill behavior on the reputation and the determination of overall trustworthiness of a seller
We use the contextual discounting and opposition scheme (see Section 2.1) to determine the additional effect on a seller's reputation. This additional knowledge refers to the fact that a seller uses a shill. We determine the reliability of reputation which is calculated on the basis of feedback after the transaction. But if the seller uses a shill their reputation measure is reduced (the reputation measure has lower predicative efficiency). Our objective in this step is to assess the effect of the evidence that a seller uses a shill on their reputation measure, to assess this effect quantitatively. The detailed procedures for this are described in Section 4.5.

4.2 The Determination of Belief Functions Based on Evaluations by Other Users (Reputation)

The user's reputation is based on evaluations by individual participants upon completion of each transaction. The users of the online auction are given a form (which can also include space for comments) which they fill out upon completion of a transaction. The users (buyers, bidders) assign points to other users (sellers) and evaluate the following aspects: the description of the sold item on the auction website (whether it corresponds to the actual item), the quality of communication with the seller, the speed of delivery, and the quality of delivery. Users can also add other remarks in the text window provided in the form.

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The reputation of a certain seller *j* is based on the rating by users who have completed a transaction with this seller. We will define the belief function m_{Rp_j} on the basis of this rating which will express a degree of trust in seller *j*.

Let us assume that seller *j* offered a number of products/services in an auction, altogether *m* items. The results of the auctions are evaluated by users who have conducted transactions with the evaluated seller (the seller *j* is evaluated by *n* users). The overall rating of the seller *j* is represented by the set $S_{Rp_j} = \{s_{1j_1}, s_{1j_2}, s_{2j_1}, \ldots, s_{ij_k}, \ldots, s_{nj_m}\}$.

Here the term s_{ij_k} represents the rating of the seller *j* in the *k*-th transaction performed by the bidder *i*. The number of transactions performed by an individual bidder can differ. This rating is calculated in the following way [6]:

We denote $\Omega = \{T, \neg T\}$ as a frame of discernment concerning the reputation; m_{Rp} is the mass function obtained from all entities which evaluate the quality of services (sold products) of a given seller.

The power set of the set Ω (the set of all subsets) 2^{Ω} has three elements (we do not consider the empty set): $2^{\Omega} = \{\{T\}, \{\neg T\}, \Omega\}$, where $\{T\}$ represents that the given seller is trustworthy, $\{\neg T\}$ means that the given seller is not trustworthy and $\{\Omega\}$ denotes ignorance. It means that we cannot judge whether a given seller is trustworthy, for example if evaluations of transactions are neutral (neither positive nor negative).

We further define two thresholds th_l and th_h ($th_l \leq th_h$) which are defined as a lower and upper threshold for reputation. For example, the seller (or their services) can be evaluated on a scale such as -2, -1, 0, 1, 2, where -2 means very bad, -1 not very good, 0 neutral (unsure), 1 acceptable, and 2 outstanding. As th_h we could take the value 1 and as th_l the value -1. The belief function formula will be defined:

$$m_{Rp_j}(\{T\}) = \frac{\sum_{i=1}^{n} \sum_{k=1}^{m} |s_{ij_k}|, \text{ where } s_{ij_k} \geq th_h}{\sum_{i=1}^{n} \sum_{k=1}^{m} |s_{ij_k}|}$$

$$m_{Rp_j}(\{\neg T\}) = \frac{\sum_{i=1}^{n} \sum_{k=1}^{m} |s_{ij_k}|, \text{ where } s_{ij_k} \leq th_l}{\sum_{i=1}^{n} \sum_{k=1}^{m} |s_{ij_k}|} \tag{18}$$

$$m_{Rp_j}(\Omega) = 1 - m_{Rp}(\{T\}) - m_{Rp}(\{\neg T\})$$

Here: s_{ij_k} is the rating of the *k*-th transaction (seller *j*, bidder *i*) and $m_{Rp_j}(\{T\})$ represents the trust in the hypothesis that the seller *j* "has a good reputation on the market" and "has been positively evaluated by many users".

Belief function m_{Rp_j} defines the degree of trust in seller *j* based on reputation, i.e. based on the experiences of other users dealing with seller *j*. This belief function is then completed with a belief function expressing illegal behavior (shill bidding) to determine the total trustworthiness of a user.

4.3 Belief Functions Representing Illegal Behavior (Shill Behavior)

This is a method where the seller agrees in advance to cooperate with other users (known as shills) to raise the price of merchandise for sale. "*The shill*" participates in the auction and bids for the auctioned item. A user who tries to obtain the auctioned item and is not in on the "*game*", tries to outbid the "*shill*" and offers a higher price. This way, the price of the item increases. In the case where the "shill" wins the auction, the item will remain in the possession of the seller. The seller will likely put the item up for auction again claiming that the "*shill*" failed to pay for the item. Such behavior is called "*shill behavior*" [1]-[3], [8], [13], [30].

One of the first efforts describing the use of the Dempster-Shafer theory to detect "*the shill*" is an essay [13], using an approach similar to the one described in this paper. In our model, we have also chosen an approach based on an application of the Dempster-Shafer theory (DST). We assume that in this case, the use of DST corresponds to the character of the modeled process. It corresponds to the type of modeled uncertainty and conveniently allows us to combine and to update characteristic attributes of shill behavior.

We have defined the following attributes of shill behavior (it is possible to define other ones as well, but it is too difficult to verify them):

1. Loyalty to the seller;
2. Early timing of bids;
3. Average timing of bids.
4. Small amount of won auctions;
5. Similarity of identification details of the seller and bidder;

We experimentally checked these attributes on both the real Aukro.cz auctions (Site 3). We monitored the parameters of 278 auctions. From them, we evaluated 32 as auctions in which a shill behavior took place. Based on experiments, we finally have excluded the attribute “Similarity of identification details of the seller and bidder”. Online auction websites (Site 3) and websites dedicated to fraud behavior in online auctions [3] insist on this being a common sign of shill behavior. Based on our experiments, we found that the incidence of this attribute is practically negligible (experiments on Aukro.cz online auctions (Site 3) and on student experimental auction system (Site 4).

4.3.1 Loyalty to Seller

This trait shows that the bidder “shill” concentrates on one or two sellers. The belief functions have the following form:

$$m_L(\{shill_i\}) = v_L \frac{N_i}{\sum_{j=1}^{n} N_{ij}}$$
$$m_L(\{\neg shill_i\}) = 0 \qquad (19)$$
$$m_L(\Theta_i) = 1 - v_L \frac{N_i}{\sum_{j=1}^{n} N_{ij}}$$

where v_L is the weight of this evidence. We can intuitively read this weight as a reliability of this evidence, N_i – the number of bids by bidder i in an online auction of a certain seller, n is the total number of sellers with whom the bidder conducted a transaction (bids).

With this equation, we have expressed the loyalty to the seller. Usually, the higher the number of bids made by bidder i to a certain seller, compared to the number of his bids to other sellers j, the higher the suspicion that the bidder is a “*shill*”. Therefore, we assume that the equation reflecting the loyalty to the seller, does not show that the bidder is not a “*shill*”, i.e. $m_L(\{\neg shill_i\}) = 0$.

4.3.2 Early Timing of Bids

Bidders-shills typically do not make bids when auctions are nearing the end to avoid the risk of winning the auction. Belief functions have the following forms:

$$m_E(\{shill_i\}) = v_E \frac{T_k - T_i}{T_{total}}$$
$$m_E(\{\neg shill_i\}) = 0 \qquad (20)$$
$$m_E(\Theta_i) = 1 - v_E \frac{T_k - T_i}{T_{total}}$$

where T_k is the time when the auction is scheduled to finish, T_i is the time when the observed bidder I places their last bid and T_{total} is the duration of the auction.

It is valid that the higher the time difference between when the auction ends and when bidder I places their last bid, compared to the overall duration of the auction, the higher the suspicion that the bidder is a “shill”. Therefore, we also assume that the given equation does not indicate that the bidder is not a “*shill*”, i.e. $m_E(\{\neg shill_i\}) = 0$. The parameter v_E is in these equations the weight of evidence. We can intuitively interpret this weight as the reliability of the given evidence.

4.3.3 Average Timing of Bids

This parameter is analogic to the previous one. The aim of a shill behavior is to stimulate bidding. Therefore, the shill bids shortly after bid of the “proper” auctioneer. The shill tries thus to some extent to put pressure on other bidders

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 7 / ISSUE 1 / APRIL 2012 / 34-50

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762012000100004

and also give them as much time as possible on their bids. The belief functions of this attribute have the following form:

$$m_A(\{shill_i\}) = v_A\left(1-\frac{\sum_{j=1}^{N}(T_j - T_{i_j})/N}{T_{total}}\right)$$

$$m_A(\{\neg shill_i\}) = 0 \tag{21}$$

$$m_A(\{\Theta_i\}) = v_A\left(\frac{\sum_{j=1}^{N}(T_j - T_{i_j})/N}{T_{total}}\right)$$

where T_j is the time when the proper auctioneer *j* puts their bid and T_{ij} is the time when the observed bidder *I* places their bid. This bid follows the bid of auctioneer *j*, T_{total} is the duration of the auction and *N* is the number of bids of auctioneer *j* in the respective auction. The v_A parameter is the weight of evidence. We can intuitively interpret this weight as the reliability of the given evidence.

It is valid that the less the time difference between the time when auctioneer j places their bid and when bidder *I* places subsequently their bid, compared to the overall duration of the auction, the higher the suspicion that the bidder is a “shill”. Therefore, we also assume that the given equation does not indicate that the bidder is not a “*shill*”, i.e. $m_A(\{\neg shill_i\}) = 0$.

4.3.4 Small Number of Won Auctions

Due to their role, bidders-shills win a limited number of auctions. The goal of the bidder-shill is not to win an auction but to drive up the price as high as possible. We use the following relations to express the assumption that the user is a shill:

$$m_W(\{shill_i\}) = v_W \frac{\sum_{j=1}^{n}(N_{ij} - Nv_{ij})}{\sum_{j=1}^{n} N_{ij}}$$

$$m_W(\{\neg shill_i\}) = 0 \tag{22}$$

$$m_W(\Theta_i) = 1 - v_W \frac{\sum_{j=1}^{n} Nv_{ij}}{\sum_{j=1}^{n} N_{ij}}$$

where Nv_{ij} is the number of wins in auctions with the participation of bidder *i* and seller *j*, N_{ij} is the number of bids of the bidder *i* in auctions of the seller *j* and *n* is the total number of sellers with whom the bidder conducted transaction (bids).

In these equations, the v_W parameter is the weight of evidence. We can intuitively interpret this weight as the reliability of the given evidence.

The higher the ratio of the difference between the number of bids and the number of wins of the bidder *i* for the seller *j*, the higher the suspicion that the bidder is a “*shill*”. Therefore, we assume that the equation does not show that the bidder is not a “*shill*”, i.e. $m_W(\{\neg shill_i\}) = 0$.

4.4 Combination of Characteristic Signs (Proofs) of Shill Behavior

Once we obtain the belief functions, we combine them in a consistent manner to get a more complete assessment of what the whole group of signs indicates. The combination of belief functions is done with the help of the Dempster’s combination rule, see equation (4). We express the assumption that a given bidder *i* is a shill with the help of belief

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 7 / ISSUE 1 / APRIL 2012 / 34-50
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This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762012000100004

function $m_V(\{shill_i\})$. We calculate the value $m_V(\{shill_i\})$ using the combination of single belief functions expressing appropriate evidence:

$$m_V(\{shill_i\})=(m_L \oplus m_E \oplus m_A \oplus m_W)(\{shill_i\}) \tag{23}$$

The operator $\oplus$ is the Dempster's rule of belief function combination (4).

We perform the combination of multiple proofs according to the Dempster's rule – first we combine two belief functions, then we combine the result with the third belief function, fourth belief function and so forth. For example, the following rules combine the first and second belief functions:

$$(m_L \oplus m_E)(\{shill_i\}) = \frac{1}{K}\left[m_L(\{shill_i\}) \cdot m_E(\{shill_i\}) + m_L(\{shill_i\}) \cdot m_E(\Theta) + m_L(\Theta) \cdot m_E(\{shill_i\})\right]$$

$$(m_L \oplus m_E)(\{\neg shill_i\}) = \frac{1}{K}\left[m_L(\{\neg shill_i\}) \cdot m_E(\{\neg shill_i\}) + m_L(\{\neg shill_i\}) \cdot m_E(\Theta) + m_L(\Theta) \cdot m_E(\{\neg shill_i\})\right] = 0 \tag{24}$$

$$(m_L \oplus m_E)(\{\Theta\}) = \frac{1}{K}\left[m_L(\Theta) \cdot m_E(\Theta)\right]$$

where K:

$$K = 1 - (m_L(\{\neg shill_i\}) m_E(\{shill_i\}) + m_L(\{shill_i\}) m_E(\{\neg shill_i\})) \tag{25}$$

4.5 Categorization of Users According to the Resulting Belief Functions Representing Shill Behavior

When constructing belief functions, we assume that they do not reflect that a given bidder is not a "*shill*" (they do not prove that bidder *i* is not a "*shill*"). It is valid that $m(\{\neg shill_i\})=0$. After calculating the belief value that bidder *i* shows the character of shill behavior, the value $m_V(\{shill_i\})$ is assigned to bidder *i* as a measure which indicates the strength of the conviction that the user *i* is a shill. Now, we will categorize users into categories according to the view that a certain user *i* is a shill. We will classify them into three categories in accordance with [15]: "Shill", "Suspect" and "Trusted user".

We have to define thresholds φ and ξ. We will categorize according to these thresholds as follows: if $m_V(\{shill_i\}) \geq \varphi$ then the user *i* is a Shill, if $\varphi > m_V(\{shill_i\}) > \xi$ then the user *i* is a Suspect, if $m_V(\{shill_i\}) \leq \xi$ then the user *i* is a Trusted user. The category "Suspect" means that the evidence is not sufficient enough to support the verdict that a user is a shill, but this user behaves more like a shill than a "Trusted user". The thresholds φ and ξ will be qualified on the basis of statistical evaluations of analyzed auctions.

4.6 The Influence of Evidence About Shill Behavior on the Total Trustworthiness of a Seller

In our model, we consider the fact that a seller uses a shill as the additional knowledge that should be reflected in the value of the seller's reputation. Reputation, as already mentioned, is calculated based on the evaluation performed after transactions carried out by other users (negative or positive or neutral comments). So the reputation measure includes the buyer's satisfaction with the transaction and delivered goods. But it does not reflect any possible fraudulent behavior of this seller that may compromise their integrity (such behavior is for example the use of shills in online auctions).

We use contextual discounting and opposition (see Section 2.3) to determine the effect of the additional knowledge that the seller uses a shill on her reputation measure (this means that a shill is presented in auction in which they offer some goods). We determine the reliability of reputation which is calculated on the basis of feedback after the transaction. If the seller uses a shill then their reputation measure is reduced (the reputation measure has lower predicative efficiency). We express the influence of evidence that the user is a "Suspect" as follows: if we find out that the seller is a "Suspect" of being a user of a shill, then the reliability of predictions based only on reputation calculated from users' feedback that the seller is trustworthy (*R*) is α_1 and the reliability of these predictions that the seller is untrustworthy is α_2. We get the frame of discernment for expressing the reliability reputation $\Theta = \{R, NR\}$, with $\theta_1 = \{R\}$ a $\theta_2 = \{NR\}$.

In the case that the user is classified as a "Shill", then we express the influence of evidence of using a shill on reputation level on the basis of the opposition scheme suggested in Section 2.3.2. In this case, the reliability of prediction that the user is trustworthy (*R*) is α_3 and similarly the reliability of prediction that the user is untrustworthy (*NR*) is α_4.

We set the values of parameters α_2 and α_4 as equal to one. If the seller uses a shill then the rate of her untrustworthiness (obtained by negative comments) will not decrease. In this case, the untrustworthiness determined on the basis of negative comments from previous transactions is a reliable indicator of this seller's untrustworthiness.

We determine the size of parameters α_1 and α_3 experimentally (see Chapter 5). The size of these parameters is based on a subjective perception of the importance of information on the use of a shill. Trustfulness and trust are largely subjective and reflect also various circumstances and experience of users.

4.7 Calculation of Total Trustworthiness

We have the reputation of a certain seller m_{Rp}, which we have calculated from the feedback evaluation of buyers after performed transactions. We also have evidence that the seller uses a shill (or is suspect of using a shill). This evidence has an influence on the reputation rate of this seller. We express this influence by the lowering of the reputation rate and by the increasing of uncertainty or distrust concerning this seller. Therefore we calculate the resulting seller's trustfulness using the scheme of contextual discounting or opposition described in Section 2.3.2.

The frame of discernment Ω concerning reputation has two components - trustworthy ($\omega_1 = T$) and untrustworthy ($\omega_2 = \neg T$). That means that $\Omega = \{T, \neg T\}$. We express the influence of evidence of suspicion of using a shill (or of actually using a shill) on the level of trustfulness as follows: if we determine that the seller is supect of using a shill (or actually uses a shill) then the reliability of predictions that the seller is trustworthy (R) is α_1 (or α_3 if we are sure that the seller uses a shill) and the reliability of predictions that the seller is untrustworthy (NR) is α_2 (or α_4). Hence we have a frame of discernment expressing the reliability of reputation calculated from direct users' feadback $\Theta = \{\theta_1, \theta_2\}$ with θ_1={R} and θ_2={NR}. We have, for example, the values: $m_{Rp}(\{T\}) = 0.95$, $m_{Rp}(\{\neg T\}) = 0.04$ and $m_{Rp}(\Omega) = 0.01$. We have further $\Theta = \{R, NR\}$ with (0.75, 1) if the seller uses a shill and (0.95, 1) when the seller is suspect of using a shill.

We have three situations now: we know that the indication of reputation is reliable in the case of when a seller does not use a shill (situation 1), less reliable when the a seller is suspected of using a shill (situation 2) and least reliable when we are sure that a seller uses a shill (situation 3). We now calculate the resulting trustfullness of a seller for these individual cases:

Situation 1 – the seller does not use a shill (and is categorized as a "Trusted user").
$m_D(T) = m_{Rp}(\{T\}) = 0.95$
$m_D(\neg T) = m_{Rp}(\{\neg T\}) = 0.04$
$m_D(\Omega) = m_{Rp}(\Theta) = 0.01$
The values of the reputation of this user have remained unchanged.

Situation 2 – the seller is suspected of using a shill (she is categorized as a "Suspect").
When calculating we will use the contextual discounting scheme set out in Section 2.3.1. In our case, the calculation is easier because it holds that both frames of discernment correspond to each other $\Theta \approx \Omega$.
$m_D(T) = \alpha_1 \cdot m_{Rp}(\{T\}) = 0.95 \cdot 0.95 = 0.9025$
$m_D(\neg T) = \alpha_2 \cdot m_{Rp}(\{\neg T\}) = 1 \cdot 0.04 = 0.04$
$m_D(\Omega) = (1 - \alpha_1) \cdot m_{Rp}(\{T\}) + (1 - \alpha_2) \cdot m_{Rp}(\{\neg T\}) + m_{Rp}(\Theta) = 0.05 \cdot 0.95 + 0 \cdot 0.04 + 0.01 = 0{,}0575$
The trustfulness of this user has decreased. The uncertainty $m_D(\Omega)$ concerning this user has increased.

Situation 3 - the seller uses a shill for sure (and is categorized as a "Shill"):
We use the contextual discounting scheme suggested in Section 2.3.2.
$m_D(T) = \alpha_3 \cdot m_{Rp}(\{T\}) = 0.75 \cdot 0.95 = 0.7125$
$m_D(\neg T) = m_{Rp}(\{\neg T\}) + (1 - \alpha_3) \cdot m_{Rp}(\{T\}) = 0.04 + 0{,}25 \cdot 0{,}95 = 0.2775$
$m_D(\Omega) = m_{Rp}(\Theta) = 0.01$
We know on the basis of pieces of evidence for sure that the user uses a shill. The trustfulness of this user has decreased and her untrustworthiness has increased.

Note 1: We keep a neutral evaluation (ignorance) when calculating of total trustworthiness. Neutral evaluation is an important indicator for online auction bidders. If the seller is untrustworthy (the value $m_D(\neg T)$ is high), then the bidder will not perform any transaction with this seller. If the value $m_D(\neg T)$ is not so high but on other hand the neutral evaluation (the value $m_D(\Omega)$ is high, then the bidder does not need to completely avoid a transaction with this seller. In this case, the bidder has to be aware of the seller's neutral evaluation and will take some additional measures (such as escrow services or others).

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 7 / ISSUE 1 / APRIL 2012 / 34-50

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762012000100004

5 Case Study and Analysis of Results

We conducted many experiments to verify our suggested trust model based on contextual information. These experiments included statistical surveys of users, and especially series of tests on real online auction system Aukro (Site 3). We describe the course and results of these experiments in the following paragraphs.

5.1 Determination of Parameters α_1 and α_3

The value of parameters α_1 and α_3 have to be found experimentally. Therefore we have conducted a statistical survey based on questionnaires.

The characteristics of the population. We conducted research among users of Aukro (Site 3) or eBay (Site 1) electronic auctions. The number of these users was 68. They were mostly students who had experience in using online auctions. We also conducted a survey of 31 students who used an electronic auction as part of their learning (Site 4).

Methods for processing and testing hypotheses. We used the basic methods of descriptive statistics for data analysis. We used the statistical software Statistica 9.1.

The description of experiments. Our experiments were based on questionnaire surveys which were supported by interviews. The aim was for respondents to think over the issue. During the interview, respondents were reminded of the concept of reputation and the situation when a seller may perform illegal activities. Respondents were asked to imagine a situation where they received information on illegal activities of a seller whom they had performed some transaction with. This seller sold large quantities of goods in an internet auction and got good feedback from all buyers. We described this situation within the interview in detail. We then asked: how would you adjust (reduce) the level of trustfulness of this seller, if you find out that they use fraud (shill) surely in their auctions or they are suspect of using fraud (shill) in their auctions?

Based on responses concerning the level of trustfulness, we calculated the average value of factor α_1 (the seller is suspected of fraudulent behavior) amounting to 0.95 and factor α_3 with a high of 0.75 (the seller performs fraudulent behavior for sure). We can interpret this value as follows: the seller's reputation based on the buyer's feedback has a value of 1.0, i.e., the seller is trustful. The seller obtained this feedback from buyers who were not aware that the seller had used a shill. After receiving information on the use of a shill, the trustfulness of this seller drops to an average value of 0.75. This is still a relatively high value. Respondents justified this value by having the experience of shopping in online auctions. They mention that they are able to evaluate a sound price of bought goods.

We can similarly interpret the value of factor α_3 when the user is "only" suspected of using a shill. Here of course, the value is higher (0.95).

In that way, we get an assessment of the impact of additional information on the use of a shill on the rate of trustfulness of the seller. This influence is now expressed as a reliability of reputation rate calculated on the basis of feedback. Its reliability measure is 0.95 for α_1 if the user is suspected of using a shill. Similarly, the reliability measure is 0.75 for α_3 if the user uses a shill for sure.

5.2 Experiment on Real Online Auctions and Calculations

To demonstrate the feasibility of the suggested reputation mechanism, we tested our methodology using real auction data from Aukro.cz (Site 3). The dataset we collected consists of completed Aukro auctions in the category of "Used computers". This dataset was collected over the course of more than 65 days. We explored the bidding history of multiple auctions and the reputations of sellers and bidders participating in 278 of these auctions, with a total of 1,615 bidders. We investigated the bidding history of every bidder who participated in this auction and we also investigated past auctions hosted by a particular seller.

We counted the total number of positive and negative comments, total number of bids, bid activity with the same seller, number of bids of single bidders in respective auctions, number of wins, time of duration of auctions, timing of bids, average time of bidding of the bidder *i* after bidding of another bidder, see the Table 1. We had to investigate all information manually because Aukro (Site 3) does not have (in contrast to eBay (Site 2) any API interface enabling automatic gathering of information.

When calculating the total trustworthiness of sellers, we first analyzed auctions to reveal the shill behavior of bidder *i* in an auction of seller *j* (using bidder *i* for shilling). Then, we investigated the reputation of seller *j* using comments written by other users after conducting a transaction with this seller *j*. Then, we calculated the total trustworthiness of seller *j* based on two proofs concerning the trustworthiness of this seller: evaluations of the seller after performed transactions (reputation) and possible evidence of illegal behavior during an online auction (shilling).

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 7 / ISSUE 1 / APRIL 2012 / 34-50

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762012000100004

Some typical results of our exploration of auctions on Aukro are presented in Tables 1 and 3. The basic masses assigned for evidence specified in our model are shown in Table 2. Table 3 also contains the values of reputation expressed by means of belief function. The resulting values are given in Table 4.

Table 1: Auction data collected from Czech online auction Aukro (Site 3)

Bidder *i*	Number of bids of bidder *i* in the auction of seller *j*	Total number of bids in all auctions in which the bidder *i* participated	Time of the bid of bidder *i* (min)	Total time of auction (duration in min)	Number of wins of bidder *i* in all auctions they participated	Average time of bidding of bidder *i* after bidding of another bidder *j* (min)
v***a	2	4	2160	14400	0	460
P***e	2	3	760	11520	0	201
m***4	2	4	690	7200	0	120
d***y	1	3	4200	8640	0	60
b***k	1	4	2200	7200	0	160
t***s	1	389	6200	8640	276	450

The belief of shill behavior and uncertainty of shill behavior are calculated using equations (19), (20), (21), (22) and (23). Calculations are presented in Table 2. The weights of evidence v_L, v_A, v_E and v_W were set in agreement with our experiments at the level 0.9, 0.7, 0.8 and 0.9. We consider the shill characters “Loyalty to seller” together with “Small number of won auctions”, as the most predicative. The character “Average timing of bids” is the less reliable in determining a shill. The values of thresholds φ and ξ were set on the basis of our experiments at the levels 0.95 and 0.97. These values correspond to our survey of the relevance of single described characteristics from examined auctions. These data also correspond to a certain degree to the data from the referenced literature [15].

Table 2: The basic masses assigned to single shill behavior characteristics (eq. (19), (20), (21), (22) and (23))

Seller *j* using bidder *i* as a shill	Bidder *i* suspect of shilling	$m_L(\{shill\})$	$m_E(\{shill\})$	$m_A(\{shill\})$	$m_W(\{shill\})$	$m_V(\{shill\})$	$m_V(\Theta)$	Result
T***t	v***a	0.40	0.65	0.70	0.09	0.94	0.06	Trusted bidder
m***2	P***e	0.53	0.74	0.70	0.14	0.96	0.04	Suspect
r***n	m***4	0.40	0.75	0.70	0.48	0.98	0.02	Shill
P***r	d***y	0.26	0.41	0.70	0.14	0.89	0.11	Trusted bidder
e***1	b***k	0.20	0.56	0.70	0.11	0.91	0.09	Trusted bidder
A***y	t***s	0	0.11	0.20	0.14	0.38	0.62	Trusted bidder

On the online auction system Aukro (Site 3) (where we were performing experiments), a user’s evaluation is based on a three-value scale. A negative evaluation is -1, neutral 0 and positive 1. We investigated data of those sellers that we suspected of engaging in shilling. The belief functions are calculated using equation (18).

Journal of Theoretical and Applied Electronic Commerce Research
ISSN 0718–1876 Electronic Version
VOL 7 / ISSUE 1 / APRIL 2012 / 34-50

This paper is available online at
www.jtaer.com
DOI: 10.4067/S0718-18762012000100004

Table 3: Reputation and belief function for sellers suspected of using shills

Seller *j*	Number of positive comments	Number of negative comments	Number of neutral comments	$m_{Rp}(\{T\})$	$m_{Rp}(\{\neg T\})$	$m_{Rp}(\Theta)$
T***t	156	2	1	0.98	0.01	0.01
m***2	48	1	3	0.92	0.02	0.06
r***n	67	1	10	0.86	0.01	0.13
P***r	27	1	4	0.84	0.03	0.12
e***1	13	3	1	0.76	0.18	0.06
A***y	1465	1	0	0.999	0.001	0

Then, we calculated the total trustworthiness of seller *j* from two belief functions expressing reputation (evaluations of performed transactions) and possible illegal behavior during an online auction (shilling). The calculations were performed according to the procedure described in Section 4.6.

Table 4: Calculation of total trustworthiness for chosen sellers

Seller	$m_D(\{T\})$	$m_D(\{\neg T\})$	$m_D(\Theta)$
T***t	0.98	0.01	0.01
m***2	0.87	0.02	0.11
r***n	0.65	0.22	0.13
P***r	0.84	0.03	0.12
e***1	0.76	0.18	0.06
A***y	0.999	0.001	0

The seller T***t does not use a shill according to our model. Their reputation values remain unchanged. The source of evidence used to determine a seller's reputation (i.e., other users' feedback) is reliable. The seller m***2 has a good reputation. But they are suspected of using a shill in their auctions. Therefore trustworthiness decreases slightly and their neutral reputation increases to the value 0.11. We can deduce on the basis of these reputation data that the user is to a certain extent trustworthy, and it is possible to conduct a transaction with them in an online auction. However, we must be aware of some uncertainty ($m_D(\Theta) = 0.11$) connected with this user and must take precautionary measures (e.g., to make sure that their identity is properly verified, to use escrow services etc.). The total trustworthiness of the seller r***n decreased notably and their untrustworthiness increased considerably. The belief that the seller r***n uses shilling is very high. Table 3 also shows that the reputation of seller r***n is not very high (0.86). But their neutral reputation is 0.13, and they have a low negative reputation (0.01). We can deduce on the basis of these reputation data that the user is to a certain extent trustworthy, and it is possible to conduct a transaction with them in an online auction. But when we take into account the belief that this seller uses shilling (Table 4), then our consideration will change. The untrustworthiness of this seller is now very high (0.22) and we would probably avoid conducting any transactions in an online auction with this user.

6 Conclusion and Future Work

In our work, we presented a computational model of trust to seller on online auctions. It is based on the seller's rating obtained after performed transactions and his possible fraudulent behavior. We verified our model on Czech online auction Aukro. We performed a number of experiments on this auction. We make certain that we can increase the prediction of trust to seller by using reputation (rating information) as a basis which is completed with evaluation of possible fraudulent behavior (shilling) as additional information. Nevertheless we are also aware that the mathematical formalization of parameters used in our model (especially the parameters v_L, v_E, v_A, v_W, φ and ξ) is necessary to increase the practical usefulness of our model.

In our future work, we want to define these parameters by the help of mathematical formulas. We will perform further statistical analyses of online auctions to verify these formulas and values of the parameters of our model. For the purposes of planned experiments, we will improve our experimental auction system which is used currently mostly for the educational purposes (Site 4). Such an experimental device is necessary because not all necessary experiments are possible to perform in real auction system and also evaluations (users' reputations) in real auctions are unrealistically positive [22].

We are convinced that the use of the Demster-Shafer theory can provide a practical approach and can be used for the calculation of users' trustworthiness in real online auctions. We hope that our study has contributed to the deepening of understanding of trust, which is an important concern in e-commerce. Effective modeling of trust provides benefits not only to potential bidders but also to sellers and online auction operators. The trust model serves to differentiate between users and is advantageous to sellers who provide high quality products and services.

Acknowledgments

We would like to express our thanks to Milan Daniel for his helpful discussions and comments.

Websites List

Site 1: eBay.
http://eBay.com

Site 2: eBay developer documentation center
http://developer.ebay.com

Site 3: Aukro
http://aukro.cz

Site 4: Podnikání a obchodování na internetu (Educational and Test E-shop) (in Czech)
http://ecom.ef.jcu.cz/web

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