Comment classification for Internet auction platforms

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1 Introduction

Reducing Internet auction fraud is one of the greatest challenges in today's electronic market. Most of the electronic auction platforms use only simple reputation system that can be easily manipulated [1,2,3]. Although reputation systems can be used to detect frauds, they provide little detailed information about the fraud itself except user comments.

In today's Internet auctions a majority of users are vulnerable to being cheated due to their inexperience. Significant experience is required to understand every aspect of Internet auctions. Despite many help pages and tutorials provided by auction platforms, in most cases it is not easy to teach users how to protect themselves from Internet fraud. To inform their users, auction services are offering insight into other user feedbacks. Yet, a large number of feedbacks presented to the user is sometimes an obstacle, rather than a support for the decision making user. Different users can have different opinions about the behavior of another user, but reputation systems treat every feedback equally. Thus it becomes necessary for the decision making user to read and analyze every comment, sometimes even proceeding recursively in order to evaluate how realiable the commenting user is. Moreover sometimes it is very difficult to infer useful information from the feedback's text.

Because of Internet fraud every party can suffer significant losses. According to the *Interned Fraud Watch*[3] average value of losses in online auctions fraud in 2007 came to $1,371.08. Buyers pay and never receive their goods, or receive damaged items. Sellers are deceived by fraudulent users who bid, but never make any payment. Because of buyers indolence sellers wait for contact with buyers for too long, and goods are blocked in their stocks (affecting their cashflow). Internet auctions service providers do not receive the handling fees because many auctions do not end correctly.

The simple reputation systems for Internet auctions cannot extract knowledge from users' feedbacks to assist inexperienced auction users. Our goal is to design automatic comment classification methods that will allow a meaningful distinction of different types of negative and neutral comments. The classification should use classes that have a clear interpretation for users, and that allow to evaluate the harmfulness of another

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[3] www.fraud.org

user's behavior. When all negative comments are treated equally by reputation algorithms, it is impossible to distinguish between malicious behavior and accidental mistakes. The proposed classification method has been evaluated on a large trace from a real Internet auction site. The classes are created using both a Top-down and a Bottom-up method through an analysis of comment contents.

We have developed a hierarchical model of user behavior in Internet auctions (separately for buyers and sellers). By checking the frequency of occurrence and the significance of reported transaction problems we have created simple classification method to detect potential threats related to users' transactions. The final decision to accept or reject a transaction still depends on the user and her preferences. We have also proposed method of rating complaints against sellers and buyers that can be used to modify the Internet auction reputation algorithms. Our solution can be deployed alternatively to the user's feedback list. Including it into the reputation system can increase trust of all parties to the auction platform and reduce user uncertainty.

The rest of this paper is organized as follows: in the next section we describe related work. In section three, we discuss the characteristics of users in electronic auction market and their risk. In section four we propose the classification of complaints for seller and for buyer. Section five describes the classification results for real data from Internet auction platform. In section six we propose a system of rating of feedback types depending on the harmfulness of reported behavior. Section seven concludes and presents ideas for future work.

2 Related work

Most of recent work has been focused only on the seller's profile [4,5]. Much work has been devoted to inducing users to behave properly [6,5] as well as detecting fraudulent users [2,1]. There are some tools dedicated detecting fraudulent sellers (*ProtoTrust*[4]) or entire cliques of fraudulent agents (*NetProbe* [7]). Gavish and Tucci [3] have presented the seller's swindling methods in Internet auctions. Gregg and Scott [4] have proposed a model of complaints against sellers. Although their model is similar to ours, they have used a manual process to classify feedbacks and did not propose a rating of feedback types. The work of Dellarocas [6] applies in situations where users can intentionally give unfair ratings to each other. The author has proposed to conceal the identities of buyers and sellers to prevent such discrimination.

3 Characteristics of agents in the electronic auction market

We can distinguish three types of agents in Internet auctions: buyers, sellers and the auction service provider. Each type of agent has different interests and can execute different actions in the auction system.

[4] utrust.pjwstk.edu.pl

3.1 The Buyer

The buyer is most vulnerable to fraud, because of the online auction architecture which in most cases requires the use of the advance payment method. Sometimes items can be paid by cash on delivery which is safer for the buyer. In general the buyer is obliged to make the payment before receiving the item. Hence a buyer's risk is much higher than a seller's.

3.2 The Seller

The sellers usually have a better position, because they do not risk any money, but the time spent on maintaining an auction indirectly affects their income. According to regulations sellers cannot interfere in their auctions, and they cannot refuse to sell the item if the auction is finished. In some cases a seller can revoke the bid of a user for a specific reason, but in most cases the seller has to deal with the winning buyer. If there is no payment after an appropriate time the seller can put this item up for auction once again. However, the seller has lost time on maintaining the auction as well as the handling fee. In some cases (specified by the auction platform) sellers can get their handling fee back. In the worst case the seller sends the item using the cash on delivery payment method and the buyer does not receive the item (the seller loses shipping costs).

3.3 The Service Provider

The third agent - the auction service provider risks no money, but its income depends directly on the total number of auctions carried out by sellers. Moreover there is a possibility (for example when the buyer does not pay for an item) that the seller can demand his handling fee back. Thus it is in the best interest of the auction service provider to discourage agents from cheating and punish frauds as quickly as possible.

4 Feedback Classification Model

Existing reputation systems do not distinguish between different kinds of negative or neutral user feedback. In addition, they use a very simple reputation algorithm. As long as we treat every negative feedback equally, we cannot distinguish purposeful behavior from an accidental one. For example, there is a great difference between sending the wrong color or size of a T-shirt and not sending it at all.

In order to create our classification model, we have obtained a real world dataset. The dataset has been acquired from *www.allegro.pl* which is the leading Polish online auction provider. We have selected the subset of 15159 negative or neutral feedbacks for 12188 different users. We have partitioned the feedbacks into two groups (for sellers and for buyers) and designed two independent classification rules for each group.

We have mined the information from the users' comments using two independent classification rules for each group - *top down* and *bottom up*. These approaches helped us to compare the outcomes - different types of complaints, on the basis of which we created a taxonomy by connecting the types according to different meanings.

4.1 Classification methods

We have used two approaches to create the taxonomy of user complaints. In the first approach we have created a simple typology tree by a semi-automatic method using our *regex creator* tool. In the second approach we have used advanced data mining techniques to cluster the co-occurring words into groups. Then we have confronted the results from both methods and created the tree structures presented in Figure 1 and 2.

The Top-Down Classification Approach In this approach we have used regular expressions for the classification of complaints. We have designed and implemented a simple tool to create regular expressions and assign patterns to complaint types (or to create new types if necessary). The tool has a built-in tokenizer and stemmer that help us to create new regular expressions through a couple of clicks (it still needs human control to find a new pattern). Because there are many spelling errors in users' feedbacks (especially not using national special characters) we have created an alternative set regular expressions without national characters.

The Bottom-Up Classification Approach In order to extract different types of complaints we have constructed six corpora for the following kinds of feedbacks: negative for buyers and sellers, neutral for buyers and sellers, as well as negative and neutral for buyers and sellers. In the next step for every corpus we have re-created a binary network of co occurring words for every bi-gram with frequency higher than 9. Such a network consisted of vertices standing for words and edges representing relations of their co-occurrence. Our aim was to recreate clusters in a given network representing groups of words which frequently exist together. In order to do so we applied the Newman Girvan algorithm [8] [9] for community detection. This approach is based on the measures of shortest paths and betweenness centrality calculated for edges.

A shortest path between two vertices is a path with minimal number of vertices between them. Edge betweenness is defined as the number of shortest paths between pairs of vertices that run along it. If there is more than one shortest path between a pair of vertices, each path is given equal weight such that the total weight of all of the paths is unity. The Newman Girvan algorithm calculates the betweenness for all edges in the network, removes the edge with the highest betweenness, then recalculates betweennesses for all edges affected by the removal and repeats removing the edges with highest betweenness and recalculating betweennesses until no edges remain.

The Newman Girvan algorithm produced a dendrogram. In order to estimate the quality of a particular division of a network, there is calculated a measure comparing the number of edges inside communities and between them, i.e. fraction of the edges inside communities minus the expected value of the same quantity in the network with the same community divisions but rundom connections between the vertices.

The effect of the application of Newman Girvan algorithm consisted of sets of words which usually occured together in our corpora. These sets were treated as meaningfull types of complaints.

4.2 A Taxonomy of User Complaints

Complaints Against the Seller. The full model of complaints against sellers is presented in Figure 1. We distinguish two kinds of losses due to fraud: time and money related. We mark complaints related to loss of time with striped lines. Those colored in light-grey are related to loss of money. We have observed that there are two general groups of complaints: seller behavior related and item related. In the first group we include the following seller behavior:

- **Fraudulent behavior.** Shill bidding or shipping overcharge. We consider only explicitly formulated accusations, not those computed from historical auction data.
- **No response.** Communications with the seller after the auction was impossible. The seller did not answer phones, nor responded to e-mails.
- **Odd behavior.** The seller behaved in a completely unpredictable manner, communication with the seller was possible but handicapped. The seller sent the item with a delay or did not define the payment method and shipping price.

The second group of complaints is related strictly to the item and consists of:

- **Item not sent or lost.** The item was not sent to the recipient. Sometimes the seller argues that the item was lost by the courier or post office.
- **No product to sell.** The seller declares that the item was already sold to another buyer, or the item is no longer on sale. In this case the item is not sent to the buyer.
- **Careless Packing.** The seller did not take care about the packaging of the items. This type also includes the situation when the received item was damaged. It is not possible to verify if the seller sent a damaged item or the item was destroyed during shipment.
- **Wrong item.** The seller made a mistake and sent a wrong item (wrong color or type) or the received item was not complete.
- **Item not as expected** The item seems to be illegal goods (a fake, or a pirate copy of software) or just does not satisfy the buyer.

Complaints Against the Buyer In Figure 2 we present the complaints model for the buyer. Similarly to the previous model we mark with striped lines complaints related to loss of time. Those colored in light-gray are related to loss of money. We can also partition complaints into user related and item related.

- **No response.** Communications with the buyer after the auction was impossible. The buyer did not answer phones, nor responded to e-mails. Complaints of this type are in most cases also classified as ’no payment’ complaints (every complaint could be classified into more than one type).
- **Odd behavior.** The buyer seems not to follow the auction rules, or did not read the information provided by the seller. Sometimes the buyers tries to force the buyer to choose a particular payment method.

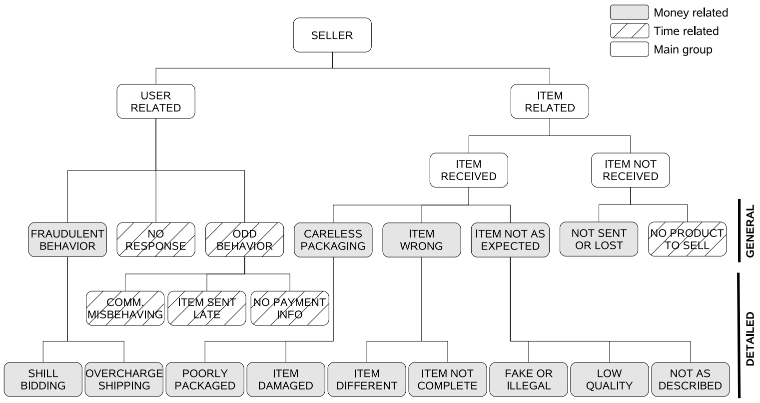

Fig. 1. Typology of complaints against seller

– **Delivery not accepted.** The buyer did not accept the delivery which should be paid for by cash on delivery. The seller must pay the round trip shipping charges, which is sometimes a significant amount of money. This is the only type of complaints against the buyer related to loss of money.
– **No intention to buy.** The buyer did not pay for the item, and did not inform seller about her plans. Sellers call such behavior childish or bidding for fun.
– **Reneged on buying.** The buyer contacts the seller and declares that she will not buy the item.

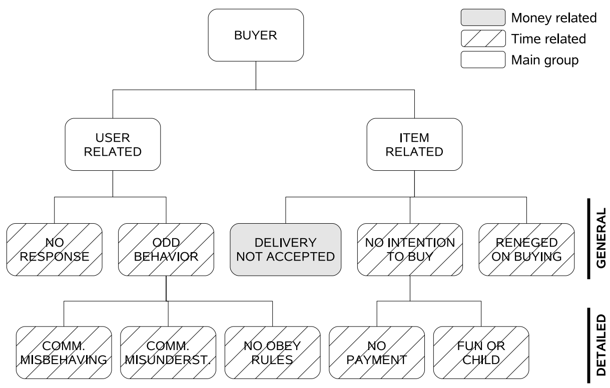

Fig. 2. Typology of complaints against Buyer

5 Classification Results

We have partitioned all negative and neutral feedbacks into the detailed types of the complaint taxonomy, using regular expressions prepared by the two classification methods. Each complaint type has its own meaning and also a unique set of regular expression patterns. In our evaluation we have used only types from the general level of the taxonomies, in order to obtain more legible results. Patterns from the detailed types are used in types from the general level.

We have tested all negative and neutral feedbacks made by sellers and buyers and assigned to types in our taxonomy (for the seller and the buyer respectively). We have matched each feedback against all patterns from our model. A feedback could be assigned to more than one pattern from different types. We present normalized results of all neutral or negative feedbacks separately. In addition we present the percentage results jointly for all nonpositive feedback (negative or neutral comments).

Our regular expression tool has matched 68% of negative comments (for the seller and the buyer equally), 54% of neutral comments for the seller and 35% of neutral comments for the buyer.

Unclassified comments contain mostly useless information (no specified reason or lots of spelling errors). The amount of such feedbacks can be reduced by enabling users to choose one of our proposed complaint types from a list instead of editing comments by themselves, keeping the possibility of editing comments afterwards to add more information if desired.

The difference in classification quality between negative and neutral feedbacks is caused by the fact that neutral comments contain less complaints which are the most useful information for classification.

5.1 Classification of complaints against the seller

Negative feedback. In Figure 3 we present the frequency of occurrence of complaints against the seller. Most of the negatives are due to a lack of response from the seller or not receiving the item (Please compare it to the taxonomy presented in Figure 1). This is predictable since users do not like to be uninformed, especially when they risk their money. A significant amount of negative feedback is due to problems with the item, like sending a wrong or low quality item. There is a small amount of direct accusations of shill bidding or excess shipping cost. We have also noticed some situations when the seller refuses to sell the item and informs the buyer about it.

Neutral feedback. Neutral feedback was sent in most cases when the item did not live up to buyers expectation or the item was different (for example different color or size) than described in the auction. Seller behavior such as problems with understanding the seller or delays in sending the item was also a frequent reason for a neutral, rather than negative feedback. In comparison with negative feedback we can observe a significant drop (almost 50%) of complaints related to not sending the item or ignoring the buyer.

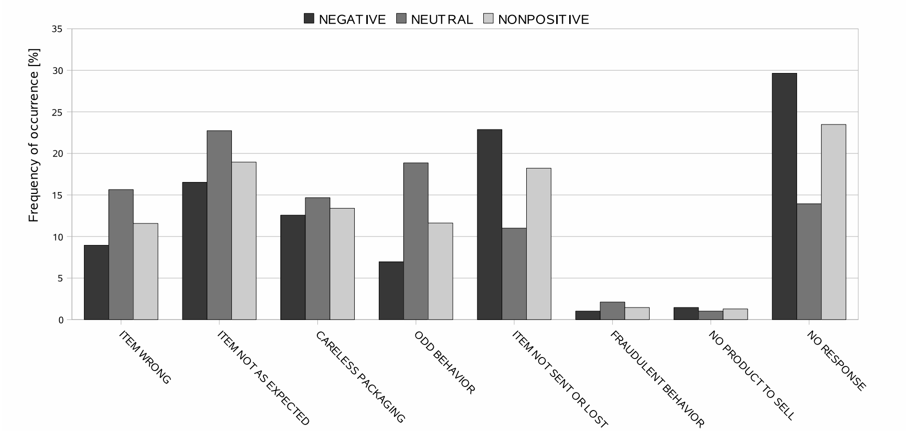

Fig. 3. Results for seller complaints

5.2 Classification of Complaints Against the Buyer

Negative feedback. We present the classification results for the buyer in Figure 4. Similar to the results for the seller, most of negative feedback was sent due to problems of communication with the buyer. There have been two main reasons to send a negative comment: the first is the lack of payment, the second is no communication at all (which often occurs simultaneously). We can observe a significant drop in the amount of negative feedback when the buyer declares that he will not buy the item (for any reason). Odd behavior of the buyer is not a serious problem for the seller (the buyer still must pay before receiving the item). To our surprise there are some cases when the buyer does not accept the delivery. This forces the seller to incur additional expenses (round trip shipping costs). Such situations can be caused by a lack of money at the time of package arrival (buyer recklessness).

Neutral feedback. As we can see sellers tolerate all strange behavior of buyers as long as they pay for the item. They are also tolerant when the buyer declares explicitly that he resigns from buying the item (item can be put for auction once again). In comparison with negative feedback we observe a considerable drop in the amount of neutral feedback when communication with buyer was not possible and thereby also no payment at all has been made.

6 Rating the harmfulness of unfair behavior

To make our research more applicable to Internet auctions we propose a simple method for rating the types of complaints along their harmfulness. We propose *harmfulness* to be the difference between the frequency of occurrence of negative and neutral feedback. We compute the *harmfulness* for every type in our complaint taxonomy. A type

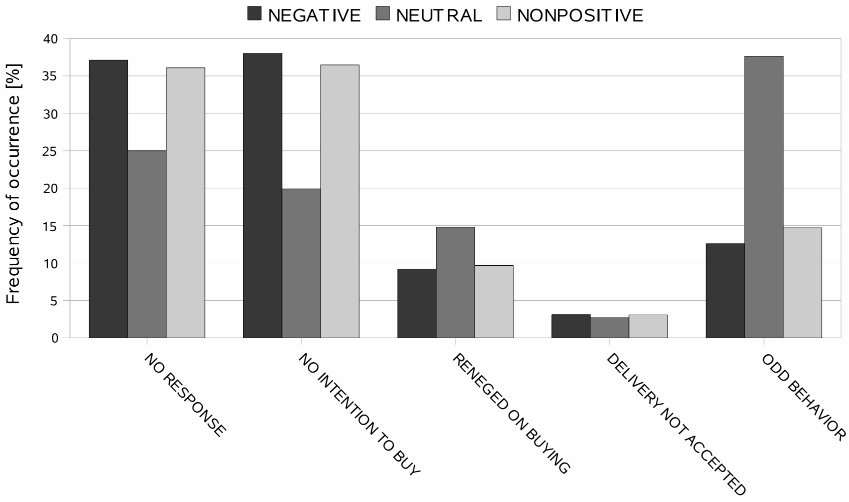

Fig. 4. Results for buyer complaints

of complaints tends to be more harmful if more negative than neutral feedback is classified into that type. We have sorted the groups of complaints along the *harmfulness* and present the detailed results in Table 1. We have also juxtaposed the *harmfulness* with the frequency of occurrence of each type of complaint. Values of the frequency of occurrence were generated from nonpositive feedbacks (negative or neutral feedback). In addition we have added the relation of each type to losses of time or money from the model presented in Figures 1 and 2. Our rating scheme does not need to be approved as is, but it can be used to detect major threats. We suggest that every user tunes this scheme to her preferences.

6.1 Most Harmful Seller Behavior

The most harmful seller behavior is lack of response (23%). To reduce this kind of unfair behavior, auction platforms can provide additional channels of communication with the seller. Another type of harmful behavior is not sending the item after the auction. This type can be reduced by charging the seller an amount which depends on the final price of an item, and to return this amount after the transaction completes successfully.

Less harmful, but also often frequent fraudulent behavior is related to the condition of an item. Our solution can help in the following manner:

Bob the buyer wants to buy some T-shirts. He finds that Sam the seller has the required object on his auction. Our system checks Sam's comments and warns Bob that items shipped by Sam are often damaged. Bob requests for package insurance and selects a proper shipping method. Consider also a similar situation, but in this case Sam often sends different or incomplete items. Since Bob is warned by our system he can contact the seller and send detailed information about the requested size and colors to ensure completeness of the package.

Table 1. Rating and the frequency of occurrence of types of nonpositive feedback

Complaint type against seller	Harmfulness [%]	Time or Money related	Frequency of occurrence [%]
NO RESPONSE	15.71	T	23.48
ITEM NOT SENT OR LOST	11.86	M	18.22
NO PRODUCT TO SELL	0.44	T	1.29
FRAUDULENT BEHAVIOR	-1.09	M	1.46
CARELESS PACKAGING	-2.1	M	13.4
ITEM NOT AS EXPECTED	-6.22	M	18.96
ITEM WRONG	-6.7	M	11.58
ODD BEHAVIOR	-11.9	T	11.62
Complaint type against buyer			
NO INTENTION TO BUY	18.11	T	36.47
NO RESPONSE	12.11	T	36.09
DELIVERY NOT ACCEPTED	0.42	M	3.07
RENEGED ON BUYING	-5.59	T	9.67
ODD BEHAVIOR	-25.06	T	14.7

6.2 Most Harmful Buyer Behavior

The most harmful buyer behavior is bidding without intention to pay for the item and lack of response after the end of an auction. The joint frequency of occurrence of both types is 72% of all non positive feedback against the buyer. A good idea can be to introduce some time threshold after which the seller can automatically put the item for an auction again without paying the handling fee. Such a solution cannot prevent fraud, but at least the seller can save some time. The seller can also request advance payment for the item if there is a high possibility that the buyer behaves unfairly (and refuse to accept any other payment method but advance payment).

Consider a situation where Sam the seller puts some items up for auction. He checks from time to time who bids in his auctions using our system. Our system checks all previous feedbacks for every bidder. Bob the bidder is classified as a buyer who often has no intention to buy after he wins the auction (bids for fun). Bob has actually the highest bid, so Sam wants to ensure that Bob pays for the item after the auction ends. He sends an e-mail with a detailed description of the item, requesting an immediate response and advance payment. Sam can also remove Bob's bid if Bob does not reply.

7 Conclusion and Future Work

In this work, we have designed a taxonomy of complaint types for buyers and sellers in Internet auctions. Our model is based on real data from *www.allegro.pl*. We have also proposed the rating of complaint types which can be a building block for an improved reputation system. Our rating scheme may be used by Internet auction platforms to detect and fight against the most harmful frauds and thereby gain more trust from the users.

In the future we are going to integrate our model with the *ProtoTrust* tool which is a part of the uTrust library. *ProtoTrust* is an interactive web browser extension which helps user in decision making process using trust management techniques. It is capable of computing more complex measures than simple reputation (Risk, Probability of Fraud, average selling price) and takes into consideration the context of an auction. Through the integration with *ProtoTrust* we hope to create a helpful, user-friendly tool that can help users to detect unreliable contractors.

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