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Shill Detection Techniques and Research Challenges in Online Auction

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Abstract--The number of Internet auction shoppers is rapidly growing. However, online auction customers may suffer from auction fraud, sometimes without even noticing it. In-auction fraud differs from pre and post-auction fraud in that it happens in the bidding period of an active auction. Since the in-auction fraud strategies are subtle and complex, it makes the fraudulent behavior more difficult to discover. Researchers from disciplines such as computer science and economics have proposed a number of methods to deal with in-auction fraud. In this paper, we summarize commonly seen indicators of in-auction fraud, provide a review of significant contributions in the literature of Internet in-auction fraud, and identify future challenging research tasks.

Keywords— online auction, in-auction fraud, fraud indicators, auction fraud prevention, shill detection

I. INTRODUCTION

The Internet revolution and advances in information and communication technology have laid the groundwork for online auction systems to become a new profitable business platform [1]. To cite just one well-known example, eBay1, the world's largest auction website, announced $2.19 billion revenue for the first quarter of 2008. Clearly many buyers and sellers are attracted to online auctions. According to one source [2], at least 31% of Americans who have Internet access regularly participate in online auctions, accounting for a sizeable total of 35 million people. According to IC3, here are several ways online auction fraud can occur: misrepresentation of a product for sale, non-delivery of merchandise or services sold, triangulation (fraudsters purchase items using a stolen credit card, selling the items to uninitiated buyers thereby retaining the cash and transferring the risk of seizure to the end recipient), fee stacking charging extra money after an auction is over), selling black market goods, multiple bidding (buyers inflate prices using aliases, which frustrates competitors, then at the last moment the high bids are withdrawn to secure a low bid), and finally shill bidding (sellers or their associates place bids on their own auctions for fraudulent purpose). In this paper, we aim to provide an overview of the state-of-the-art Internet in-auction fraud prediction, prevention and detection techniques, and to highlight challenging research issues in this interesting new area. The surveyed countermeasures are from both the economics and the computer science perspectives. The rest of the paper is organized as follows. Section 2 discusses important concepts and indicators of in-auction fraud, revealing motivations behind fraudulent behaviors. Section 3 presents existing solutions to the problem of in-auction fraud, while Section 4 identifies some problems and
tasks that remain as research challenges in this domain. Section 5 concludes the paper and mentions future work.

In-auction fraud may include shill bidding, bid shading, false bidding, multiple bidding, and bidding rings. Shill bidding happens in open auctions in which, by definition, bidders are allowed to compete with each other to bid multiple times. It could not happen in a sealed-bid auction due to the nature of concealed bids. Bid shading and false bidding are specific terms for cheating behaviors for first-price auctions and second-price auctions, respectively

II. THE NATURE OF ONLINE IN-AUCTION FRAUD

Current and emerging state-of-the-art auction platforms rely heavily on information technology, and hence any weakness in information systems could be utilized by malicious users to maximize their own profits. Although in-auction fraud has an important influence on new technology-based sectors of the economy such as e-commerce, there is a lack of mechanisms to fight against in-auction fraud.

Shill Bidding includes any activity in which a seller or an associate of a seller bids on the seller's own item in an auction. Shill bidding can be performed either by the seller or by individuals associated with the seller (including friends and family members), who may have a level of access to the seller's item information that is not available to the general community [12]. The types of shilling behaviour are as follows.

(1) Competitive shilling is a bidding behavior that artificially drives up the bidding price of the auctioned item with no intention of actually buying. The purpose is to make a legitimate winner pay more than this person would otherwise pay, so that the seller can gain more profit [7]. The competitive shilling behavior can occur in both live and online auctions as long as the collusion between the seller and the shills remain unknown to the auction house and the other bidders. Intuitively, one can surmise that the shill bidders engaged by sellers pretend to be legitimate competing bidders, and use the shill bid to lure legitimate high-value buyers not only to bid up to their valuations but also to exceed them. This behavior cheats other bidders by inducing them to pay more for the item than they would have without the shill bids. To better understand

Competitive shilling, consider the following example situation. A seller hosts an auction of an item, say an unlocked cell phone. Initially, nobody places any bid at the auction. So, to attract some bidders to the auction, the seller, acting under another alias, places a competitive shill bid for the purpose of stimulating other bids. After someone outbids the shill bid, the seller places another shill bid for the purpose of driving up the bidding price. The seller hopes other legitimate bidders will outbid all further shill bids. All bids placed on behalf of the seller can be regarded as competitive shill bids and the bidding behavior is called competitive shilling.

(2) ***Reserve price shilling,*** first defined by Kauffman and Wood [7], is a bidding behavior motivated by the desire to avoid payment of the reserve price fee. By accepting the reserve price service, a seller is agreeing to pay the auction house a fee for the service. To minimize the payment of auction house fees but still reserve the item below a certain price, some high volume sellers will not set an "official" reserve price but instead engage shills to place bids on their auctions. For example, a seller may wish to sell an item at $200. If the seller chooses eBay's optional service to set a reserve price of $200, this seller would automatically incur an insertion fee of $3.00 according to eBay's fee structure of 2008. To avoid payment of the reserve price fee but still reserve the item if the final bid for the item is under $200, the seller might first list the item at $9.99, paying the auction house a low insertion fee of $0.35. Then, either an associate of the seller, or the seller himself, places a bid at the price of $200 in hopes that a legitimate bidder will make a purchase at $201 or more. In fact, eBay in its rules against shill bidding also gives an example of reserve price shilling [3]. Note that sellers do take a monetary risk when employing reserve price shilling: if nobody makes a purchase at more than the hidden reserve price, the seller must still pay both an insertion fee and a final value fee.

(3) ***Buy-back shilling***, which to our knowledge has not been previously identified in the literature, is a bidding behavior employed by sellers, or other shills as agents of the seller, when the legitimate bidders do not bid an acceptably high price. The seller or shills would rather buy back the item and sell it again than sell the item now at a low price that does not reach their expectation. In this situation, shills behave as a normal bidder with the goal of buying the item at a bargain price and completing the transaction. Such activity cheats the other bidders by depriving them of purchasing an item at a bargain price. For example, as in the previous example a seller may wish to sell an item at $200 but initially sets the starting price at $9.99, producing an insertion fee of $0.35. When the auction is close to termination, if the highest bid has only reached $15, the seller may place a shill bid at $16.00 in order to buy the item back, even though the seller must pay the auction house a final value fee of $1.40 in addition to the $0.35 insertion fee. Nonetheless, this cost to the seller is trivial compared to the profit-loss the seller would have incurred if the item was sold at $15. The profit of buy-back shilling is obvious; hence we speculate that the buy-back shilling behavior does actually exist in online auctions.

Any of the above three shill bidding types can be enacted in one of the different forms described below, depending on who acts as the shill:
1. Acting alone: A seller, or owner of the item for sale, carries out shill bids by himself or herself. The seller is able to register several IDs in an auction house, e.g., eBay or uBid. Using different IDs and pretending to be different legal bidders in order to bid multiple times in the seller's own auction, the seller can inflate the final auction price and profit.
2. Seller collusion: Several sellers help each other to place bids on each others' transactions for their mutual benefits.
3. Accomplice: A seller hires or invites family members and friends to serve as shills who will place bids on the seller's item, but instructs them to avoid winning.

(4)False bidding**:** In a second price sealed-bid auction, each bidder bids only once in the auction and the winner pays the second highest bid rather than the highest. An auctioneer can help a seller profitably cheat by examining the bids under the table after all buyers have submitted their bids. Knowing all bids, the auctioneer can submit an extra bid to make the second highest price very close to the current highest price such that the seller can gain more profit [14]. For example, after all buyers have submitted their maximum bids, the auctioneer learns that the highest bid is $200.00 for the auctioned Razor cell phone and the second highest bid is $120.00. The auctioneer (who could possibly be working on behalf of the seller) can help the seller insert an extra bid, say $198.00, which is quite close to the highest bid $200.00, but not beyond the highest bid. After the auction ends, the seller receives $198.00 rather than $120.00, and the extra $78.00 in revenue is gained by false bidding. This type of auction fraud may appear in auctions held by eBay when bidders are using the auction site's automatic bidding proxy system. Every buyer using the bidding proxy has to submit a sealed maximum bid to the bidding proxy. The bidding proxy then bids repeatedly by setting increments until the bid exceeds the buyer's predetermined maximum bid. When the seller is able to obtain all existing maximum bids, this seller can then place a second highest bid as a shill bid, which is slightly lower than the highest maximum bid. By doing so, the seller's revenue increases. In addition to sellers' in-auction fraud, buyers can also cheat in Internet auctions. Bid shading, multiple bidding and bidding rings are common cheating approaches used by buyers:

Bid shading**:** In first price sealed-bid auctions, the winner of the auction pays the highest bid. If a bidder could use an unfair method to know the highest bid before the bids are disclosed, then the bidder could insert a bid just above the highest bid. The fraudulent bidder would thereby increase the probability of winning while minimizing the payment to the seller [15]. Let's take an auction of the game console Wii as an example. Assume Bidder 6 is willing to pay up to $400 for the game console before submitting any bid. When the auction begins, all bidders except Bidder 6 submit their bids. These bid values are lower than Bidder 6's valuation, ranging from $200 to $300. Since the auction is a sealed one, a bidder typically cannot see the highest bid. By knowing the highest bid in some unusual way, Bidder 6 may guarantee a win by placing a bid at $301.

Another slightly different bidding strategy that is not regarded as fraudulent also goes by the name of bid shading [16]. In this case, bidders place bids below their true valuation of the item in order to avoid overpaying for the auctioned item.

***Multiple bidding*:** Multiple bidding, also known as bid shielding, is similar to shill bidding except that it is a fraudulent behavior of buyers rather than sellers. The buyers register several aliases and use them to place multiple bids for the same item. By driving up the price with multiple auction identities, the buyers discourage other potential competitors. After that, they retract all high bids, leaving the lowest winning bid on the auction. At the end, the winner gets the auctioned item at a much lower price. For instance, consider a scenario for a Motorola Razor cell phone auction in which Bidder 3 bids $134.90. Bidder 1, who may have bid previously on this item, now realizes that Bidder 3 is a potential competitor. In order to try and force Bidder 3 out of the competition, Bidder 1 places 3 bids consecutively, namely $135.00, $270.00 and $280.00. The last two bids are obviously much higher than the previous bids; thus, when risk-neutral bidders see this situation, they will quit the auction instead of paying beyond the valuation. Therefore, Bidder 1 can secure the winning position. But, the cheating behavior comes about when Bidder 1 retracts the two high bids at the last minute of the auction, leaving only the $135.00 bid, which is the lowest cost to win the auction. This cheating method works only at auction websites that allow retracting bids. While almost all current auction websites' rules generally disallow retracting bids, they still allow retracting bids under exceptional circumstances such as a typographical error in entering the bid [17].As we observe, bids retractions occur often in many active auction websites.

***Bidding Rings*:** Bidding rings is also a term related to bidders' fraud. It refers to collusive auction fraud behaviors conducted by several bidders. Several fraudulent bidders form a ring, and the ring members have an agreement not to bid against each other, either by avoiding bidding on the auction or by placing phony (phantom) bids to not compete with each other. The result is that the winner can win the auctioned item at a very low price.

III. SOLUTIONS FOR ONLINE IN-AUCTION FRAUD

In this section, we present some solutions to online in-auction fraud in the following categories: trust management framework, prediction/prevention approaches, and detection approaches.

3.1 Trust Management Framework

Internet fraud has severely undermined the trust on which members of electronic application communities used to rely. Current existing electronic commerce applications such as online auction systems do not provide completely trustworthy services. There is a high demand for trusted online auction systems that provide trusted, secure and worry-free services. Xu, et al. recently presented an agent-based trust management (ATM) framework for online auctions . The ATM is defined as a multi-agent system [18] that consists of a security agent, an analysis agent, a set of monitoring agents, auction agents, and bidding agents. Human bidders can specify flexible and complex bidding strategies in the interface of bidding agents so a bidding agent, on behalf of a human bidder, can communicate with auction agents to place bids automatically [19]. Meanwhile, the security agent can dispatch monitoring agents to watch for bidding activities and detect suspicious users, and an analysis agent is responsible for analysing users' bidding behaviours using live auction data and users' history information. Based on the analytical results, the security agent can re-evaluate a user's trust values in order to verify whether a suspect is a shill bidder. The proposed agent-based trust management module facilitates real-time trust re-evaluation by updating user roles and access permissions dynamically. As a result, the framework provides a solid foundation towards building a trustworthy networked system.

3.2 Prediction/Prevention Approaches

Preventive measures can be more effective in online auctions than reactive measures. Wily traders usually exploit loopholes left in procedural rules to "attack" honest users and challenge system and mechanism designers. If the auction procedural rules embedded in the software programs of online information technology applications are airtight, fraud activities can be easily prevented, avoided and eliminated. Wang, et al. designed a Shill-Deterrent Fee Schedule (SDFS) mechanism, which could reduce the extra profit brought by shill bidding in the context of independent private value (IPV) English auctions so as to deter opportunistic shills [6]. Under the SDFS mechanism, the auctioneer charges the seller a listing fee and a commission fee. The seller sets only a single starting bid or a reserve price, without the option of setting both a low starting bid and a higher secret reserve price to lure in buyers (as currently allowable on eBay). The listing fee is a function of this initial reserve price, and the commission fee is calculated by the product of the commission rate and the difference between the winning bid and the reserve price. If the reserve price is too high, then the listing fee will be higher and the seller will probably lose the chance to sell the goods. If the reserve price is set too low in an effort to lower the listing fee, then the difference between the reserve price and the selling price will be high, with a correspondingly high commission fee. Therefore, SDFS encourages the sellers to set the reserve prices honestly. The commission rates vary from market to market and are mathematically determined by the online auction systems to guarantee no extra profit for shill bidding compared to honest sale. On the whole, SDFS is reasonable to inhibit shilling behaviour. Some items are not sold in the first round of an auction. This can occur for many reasons, including no bidders having placed bids on the auction, the final price of the auction not reaching the reserve price of the auction, or a seller engaged in a shill and accidentally won the auction. When an item is not sold the first time it goes up for auction, it will typically be offered for resale in a next round. Because there are a significant number of identical auctioned items in the same auction house, a great number of goods are sold after multiple rounds. Wang, et al. analysed shill bidding in multi-round online English auctions, and proved that there is no equilibrium without shill bidding in these auctions [8]. They interpreted the finding as an incentive for shills and suggested a corrective pricing such as SDFS and a fair intermediary should be used to reduce the damage to the market. Preventing in-auction fraud from happening is possibly the best solution, nonetheless, in some cases, when in-auction fraud cannot be prevented, approaches that can predict its occurrence can also reduce the risk to auction participants. Kauffman and Wood [7] examined how the fee structure on eBay may motivate shill bidding and first identified "reserve price shilling" based, in part, on their research into eBay auctions of rare coins in April 2001.They tested whether some questionable bidding behaviours are attributable to reserve price shilling. According to the test results, they built an empirical probit model to predict reserve price shilling based on the seller's previous behaviour before the auction begins.

3.3 Fraud Detection Approaches

3.3.1 Using Statistical Methods

Current Internet auction systems rely solely on feedback based reputation systems to evaluate both buyers and sellers. Nevertheless, the existing traditional reputation system for auction houses has already shown its weakness in providing trusted information. Several researches have shown that the reliability of the reputation system of current auctions house, e.g., eBay, is debatable [27-30]. First, the positive feedbacks are overwhelming but the negative feedbacks are deflated. Deceptive auction users take advantage of the weakness of current rating mechanisms in reputation systems by helping each other artificially build up a good reputation history regardless of their actual behaviors. Rubin, et al. found 95% of eBay sellers have good reputation and 98% of their feedbacks are positive [31]. Furthermore, existing reputation systems are easily manipulated. Malicious users could first accumulate a high feedback score by selling low value goods, and then deal high value goods with that good reputation. For example, a seller first sold pencils and gained a good rating. Now the same seller is selling used cars on the same auction site. Can we trust this seller? No. Because the seller could cheat some used car buyers and then shift again to rebuild a reputation from pencil buyers.

Moreover, the existing reputation system provides little information about sellers' degree of honesty. Users may find auction fraud information in feedbacks but when dealing with a seller with a long history, it is impractical to look at the feedbacks page by page. Unfortunately, the anti-fraud information has not been directly reflected in the reputation system so far. In all, the current reputation system can no longer satisfy people's need for evaluating trustworthiness in online transactions.

The another feedback management agent is used to calculate the reputation of all the users taking part in the auctions either directly or indirectly. By trustworthiness, we mean that we are finding the weight value of the rater or user. This can be done on the basis of several factors like feedback decay, recent price, rater's trustworthiness etc. In feedback rating the rater generally rates the host according to several critical attributes which may be the quality of service provided, the type of technical support provided, the delivery of the product, the item's condition on delivery etc. Thus feedback rating as considered in the present methodologies is not a scalar but a vector quantity. Thus it can lie in the closed interval of -1 to 1 and not strictly one of the extremes.

The feedback management agent calculates the reputation and trust worthiness of the client taking into consideration the number of participants from the time t-1 to t. The feedback management agent involves the functionalities of all the previous methods such as the accumulative, the ratio and the weight value models.

The feedback management model depicts the entire flow of the auction system which includes the working methodologies of the various agents such as the buyer agent, seller agent, feedback management agent etc. There are three methodologies depicted in the model. They are the purchasing part, the hosting of an auction and the final part is the feedback and trust calculation methodology.

3.3.2 Using Data Mining

Data mining (also called knowledge discovery) is a powerful computer-assisted process designed to analyse and extract useful information from historical data [35]. It allows users to analyse data from different dimensions or perspectives in order to uncover consistent patterns, anomalies and systematic correlations between data elements. The ultimate goal of data mining is to predict future behaviours and trends based on the discovered patterns and association rules. Several researchers have adopted data mining methods to detect shill associations and suspicious patterns. Pandit, et al. designed and implemented an online auction fraud detection system named NetProbe [36]. The key idea of the NetProbe is to infer properties of a user by properties of other related users. In particular, given a graph representing associations between auction users, the likelihood of a user as a fraudster is inferred by looking at the behaviour of the user's immediate neighbours. The NetProbe system models auction data as a network graph in which sellers and bidders are represented by nodes, and transactions are represented by edges between sellers and bidders.

Data mining approaches, like reputation approaches, also require analysing huge amounts of historical data, and therefore take a very long time to get results. Although incremental NetProbe can reduce the execution time to almost half of the original, it still cannot achieve real-time performance so far. As a trade-off, data mining approaches do have the advantage of accuracy compared to other approaches.

IV. RESEARCH CHALLENGES

In-auction fraud is quite different from pre- and post-auction fraud in that the latter two can be easily detected by the victims while in-auction fraud cannot. This difference makes solutions to pre-auction and post-auction fraud not adoptable for in-auction fraud. Research on combating in-auction fraud has only recently begun and several challenging research tasks are still open problems. Since this is a new research area, we identify, and briefly discuss, some research challenges that we feel are important in this area.

Development of effective reputation systems. Reputation systems are the easiest accessible tool that online auction participants can rely on to evaluate a seller or a buyer. However, as we analysed previously in this paper, current reputation systems in major auction houses fail to provide users trustworthy and accurate information. Thus, it is important to propose effective reputation mechanisms to provide users with convincible ratings. By giving users an explicit indication of the genuineness of the rated user behind the reputation score, next-generation online reputation systems should be able to encourage trustworthy behaviours and significantly prevent in-auction fraud.

Real-time fraud detection. The most efficiency way to reduce the loss resulting from in-auction fraud is to detect the fraudsters as early as possible. If the auction system can successfully detect the presence of auction fraud immediately after it happens, the auction house can cancel involved auctions so that the shills can be caught, and the victim can be protected from losing money and property. However, most existing fraud detection techniques cannot guarantee real-time detection of in-auction fraud. Efficient shill detection algorithms such as using a model checking based approach could be a very promising approach for real-time shill detection.

The lack of ground truth. Development of techniques and tools that aim to assist with detection of in-auction fraud, such as shilling behaviour, is clearly not an easy task. But, even more challenging is the assessment of effectiveness of such techniques. How well do they really work in practice? This assessment is complicated by the subtle behaviors associated with such fraud and the lack of example data that includes actual, verified fraud behavior – we cannot count on obtaining shill confessions. So, how to obtain the ground truth becomes a problem. How does one demonstrate that a shill-detection technique is effective on a set of sample auction data, when the existence of actual shill behavior in the sample data is not known?

Capture of in-auction fraud evidence. As we have discussed in Section II, researchers have summarized several in-auction-fraud-bidding pattern. However, these patterns cannot serve as direct evidence of auction fraud because even if the bidders are detected to employ these bidding patterns, they still can be innocent. There may be other reasonable explanations to the questionable behaviours. Further quantitative and qualitative analyses of auction fraud are critical for capturing in-auction fraud evidence. Once sufficient auction fraud evidence can be retrieved, the suspicious in-auction fraud could be verified automatically and accurately.

Adaptive anomaly detection. Similar to computer and network security, auction fraud detection faces the difficulty of becoming a battle between fraudulent online auction users and auction integrity researchers. Driven by the opportunity to achieve monetary profits, it can be expected that fraudulent auction participants will not stop fraud practices, but instead change their habitual bidding behaviours to circumvent existing anomaly detection systems. In order to make auction houses trustworthy, it is important to develop adaptive anomaly detection algorithms for capturing in-auction fraud. The adaptive anomaly detection algorithms must be adaptive to new conditions, and thus able to effectively detect and respond to new forms of fraud.

Fraud detection and verification using artificial intelligence techniques. Detection and verification of in-auction fraud requires human knowledge and reasoning capability. This provides motivation for exploring the challenging task of adapting artificial intelligence techniques (e.g., agent-based architectures and reasoning) to represent human knowledge for shill detection and verification. Success in this area would be valuable for achieving the goal of automated detection and verification of in-auction fraud.

V. CONCLUSION AND FUTURE WORK

With the prevalence of Internet auctions, auction fraud has become one of the major concerns in electronic commerce. In-auction fraud happens during the auction process and is often covered up. Hence it often makes victims suffer without notice. In-auction fraud produces undesirable effects not only on the auction participants but also on the auction mechanism itself as a resource allocation market. In the worst case scenario, in-auction fraud could lead to auction market failure. Because most of the existing online auction systems suffer from user distrust, trustworthy systems that could provide reliable services are highly desired. Current work on Internet auction fraud prevention and detection has taken a simplistic approach, which is not rigorous or complete enough to solve the problem. To prevent in-auction fraud, robust auction rules need to be proposed by economists. On the computer technology side, there is a need of airtight transaction process design to foil the efforts of fraudsters. In this paper, we summarized the indicators of in-auction fraud, and pointed out that because no single indicator will be accurate or strong enough to assure the presence of in-auction fraud, a combinatorial way using multiple indicators would be more effective and precise. The volume of transactions in online auctioning business is compounding each year, and unfortunately so is in-auction fraud. Now is the time to act to reduce and stop in-auction fraud. We hope that the ideas from many researchers summarized in this survey can help auction policy makers and information technology designers develop future trustworthy environments for online auctions

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