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DEMONSTRATION OF ACTIVE MODERATION SYSTEM FOR AUCTION FRAUD REVEALING

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ABSTRACT

The world of people are enjoying the features of world wide web. The web sites providing online shopping and online auction are more popularized. The people are enjoying the benefits of online trading at the same time criminals also enjoying with their fraudulent activities to gain the illegal profits. We focus on creating online machine-learned models for detecting auction frauds. we propose a framework which takes online feature selection, coefficient bounds from human knowledge and multiple instances learning into account simultaneously. Online auction fraud detection can potentially detect more frauds and significantly reduce customer complaints compared to several baseline models and the human-tuned rule-based system.

Key words: *online auctions, fraud detection systems, machine learning, online modeling.*

INTRODUCTION

An online auction is an auction which is held over the internet. Online auctions come in many different formats, but most popularly they are ascending English auctions, descending Dutch auctions, first-price sealed-bid, Vickrey auctions, or sometimes even a combination of multiple auctions, taking elements of one and forging them with another. The scope and reach of these auctions have been propelled by the Internet to a level beyond what the initial purveyors had anticipated.[1] This is mainly because online auctions break down and remove the physical limitations of traditional auctions such as geography, presence, time, space, and a small target audience.[1] This influx in reach ability has also made it easier to commit unlawful actions within an auction.[2] In 2002, online auctions were projected to account for 30% of all online e-commerce due to the rapid expansion of the popularity of the form of electronic commerce.[3]

Online auctions were taking place even before the release of the first web browser for personal computers, NCSA Mosaic. Instead of users selling items through the Web they were instead trading through text-based newsgroups and email discussion lists. However, the first Web-based commercial activity regarding online auctions that made significant sales began in May 1995 with the company On sale. In September that same year eBay also began trading.[4] Both of these companies used ascending bid, English auctions and were the first of their kind to take advantage of the new technological opportunities. The Web offered new advantages such as the use of automated bids via electronic forms, a search engine to be able to quickly find items and the ability to allow users to view items by categories.[4]

Online auctions have greatly increased the variety of goods and services that can be bought and sold using auction mechanisms along with expanding the possibilities for the ways auctions can be conducted and in general created new uses for auctions.[5] In the current web environment there are hundreds, if not thousands, of websites dedicated to online auction practices.[5]

First-Price Sealed-Bid

First-price sealed-bid auctions are when a single bid is made by all bidding parties and the single highest bidder wins, and pays what they bid. The main difference between this and English auctions is that bids are not openly viewable or announced as apposed to the competitive nature which is generated by public bids. From the game-theoretic point of view, the first-price sealed-bid auction is strategically equivalent to the Dutch auction; that is, in both auctions the players will be using the same bidding strategies.[6]

Vickrey Auction

A Vickrey auction, sometimes known as a Second-price sealed-bid auction, uses very much the same principle as a first-price sealed bid. However, the highest bidder and winner will only pay what the second highest bidder had bid. Online auctions where bidders utilise a proxy bidding system is a close resemblance to that of a Vickrey design for single item auctions, however due to the fact that the bidder is able to change their bid at a later date means it is not a true representation of the Vickrey auction.[7] The Vickrey auction is suggested to prevent the incentive for buyers to bid strategically, due to the fact it requires them to speak the truth by giving their true value of the item.[8][9]

Reverse Auction

Reverse auctions are where the roles of buyer and seller are reversed. Multiple sellers compete to obtain the buyer's business and prices typically decrease over time as new offers are made. They do not follow the typical auction format in that the buyer can see all the offers and may choose which they would prefer. Reverse auctions are used predominantly in a business context forProcurement.[10]

The term reverse auction is often confused with Unique bid auctions, which are more akin to traditional auctions as there is only one seller and multiple buyers. However, they follow a similar price reduction concept except the lowest unique bid always wins, and each bid is confidential.

Bidding Fee Auction

A Bidding fee auction (also known as a penny auction) requires customers to pay for bids, which they can increment an auction price one unit of currency at a time. On English auctions for example, the price goes up in 1 pence (0.01 GBP) increments. There has been criticism that compares this type of auction to gambling, as users can spend a considerable amount of money without receiving anything in return (other than the spent bids trying to acquire the item). The auction owner (typically the owner of the website) makes money in two ways, the purchasing of bids and the actual amount made from the final cost of the item.

Legalities

Shill Bidding

Placing fake bids that benefits the seller of the item is known as Shill Bidding. This is a method often used in Online auctions but can also happen in standard Auctions. This is seen as an unlawful act as it unfairly raises the final price of the auction, so that the winning bidder pays more than they should have. If the shill bid is unsuccessful, the item owner needs to pay the auction fees.

Fraud

The increasing popularity of using online auctions has led to an increase in fraudulent activity.[2] This is usually performed on an auction website by creating a very appetising auction, such as a low starting amount. Once a buyer wins an auction and pays for it, the fradulent seller will either not pursue with the delivery,[20] or send a less valuable version of the purchased item (replicated, used, refurbished, etc.). Protection to prevent such acts has become readily available, most notably Paypal's buyer protection policy. As Paypal handles the transaction, they have the ability to hold funds until a conclusion is drawn whereby the victim can be compensated.

Sale of Stolen Goods

Online auction websites are used by thieves or fences to sell stolen goods to unsuspecting buyers. According to police statistics there were over 8000 crimes involving stolen goods, fraud or deception reported on eBay in 2009. It has become common practice for organised criminals to steal in-demand items, often in bulk. These items are then sold online as it is a safer option due to the anonymity and worldwide market it provides. Auction fraud makes up a large percentage of complaints received by the FBI's Internet Crime Complaint Center (IC3). This was around 45% in 2006 and 63% in 2005.

EXISTING SYSTEM

The traditional online shopping business model allows sellers to sell a product or service at a preset price, where buyers can choose to purchase if they find it to be a good deal. Online auction however is a different business model by which items are sold through price bidding. There is often a starting price and expiration time specified by the sellers. Once the auction starts, potential buyers bid against each other, and the winner gets the item with their highest winning bid.

PROPOSED MODEL

We propose an online probit model framework which takes online feature selection, coefficient bounds from human knowledge and multiple instance learning into account simultaneously. By empirical experiments on a real-world online auction fraud detection data we show that this model can potentially detect more frauds and significantly reduce customer complaints compared to several baseline models and the human-tuned rule-based system.

Human experts with years of experience created many rules to detect whether a user is fraud or not. If the fraud score is above a certain threshold, the case will enter a queue for further investigation by human experts. Once it is reviewed, the final result will be labeled as Boolean, i.e. fraud or clean. Cases with higher scores have higher priorities in the queue to be reviewed. The cases whose fraud score are below the threshold are determined as clean by the system without any human judgment.

MODULES

Rule-based features

Human experts with years of experience created many rules to detect whether a user is fraud or not. An example of such rules is “blacklist”, i.e. whether the user has been detected or complained as fraud before. Each rule can be regarded as a binary feature that indicates the fraud likeliness.

Selective labeling

If the fraud score is above a certain threshold, the case will enter a queue for further investigation by human experts. Once it is reviewed, the final result will be labeled as boolean, i.e. fraud or clean. Cases with higher scores have higher priorities in the queue to be reviewed. The cases whose fraud score are below the threshold are determined as clean by the system without any human judgment.

Fraud churn

Once one case is labeled as fraud by human experts, it is very likely that the seller is not trustable and may be also selling other frauds; hence all the items submitted by the same seller are labeled as fraud too. The fraudulent seller along with his/her cases will be removed from the website immediately once detected.

User Complaint:

Buyers can file complaints to claim loss if they are recently deceived by fraudulent sellers. The Administrator view the various type of complaints and the percentage of various type complaints. The complaints values of a products increase some threshold value the administrator set the trustability of the product as Untrusted or banded. If the products set as banaded, the user cannot view the products in the website.

Online Probit Regression

Consider splitting the continuous time into many equalsize intervals. For each time interval we may observe multiple expert-labeled cases indicating whether they are fraud or non-fraud. At time interval t suppose there are n_t observations. Let us denote the i-th binary observation as y_{it}. If $y_{it} = 1$, the case is fraud; otherwise it is non-fraud. Let the feature set of case i at time t be x_{it}. The probit model [3] can be written as $P[y_{it} = 1|x_{it}, \beta_t] = \Phi(x'_{it}\beta_t)$, where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution N(0, 1), and β_t is the unknown regression coefficient vector at time t.

Through data augmentation the probit model can be expressed in a hierarchical form as follows: For each observation i at time t assume a latent random variable zit. The binary response yit can be viewed as an indicator of whether zit > 0, i.e. yit = 1 if and only if zit > 0. If zit <= 0, then yit = 0. zit can then be modeled by a linear regression zit ~ N(x it βt, 1).

In a Bayesian modeling framework it is common practice to put a Gaussian prior on βt, βt ~ N(μt,Σt), where μt and Σt are prior mean and prior covariance matrix respectively.

CONCLUSION

Finally we build online models for the auction fraud moderation and detection system designed for a major Asian online auction website. By empirical experiments on a real world online auction fraud detection data, we show that our proposed online probit model framework, which combines online feature selection, bounding coefficients from expert knowledge and multiple instance learning, can significantly improve over baselines and the human-tuned model.

Note that this online modeling framework can be easily extended to many other applications, such as web spam detection, content optimization and so forth. Regarding to future work, one direction is to include the adjustment of the selection bias in the online model training process. It has been proven to be very effective for offline models in [3]. The main idea there is to assume all the unlabeled samples have response equal to 0 with a very small weight. Since the unlabeled samples are obtained from an effective moderation system, it is reasonable to assume that with high probabilities they are non-fraud. Another future work is to deploy the online models described in this paper to the real production system, and also other applications.

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