ISSN: 2320-1363

Computer Network of Proactive Moderation system for Auction Fraud Catching

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Abstract

Online auction and shopping are gaining popularity with growth of web based ecommerce. Criminals are also taking advantage of these opportunities to conduct fraudulent activities against honest parties with the purpose of description and illegal profit. In practice and proactive moderation systems are deployed to detect suspicious events for further inspection by human experts. It motivated by real world applications in commercial auction sites in Asia, we develop various advanced machine learning techniques in the proactive moderation system. In this article we proposed system is formulated as optimizing bounded generalized linear models in multi instance leaning problems, with intrinsic bias in selective labeling and massive unlabeled samples. Hence proactive fraud-catching moderation systems are commonly applied in practice to detect and prevent such illegal and fraud activities. In both offline evaluations and online bucket tests the proposed system significantly outperforms the rule based system on various metrics, including area under ROC, loss rate of labeled frauds and customer complaints. We also show that the metrics of loss rate more effective than AUC in our cases.

Keywords: Auction, Fraud Catching, Multi-Instance Learning

1. Introduction

Since the commercialization of the World Wide Web in the mid 1990's, online marketplaces have been widely explored by commercial organizations for brand awareness and revenue sources. Individuals are able to buy and sell a broad variety of goods and services worldwide on online auction and shopping websites e.g. eBay and Amazon. However, criminals have also attempted to conduct fraudulent activities against honest parties for the purpose of illegitimate profit. On Internet auction sites, auction fraud mainly involves fraud attributable to the misrepresentation of a product advertised for sale or the non-delivery of products purchased through an Internet auction site. Malicious sellers may post an (even non-existing) item for bidding with false description to deceive the buyer concerning its true value, and request payments to be wired directly to them. By using wire transfer services, the money is virtually unrecoverable for the victim. Similarly malicious buyers may make a purchase via a fraudulent credit card where

ISSN: 2320-1363

the address of the card holder does not match the shipping address. Both consumers and merchants can be victims of online auction fraud, as well as the commercial auction websites. Patterns of auction fraud are changing dynamically and rapidly. To maintain the selection or filter accuracy, moderation systems have to be updated periodically to catch the drifting patterns. It is desirable to design a learning system that is capable of automatically optimizing weights for the rules based on recent observations. Motivated by applications in a commercial online auction website, we develop various advanced machine learning techniques in the proactive moderation system. By noting the imbalanced labels and the limitation of rule-based features designed for the fraud catching, we improve the system by constraining the weights to be positive and introducing imbalanced/weighted loss functions. To overcome the selection bias in labeling, we also include the remaining unlabeled cases into training for unbiasedness. Being aware of specific noise patterns in the expert labels, we further enhance the optimization as done in multi-instance learning problems. The final model is formulated as optimizing unbounded generalized linear models in multi-instance learning problems, with intrinsic bias in selective labeling and massive unlabeled samples.

2. Methodology

Our application is one of the major online auction sites in Asia. Lots of items are posted for bidding every day. Each item is sent o the proactive anti-fraud system to assess the risk of being a fraud. The existing is featured by:

- ✓ Rule based features: Human experts with many years of experience created more than 30 rules for fraud catching. Each rule can be regarded as a binary feature that indicates the fraud likeliness. However we cannot list the rules and their importance here due to confidentiality.
- ✓ Linear scoring function: The existing system only supports linear models. Given a set of weights on features the fraud score is computed as the weighted sum.
- ✓ Selectivity labeling: If the fraud score is above a certain threshold the item will be investigates by human experts otherwise it will be passed by the system. The final result is labeled as fraud or clean. Item of higher score have higher priority to be reviewed experts.
- ✓ Fraud churn: Once one item is judged as fraud it is very likely that the seller is not trustable and may be also selling other fraud, therefore all the item submitted by the same seller are labeled as fraud too and the seller's account will be suspended by the website immediately.
- ✓ Feedback: buyers can file a claim if they become victims of fraud. Similarly sellers may also complain if his/her items have been judged as fraud mistakenly.

Motivated by these specific attributes in the existing moderation system we propose

ISSN: 2320-1363

several statistical machine learning models incrementally to improve the fraud catching performance.

2.1 Logistic Regression

Let us denote the binary response variable from the expert labeled data as y, i.e. fraud if y=1, otherwise y=0. For each observation I, denotes the corresponding feature set as x_i. the logistic regression, one of the most natural probabilistic model is defined as $P[y_i =1] = 1/1+\exp(-x_i'\beta)'$, where β is the unknown coefficients vector. Suppose each observation i is further associated with a weight ω_i. the corresponding loss function with L_k penalty on β becomes

$$£ = \sum_i \omega_i [y_i \log(1+\exp(-x_i'\beta))$$
$$+ (1-y_i) \log(1+\exp(-x_i'\beta)) + \rho||\beta||_k] \quad (1)$$

Where ρ is the trade off parameter to control the shrinkage of β and can be estimated by cross validation. In this article we mainly consider k=2, which is equivalent to assigning a Gaussian prior $N(0, \delta I)$ on β, where $\delta = 1/(2\rho\sum_i \omega_i)$.

In this paper we assume all positive samples have the same weight ω_1, and all the negative samples have weight 1. The optimal ω_1, can be determined by cross validation in criterion of predictive performance. We call the Weight Logistic Regression as WLR. We optimize the models by minimizing the loss functions through the standard L-BFGS algorithm.

2.2 Coefficients of Bounds for Fraud Catching

It is always important to incorporate domain knowledge into the model, which can sometimes boost the model performance. In out fraud catching system the feature ser x was proposed by experts with years of experience. Currently all the features are in fact binary rules, i.e. any violation of one rule should somehow increase the probability of fraud. Hence we bound the coefficients of those binary rules to force them to be equal or greater than 0. Specifically, we consider the following optimization problem

$$\beta = \sum_i \omega_i [y_i \log(1+\exp(-x_i'\beta))$$
$$+ (1-y_i)\log(1+\exp(x_i'\beta)) + \rho||\beta||_k] \quad (2).$$

Such that $\beta \geq T$. where for feature j,T_j is 0 in our problem. Note that T_j can also be set as other values if domain knowledge is available. When $w_i = 1$ for all i we call the model BLR(Bounded Logistic Regression). For predefined ω_i values we call the model WBLR(Weighted BLR).

2.3 Removing the selection bias

Note that in the real world many such online auction fraud catching system would not allow an entirely random selection scheme to generate the training data: it is simply too expensive and ineffective. Instead usually a set of hand tuned rules are used in the initial system to provide the basic fraud catching function. Therefore it is important to correct the selection bias and leverage the data without labels to improve the model. The simplest idea to remove the selection bias is to assume all events that are not labeled by the current system are defined as not fraud with a low confidence. Mathematically, denoting Z_j to be the feature set for an unlabeled event j, we want to solve

$$\text{Min } \beta = \sum_i \omega_i [y_i \log(1+\exp(-x_i'\beta))$$
$$+ (1-y_i)\log(1+\exp(x_i'\beta)) + \rho||\beta||_k]$$
$$+ \sum_i \square\omega_j [y_i \log(1+\exp(-z_i'\beta)) + \rho||\beta||_k], \quad (3).$$

ISSN: 2320-1363

Such that $\beta \geq T$. for simplicity we could assume all $\omega_j = \omega$, i.e all the unselected events having the same confidence to be non fraud.

2.4 Multiple instance learning

when we looked into the actual expert reviewing and labeling process, we noted that the experts actually assign labels in a "bagged" fashion, i.e for each seller id, one expert looks through all of his/her posted items and if the expert finds any item as fraud all of this seller id's posted items are labeled as fraud. The multiple instance learning models with logistic function becomes

$P[y_i = 1] = 1 - \prod_{j=1}^{Ki} \frac{1}{1} + \exp(xj'\beta)'$ which is essentially a noisy or likelihood function. The noisy or likelihood function only requires subsets of the events in the bag are fraud rather than all are fraud events. The optimization problem can thus be written as

$\text{Min } \beta = \sum_i \omega_i [-y_i \log(1 - \prod_{j=1}^{Ki} \frac{1}{1} + \exp(xj'\beta)') + (1-y_i)\log(1+\exp(x_i'\beta)) + \rho\|\beta\|_k] + \sum_i \omega_j [y_i \log(1+\exp(-z_i'\beta)) + \rho\|\beta\|_k]$, (4).

Such that $\beta \geq T$ we call this model WBMILRSB (Weighted and Bounded (WB) Multiple Instance Learning (MIL) after Removing Selection Bias (RSB)).

3. Experiments

With experiment settings and metrics in evaluation and then report extensive experimental results of both offline evaluation and online bucket tests to demonstrate the performance of the various proposed techniques.

3.1 experiment settings

Our proposed model data from a major Asian online auction website which attractive a big volume of items posted for bidding every day. For online A/B test, we compared our best model WBMILRSB based on the offline experiments with the expert model, which was used by the system with expert crafted rules and weights. For offline evaluation we created our training and test data set via bias sampling scheme for the real data set to avid releasing the company confidential information. Out training data contains around 1M labeled cases with around 12k fraud cases.

Model	AUC	Loss Rate of Frauds	Loss Rate of Complaints
Expert	0.724	0.00%	34.66%
LR	0.903	16.07%	55.61%
BLR	0.924	7.40%	40.56%
WBLR	0.923	4.21%	26.17%
WBLRRSB	0.922	2.83%	20.75%
WBMILRSB	0.926	2.07%	20.73%

Table1: offline evaluation of the model performance. The loss rate of labeled frauds and customer complaints are obtained given 100% workload rate.

The offline experiments and results are shown. Note that due to the company policy concerns. We are unable to reveal what features are used in our experiments.

3.2 metrics for offline evaluation

We considered three metrics for offline model evaluation: area under ROC curve (AUC), the loss rate of labeled frauds and the loss rate of customer complaints. The AUC is a traditional metric that people use a lot for measuring model performance.

ISSN: 2320-1363

However for our scenario with labeling bias, we will show in section 3.3 that simply using AUC might not be optimal.

Note that the training and test data were generated as follows: for each case the existing rule based moderation system uses a human tuned linear scoring function to determine whether to send it for expert labeling. If so experts review it and make a fraud or non-fraud judgment: otherwise it would be considered as clean and not reviewed by anyone. Therefore two concerns arise: a) for those cases that are not reviewed by experts, we would never know whether they are fraud or not. b) if we want to propose a new machine learned scoring model to replace the existing one, we have to make sure it is able to catch more frauds with the same or lower expers labeling workload.

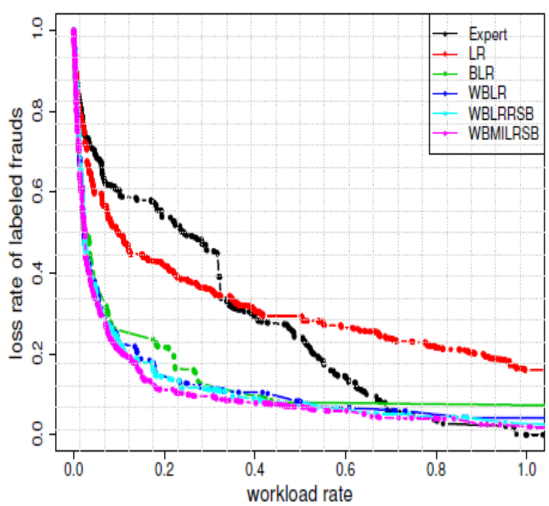

Figure3.2.1: Offline evaluation: Workload rate versus the loss rate of labeled frauds for all the models.

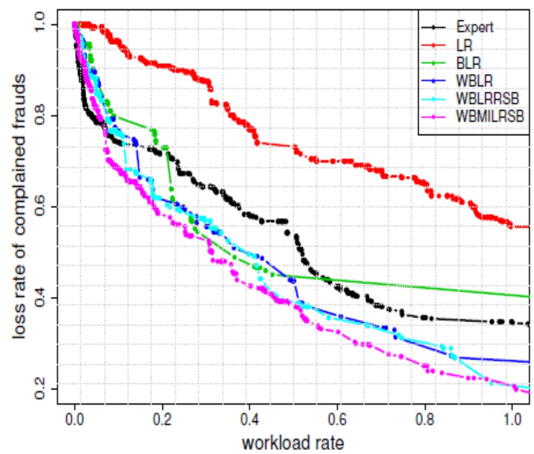

Figure 3.2.2: Offline evaluation: Workload rate versus the loss rate of customer complaints for all the models.

3.3 Offline Experiments

In this section we show the performance of the test data for six models: Expert, LR, BLR, WBLR, WBLRRSB and WBMILRSB. Table 1 summarizes the three metrics discussed in section 3.2: AUC, the loss rate of labeled frauds, and the loss rate of customer complaints. The latter two are obtained given 100% workload rate. Note the loss rates of the labeled frauds as well as customer complaints given different workload rates for all the models. According to the AUC number the machine learned LR is much better than the human tuned model Expert. It is also seems obviously that the four models BLR, WBLR, WBLRRSB and WBMILRSB and better than LR, although among them there is very little difference when computing AUC. We saw a significant performance difference between BLR and WBMILRSB, and we started to doubt that LR and BLR can work well in the real

ISSN: 2320-1363

auction fraud catching system since their loss rates of customer complaints look much worse than the Expert model! On the other hand, the numbers in the table suggest WBMILRSB to be the winning model that would improve the existing moderation system significantly.

3.4 Online A/B Test

We performed online A/B test during 2011, which compared two models: our best model WBMILRSB and the Expert crafted Expert model. We used the last 30 days data for the daily training and tuned the threshold of WBMILRSB scores so that the workload generated by this model is roughly the same every day. Running 4 weeks of A/B test, we observed that WBMILRSB significantly outperformed Expert by catching 25.5% more frauds and reducing the customer complaints by 15.7%, while using only 74.2% of the expert workload.

4. Conclusion

In this article, we introduced various advanced machine learning techniques for real world auction fraud catching system. By ex-techniques offline experiments and online bucket test, we have shown our proposed model significantly outperforms the existing human tuned rule based system. Compared with baselines we show that the multiple instance learning model with bounded coefficients and properly weighted observations after removing the selection bias performs the best. Hence we have pushed this model to production. For model evaluation, besides using traditional metrics such as area under ROC (AUC), we introduced two extra metrics under this fraud catching frame work. We show that these metrics are more effective than AUC or ROC for distinguishing the best models.

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ISSN: 2320-1363

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