Decision Support for Online Auction Sellers with Two-Task Multiple Binary Classifier Estimation

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Outline

- Introduction
- Related Work
- Cost-sensitive decision making
  - End-Price prediction
  - Probability estimation
- Two problems
  - Sample Selection Bias Problem
  - Probability Calibration
- Experiments
- Conclusion and Future Work
Introduction

- **Online auction**
  - No time and space limitation
  - The marketplace for e-commerce
  - Low doorsill: individuals and small business
  - Keen competition for sellers

- **Sellers have to decide an auction setting before listing their commodities**
  - Starting bid, buyitnow price, duration time, etc.
Introduction (Cont.)

- Given a listing option, what the auction result will be?
- End-price prediction [Ghani and Simons, 2004]
  - Multiple binary classification > Multiclass classification
  - How to make decision based on the end-price?
  - Sample selection bias problem
- Argument
  - Probability is also important in decision making
  - Well-calibrated probability
- Cost-sensitive Decision making
Related Work

- **Seller Agent in Online Auction**
  - Official agent
    - Search closed auction, Monitor bidding condition and Block blacklist bidder
  - Third-Party agent (ex. BidXS.com, McFind.com)
    - provide past price trend information of multiple auction sites

- **Online Auction Research in Economics Domain**
  - Empirical or exploratory analysis works are lack of predictive model
  - Some works simulate online auction scenario to estimate seller’s profit. But they often consider very few factors or make more assumptions
Related Work (Cont.)

- **End-Price Prediction**
  - Functional Data Analysis [Wang, Jank and Shmueli, JBES 2006]
    - Auction price evolution and price dynamics: useful for buyers
  - Machine Learning Method [Ghani and Simmons, 2004]
    - Regression
    - Multi-Class classification
    - Multiple binary classification

- **Shortcomings**
  - Ignore sold probability tend to scare away possible buyers
  - End-price is not equal to profit. Seller have to consider listing cost
  - Cannot apply to buy-it-now listing item
We collect 5 kinds of digital cameras category from eBay for two month, total 4852 listings.

<table>
<thead>
<tr>
<th>Model</th>
<th>Amount</th>
<th>Sale Ratio</th>
<th>Average Price</th>
<th>Amount</th>
<th>Sale Ratio</th>
<th>Average Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>A530</td>
<td>427</td>
<td>0.92</td>
<td>172.12</td>
<td>454</td>
<td>0.35</td>
<td>189.46</td>
</tr>
<tr>
<td>SD600</td>
<td>394</td>
<td>0.96</td>
<td>292.75</td>
<td>437</td>
<td>0.34</td>
<td>304.06</td>
</tr>
<tr>
<td>SD550</td>
<td>322</td>
<td>0.76</td>
<td>313.31</td>
<td>485</td>
<td>0.22</td>
<td>338.07</td>
</tr>
<tr>
<td>S2</td>
<td>538</td>
<td>0.96</td>
<td>339.98</td>
<td>483</td>
<td>0.46</td>
<td>409.95</td>
</tr>
<tr>
<td>A620</td>
<td>626</td>
<td>0.94</td>
<td>258.30</td>
<td>686</td>
<td>0.30</td>
<td>301.06</td>
</tr>
</tbody>
</table>
Two Data Sets

- **Auction Listing Type** (set starting price option)
  - Most products are sold
  - The higher starting price, the higher listing cost and the lower sold probability

- **BuyItNow Listing Type** (set buyitnow price option)
  - The higher the buyitnow price, the lower the sold probability
  - Most sellers spend more listing cost to attract buyers
Two Kinds of Tasks

- Probability Estimation
  - \( P(S=1| X) \)

- End-Price Prediction
  - Multiple Binary Classification
  - [Ghani, 2002, 2005]
  - Price < 40? N
  - Price < 45? N
  - Price < 50? Y
    - if one of classifier make wrong prediction, we will get wrong result

- Expected end price
  \[
  E(Y | X) = y(x) \times P(S = 1 | X)
  \]
Data Features

<table>
<thead>
<tr>
<th>Item Features</th>
<th>Seller Features</th>
<th>Listing Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>bundled kits (bag, battery, memory, tripod, lens, memory reader)</td>
<td>feedback score, negative feedback, positive feedback, IsPowerSeller, HasAboutMePage, HasEBayStore, ActivePeriod, SellerType (number of product listed by seller)</td>
<td>Auction Listing type / Buy-It-Now Listing type, starting price, buy-it-now price, shipping cost, duration, start time, end time, pictures, presence of reserve price, payment methods, listing upgrade features (bold, subtitle…etc), some pre-defined words in title or subtitle (no reserve, fast ship…etc)</td>
</tr>
<tr>
<td>memory size</td>
<td>warranty</td>
<td></td>
</tr>
</tbody>
</table>

Problems in End-Price Prediction of Two-Class Estimation

- **Sample Selection Bias Problem**
  - If the commodity is unsold ($s=0$) then end-price $y$ will be unknown. This means we only use $s=1$ data as training set to predict $P(y|s=1,x)$, instead of $P(y|x)$. We may get inaccurate prediction results.

- **Four Conditions**
  - Complete Independent: $P(s|x,y) = P(s)$
  - Feature Bias: $P(s|x,y) = P(s|x)$, $P(x) \neq P(x|s=1)$
  - Class Bias: $P(s|x,y) = P(s|y)$, $P(y) \neq P(y|s=1)$
  - Complete Bias: $P(s|y,x)$
Correcting Sample Selection Bias

- We consider our condition as **Feature Bias** because commodity with the same feature should have the same value (price), no matter it is sold or not
  - \( P(s|x,y) = P(s|x) \) implicit two additional assumptions
    - \( P(s=1|x) > 0 \) or \( P(x,s=1) > 0 \)
    - \( P(y|x,s=1) = P(y|x) \) is approximately correct for a large number of sample examples

- We use Zadrozny’s **Reweighting** method to correct the feature bias before we predict end-price
Zadrozny’s Reweighting

- Zadrozny corrects the distribution $D$ of examples through re-sampling and then apply the classifier learner to corrected distribution $\hat{D}$.

\[
E_{x,y} \sim \hat{D}[l(h(x), y) \mid s = 1]
\]
\[
= \sum_{x,y} l(h(x), y) \hat{P}_D(x, y \mid s = 1)
\]
\[
= \sum_{x,y} l(h(x), y) \frac{P_D(s = 1)}{P_D(s = 1 \mid x)} \hat{P}_D(x, y \mid s = 1)
\]
\[
= \sum_{x,y} l(h(x), y) \frac{P_D(s = 1)}{P_D(s = 1 \mid x)} \frac{P_D(x, y) P_D(s = 1 \mid x, y)}{P_D(s = 1)}
\]
\[
= \sum_{x,y} l(h(x), y) P_D(x, y)
\]
\[
= E_{x,y} \sim D [l(h(x), y)]
\]

Under Feature Bias

$P(s=1|x,y) = P(s=1|x)$

Reweighting

$\hat{D}(x, y, s) \equiv P(s = 1) \frac{D(x, y, s)}{P(s = 1 \mid x)}$
Zadrozny’s Reweighting (Cont.)

- Re-sampling by Zadrozny’s cost-proportionate rejection sampling with aggregation (costing)
  
  Algorithm: Costing (Learner A, Sample Set S, Count t)
  1. For $i = 1$ to $t$ do
     a. $S’ =$ rejection sample from $S$ with acceptance probability $c/Z$. ($Z = \max_{(x,y,c) \in S \times C}$)
     b. Let $h_i \equiv A(S’)$
  2. Output $h(x) = \text{sign}(\sum_{i=1}^{t} h_i(x))$

- Advantage
  - Rejection Sampling can avoid over-fitting to get better performance
  - Averaging can improve performance
  - Costing obtain a sample of smaller size (reduce computational cost), which is at least as informative as the original

Multiple Binary Classification for End-Price Prediction
Problems in Probability Estimation

- Most classifies generate score to classify examples, but the score is not equal to actual probability value.
  - Naïve Bayes Classifier
    - Induce bias when we violate independence assumption
    - Calibration Method: Binning [Zadrozny and Elkan]
  - Decision Tree
    - Bias cause by error-minimizing split and curtailment method
    - Calibration Method: Smoothing + Curtailment [Zadrozny and Elkan]
  - SVM
    - Bias cause by distance between data point and hyper-plane is not equal to class member probability
    - Calibration Method: Platt Calibration [Platt]
Platt Calibration for SVM

- The sigmoid model is equivalent to assuming that the output of SVM is proportional to the log odds of a positive example

\[ P(y = 1 | f) = \frac{1}{1 + \exp(Af + B)} \]

Gradient descent is used to find A and B such that they are the solution to:

\[ \arg\min_{A,B} \left\{ -\sum_i y_i \log(p_i) + (1 - y_i) \log(1 - p_i) \right\} \]

where \( p_i = \frac{1}{1 + \exp(Af_i + B)} \)
Two-Task Multiple Binary Classifier Estimation

Auction Listing Dataset $D_A$

- Sold Probability Estimation
- Sold Probability Calibration

- Solve Sample Selection Bias Problem using Reweighting method

- Multiple Binary Classification
  - Price $< 40$?
  - Price $< 45$?
  - Price $< 50$?

Expected End-Price
Experiments

- We collect 5 kinds of camera, total 4852 examples. For each kind of camera, we repeat 5 times to split dataset into training set (70%) and testing set (30%) randomly and average the results of them.

- Result

<table>
<thead>
<tr>
<th>DataSet</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>A530</td>
<td>91.9%</td>
</tr>
<tr>
<td>SD600</td>
<td>96.1%</td>
</tr>
<tr>
<td>SD550</td>
<td>92.9%</td>
</tr>
<tr>
<td>S2</td>
<td>94.5%</td>
</tr>
<tr>
<td>A620</td>
<td>92.1%</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>93.5%</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DataSet</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>A530</td>
<td>71.5%</td>
</tr>
<tr>
<td>SD600</td>
<td>76.8%</td>
</tr>
<tr>
<td>SD550</td>
<td>84.8%</td>
</tr>
<tr>
<td>S2</td>
<td>71.4%</td>
</tr>
<tr>
<td>A620</td>
<td>76.5%</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>76.2%</strong></td>
</tr>
</tbody>
</table>

Auction Listing

BuyItNow Listing
Statistics of Each Interval in Auction Listing Testing Set
Statistics of Each Interval in BuyItNowListing Testing Set

SD600

SD550
Trade-off Between Sold Probability and BuyItNow Price In BuyItNow Listing Testing Set

**SD600**

![Graph SD600](image)

**SD550**

![Graph SD550](image)
Accuracy of Multiple Binary Classification Without Reweighting for End-Price Prediction

- In Multiple Binary Classification, we pick 10% average price as interval size and use SVM predict the price are larger then $X or not
- Although the accuracy for perfect predication is not good, but the accuracy within one interval size error is almost 90%

<table>
<thead>
<tr>
<th>Model</th>
<th>Max-Min End-Price</th>
<th>Interval Size</th>
<th>Cumulative Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Perfect prediction</td>
</tr>
<tr>
<td>A530</td>
<td>92-319</td>
<td>17</td>
<td>48.7%</td>
</tr>
<tr>
<td>SD600</td>
<td>192-409</td>
<td>29</td>
<td>59.8%</td>
</tr>
<tr>
<td>SD550</td>
<td>233-469</td>
<td>31</td>
<td>46.3%</td>
</tr>
<tr>
<td>S2</td>
<td>256-535</td>
<td>33</td>
<td>52.9%</td>
</tr>
<tr>
<td>A620</td>
<td>173-428</td>
<td>25</td>
<td>46.9%</td>
</tr>
<tr>
<td>Average</td>
<td>--</td>
<td>--</td>
<td>50.9%</td>
</tr>
</tbody>
</table>
End-Price Prediction: Value of High Starting Bid and Unsold Commodities

- We use starting price feature and feedback score feature to train $p(s=1|x)$ model for reweighting.
- For each training set, we run 10 times rejection sampling to generate 10 smaller dataset and average the prediction.

<table>
<thead>
<tr>
<th>Model</th>
<th>Average Starting Price</th>
<th>Multiple Binary Classifier</th>
<th>Linear Regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Without Reweighting</td>
<td>With Reweighting</td>
</tr>
<tr>
<td>A530</td>
<td>190.77</td>
<td>181.02</td>
<td>180.17</td>
</tr>
<tr>
<td>SD600</td>
<td>389.09</td>
<td>310.80</td>
<td>328.1</td>
</tr>
<tr>
<td>SD550</td>
<td>366.46</td>
<td>341.60</td>
<td>355.22</td>
</tr>
<tr>
<td>S2</td>
<td>289.20</td>
<td>273.2</td>
<td>293.0</td>
</tr>
<tr>
<td>A620</td>
<td>296.21</td>
<td>294.0</td>
<td>304.5</td>
</tr>
</tbody>
</table>
Accuracy of Multiple Binary Classification With Reweighting for End-Price Prediction

<table>
<thead>
<tr>
<th>Model</th>
<th>Max-Min End-Price</th>
<th>Interval Size</th>
<th>Perfect prediction</th>
<th>Cumulative Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>1 Interval Error</td>
<td>2 Interval Error</td>
</tr>
<tr>
<td>A530</td>
<td>92 -319</td>
<td>17</td>
<td>47.2%</td>
<td>84.0%</td>
</tr>
<tr>
<td>SD600</td>
<td>192-409</td>
<td>29</td>
<td>58.5%</td>
<td>95.5%</td>
</tr>
<tr>
<td>SD550</td>
<td>233-469</td>
<td>31</td>
<td>42.8%</td>
<td>92.7%</td>
</tr>
<tr>
<td>S2</td>
<td>256 -535</td>
<td>33</td>
<td>54.9%</td>
<td>94.6%</td>
</tr>
<tr>
<td>A620</td>
<td>173 -428</td>
<td>25</td>
<td>48.2%</td>
<td>90.1%</td>
</tr>
<tr>
<td>Average</td>
<td>--</td>
<td>--</td>
<td>50.3%</td>
<td>91.3%</td>
</tr>
</tbody>
</table>
End-Price Prediction Conclusions

- Reweighting not only keep the same accuracy for sold commodity but also make more accurate prediction for unsold commodity
- Reweighting is more benefit to end-price prediction when the dataset has many unsold commodities
Profit We Make

- Profit we make $\sum_x M(i, j, x)$
  - $M(i, j, x)$ is the cost of predicting class $i$ for $x$ when true class of $x$ is $j$

<table>
<thead>
<tr>
<th>True Outcome</th>
<th>Sold</th>
<th>Unsold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sold</td>
<td>a</td>
<td>b</td>
</tr>
<tr>
<td>Unsold</td>
<td>c</td>
<td>d</td>
</tr>
</tbody>
</table>

- We compare sellers’ profit with the average profit of other sellers‘

<table>
<thead>
<tr>
<th>Prediction</th>
<th>Sold</th>
<th>Unsold</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sell</td>
<td>$y(x) - \text{Avgp}(x) - l_c(x)$</td>
<td>$- l_c(x) - u_c$</td>
</tr>
<tr>
<td>Not to Sell</td>
<td>$-y(x) + \text{Avgp}(x) + l_c(x)$</td>
<td>$l_c(x) + u_c$</td>
</tr>
</tbody>
</table>

Commodity: $x$
End-price: $y(x)$
Listing cost: $l_c(x)$
Unsold cost: $u_c$
$\text{Avgp}(x) = \sum_{x' \sim x} \text{Profit}(x')$
To Sell or Not to Sell? Three Strategies

- **Sales Amount Maximization Strategy**
  - \( P(s=1|x) > 0.5 \)

- **End-Price Maximization Strategy**
  - \( y(x) > \text{avg } y \)

- **Cost-Sensitive Decision Making [Zadrozny and Elkan]**
  - The optimal prediction for \( x \) is the class \( i \) that leads to the highest expected profit

\[
\arg \max \sum_j P(j \mid x) M(i, j, x)
\]
Average Profit Increase

Average Profit of Selling Strategy in BuyItNow Listing Testing Set

- Sell All
- Sales Amount Maximization
- End-Price Maximization
- Profit Maximization Without Calibration
- Profit Maximization With Calibration

Average Profit of Selling Strategy in Auction Listing Testing Set

- Sell All
- Sales Amount Maximization
- End-Price Maximization Without Reweighting
- End-Price Maximization With Reweighting
- Profit Maximization of Two-Class Estimation
Selling Strategy Conclusions

- Selling Strategy Comparison
  - Profit Maximization strategy can get highest profit
  - End-Price Maximization strategy tend to fail in auction
  - Sales Amount Maximization strategy lead to lower profit
- Probability calibration can get more accurate probability, thus increase profit, especially in multi-class classification task
- Correcting sample selection bias problem can improve profit when there exists a lot of unsold commodities in the database
- Multi-Class Estimation with probability calibration outperforms Two-Class Estimation under some situations
Conclusions

- Machine learning approach for
  - End-price predication
  - Probability estimation

- Two problems to be noted
  - Sample selection bias
  - Probability calibration

- Future work
  - Analyze auction page text to improve prediction accuracy, further provide a guideline for writing commodity description.
  - It is unrealistic to build prediction model for every kind of commodity. Transfer Learning technique is a promising way to predict “similar” commodity.