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 predication
  - Probability estimation
- Two problems
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  - 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 predication [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

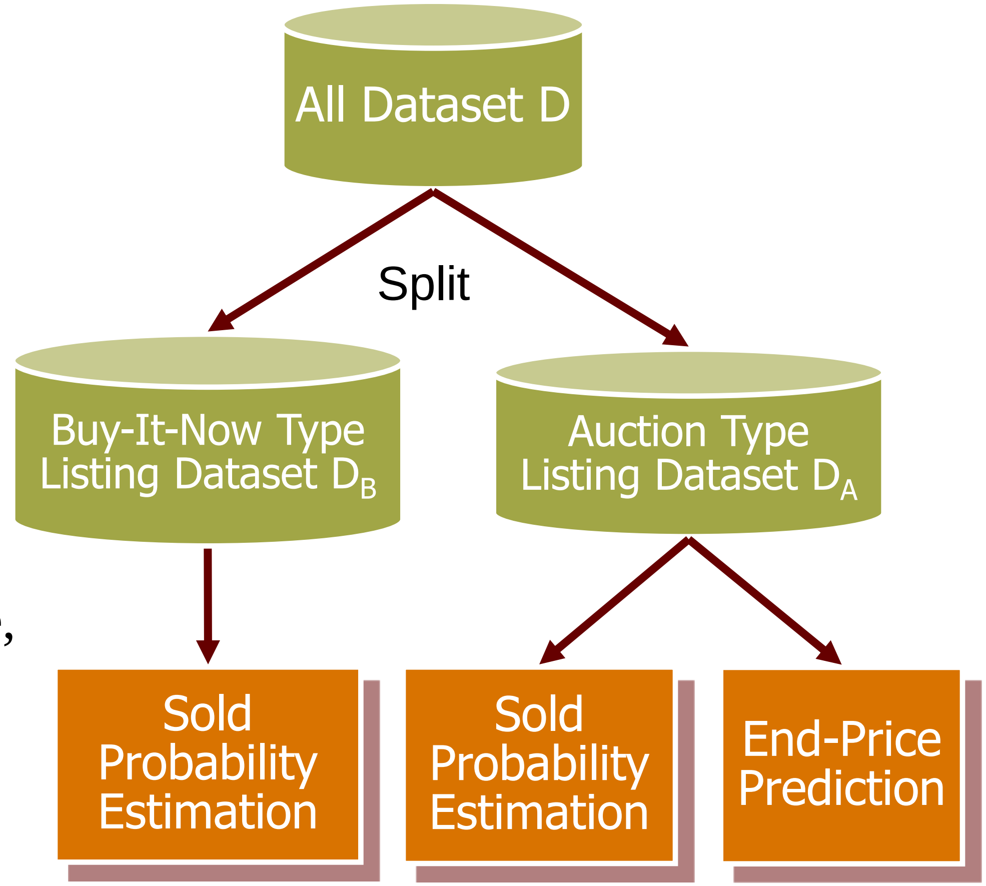
Data Analysis

- We collect 5 kinds of digital cameras category from eBay for two month, total 4852 listings.

	Auction Listing			BuyItNow Listing		
Model	Amount	Sale Ratio	Average Price	Amount	Sale Ratio	Average Price
A530	427	0.92	172.12	454	0.35	189.46
SD600	394	0.96	292.75	437	0.34	304.06
SD550	322	0.76	313.31	485	0.22	338.07
S2	538	0.96	339.98	483	0.46	409.95
A620	626	0.94	258.30	686	0.30	301.06

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

$$E(Y \mid X) = y(x) \times P(S = 1 \mid X)$$

- For each product, we build
  - 1 SVM classifier for sold or not
  - About 10 SVM classifiers for end-price predication

Data Features

Item Features

- bundled kits (bag, battery, memory, tripod, lens, memory reader)
- memory size
- warranty

Seller Features

- feedback score,
- negative feedback,
- positive feedback,
- IsPowerSeller,
- HasAboutMePage,
- HasEBayStore,
- ActivePeriod,
- SellerType (number of product listed by seller)

Listing Features

- 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)

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 maybe 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 $\hat{D}$

Reweighting

$$\hat{D}(x,y,s) \equiv P(s=1)\frac{D(x,y,s)}{P(s=1|x)}$$

$$E_{x,y,s\sim\hat{D}}[l(h(x),y)\,|\,s=1]$$

$$=\sum_{x,y} l(h(x),y)P_{\hat{D}}(x,y\,|\,s=1)$$

$$=\sum_{x,y} l(h(x),y)\boxed{\frac{P_D(s=1)}{P_D(s=1|x)}P_D(x,y\,|\,s=1)}$$

$$=\sum_{x,y} l(h(x),y)\frac{P_D(s=1)}{P_D(s=1|x)}\frac{P_D(x,y)P_D(s=1|x,y)}{P_D(s=1)}$$

$$=\sum_{x,y} l(h(x),y)P_D(x,y)$$

$$=E_{x,y\sim D}[l(h(x),y)]$$

P(s=1|x,y) = P(s=1|x)
Under Feature Bias

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 accpetance probability c/Z. $(Z = \max_{(x,y,c) \in S} c)$

   (b) Let $h_i \equiv A(S')$

2. Output $h(x) = \mathrm{sign}(\sum_{i=1}^{t} h_i(x))$

Multiple Binary Classification for End-Price Prediction

- 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

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

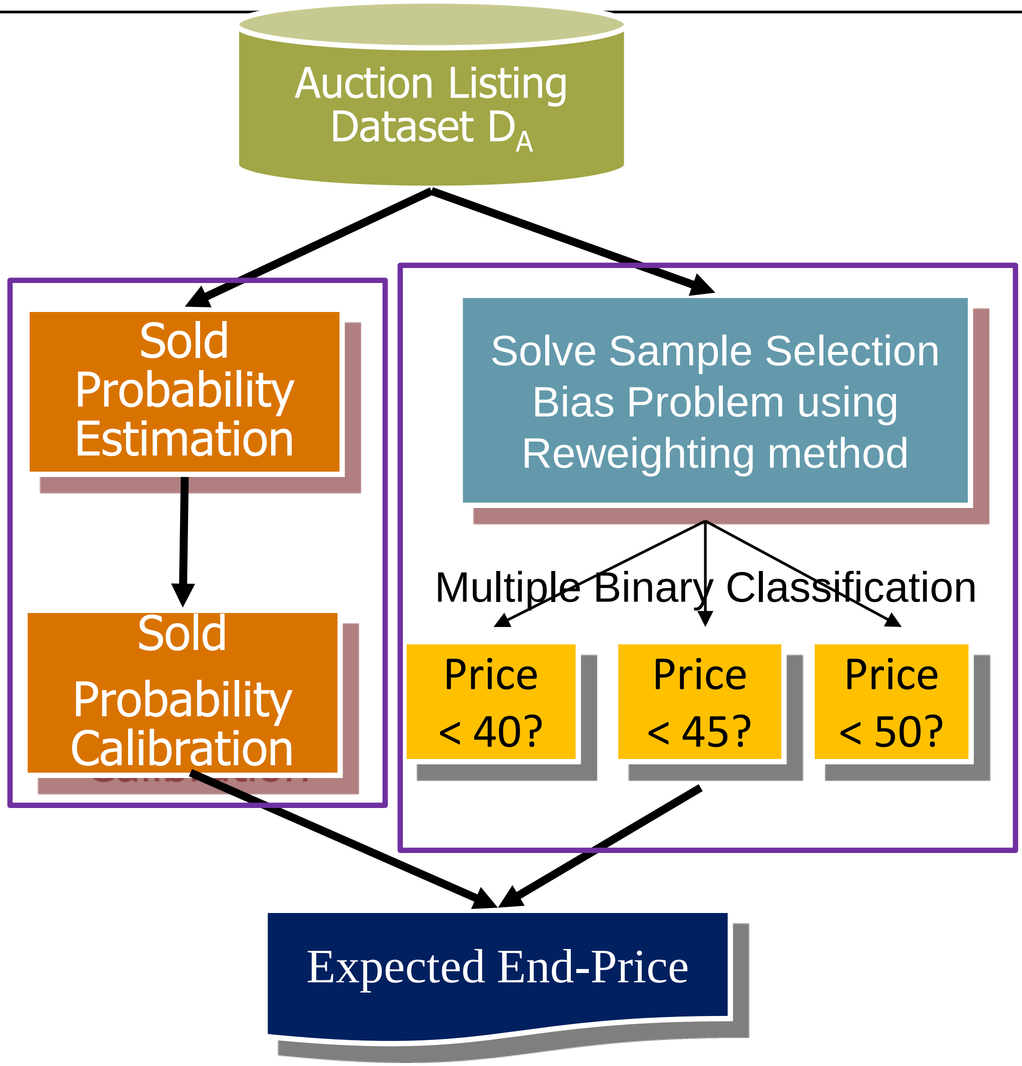
$$P(y=1 \mid f) = \frac{1}{1+\exp(Af+B)}$$

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

$$\underset{A,B}{\operatorname{argmin}} \left\{ -\sum_i y_i \log(p_i) + (1-y_i)\log(1-p_i) \right\}$$

where $p_i = \dfrac{1}{1+\exp(Af_i+B)}$

Two-Task Multiple Binary Classifier Estimation



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

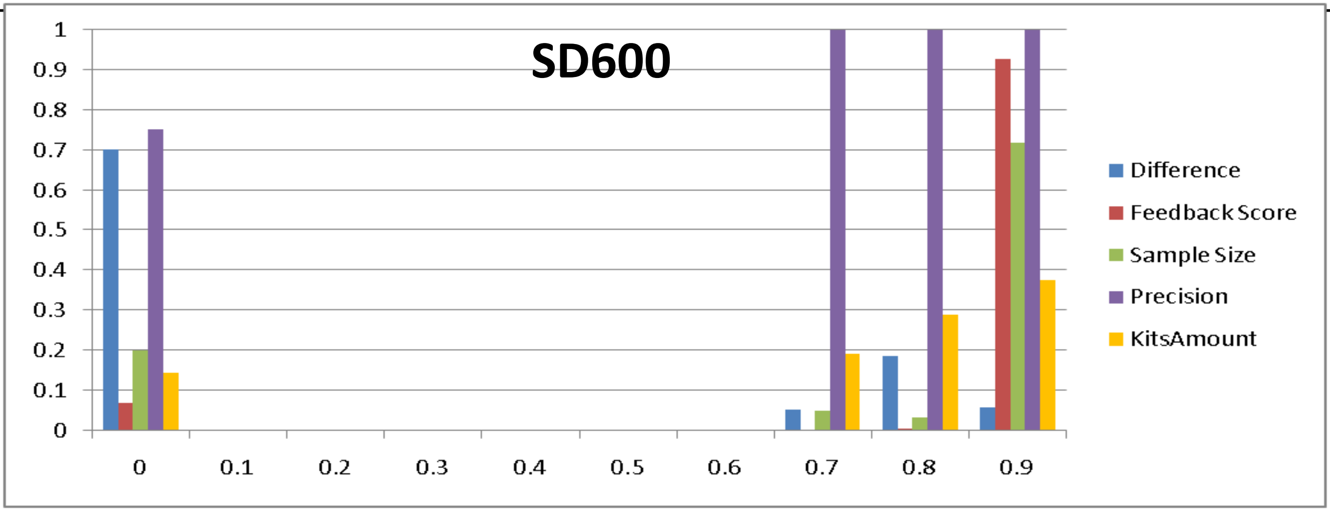
Auction Listing

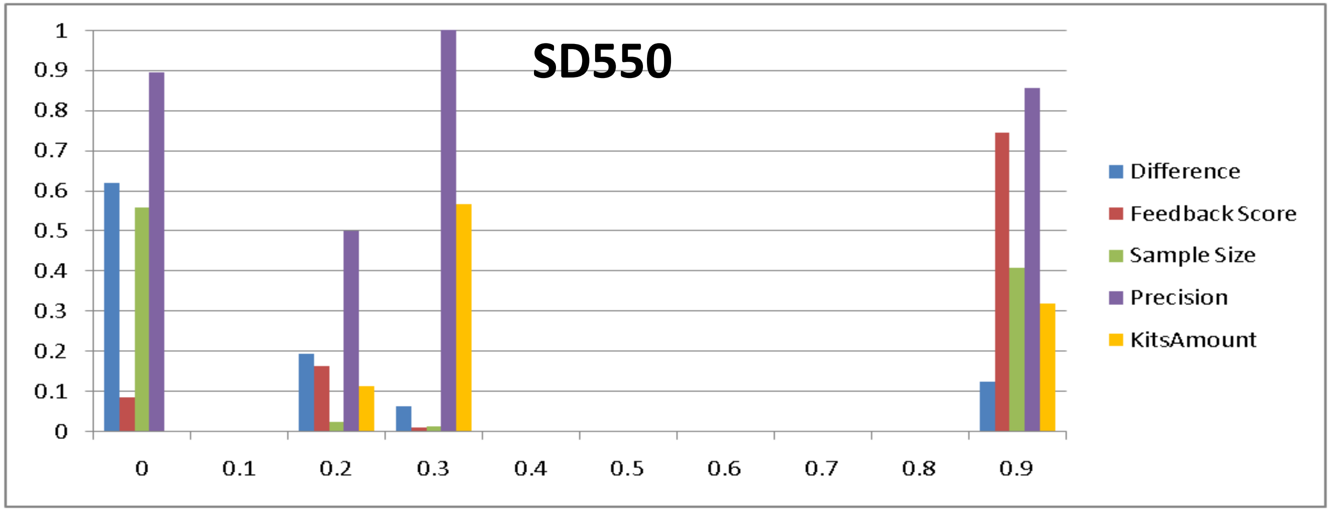
DataSet	Accuracy
A530	91.9%
SD600	96.1%
SD550	92.9%
S2	94.5%
A620	92.1%
Average	93.5%

BuyItNow Listing

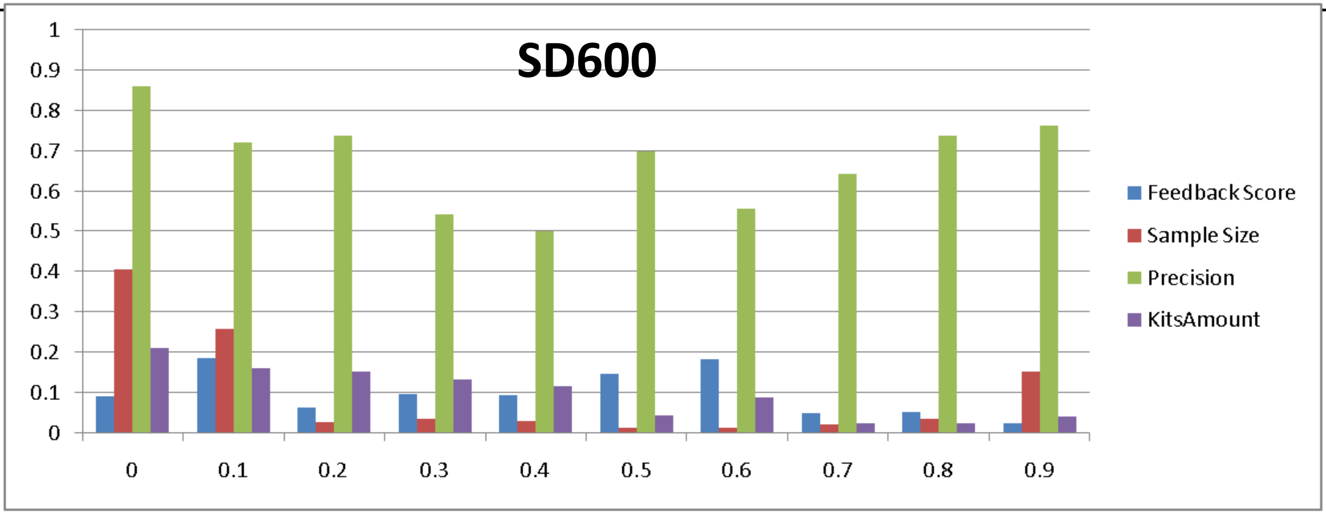
DataSet	Accuracy
A530	71.5%
SD600	76.8%
SD550	84.8%
S2	71.4%
A620	76.5%
Average	76.2%

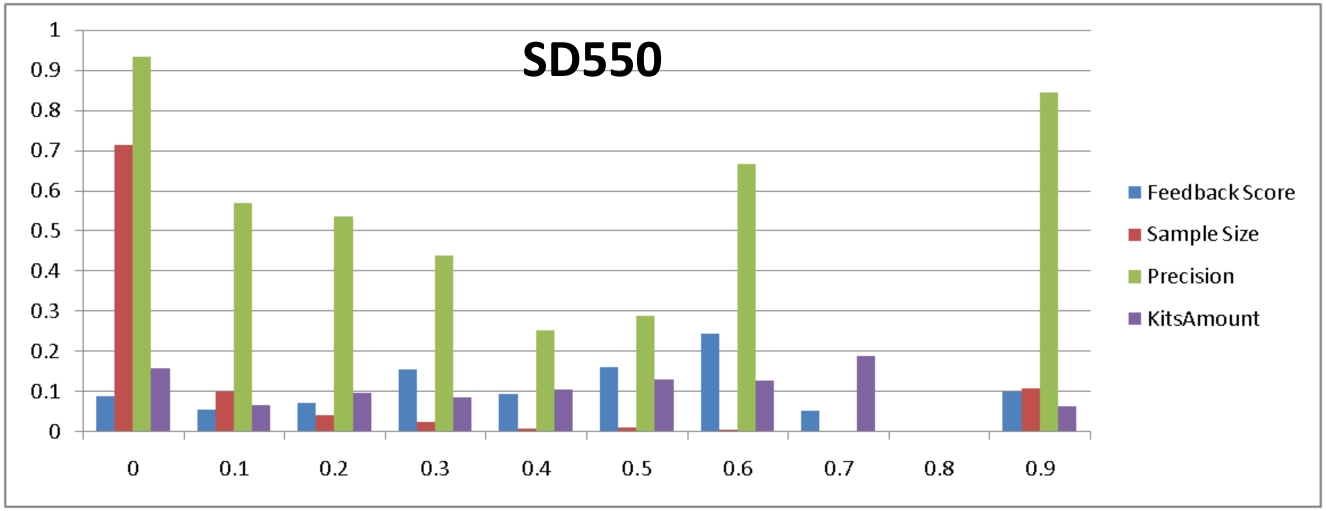
Statistics of Each Interval in Auction Listing Testing Set



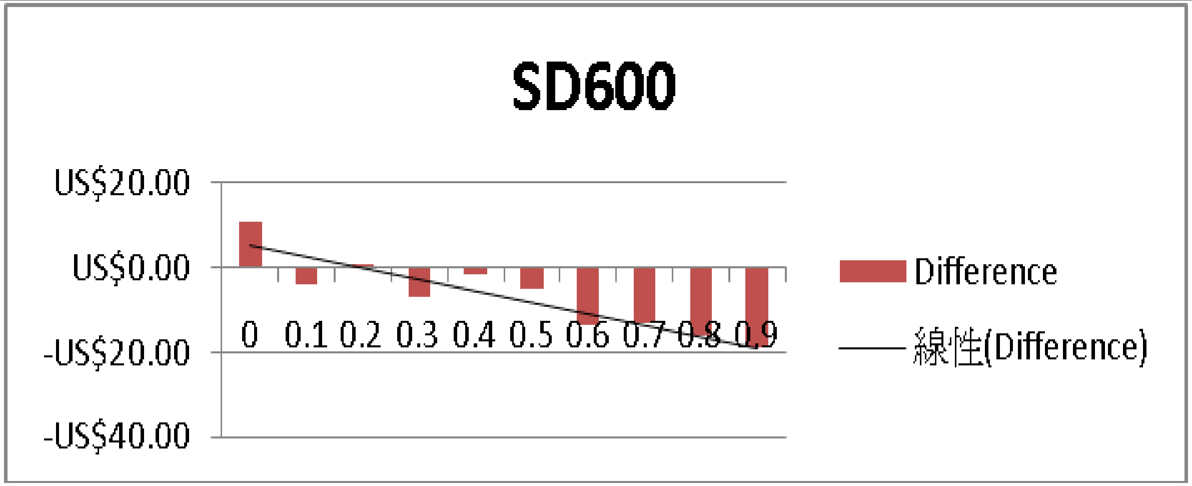


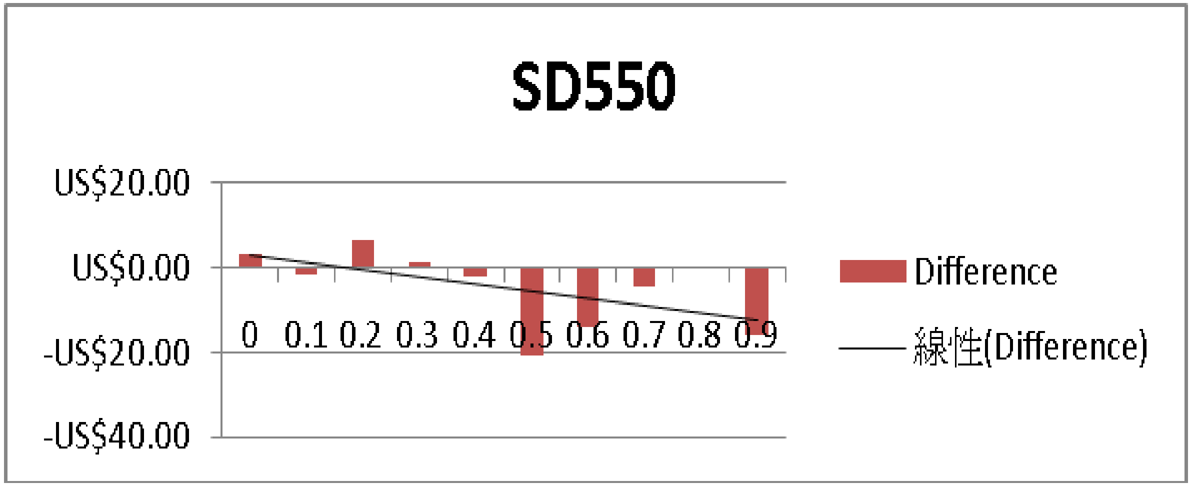
Statistics of Each Interval in BuyItNowListing Testing Set





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





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%

Model	Max-Min End-Price	Interval Size	Cumulative Accuracy					
			Perfect prediction	1 Interval Error	2 Interval Error	3 Interval Error	4 Interval Error	5 Interval Error
A530	92 -319	17	48.7%	83.6%	95.0%	99.5%	99.8%	100.0%
SD600	192-409	29	59.8%	95.4%	99.6%	99.8%	100.0%	--
SD550	233-469	31	46.3%	87.4%	98.9%	100.0%	--	--
S2	256 -535	33	52.9%	93.9%	98.3%	99.5%	99.9%	100.0%
A620	173 -428	25	46.9%	89.1%	98.0%	99.7%	100.0%	--
Average	--	--	50.9%	89.9%	97.9%	99.7%	99.9%	100%

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

Model	Average Starting Price	Multiple Binary Classifier			Linear Regression		
		Without Reweighting	With Reweighting	Prediction Increment	Without Reweighting	With Reweighting	Prediction Increment
A530	190.77	181.02	180.17	-0.85	190.85	192.83	+1.98
SD600	389.09	310.80	328.1	+17.3	300.27	300.04	-0.23
SD550	366.46	341.60	355.22	+13.62	293.03	323.52	+30.49
S2	289.20	273.2	293.0	+19.8	264.33	264.41	+0.12
A620	296.21	294.0	304.5	+10.5	259.21	261.38	+2.17

Accuracy of Multiple Binary Classification With Reweighting for End-Price Prediction

Model	Max-Min End-Price	Interval Size	Cumulative Accuracy					
			Perfect prediction	1 Interval Error	2 Interval Error	3 Interval Error	4 Interval Error	5 Interval Error
A530	92 -319	17	47.2%	84.0%	94.8%	99.6%	99.7%	100.0%
SD600	192-409	29	58.5%	95.5%	99.5%	100.0%	--	--
SD550	233-469	31	42.8%	92.7%	99.5%	100.0%	--	--
S2	256 -535	33	54.9%	94.6%	98.7%	99.6%	99.9%	100.0%
A620	173 -428	25	48.2%	90.1%	98.7%	99.8%	100.0%	--
Average	--	--	50.3%	91.3%	98.2%	99.8%	99.9%	100%

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

True Outcome

Prediction		Sold	Unsold
	Sold	a	b
	Unsold	c	d

  - We compare sellers' profit with the average profit of other sellers'

	Sold	Unsold
Sell	y(x)-Avgp(x)-lc(x)	-lc(x)-uc
Not to Sell	-y(x)+Avgp(x)+lc(x)	lc(x)+uc

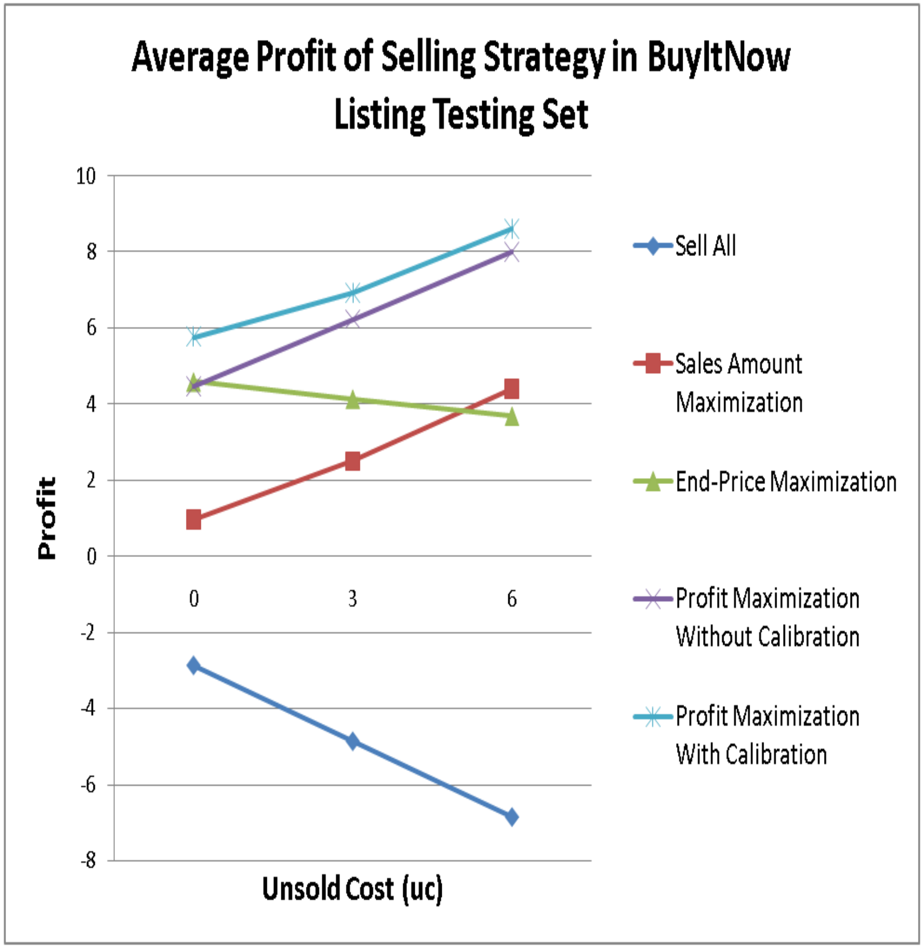
Commodity: x
End-price: y(x)
Listing cost: lc(x)
Unsold cost: uc
Avgp(x)= $\Sigma_{x'\sim x}$ Profit(x')

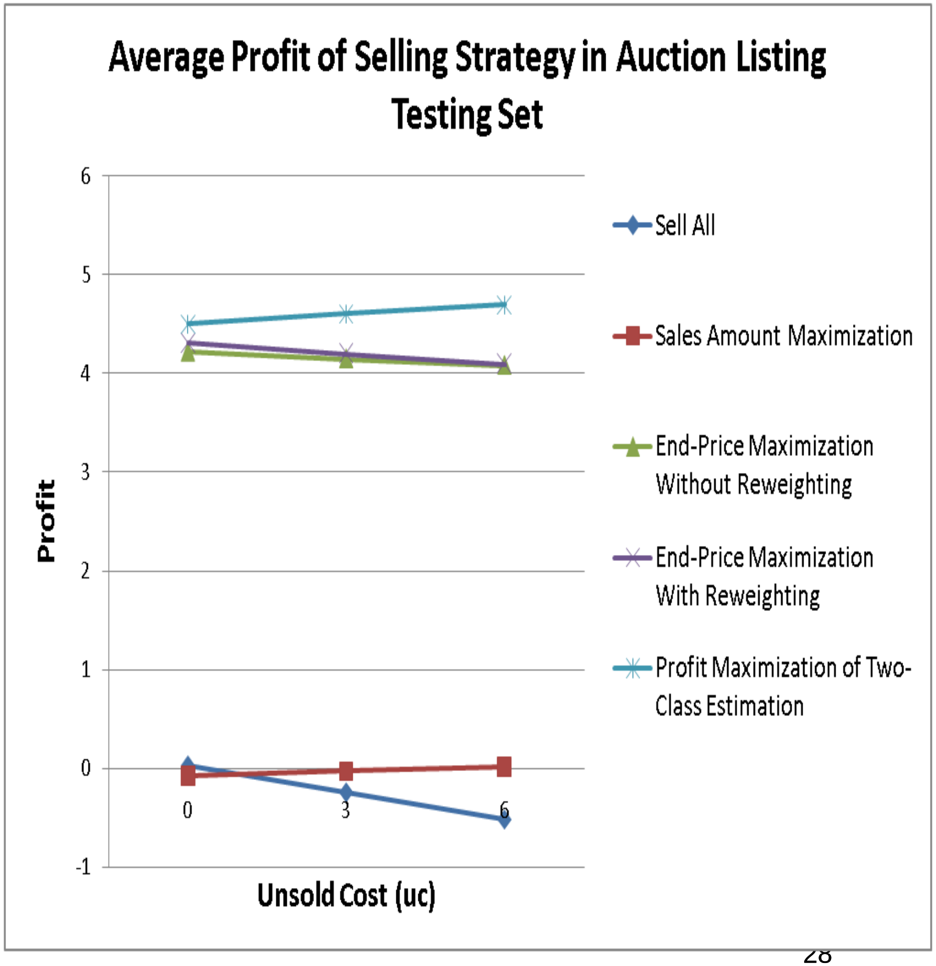
To Sell or Not to Sell? Three Strategies

- 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

$$\arg\max_i \sum_j P(j \mid x) M(i, j, x)$$

Average Profit Increase





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.