Predicting eBay Listing Conversion

Ted Tao Yuan
eBay Inc.
2145 Hamilton Avenue
San Jose, California 95125 USA
1(408) 376-5477
teyuan@ebay.com

Zhaohui Chen
eBay Inc.
2145 Hamilton Avenue
San Jose, California 95125 USA
1(408) 376-6794
zhachen@ebay.com

Mike Mathieson
eBay Inc.
2145 Hamilton Avenue
San Jose, California 95125 USA
1(408) 376-5739
mike.mathieson@ebay.com

ABSTRACT
At eBay Market Place, listing conversion rate can be measured by number of items sold divided by number of items in a sample set. For a given item, conversion rate can also be treated as the probability of sale. By investigating eBay listings' transactional patterns, as well as item attributes and user click-through data, we developed conversion models that allow us to predict a live listing's probability of sale. In this paper, we discuss the design and implementation of such conversion models. These models are highly valuable in analysis of inventory quality and ranking. Our work reveals the uniqueness of sales-oriented search at eBay and its similarity to general web search problems.

Categories and Subject Descriptors
H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *information filtering.*

General Terms
Algorithms, Design.

Keywords
Online auction, ecommerce, predictive model, ranking.

1. INTRODUCTION
eBay's online inventory is a collection of listing pages that have short lifespan comparing to that of normal web pages, i.e., listings are generally for sale in days versus months or years availability of web pages. At present, the majority of eBay's search result pages (SRP) are item based with category navigation. In addition to query-item relevance, customer satisfaction is measured by how easily and quickly they can find items they are interested in, and sale transaction efficiency.

2. Design Consideration
eBay's search ranker is built on top of intermediate factor models; each targets a specific goal, and can be implemented at different stages of the business workflow. Predicted item conversion model is a lower-tier model and computationally intensive. We choose to run such model at listing stages, and append the model output to items as listing attributes. Runtime models are less computationally intensive but can achieve higher accuracy by incorporating observed user behavioral data.

SIGIR'11, July 24–28, 2011, Beijing, China.
ACM 978-1-4503-0757-4/11/07.

In this study, we averaged out queries that bring search impressions, item views that lead to sales, and focused on the intrinsic properties of a listing as well as market statistics. A runtime item conversion model is built to incorporate observed user demand measurements.

3. Predicting Item Conversion
3.1 Factor Exploration
Our conversion models rely on informative factors. We identified repetitive conversion patterns, and found that item price, clicks, listing category, duration, seller feedback, sale format such as auction or fixed price (Buy-It-Now) are crucial factors. We notice previous studies on predicting listings' final prices[1,2]. Our pricing model is to establish item's fair market price based on similar items sold on eBay. Statistics on sold similar items reveal important demand measurements such as past sales count, clicks and bids, etc.. They provide good normalization base for an active listing. For instance, the ratio of initial total price to the median total price of recently sold similar items is highly correlated with conversion (Figure 1). Seller past conversion rate is also a strong indicator. Low seller conversion rate tends to underestimate item conversion, but overestimates when it is at high end.

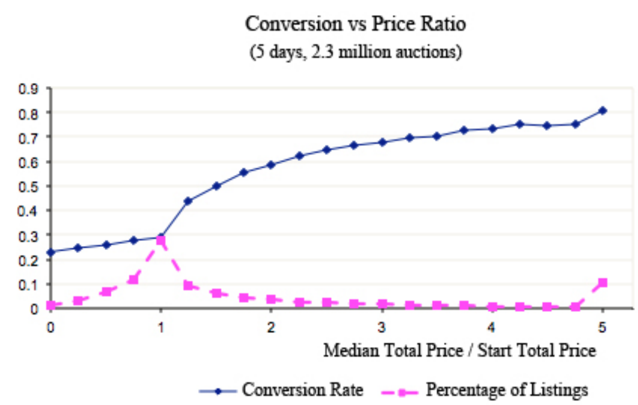

Figure 1. Item conversion and population versus price ratio

3.2 Training and Validation Sets
Training data were sampled from eBay's item database. They maintain the statistical distribution of eBay production listings, i.e., mix of sold/unsold, different products, formats, etc. Certain noises and outliers were removed. Both temporal and static factors are collected. Static factors are available at listing time, such as item features specified by sellers, seller historical metrics and other market priors. Dynamic or temporal factors such as item

page views, watch and impression counts are also used in the final predictive model. Validation sets were sampled without overlapping with the training data.

3.3 Heuristic Model

We assumed that item conversion probability is a multiplication of supply quality and demand attractiveness. The heuristic model assumes independency of supply and demand, therefore it tends to underestimate the interaction or correlation among factors on both supply and demand sides. The binary classification model was implemented using curve fitting to capture information gain from predicting factors. Its accuracy is reported in Table 1.

3.4 Machine Learning Models

3.4.1 Gradient Boosted Decision Trees

Gradient boosted decision trees (GBDT) gain popularity in data mining and machine learning community in recent years[3]. GBDT has the reputation of working well for non-linear complex classification and regression models with large number of correlated factors. The result is stable even when some important factors are missing at runtime.

3.4.2 Listing Time Conversion Model

Our listing-time conversion prediction model uses only factors known at the listing start time. Several predictors from the heuristic model were also used. The binary regression decision trees compute score between 0 and 1 for each item, and the result is stored as item feature. When comparing with the heuristic model, we found GBDT model greatly improved the prediction result of item at listing start-time.

3.4.3 Runtime Conversion Model

To predict conversion dynamically at runtime, we combined the saved listing time prediction score with seller level priors, and a number of dynamic factors observed at listing end time, such as item's recorded impressions, page views, click through rate, etc. We chose to use logistic regression which is lighter in CPU cycles. By incorporating user behavioral information, the runtime model achieved higher prediction accuracy.

Comparisons of the prediction results are shown in Figure 2, 3 and Table 1.

4. ACKNOWLEDGMENTS

Our thanks go to eBay Search organization for continuous support.

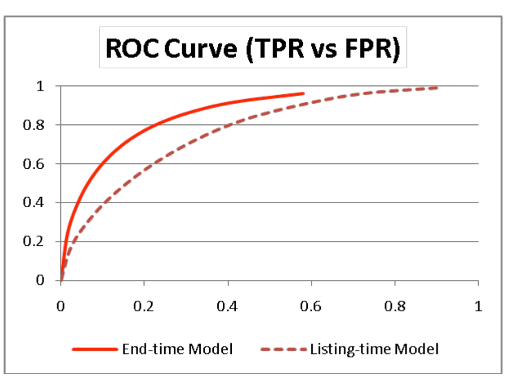

Figure 2. Comparison of two machine learned models

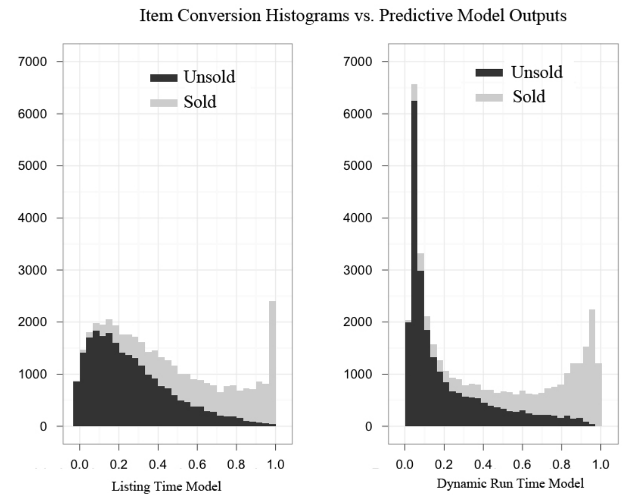

Figure 3. Stacked histograms of listing and runtime models

Table 1. Model Comparison

Model	Purpose	Detail	Accuracy
Heuristic	Predict item conversion	~20 factors, price, shipping, price history, seller quality, clicks, past demand data	64% (at listing time) 80% (with demand observations)
GBDT (50 trees, 50 leaf nodes)	Predict conversion at listing time	~100 factors, listing attributes, seller quality, duration, format, site category, recent similar sale price, sales count, views, impression	82%
Logistic Regression with GBDT result	Predict conversion at runtime	< 10 factors, GBDT result, CTR, clicks, seller past conversion	88%

5. REFERENCES

[1] Van Heijst, D., Potharst, R. and Van Wezel, M. 2008. A Support System for Predicting Ebay End Prices. *Decision Support Systems*. v44 i4, pp. 970-982, 2008. DOI= http://portal.acm.org/citation.cfm?id=1342702.

[2] Gregg, D.G. and Walczak, S.. Auction Advisor: An Agent-Based Online Auction Decision Support System. *Decision Support Systems*. v41 n2, pp. 449-471, 2004.

[3] Friedman, J. H. Greedy Function Approximation: A Gradient Boosting Machine.1999. DOI=http://www-stat.stanford.edu/~jhf/ftp/trebst.pdf.