Happy for Two (or Three)
Joint Revenue Optimization for 2-Sided Parties for Promoted Listings

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Liangjie Hong
Head of Data Science, Etsy Inc.

Workshop on Two-sided Marketplace Optimization: Search, Pricing, Matching & Growth
Etsy – A Global Marketplace
Etsy – A Global Marketplace

What can you sell on Etsy?

- Handmade Goods
- Vintage
- Craft Supplies

(20 years or older)
By The Numbers

- 1.9M active sellers
- 31.7M active buyers
- $2.8B annual GMS
- 45+M items for sale

Photo by Kirsty Lyn Jameson
Work and Culture

852 employees around the world

9 offices in 7 countries

54% female employees

46% male employees
Work and Culture

1.6M active sellers
AS OF MARCH 31, 2016

86% of sellers are women
2014 ETSY SELLER SURVEY

95% of sellers run their Etsy shop from home
2014 ETSY SELLER SURVEY

76% consider their shop a business
2014 ETSY SELLER SURVEY
Passionate and Loyal Business Owners

30% focus on their creative businesses as their sole occupation

65% started their Etsy shop as a way to supplement income

79% started their Easy shop as an outlet for creativity

2014 ETSY SELLER SURVEY
Engaged and Thoughtful Buyer Base

25M active buyers
AS OF MARCH 31, 2016

87% of Etsy buyers are women
2014 ETSY BUYER SURVEY

92% of buyers agree Etsy offers products they can't find elsewhere
2014 ETSY BUYER SURVEY

Photo by Jean-Michael Seminaro
AI in E-commerce

AI Challenges

For Buyers

• How to choose unique and satisfied products among millions?
  How to lead and guide buyers to discover products that they wouldn't buy at the first place?
  How to recommend appropriate products for different occasions?

For Sellers

• How to reach larger audience and potential buyers?
  How to run advertising campaign more effectively?
  How to communicate with buyers through different channels?

For Platform

• How to build a healthy platform?
  How to speed-up buyer and seller communication?
AI in E-commerce

AI Challenges

• **Search and Discovery**
  Query Modeling
  User Intent Modeling
  Learning to Rank

• **Personalization and Recommendation**
  User Profiling
  Item Modeling
  Recommender Ranking

• **Computational Advertising**
  Click-Through Rate Modeling
  Conversion Rate Modeling
  Bid Optimization
AI in E-commerce

AI in E-commerce at Etsy

• Multi-modal Deep-learning based Search Solution (KDD 2016)

• Probabilistic Graphical Model based Personalization Recommendation (KDD 2014)

• Ensemble Learning based CTR Prediction Solution (AdKDD 2017/KDD 2017)

• Buzzsaw: A System for High Speed Feature Engineering (SysML 2018)
Promoted Listings
Promoted Listings at Etsy
Promoted Listings at Etsy
Promoted Listings at Etsy

For Sellers

• Specify a campaign with listings

• Specify daily budget (maximum you want to spend daily)
Promoted Listings at Etsy

For Sellers

• Specify a campaign with listings
• Specify daily budget (maximum you want to spend daily)

• No need to specify which queries or keywords
• In general, bidding is automated but could specify bids
• Could set a maximum Cost-Per-Click (CPC)
Promoted Listings at Etsy

For Etsy

• Determine queries

• Determine bids (most of time)

• Determine whether to show the promoted listings
Promoted Listings at Etsy

For Etsy

• Determine queries

• Determine bids (most of time)

• Determine whether to show the promoted listings

• Charge a fee per click (CPC)

• Revenue attributed to this click – purchase within 30 days
For Etsy

- $0.20 USD to list an item
- a 3.5% transaction fee
  a 3.0% transaction fee + $0.25
Promoted Listings at Etsy

Buyers

Buy an Item

Etsy

3.5% of Transaction Charge $
+ Cost of Prolist Click

Sellers

Transaction Charge $$
Promoted Listings at Etsy

Etsy

Cost of Prolist Click

Buyers

Sellers
Promoted Listings at Etsy

Sellers

• Increase sales while keep cost minimized

Etsy

• Increase both Promoted Listing’s revenue and/or transaction revenue

Buyers

• Find most relevant/interesting item to purchase
Promoted Listings at Etsy

Sellers

• No increased sales while the Promoted Listing cost remains/increase

Etsy

• Increased both Promoted Listing’s revenue

Buyers

• Not finding most relevant/interesting item to purchase

WARNING
Other Promoted Listings
Joint Revenue Optimization
Joint Revenue Optimization

- **Wei Qian**, PhD candidate in Operations Research from Cornell University
- **Kamelia Aryafar**, Director of Machine Learning at Overstock.com
- **Liangjie Hong**, Head of Data Science at Etsy
Joint Revenue Optimization

Assumptions

• Each seller manages one promoted listing and \( k \) slots are allocated for each search query.

• For each seller, Click-Through-Rate (CTR) and Conversion-Rate (CVR) are the same across all slots.

• For simplicity, only discuss First-Price-Auction.
Joint Revenue Optimization

Main Utility

The expected utility of $a_j$ to the platform with bid $B_{i,j}$ for search query $q_i$ is given by:

$$\text{Expected Utility} = c_{i,j} \times B_{i,j} + c_{i,j} \times p_{i,j} \times R_j \times r$$

where
- $c_{i,j}$ is the click-through rate
- $B_{i,j}$ is the bid
- $p_{i,j}$ is the conversion rate
- $R_j$ is the sales revenue
- $r$ is the shared revenue
Joint Revenue Optimization

Main Constraints

$W_{i,j}$ indicates whether seller $q_j$ wins the auction for search query $q_i$.

*allocation constraint*

$$\sum_{j=1}^{M} W_{i,j} = k \quad \forall i$$

*budget constraint:

$$\sum_{i=1}^{N} c_{i,j} W_{i,j} B_{i,j} \leq B_j \quad \forall j$$

*bidding constraint:

$$B_{i,j} \leq mCPC_j \quad \forall i, j$$
Joint Revenue Optimization

Main Constraints

$W_{i,j}$ indicates whether seller $q_j$ wins the auction for search query $q_i$.

- **performance constraints:**
  The performance constraints are designed by the platform to balance the performance of itself and the advertisers. If it sets the goal for total number of clicks, then the constraint is of the following form:
  \[
  \sum_{i=1}^{N} \sum_{j=1}^{M} W_{i,j} c_{i,j} \geq G_{\text{click}} N
  \]
  where $G_{\text{click}} \in (0, 1)$ is the target global click through rate. If it sets the goal for the purchase revenue, then it is:
  \[
  \sum_{i=1}^{N} \sum_{j=1}^{M} W_{i,j} c_{i,j} p_{i,j} R_j \geq G_{\text{attribute}}
  \]
  where $G_{\text{attribute}} \in \mathbb{R}^+$ is the target amount of the purchase revenue. If it sets the goal for the global rate of return for the advertisers, then it is:
  \[
  \sum_{i=1}^{N} \sum_{j=1}^{M} W_{i,j} c_{i,j} p_{i,j} R_j \cdot (1 - r) \geq G_{\text{ROI}} \sum_{i=1}^{N} \sum_{j=1}^{M} W_{i,j} c_{i,j} B_{i,j}
  \]
  where the left hand side is the expected revenue obtained by an advertiser, the right hand side is its expected spending and $G_{\text{ROI}} > 0$ is the target rate of investment.
Joint Revenue Optimization

Main Objective

\[
\max \sum_{i=1}^{N} \sum_{j=1}^{M} W_{i,j} c_{i,j} (B_{i,j} + p_{i,j} \times R_j \times r)
\]
Joint Revenue Optimization

Main Objective

\[
\max \sum_{i=1}^{N} \sum_{j=1}^{M} W_{i,j} c_{i,j} (B_{i,j} + p_{i,j} \times R_j \times r)
\]

Model Parameters

Known
Joint Revenue Optimization

Main Objective

\[
\max \sum_{i=1}^{N} \sum_{j=1}^{M} W_{i,j} c_{i,j} (B_{i,j} + p_{i,j} \times R_j \times r)
\]

Non-Convex! Need Approximation
Relaxation
Relaxation

Relaxed Objective

• Let $Z_{i,j} = W_{i,j}B_{i,j}$

• Relax $W_{i,j}$ to $[0, 1]$
Relaxed Objective

- Let $Z_{i,j} = W_{i,j} B_{i,j}$
- Relax $W_{i,j}$ to $[0, 1]$

$$\text{max} \sum_{i=1}^{N} \sum_{j=1}^{M} c_{i,j} Z_{i,j} + c_{i,j} p_{i,j} W_{i,j} R_j \times r$$

s.t.

- $\sum_{j=1}^{M} W_{i,j} \leq k \ \forall i$ \quad $[\beta_i]$
- $\sum_{i=1}^{N} c_{i,j} Z_{i,j} \leq B_j \ \forall j$ \quad $[\alpha_j]$
- $Z_{i,j} \leq mCPC_j W_{i,j} \ \forall i, j$ \quad $[\theta_{i,j}]$
- $W_{i,j}, Z_{i,j} \geq 0 \ \forall i, j$
- $W_{i,j} \leq 1 \ \forall i, j$ \quad $[\gamma_{i,j}]$
Relaxation

Dual Linear Programming Formulation

\[
\begin{align*}
\min & \sum_{i=1}^{N} k\beta_i + \sum_{j=1}^{M} B_j\alpha_j + \sum_{i,j} y_{i,j} \\
\text{s.t} & \quad \theta_{i,j} + c_{i,j}\alpha_j \geq c_{i,j} \quad \forall i,j \\
& \quad \beta_i - \theta_{i,j} m \text{CPC}_j + y_{i,j} \geq c_{i,j} p_{i,j} R_j \times r \quad \forall i \\
& \quad \alpha_j, \beta_i, \theta_{i,j}, y_{i,j} \geq 0 \quad \forall i,j
\end{align*}
\]
Proposition 3.1 (Solution Structure). There exists a dual optimal solution \( \{\alpha_j^*\}, \{\beta_j^*\}, \{q_{i,j}^*\} \) and \( \{y_{i,j}^*\} \) that will satisfy the following conditions:

- \( \alpha_j^* \in [0, 1] \quad \forall j \)
- \( \theta_{i,j}^* = (1 - \alpha_j^*) c_{i,j} \quad \forall i, j \)
- \( \beta_i^* = \max_{j}^{k+1} c_{i,j} \left( (1 - \alpha_j^*) m \text{CPC}_j + p_{i,j} R_j \times r \right) \quad \forall i, j \)
- \( y_{i,j}^* = \max (c_{i,j}, (1 - \alpha_j^*) m \text{CPC}_j + p_{i,j} R_j \times r) - \beta_i^* \) \quad \forall i, j

where \( \max^{k+1} \) means the \( k + 1 \)th largest value. Moreover, let

\[ s_{i,j} = c_{i,j} \left( (1 - \alpha_j^*) m \text{CPC}_j + p_{i,j} R_j \times r \right) \quad \forall i, j \]

If the top \( k \) scores are distinct for all query \( i \), there exists a primal optimal solution \( \{W_{i,j}^*\}, \{Z_{i,j}^*\} \), where \( W_{i,j} \in \{0, 1\} \) for all \( i, j \).
Relaxation

Optimal Solution Structure

Assume that the optimal solution $\alpha_j^*$’s are known, the following simple bidding and allocation rule will be used: set the bid for ad $j$ to be $mCPC_j$ for each query $i$, and rank the ads by the following score:

$$c_{i,j} \left( (1 - \alpha_j^*)mCPC_j + p_{i,j}R_j \right)$$

The advertisers with top $k$ ranking scores will be allocated for the ad slots. In the case of first price auction, each winner will pay their $mCPC$. In the case of the second price auction, each winner will pay the amount of money such that the its ranking score is equal to the second highest ranking score (below him), i.e.,

$$\max(0, \frac{c_{i,j+1}((1 - \alpha_{j+1}^*)mCPC_{j+1} + p_{i,j+1}R_{j+1} * r)}{c_{i,j} - p_{i,j}R_j * r}/1 - \alpha_j)$$
Relaxation

Optimal Solution Structure

We do not know $\alpha_j^*$ a-priori.

Need to solve LP offline. Very expensive.
Relaxation

Optimal Solution Structure

Use Adaptive Control to estimate $\alpha_j^*$'s.

Throughout a day's auction, we set a few checkpoints to update $\alpha_j$'s. Let $N_0 = 0 < N_1 < N_2 < \cdots < N_T$ be the checking points, and define:

$$S_j(t) = \sum_{i=0}^{N_t} B_{i,j} \mathbb{I}[\text{clicked} == 1]$$

$S_j(t)$ is the actual spending of advertiser $j$ between 0 and $N_t$ search queries/impressions. Let $B_j(t)$ be the planned spending budget between 0 and $N_t$ search queries. The updating formula for $\alpha$ is:

$$\alpha_j(0) = \alpha_0$$

$$\alpha_j(t + 1) = \max(\alpha_j(t) \exp(\gamma \left(\frac{S_j(t)}{B_j(t)} - 1\right), 1) \quad (7)$$
Relaxation

Algorithm I without Performance Constraints

Data: Ads budget, maximal CPC \( \{\alpha_0\} \), \( \gamma \), checkpoints.

while not the end of day do
  current query = \( q_1 \);
  for advertiser \( j = 1 \ldots M \) do
    predict \( c_{i,j}, p_{i,j} \) for all ad campaigns using pre-trained click and purchase model;
    set \( b_{i,j} = \min(mCPC_j, \text{remaining budget}) \);
    compute ranking score:
      \[
      s_{i,j} = c_{i,j}((1 - \alpha_j)b_{i,j} + r \cdot p_{i,j}R_j);
      \]
  end
  determine the actual CPC for winners;
  update the remaining budget for winners depending on user actions(click);
  if time is a checkpoint then
    update \( \alpha_j \) using eq (7) for all advertisers;
  end
end

Algorithm 1: The Bidding and Ranking Algorithm for the Simple model Without Performance Constraints
Summary

1. Joint Revenue Optimization
   Non-Convex

2. Relaxation

3. Dual

4. Adaptive Control
Experiments
Experiments

Data

• Log
  2 weeks of search logs with timestamps and queries

• Ads
  id, description, price, historical clicks, purchase information and

• Auction
  budget, predicted CTR, bid, max bid, pacing factor

• Label
  clicks and purchase
Experiments

CTR and CVR

• Logistic Regression

• Features
  word2vec, historical features, ...
Experiments

Simulation Setup

- For each query, we rank promoted listings for 8 slots, treating the first 4 slots winning.

<table>
<thead>
<tr>
<th>Category</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Click</td>
<td>$\sum_{i,j} c_{i,j} W_{i,j} \geq G_{\text{click}} N$</td>
</tr>
<tr>
<td>Dual</td>
<td>Ranking function $\theta_c = \left(1 - \alpha_j\right)mCPC_j + \theta_c + p_{i,j}R_j r$</td>
</tr>
</tbody>
</table>

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<tr>
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<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP</td>
<td>$\sum_{i,j} c_{i,j} W_{i,j} p_{i,j} R_j \times r \geq G_p$</td>
</tr>
<tr>
<td>Dual</td>
<td>Ranking function $\theta_p = \left(1 - \alpha_j\right)mCPC_j + p_{i,j}R_j (r + \theta_p)$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Category</th>
<th>Constraints</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROI</td>
<td>$\sum_{i,j} c_{i,j} W_{i,j} p_{i,j} R_j \times (1 - r) \geq G_r (\sum_{i,j} c_{i,j} Z_{i,j})$</td>
</tr>
<tr>
<td>Dual</td>
<td>Ranking function $\theta_r = \left(1 - \alpha_j - \frac{G_r}{1 - \theta_r} \theta_r\right)mCPC_j + p_{i,j}R_j (\theta_r + r)$</td>
</tr>
</tbody>
</table>

Table 1: Constraints and Ranking functions
Experiments

Evaluation Metrics

\[
eCPC = \frac{\text{total bidding cost}}{\text{total number of clicks}}
\]

\[
RP = \frac{\text{total purchase revenue}}{\text{total number of purchases}}
\]

\[
CR = \frac{\text{total bidding revenue}}{\text{total first price revenue}}
\]

\[
ROI = \frac{\text{total purchase revenue}}{\text{total bidding cost}}
\]

\[
\text{change of percentage} = \frac{\text{metric}_{\text{proposed}} - \text{metric}_{\text{current}}}{\text{metric}_{\text{current}}}
\]
Experiments

Logged Budget

Figure 1: Comparison Between Current Model and Proposed Model: Revenue and ROI
Experiments

Logged Budget

Figure 2: Comparison Between Current Model and Proposed Model: RP and CR
Experiments

Varying Click Penalty

Figure 3: Varying Click Penalty
Experiments

Varying Shared Revenue Percentage

Figure 4: Varying Shared Revenue Percentage
Experiments

Tight Budget

**Budget Ratio 0.8:** We modified the budget for each advertiser to be $0.8 \cdot \max(\text{actual spending}, \text{mCPC})$, where \text{actual spending} is the amount of money that has been spent by that advertiser under the current system with logged budget, and \text{mCPC} is the max bid it is willing to pay (same as the first set of experiments). The adaptive updating rule of $\alpha$ is designed based on the discrepancy between the planned budget and actual spending. Intuitively, we want the planned budget guided the actual spending throughout the day. To verify this hypothesis, we compared three types of planned budget spending $\{B_j(t)\}$:

- **uniform:** $B_j(t) = \frac{t}{T} \cdot B_j$. The budget spending is linear with respect to time.
- **convex:** $B_j(t) = (\frac{t}{T})^4 \cdot B_j$. The budget spending is convex with respect to time.
- **concave:** $B_j(t) = (\frac{t}{T})^{0.25} \cdot B_j$. The budget spending is concave with respect to time.
Experiments

Tight Budget

Figure 5: Budget Utilization for Multiple Clicked Advertisers
Conclusion
Conclusion

• Etsy is a three-party marketplace.

• Promoted Listing program needs multi-objective optimization.

• Proposed a joint-revenue optimization solution and demonstrated its relaxation.

• Simulation experiments shows that the proposed framework is effective.