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

Feb 9, 2018

Liangjie Hong
Head of Data Science, Etsy Inc.

Workshop on Two-sided Marketplace Optimization: Search, Pricing, Matching & Growth

Etsy

Etsy – A Global Marketplace

Artifact Bags
Omaha, NE
Photo by: Dana Damewood and Jackie Sterba

Clap Clap
Los Angeles, CA
Photo by: Bert Youn and Mimi Kim

redravenstudios
Pittsburgh, PA
Photo by: Janelle Bendycki

Little Hero Capes
Somerset, MA
Photo by: Rich Vintage Photography

Cattails Woodwork
Hermitage, PE, Canada
Photo by: Cattails Woodwork

Room for Emptiness
Berlin, Germany
Photo by: Room for Emptiness

sukrachand
Brooklyn, NY
Photo by: sukrachand

Nicole Porter Design
Saint Paul, MN
Photo by: Nicole Porter Design

noemiah
Montreal, QC, Canada
Photo by: noemiah

Lorgie
Fremantle, WA, Australia
Photo by: Lorgie

Jeremiah Collection
San Francisco, CA
Photo by: Matthew Reamer

Docksmith
Brunswick, ME
Photo by: Docksmith

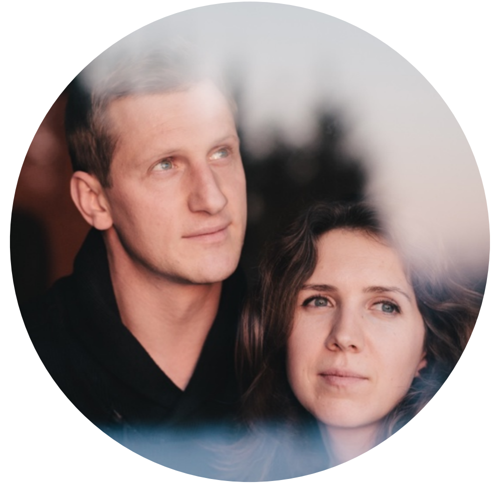
purlBKnit
Brooklyn, NY
Photo by: purlBKnit

Julia Astreou
Nicosia, Cyprus
Photo by: Panagiotis Mina

Moira K. Lime
Omaha, NE
Photo by: Moira K. Lime

Nested Yellow
Portland, OR
Photo by: Jessica Dremov and Nested Yellow

Habitables
Madrid, Spain
Photo by: Habitables



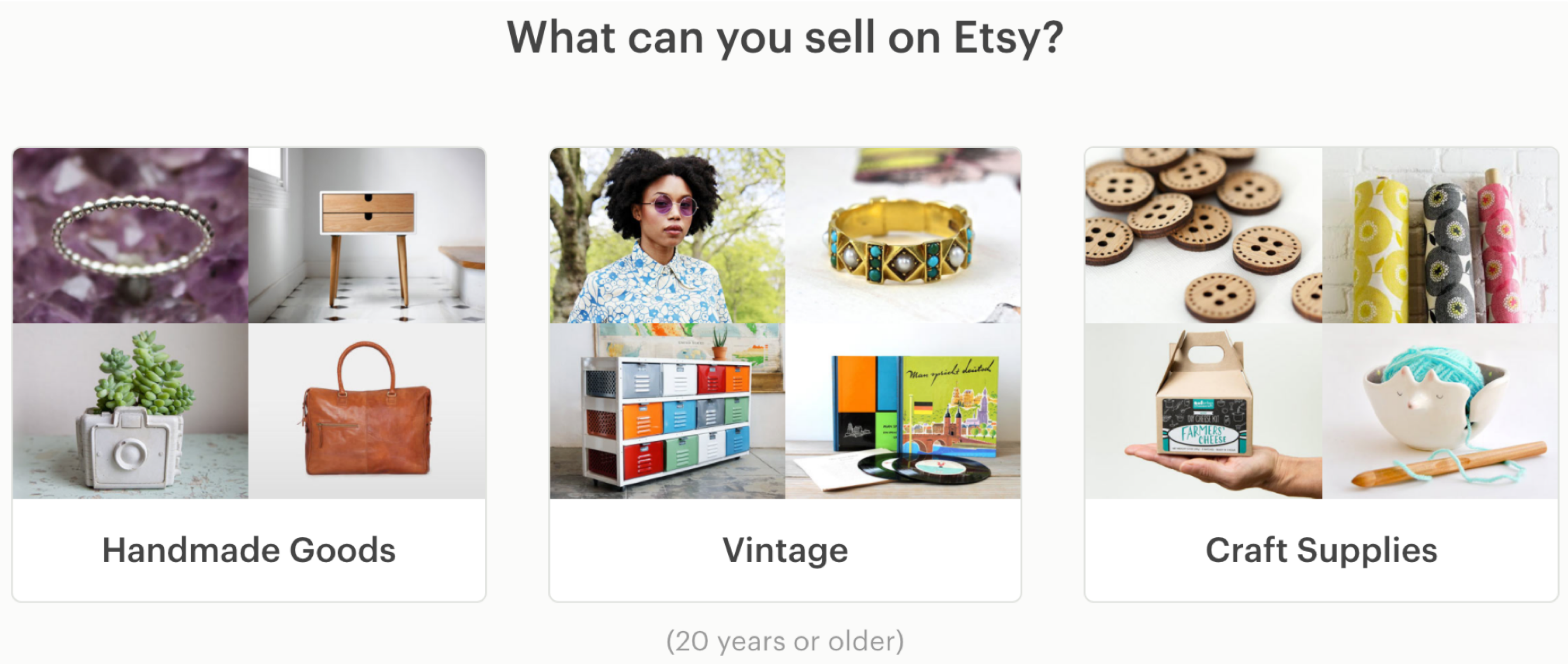
Woodstorming
Kaunas, Lithuania
Photo by: Ilona & Martynas from Instudija

karoArt
Dublin, Ireland
Photo by: Christine Burns

ADIKILAV
Jerusalem, Israel
Photo by: Shlomit Koslowe

My A La Mode Boutique
Ecuador
Photo by: My A La Mode Boutique

Etsy – A Global Marketplace



By The Numbers

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

Work and Culture

852
employees around the world
AS OF MARCH 31, 2016

9
offices in 7 countries
AS OF MARCH 31, 2016

54%
female employees

46%
male employees
AS OF DECEMBER 31, 2015

Photo by Emily Andrews

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


Photo by Moira K. Lime

Passionate and Loyal Business Owners

30%

focus on their creative businesses as their sole occupation

2014 ETSY SELLER SURVEY

65%

started their Etsy shop as a way to supplement income

2014 ETSY SELLER SURVEY

79%

started their Easy shop as an outlet for creativity

2014 ETSY SELLER SURVEY

Photo by Panagiotis Mina

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

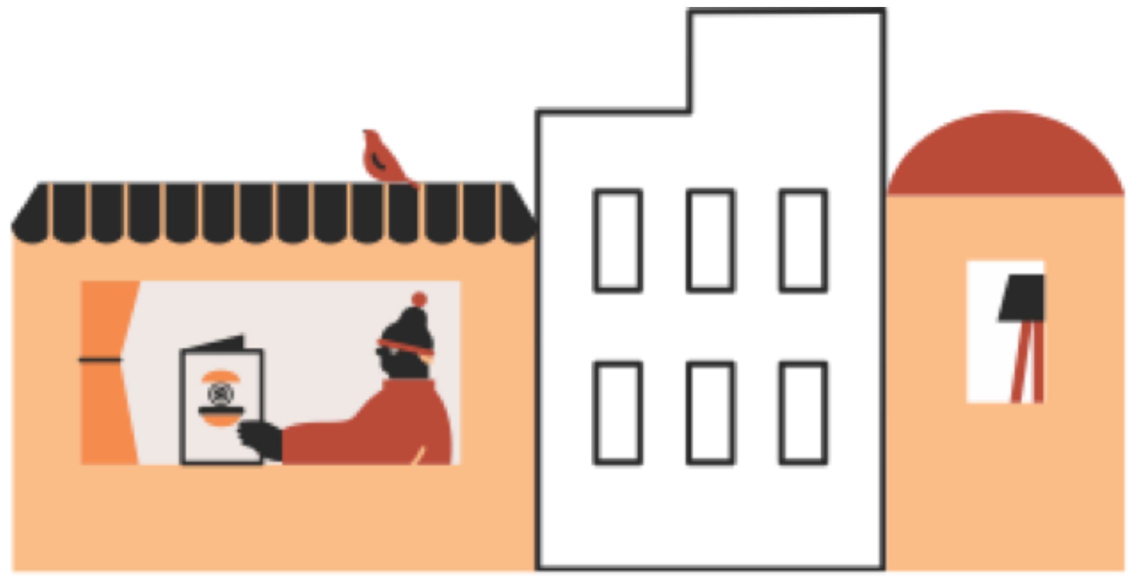
- How to choose unique and satisfied products among millions?
  How to lead and guide buyers to discover products that they wouldn't buy at the first place?
  How to recommend appropriate products for different occasions?

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?



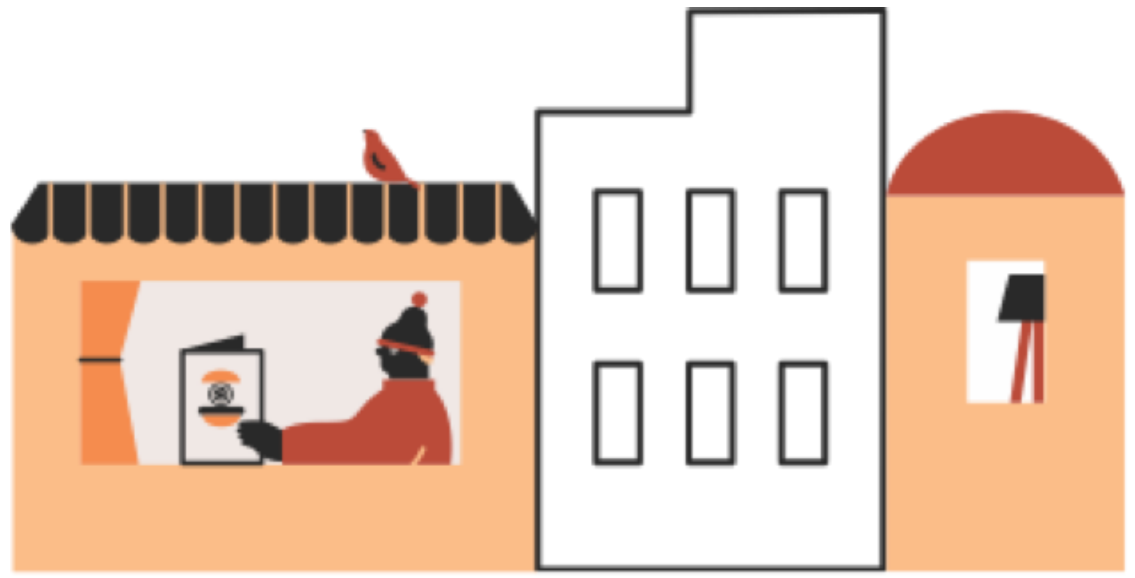
AI in E-commerce

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



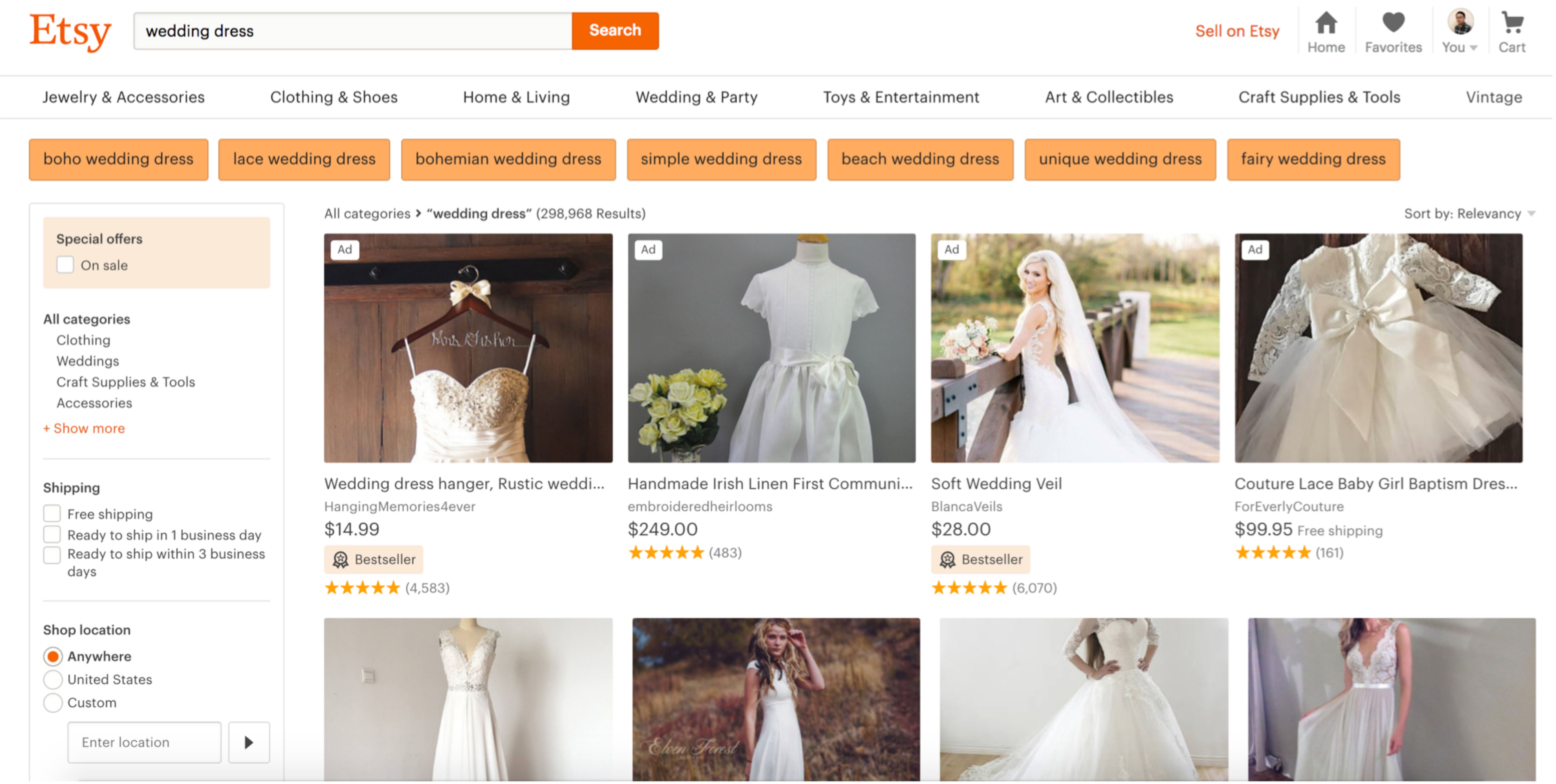
AI in E-commerce

AI in E-commerce at Etsy

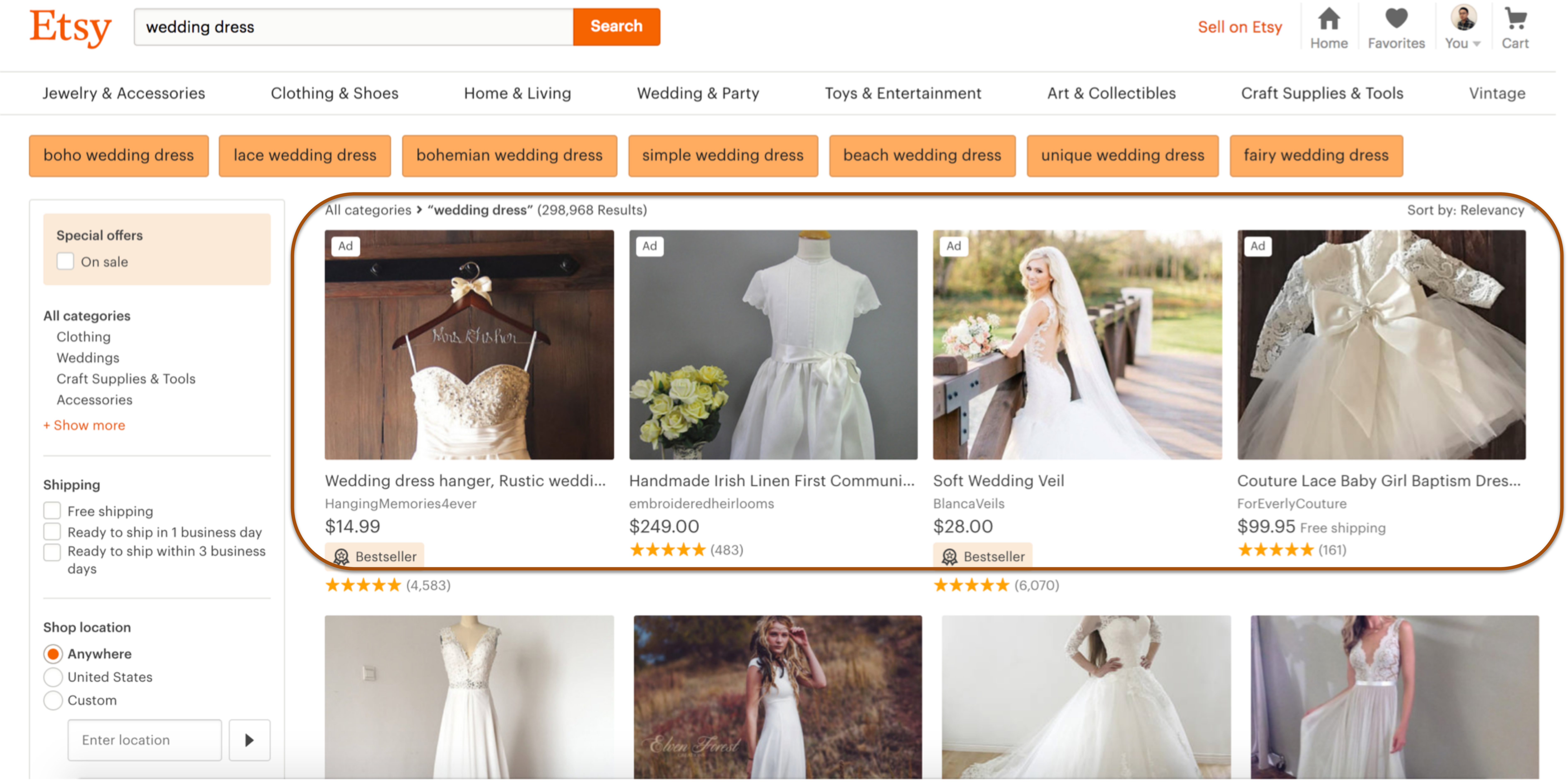
- Multi-modal Deep-learning based Search Solution (KDD 2016)
- Probabilistic Graphical Model based Personalization Recommendation (KDD 2014)
- Ensemble Learning based CTR Prediction Solution (AdKDD 2017/KDD 2017)
- Buzzsaw: A System for High Speed Feature Engineering (SysML 2018)

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

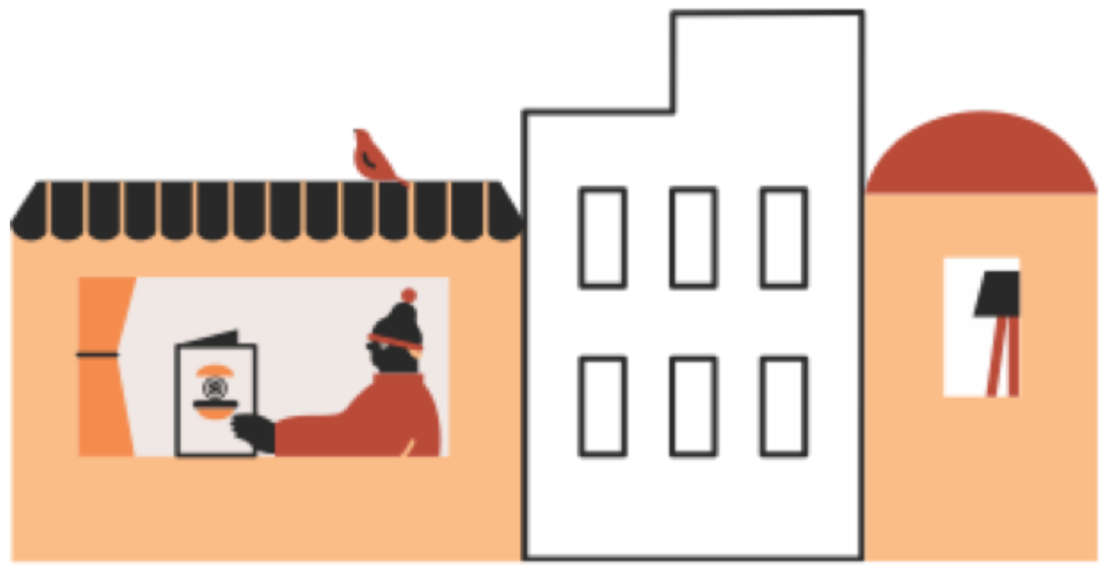
- Specify a campaign with listings
- Specify daily budget (maximum you want to spend daily)

- 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

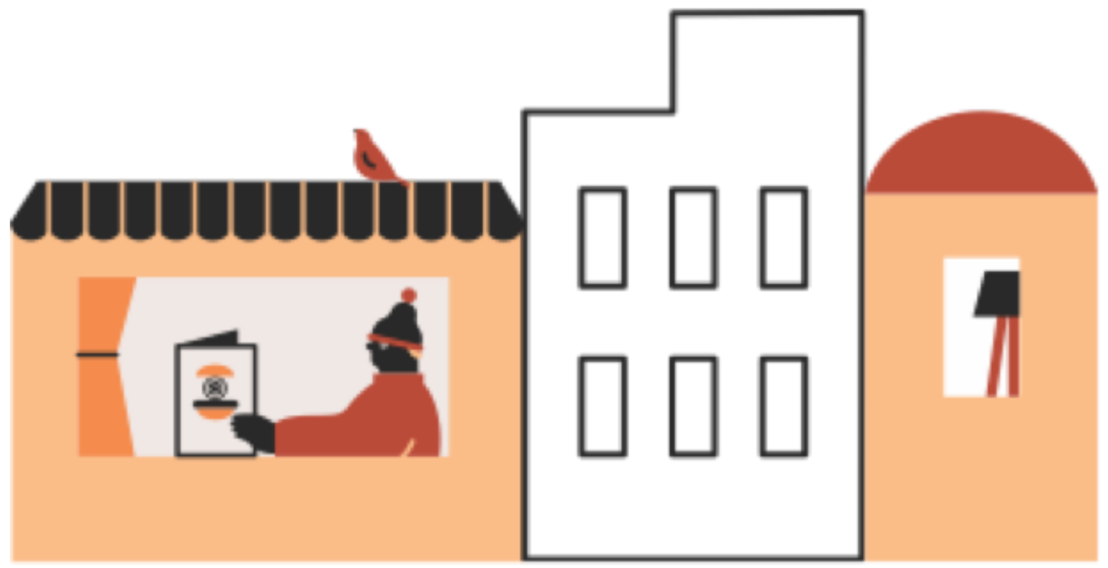


Promoted Listings at Etsy

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

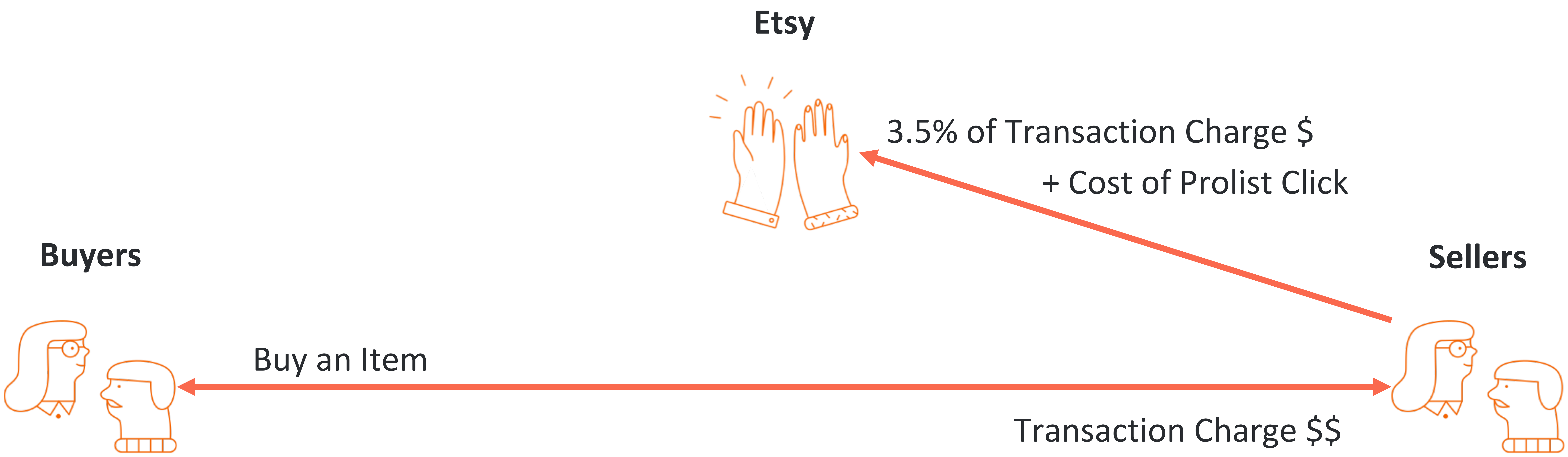


Promoted Listings at Etsy

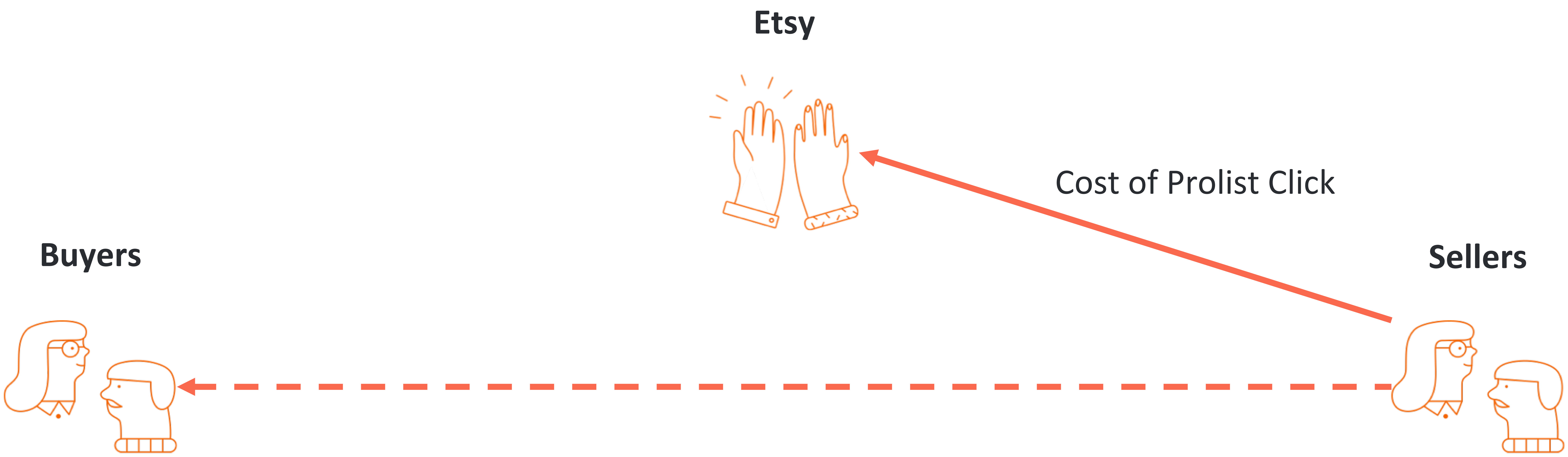
For Etsy

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

Promoted Listings at Etsy



Promoted Listings at Etsy



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

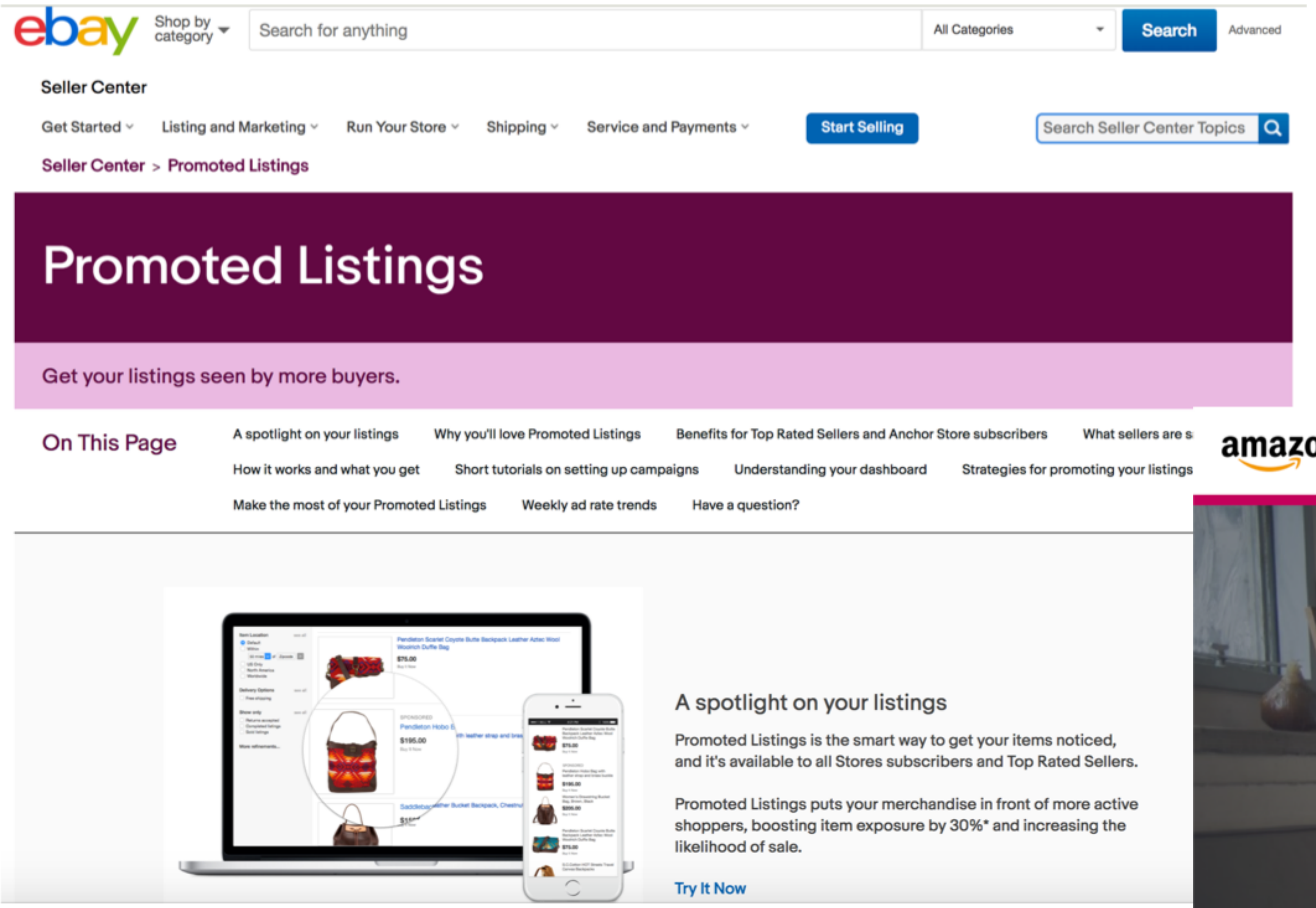
Etsy

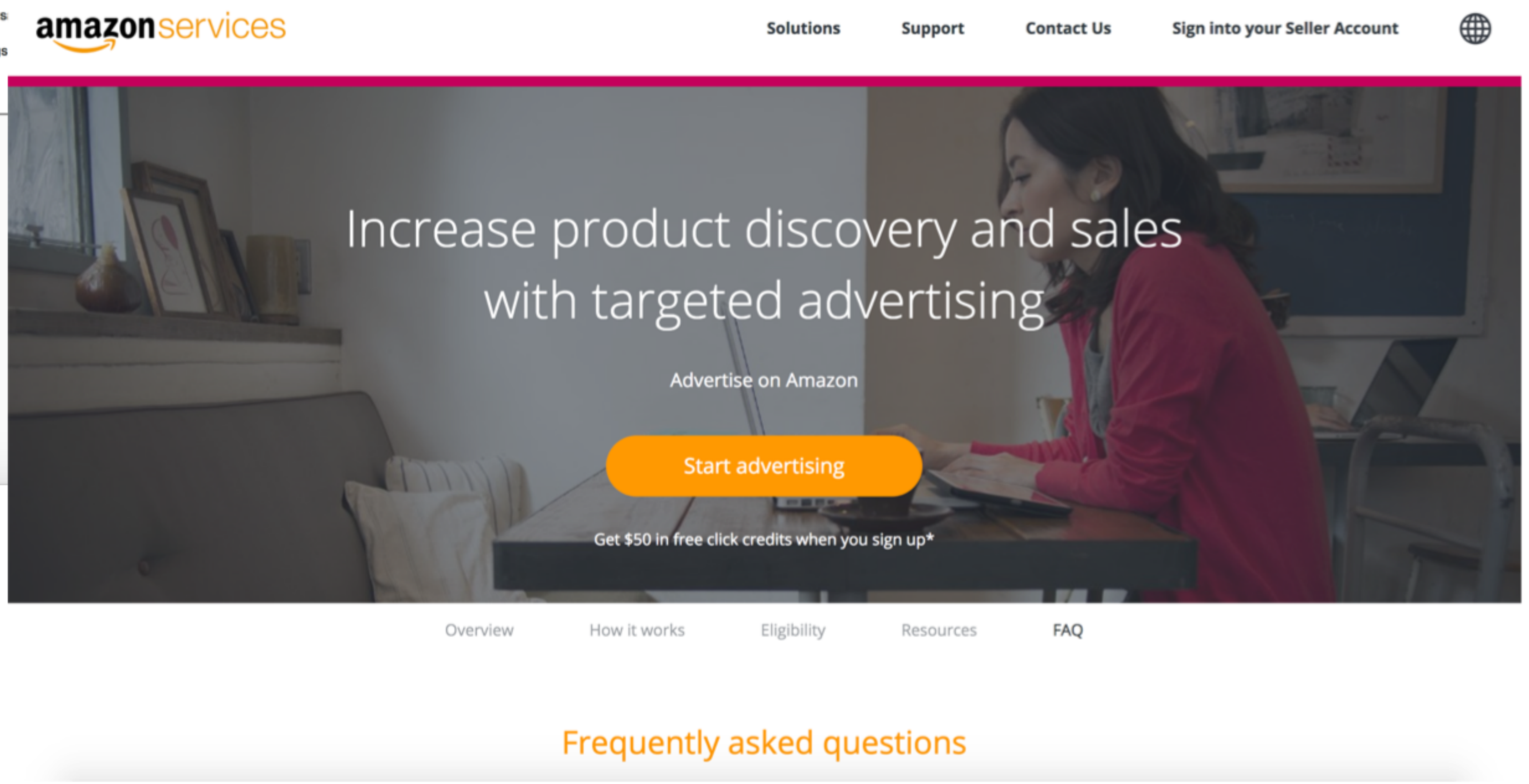
- Increased both Promoted Listing's revenue

Buyers

- Not finding most relevant/interesting item to purchase

Other Promoted Listings



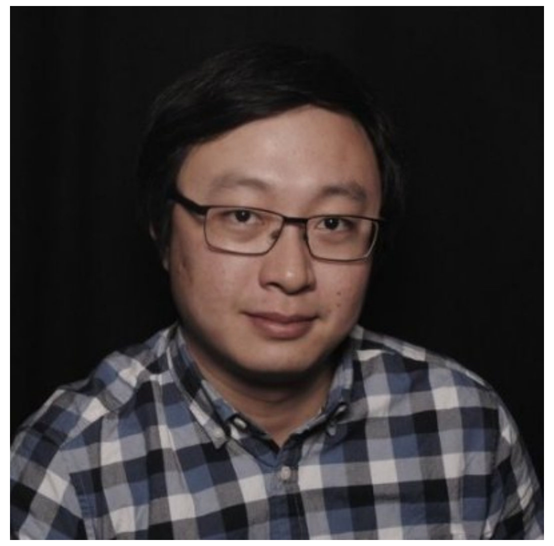


Joint Revenue Optimization

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

$$\underbrace{\boxed{c_{i,j}} \times \boxed{B_{i,j}}}_{\text{expected bidding}} + \underbrace{c_{i,j} \times \boxed{p_{i,j}} \times \boxed{R_j} \times \boxed{r}}_{\text{expected shared purchase}}$$

Click-Through-Rate **Bid** **Conversion-Rate** **Sales Revenue** **Shared Revenue**

Joint Revenue Optimization

Main Constraints

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

allocation constraint

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

budget constraint:

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

bidding constraint:

$$B_{i,j} \leq mCPC_j \ \ \forall i, j$$

Joint Revenue Optimization

Main Constraints

$W_{i,j}$, indicates whether seller a_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:

  $$\sum_{i=1}^{N}\sum_{j=1}^{M} W_{i,j}c_{i,j}p_{i,j}R_j \geq G_{\text{attribution}}$$

  where $G_{\text{attribution}} \in \mathbb{R}^+$ 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:

  $$\sum_{i=1}^{N}\sum_{j=1}^{M} W_{i,j}c_{i,j}p_{i,j}R_j \cdot (1-r) \geq G_{ROI}\sum_{i=1}^{N}\sum_{j=1}^{N} W_{i,j}c_{i,j}B_{i,j}$$

  where the left hand side is the expected revenue obtained by an advertiser, the right hand side is its expected spending and $G_{ROI} > 0$ 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

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

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]

Relaxation

Relaxed Objective

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

$$
\begin{aligned}
\max \quad & \sum_{i=1}^{N}\sum_{j=1}^{M} c_{i,j}Z_{i,j} + c_{i,j}p_{i,j}W_{i,j}R_j \times r \\
\text{s.t} \quad & \sum_{j=1}^{M} W_{i,j} \le k \ \ \forall i && [\beta_i] \\
& \sum_{i=1}^{N} c_{i,j}Z_{i,j} \le B_j \ \ \forall j && [\alpha_j] \\
& Z_{i,j} \le mCPC_j W_{i,j} \ \ \forall i,j && [\theta_{i,j}] \\
& W_{i,j}, Z_{i,j} \ge 0 \ \ \forall i,j \\
& W_{i,j} \le 1 \ \ \forall i,j && [\gamma_{i,j}]
\end{aligned}
$$

Linear-Programming Problem

Relaxation

Dual Linear Programming Formulation

$$
\begin{aligned}
\min\ & \sum_{i=1}^{N} k\beta_i + \sum_{j=1}^{M} B_j\alpha_j + \sum_{i,j} \gamma_{i,j} \\
\text{s.t}\ & \theta_{i,j} + c_{i,j}\alpha_j \geq c_{i,j} \quad \forall i,j & [Z_{i,j}] \\
& \beta_i - \theta_{i,j} mCPC_j + \gamma_{i,j} \geq c_{i,j} p_{i,j} R_j \times r \quad \forall i & [W_{i,j}] \\
& \alpha_j, \beta_i, \theta_{i,j}, \gamma_{i,j} \geq 0 \quad \forall i,j
\end{aligned}
$$

Relaxation

Optimal Solution Structure

PROPOSITION 3.1 (SOLUTION STRUCTURE). *There exists a dual optimal solution* $\{\alpha_i^*\}$, $\{\beta_j^*\}$, $\{\theta_{i,j}^*\}$*s' and* $\{\gamma_{i,j}^*\}$*s' that will satisfy the following conditions:*

- $\alpha_j^* \in [0, 1] \quad \forall j$
- $\theta_{i,j}^* = (1 - \alpha_j^*)c_{i,j} \quad \forall i, j$
- $\beta_i^* = \max_j^{k+1} c_{i,j}\Big((1 - \alpha_j^*)mCPC_j + p_{i,j}R_j \times r\Big) \quad \forall i, j$
- $\gamma_{i,j}^* = \max(c_{i,j}\Big((1 - \alpha_j^*)mCPC_j + p_{i,j}R_j \times r\Big) - \beta_i^*, 0)$

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

$$s_{i,j} = c_{i,j}((1 - \alpha_j^*)mCPC_j + p_{i,j}R_j \times r) \quad \forall i, j$$

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 α_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:

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

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 α_j^*s a-priori.

Need to solve LP offline. Very expensive.

Relaxation

Optimal Solution Structure

Use Adaptive Control to estimate α_j^*s .

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

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

$S_j(t)$ 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 α is:

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

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

Relaxation

Algorithm I without Performance Constraints

```
Data: Ads budget, maximal CPC
{α_0}, γ, checkpoints ;
while not the end of day do
    current query = q_i;
    for advertiser j = 1...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, remaining budget);
        compute ranking score:
          s_{i,j} = c_{i,j}((1 − α_j)b_{i,j} + r ∗ 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 check point then
        update α_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.

Category	**Constraints**
Click	$\sum_{i,j} c_{i,j} W_{i,j} \geq G_{\text{click}} N$
Dual	**Ranking function**
θ_c	$c_{i,j}\Big((1-\alpha_j)mCPC_j + \theta_c + p_{i,j}R_j r\Big)$
Category	**Constraints**
SP	$\sum_{i,j} c_{i,j} W_{i,j} p_{i,j} R_j \times r \geq G_p$
Dual	**Ranking function**
θ_p	$c_{i,j}\Big((1-\alpha_j)mCPC_j + p_{i,j}R_j(r+\theta_p)\Big)$
Category	**Constraints**
ROI	$\sum_{i,j} c_{i,j} W_{i,j} p_{i,j} R_j \times (1-r) \geq G_r(\sum_{i,j} c_{i,j} Z_{i,j})$
Dual	**Ranking function**
θ_r	$c_{i,j}\Big((1-\alpha_j - \frac{G_r}{1-r}\theta_r)mCPC_j + p_{i,j}R_j(\theta_r + r)\Big)$

Table 1: Constraints and Ranking functions

Experiments

Evaluation Metrics

$$\mathrm{eCPC} = \frac{\text{total bidding cost}}{\text{total number of clicks}}$$

$$\mathrm{RP} = \frac{\text{total purchase revenue}}{\text{total number of purchases}}$$

$$\mathrm{CR} = \frac{\text{total bidding revenue}}{\text{total first price revenue}}$$

$$\mathrm{ROI} = \frac{\text{total purchase revenue}}{\text{total bidding cost}}$$

$$\text{change of percentage} = \frac{\text{metric}_{\text{proposed}} - \text{metric}_{\text{current}}}{\text{metric}_{\text{current}}}$$

Experiments

Logged Budget

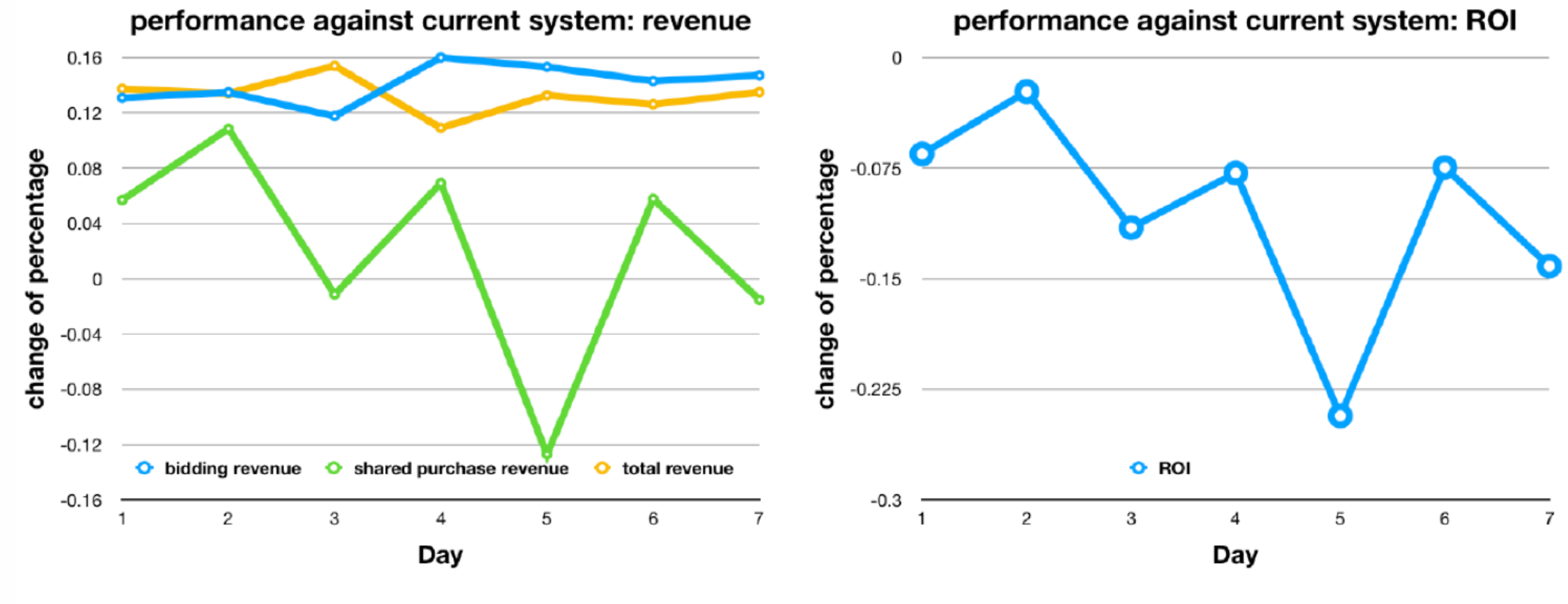


Figure 1: Comparison Between Current Model and Proposed Model: Revenue and ROI

Experiments

Logged Budget

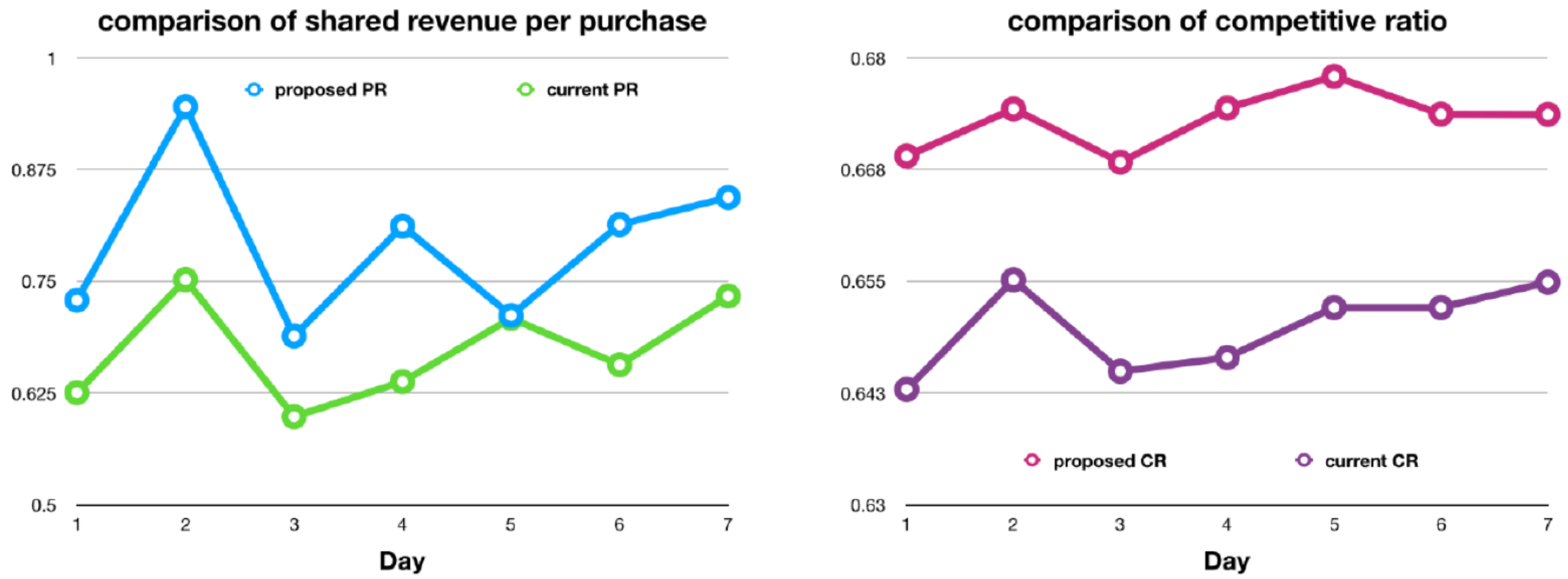


Figure 2: Comparison Between Current Model and Proposed Model: RP **and** CR

Experiments

Varying Click Penalty

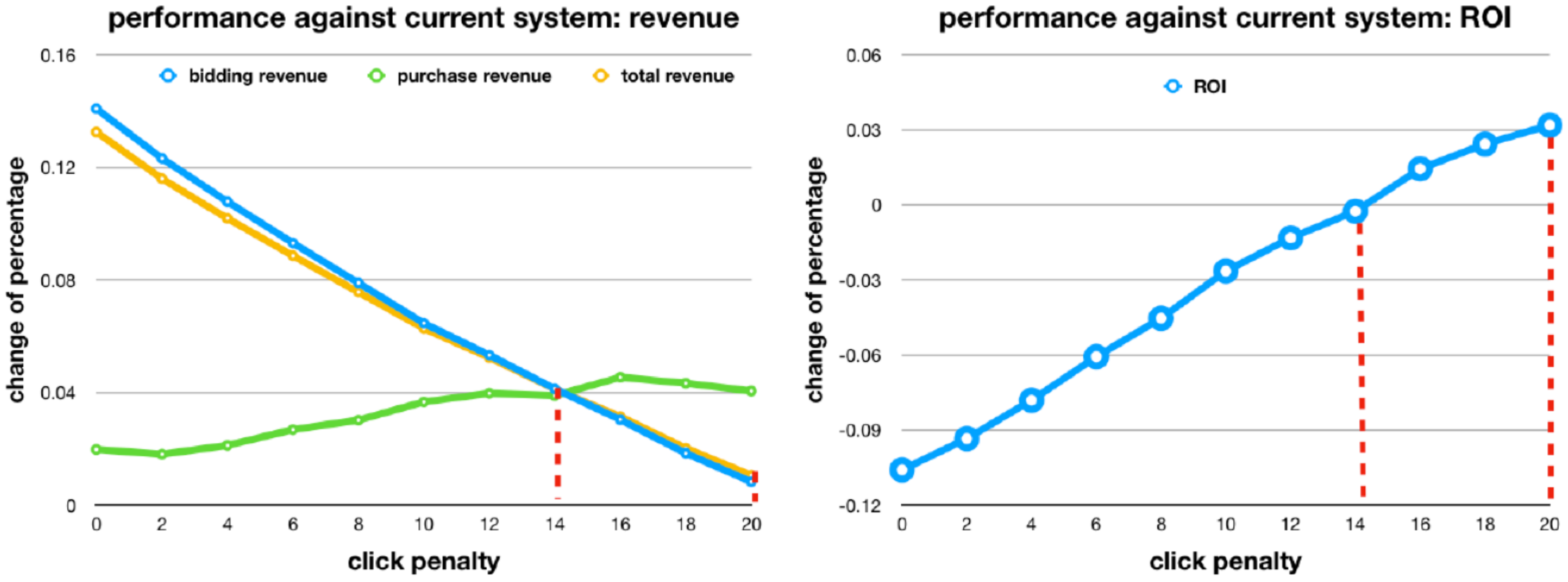


Figure 3: Varying Click Penalty

Experiments

Varying Shared Revenue Percentage

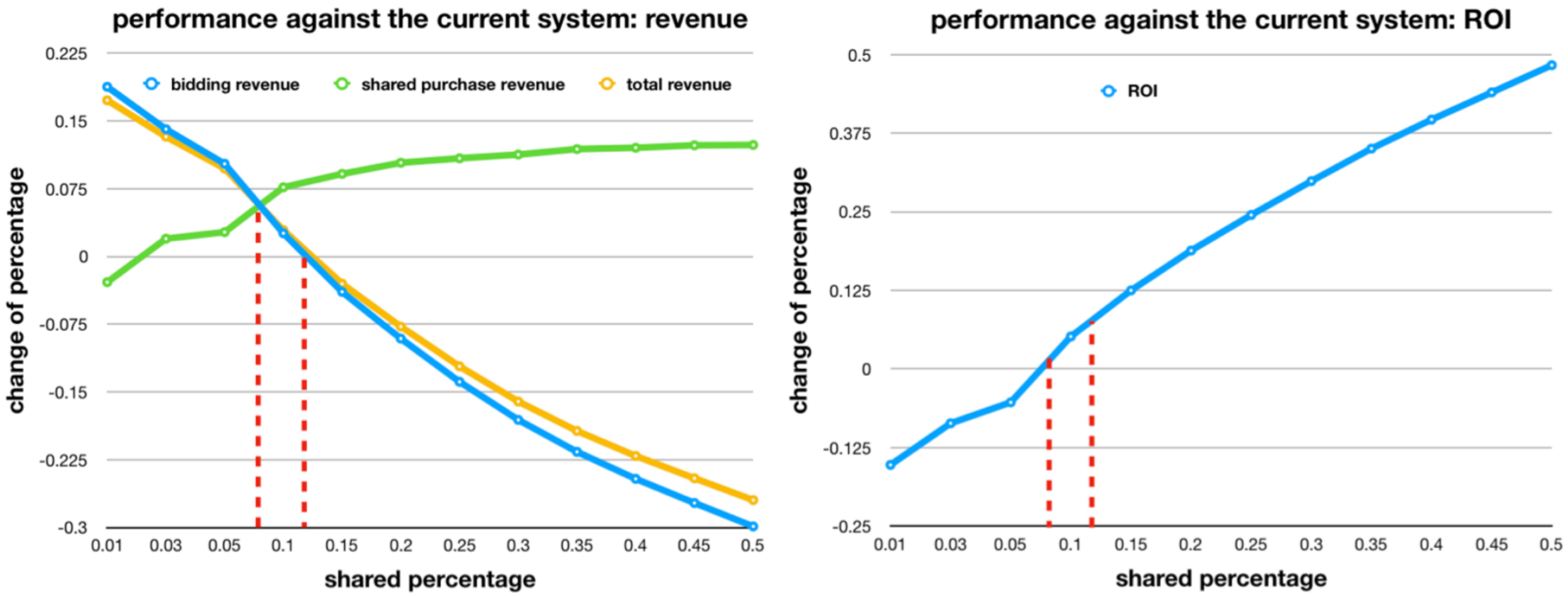


Figure 4: Varying Shared Revenue Percentage

Experiments

Tight Budget

Budget Ratio 0.8: We modified the budget for each advertiser to be $0.8 * \max(\texttt{actualspending}, \texttt{mCPC})$, where `actualspending` is the amount of money that has been spent by that advertiser under the current system with logged budget, and `mCPC` is the max bid it is willing to pay (same as the first set of experiments). The adaptive updating rule of α 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 three types of planned budget spending $\{B_j(t)\}$:

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

Experiments

Tight Budget

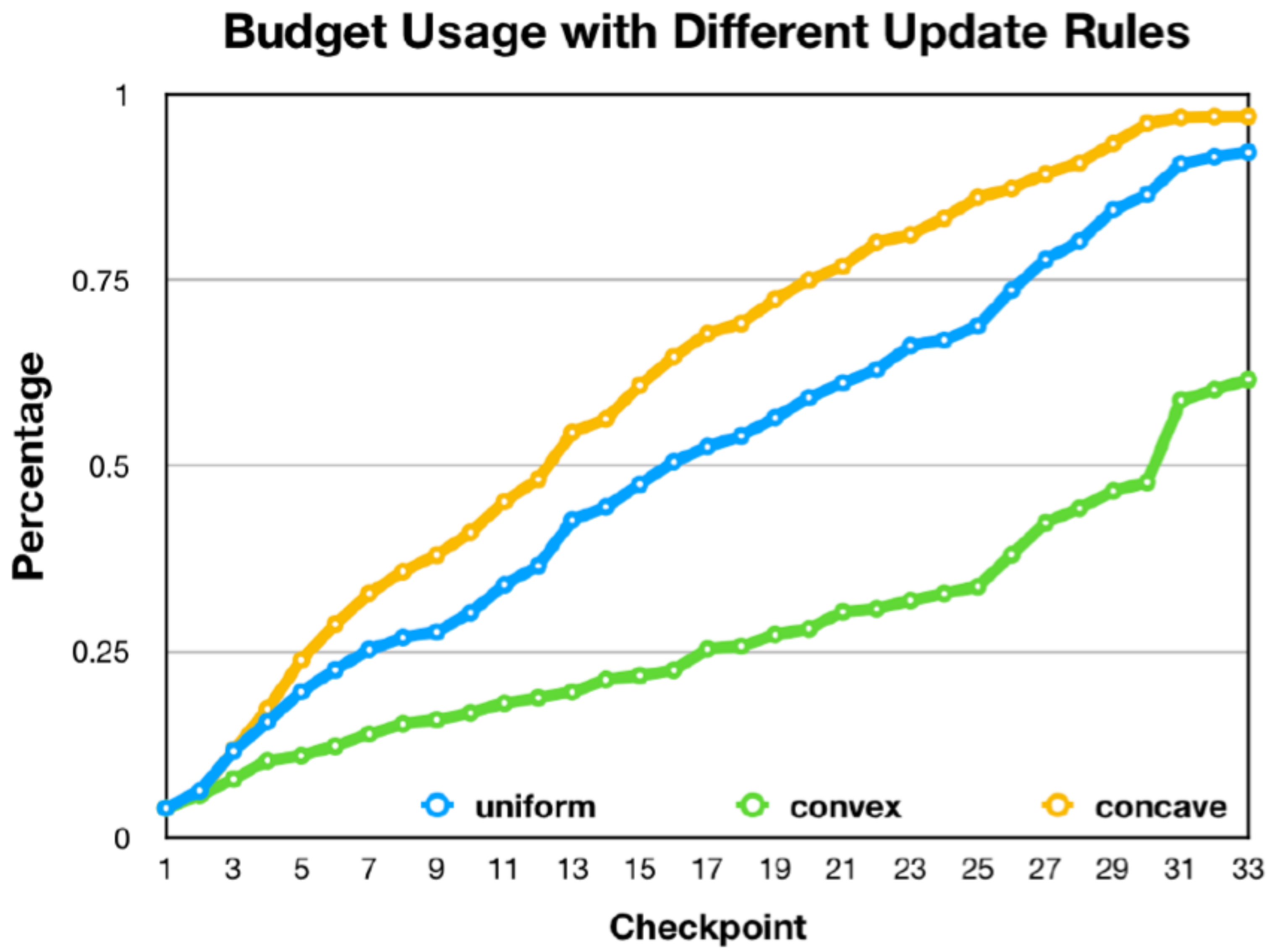


Figure 5: Budget Utilization for Multiple Clicked Advertisers

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.

Questions?