Matching Ads to Users: Performance analysis of an Advertising Search Engine

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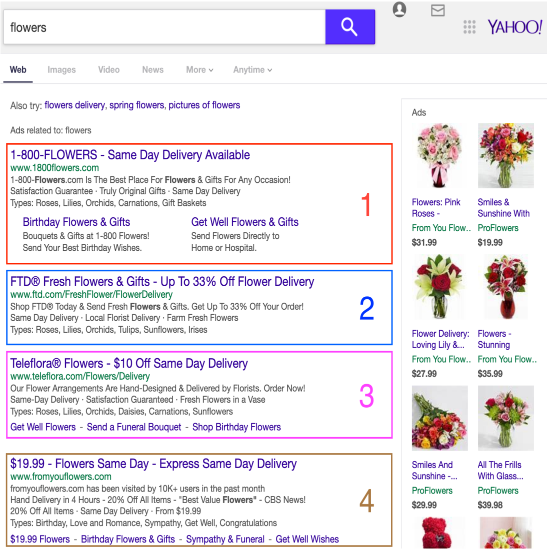
Introduction:



- Sponsored Search Ads

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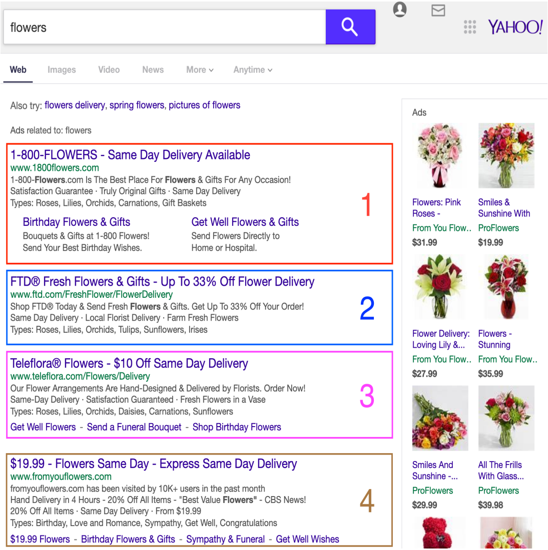

- Sponsored Search Ads

- Allocation Rule (GSP)
  - Users
  - Advertisers

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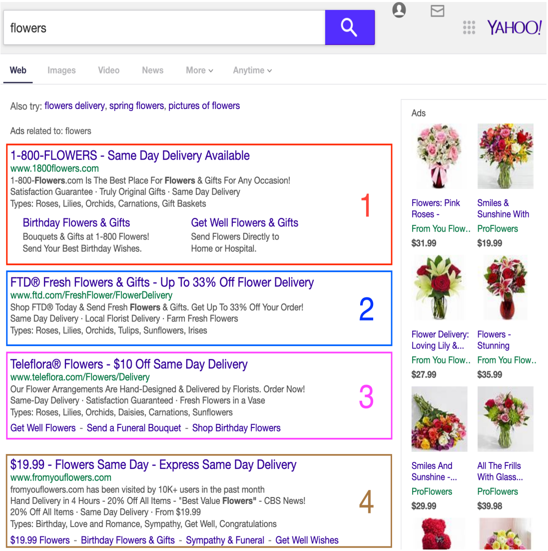

- Sponsored Search Ads
- Allocation Rule (GSP)
  - Users
  - Advertisers
- Different rules impact
  - User engagement
  - Short vs long-term revenue

Introduction

- Objectives & Contributions:
  - Study the bias of Yahoo's search engine towards (at scale):
    - Allocation maximizing users' welfare
    - Allocation maximizing value-per-click of advertisers
  - Relationship between users' perceived ad quality and value-per-click of advertisers

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- Problem: Marketplace researchers do not observe:
  - Long-term impact of different allocation rules (tempting rules)
  - Value-per-click of advertisers (allocation rule is not truthful)
  - Perceived quality of ads by users (ad-quality and position effect)

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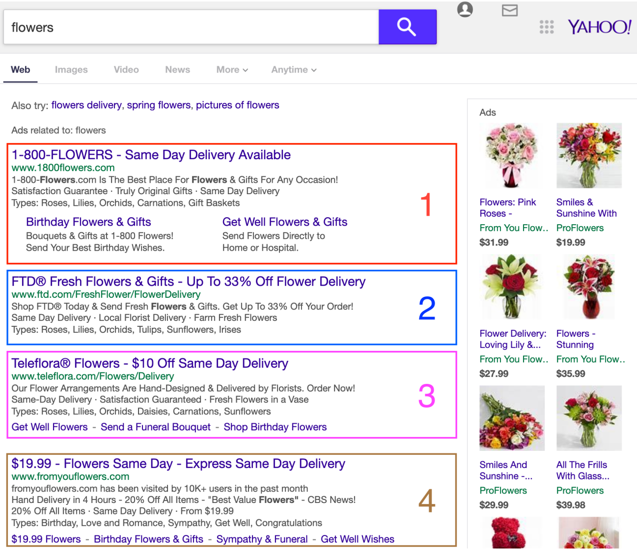
  - Perceived quality of ads by users (ad-quality and position effect)
- Data:
  - Yahoo's search engine (2017)
    - Production logs
    - Experiment (Identification)
  - Displayed Queries: "cheap flight","map","game","United Airlines","100 Popular Keywords"

Rest of the Presentation

- **Allocation & Pricing Rule: Generalized Second Price Auction**
- Inference of Value-per-Click of Advertisers
- Inference of Perceived Ad-Quality by Users
- How to compare sequences of ads: Optimal Matching
- Results
- Conclusions

Generalized Second Price Auction



Generalized Second Price Auction

Allocation Mechanism

- $\mathcal{J}$ advertising slots in the search results page (5 slots in desktop max)
- $\mathcal{I}$ advertisers $> \mathcal{J}$
- Each $i \in \mathcal{I}$ places a per click bid b_i on a single search Keyword
- Yahoo's search engine assigns a scoring factor to advertisers (s_i)
  - Click probability of ad i appearing in position 1 ($s_i = Pr_{i1}$)
  - Squashing factor ($s_i = Pr_{i1}^{\theta}$ where $\theta >= 0$)
  - Coarsening - less accurate estimator for "clickability" (e.g. no gender)

  different scoring rule may impact revenue and/or ranking
- Advertisers are ranked by their rank-score q_i

$$q_i = \underbrace{b_i}_{Advertiser} \times \underbrace{s_i}_{f(Clickability)}$$

Generalized Second Price Auction

Pricing Rule

- Advertiser i in position j only pays if user clicks
- Payment: Cost-per-click is the minimal bid i has to place to keep its position

$$c_{ij}(b) = \frac{s_{\pi(j+1)} \cdot b_{\pi(j+1)}}{s_i} \mathbb{1}[j \in \mathcal{J}]$$

where $\pi(j+1)$ denotes the advertiser that is located in position $j+1$

Generalized Second Price Auction

Example 1

$$q_i = s_i \times b_i$$

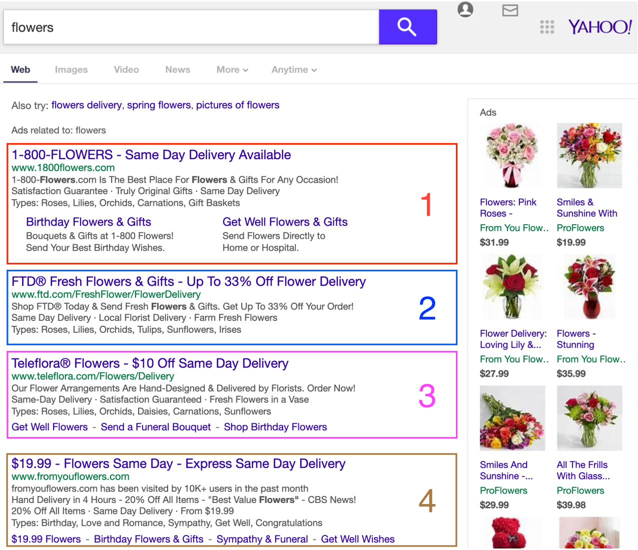
$$q_a = 0.07 \times 1$$

$$q_b = 0.05 \times 1$$

$$q_c = 0.025 \times 1$$

$$q_d = 0.01 \times 1$$

$$q_e = 0.001 \times 1$$



Generalized Second Price Auction

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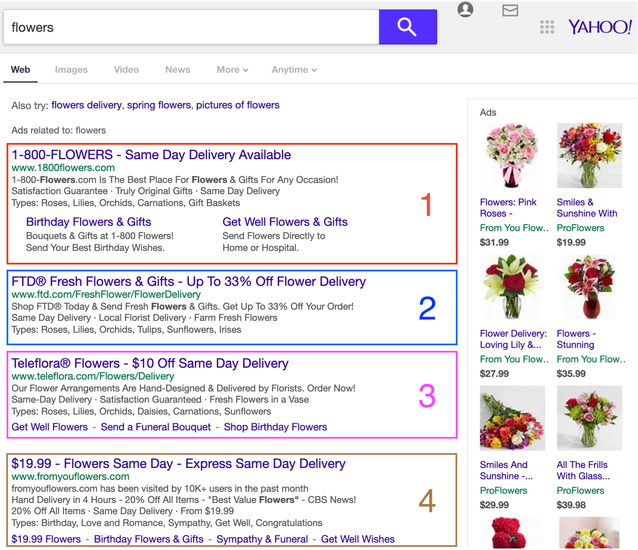


$q_a = 0.07 \times 1$

$c_{a,1} = \frac{0.05 \times 1}{0.07} = 0.7$

$q_b = 0.05 \times 1$

$c_{b,2} = \frac{0.025 \times 1}{0.05} = 0.5$

$q_c = 0.025 \times 1$

$c_{c,3} = \frac{0.01 \times 1}{0.025} = 0.4$

$q_d = 0.01 \times 1$

$c_{d,4} = \frac{0.001 \times 1}{0.01} = 0.1$

$q_e = 0.001 \times 1$

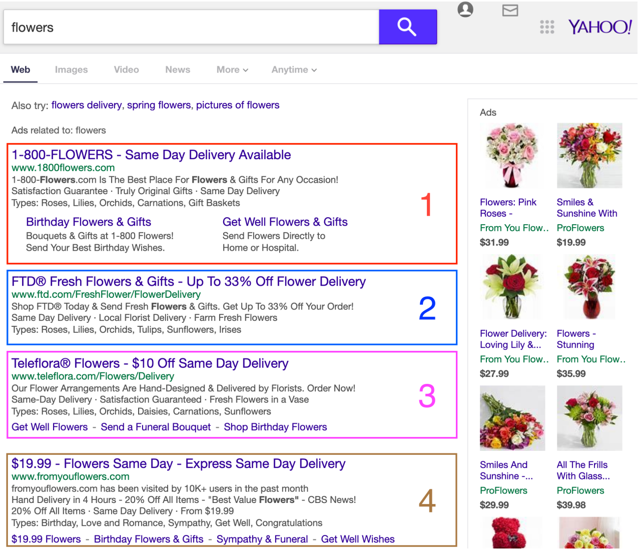
Generalized Second Price Auction

Example 2

$q_i = s_i \times b_i$

$q_a = 0.05 \times 2 = 0.10$

$q_b = 0.07 \times 1 = 0.07$



Generalized Second Price Auction

- Truth-telling is **NOT** a dominant strategy for advertisers

Generalized Second Price Auction

- Truth-telling is **NOT** a dominant strategy for advertisers
- Expected profit of bidder i

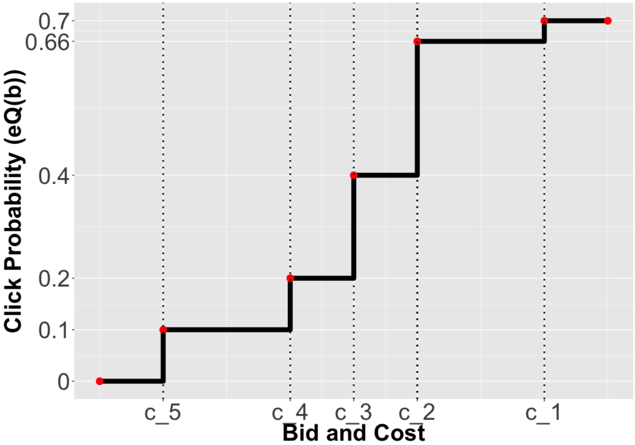
$$\pi_i(b; v_i) = (v_i - c_{i\sigma_i(b)}(b))eQ_i(b)$$

where

- v_i: Value-per-click of advertiser i (Unobserved)
- $c_{i\sigma_i(b)}(b)$: cost at position $\sigma_i(b)$
- $eQ_i(b)$: Allocation probability

Generalized Second Price Auction

Truth-telling is NOT a dominant strategy



$$c_1 >> c_2 \qquad 0.7 \approx 0.66$$

Generalized Second Price Auction

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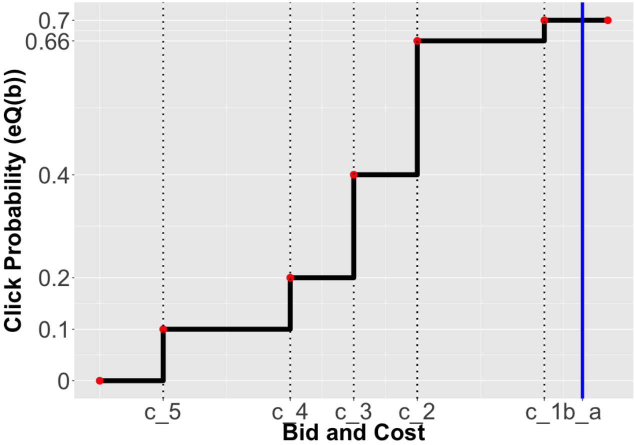
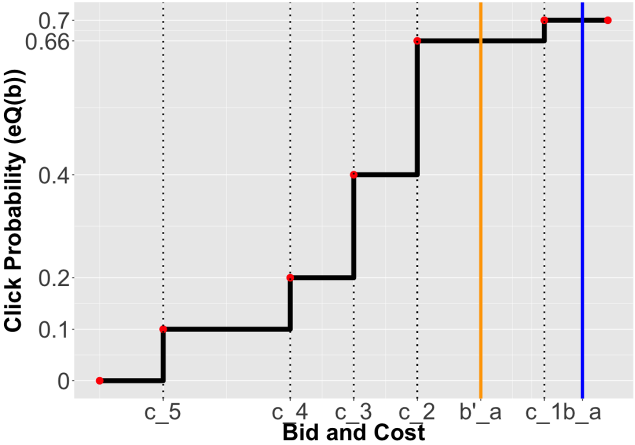


$$\pi_a(b_a; v_a) = (v_a - c_1(b))0.7$$

Generalized Second Price Auction

Truth-telling is NOT a dominant strategy



$$\pi_a(b_a'; v_a) = (v_a - c_2(b_a'))0.66$$

Generalized Second Price Auction

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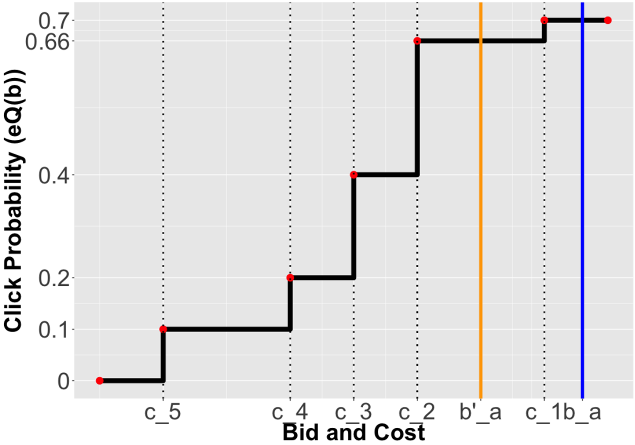

$$\pi_a(b_a'; v_a) = (v_a - c_2(b_a'))0.66 > \pi_a(b_a; v_a) = (v_a - c_1(b_a))0.7$$

- Allocation & Pricing Rule: Generalized Second Price Auction
- **Inference of Value-per-Click of Advertisers**
- Inference of Perceived Ad-Quality by Users
- How to compare sequences of ads: Optimal Matching
- Results
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Advertiser's Value-per-Click

- Truth-telling is **NOT** a dominant strategy $\Rightarrow$ Infer Value-per-click
- Infer advertisers' value-per-click using the concept of no-regret learning (Nekipelov, Syrgkanis, and Tardos (2015))
  - Experimenting with bids as off-equilibrium (market exploration)
  - Weaker assumptions than Nash equilibrium
  - Assume that bidders are learning over time the strategy that maximizes their expected profits

Advertiser's Value-per-Click

- We can express the expected utility of bidder i at t as

$$\pi_{it}(b_{it}, {\color{red} v_i}) = {\color{red} v_i} \quad \underbrace{eQ_{it}(b_{it})}_{\text{Click Probability}} \quad - \quad \underbrace{eC_{it}(b_{it})}_{ExpectedCost}$$

  where at each time t bidder i bids b_{it}

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- Rationalizable Set: A pair (ϵ_i, v_i) of value v_i an error ϵ_i is a rationalizable pair for player i if it satisfies the below equation.

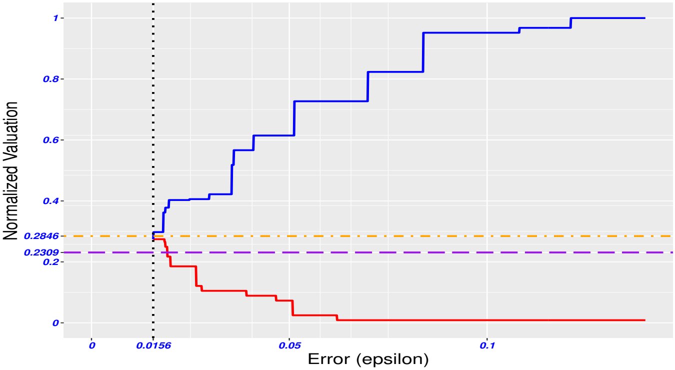
$$\forall b' \in \mathcal{B} : \frac{1}{T}\sum_{t=1}^{T}\pi_{it}(b_{it}, v_i) \geq \frac{1}{T}\sum_{t=1}^{T}\pi_{it}(b', v_i) - \epsilon_i$$

  where b' corresponds to a fixed bid from the bid sequence $\{b_{it}\}_{t=1}^{T}$
  Nash Equilibrium Condition $\rightarrow \epsilon_i = 0 \ \forall i$

Advertiser's Value-per-Click

- For any error ϵ, the set of values that belongs to the rationalizable set is

$$v_i \in \left[\max_{b' : \Delta eQ(b'_i) < 0} \frac{eC_{it}(b'_i) - eC_{it}(b_{it}) + \epsilon}{eQ_{it}(b'_i) - eQ_{it}(b_{it})}, \min_{b' : \Delta eQ(b'_i) > 0} \frac{eC_{it}(b'_i) - eC_{it}(b_{it}) + \epsilon}{eQ_{it}(b'_i) - eQ_{it}(b_{it})} \right]$$



- Value-per-click (v_i): the smallest rationalizable error ϵ can be viewed as a point prediction for the value of the advertiser

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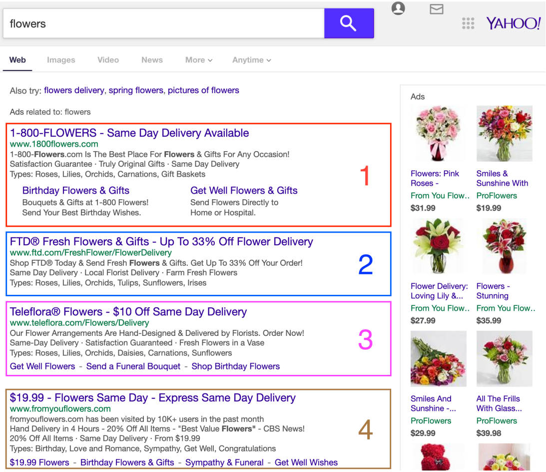
Users' Perceived Ad-Quality



- Disentangle ad effect from position effect
- The model accommodates multiple clicks and unobserved correlation across ads within the impression (Jiziorski and Segal (2015)).

Users' Perceived Ad-Quality

- Utility-maximizing model (allow counterfactuals)
- Assuming no-unobserved correlation among ads, the user's value of clicking on ad *a* located in position *n*

$$\mathcal{U}_{ian} = u_a(x) - f_n + \epsilon_i$$

  where
  - $u_a(x)$: Perceived utility of ad *a* with features *x*
  - f_n : Cost of position *n* (e.g. scrolling effort, attention)
  - ϵ_i : idiosyncratic shock
- Objective: Infer $u_{a(n)}(x)$ and f_n $\forall n, a$
  - $\epsilon \sim$ EV Type 1 Distribution - Logistic Model (Maximum likelihood)
  - $\epsilon \sim$ Normal Distribution - OLS
- Identification: Randomization of displayed ads

Users' Perceived Ad-Quality

- Assuming unobserved correlation among ads, the user's value of engaging with an impression

$$U_i(\mathcal{C}) = \left(\sum_{n \in \mathcal{C}} \left(u_{a(n)}(x) \right)^{1+R} \right)^{1/(1+R)} - \sum_{n \in \mathcal{C}} f_n + \tau_i$$

  where
  - $\mathcal{C}$: set of clicked positions in impression
  - $u_{a(n)}(x)$: Perceived utility of ad a displayed in n with features x
  - f_n : Cost of position n (e.g. scrolling effort, attention)
  - $R \in (-1, \infty)$ captures unobserved correlation among ads in a keyword
  - τ_i: idiosyncratic shock

- Objective: Estimate $u_{a(n)}(x)$, f_n and R $\forall n, a$
- Formulate problem as a finite-horizon Markov Decision Process
  - State Variables: displayed ads in an impression
  - Actions: clicks on ads, click on organic links, or conclude search

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Optimal Matching

- How to compare sequences of ads: sponsored, rankings maximizing users' welfare and advertisers' value-per-click (Optimal Matching)
- The optimal matching distance equals the smallest number of operations needed to turn one sequence into another
- Operations: insertion, deletion, and substitution (cost)
- The higher the distance, the more dissimilar the ad sequences
- Challenge: size asymmetry of sequences

Optimal Matching

- Example: Compare impressions with users' optimal sequence

Table: Impression Ads

Position 1	*avf.com*
Position 2	*isw.com*
Position 3	*pow.com*

Table: Users' Optimal Sequence

Position 1	*cnn.com*
Position 2	*avf.com*
Position 3	*pow.com*
Position 4	*fij.com*
Position 5	*isw.com*
Position 6	*kks.com*

Optimal Matching

- In users' sequence, discard non-displayed ads with ranking below the worse ad in the impression

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Optimal Matching

- In users' sequence, discard non-displayed ads with ranking below the worse ad in the impression (we do not care about the tail)

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Optimal Matching

- Transformation 1 - Deletion. Remove non-displayed ads
- Edit cost: $+1 +1 = 2$

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Optimal Matching

- Transformation 2 - Substitution. *isw.com* by *pow.com*
- Edit cost: $2 + 2 = 4$

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Optimal Matching

- Transformation 3 - Substitution. *pow.com* by *isw.com*
- Edit cost: $4 + 2 = 6$

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Position 3	*pow.com*

Optimal Matching

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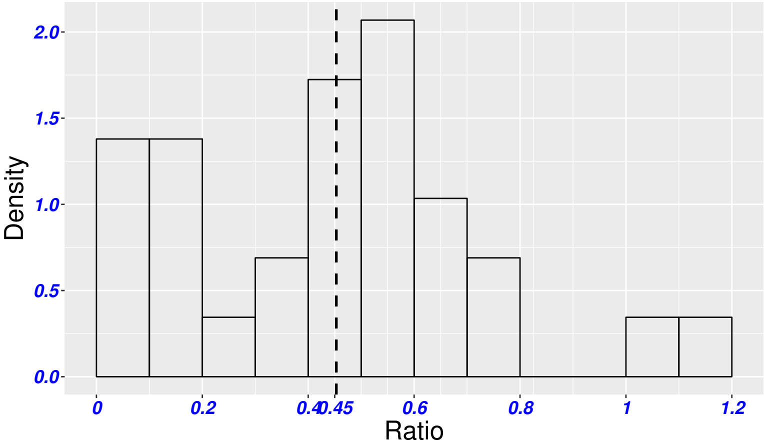
Data

- Canonized Keywords: "game", "cheap flight", "united airlines", "ups", "map", "100 keywords"
- Individual impression logs from Yahoo's desktop searches collected during the second semester of 2017
- Supplement Yahoo's data with traffic information of ad domains using information from "Alexa.com"
- Users' utility function: experiment where the order of ads is randomized (Identification - disentangle ad-quality from position effects)
- Advertisers' value-per-click: production logs (all traffic)

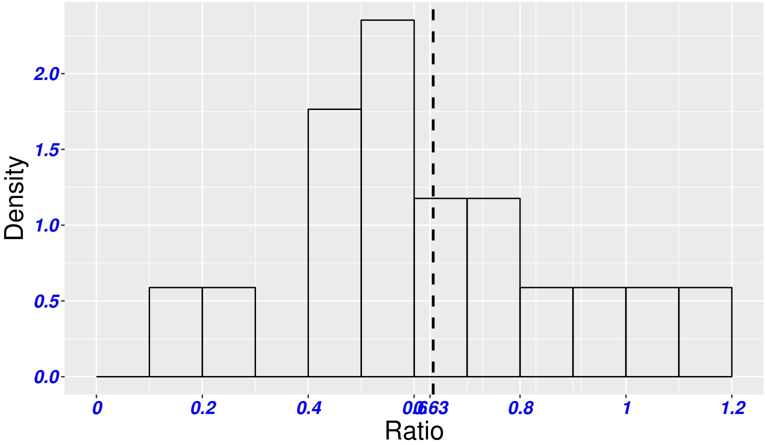
Results: Advertisers' Value-per-Click

Figure: Game: Average bid to predicted value ratio



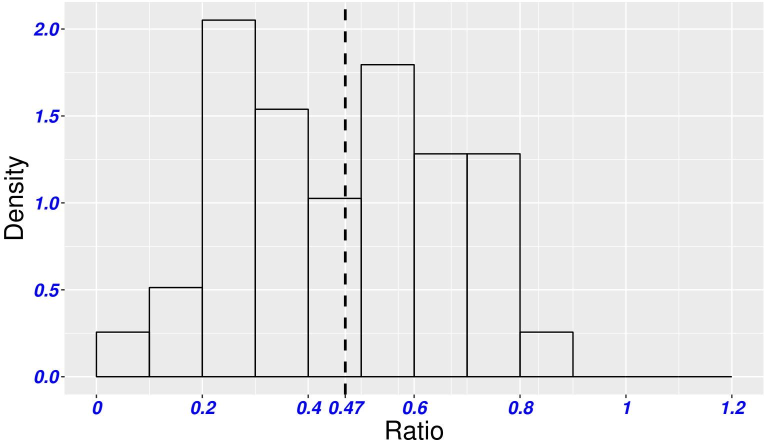
Results: Advertisers' Value-per-Click

Figure: Cheap flight: Average bid to predicted value ratio



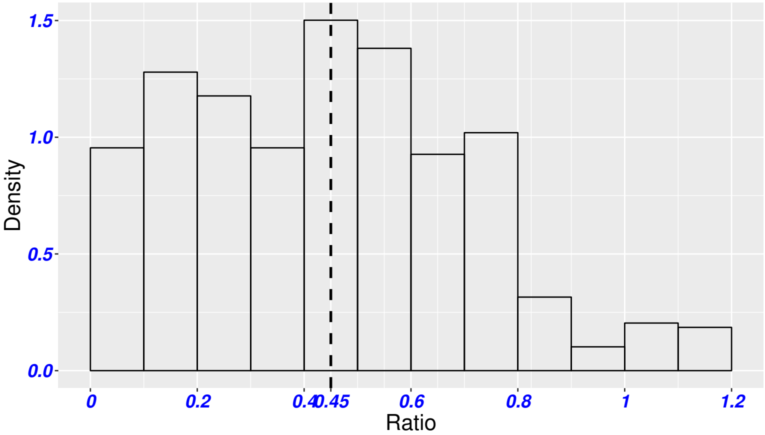
Results: Advertisers' Value-per-Click

Figure: United Airlines: Average bid to predicted value ratio



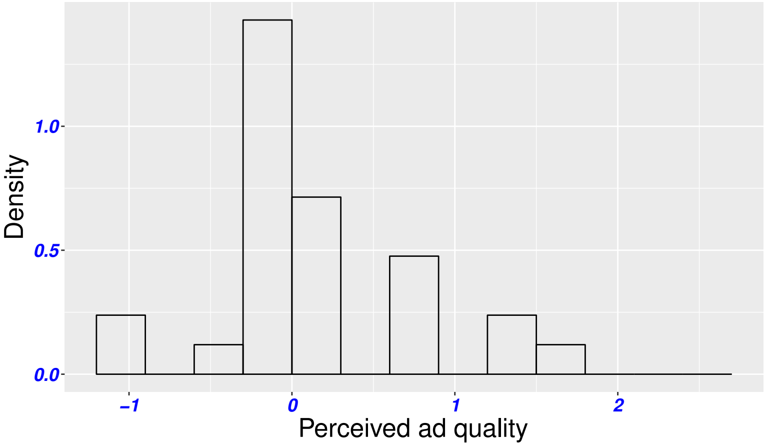
Results: Advertisers' Value-per-Click

Figure: 100 Keywords: Average bid to predicted value ratio



Results: Users' Ad-Quality

Figure: Game: Ads Utility Distribution



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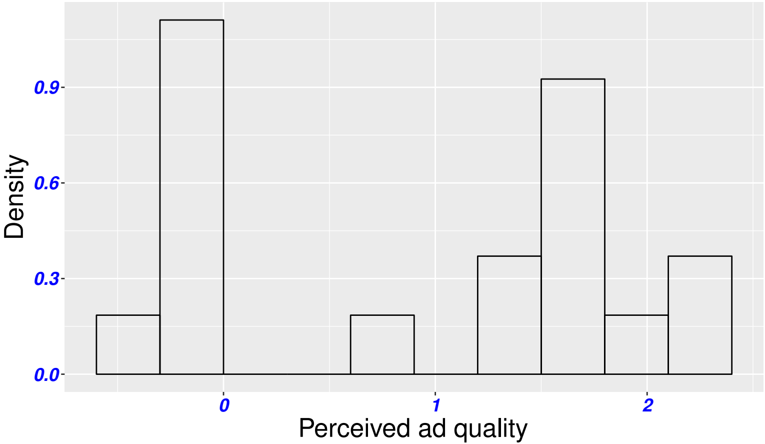

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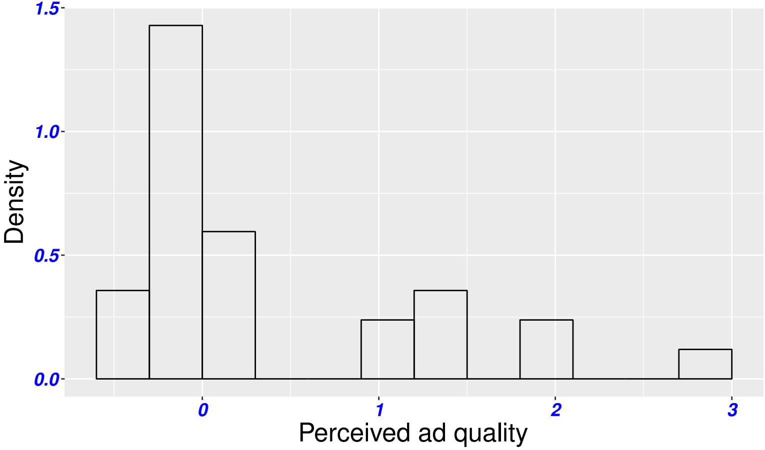

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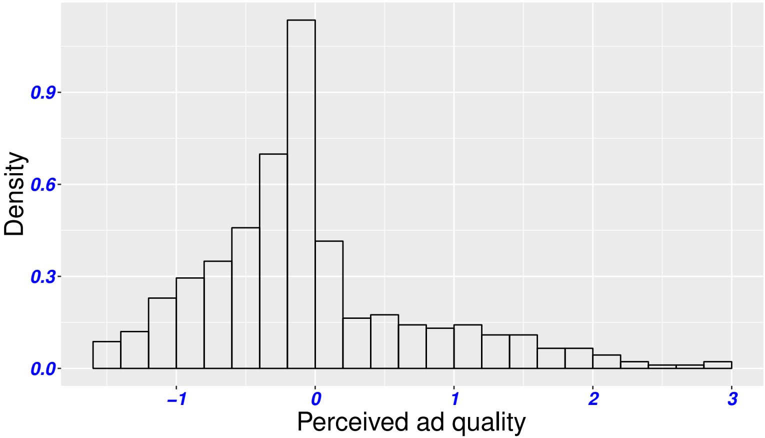


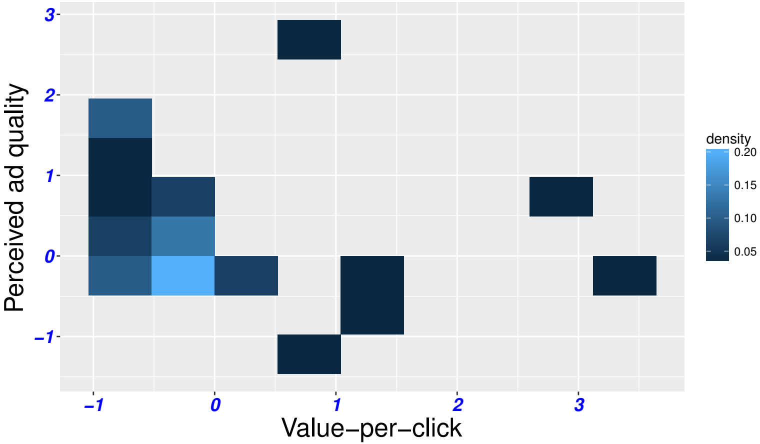
Results: Ad-Quality vs Value-per-Click

- Question: Is there any relationship between users' perceived quality and advertisers' value-per-click?

  Answer: Hard to tell

Results: Ad-Quality vs Value-per-Click

Figure: Game: Ad-quality vs Advertiser's value-per-click



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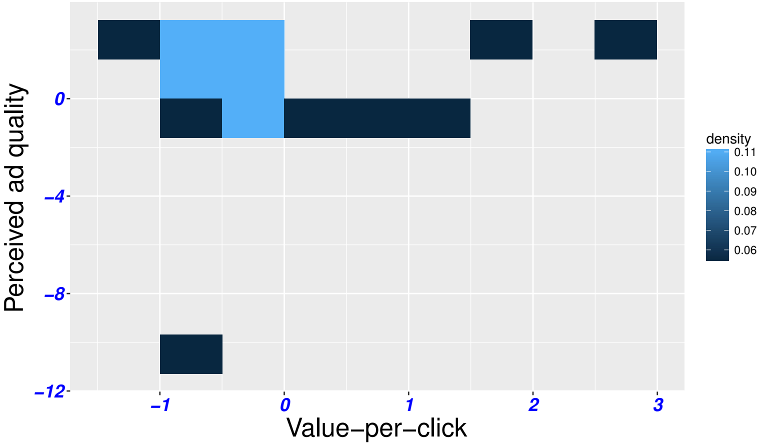
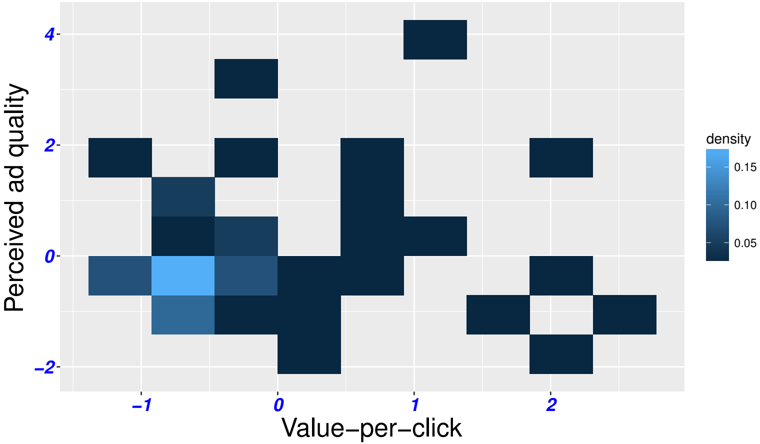


Figure: Cheap flight: Ad-quality vs Advertiser's value-per-click

Results: Ad-Quality vs Value-per-Click

Figure: United Airlines: Ad-quality vs Advertiser's value-per-click



Results: Optimal Matching

- Question: Quantify the bias of Yahoo's search engine

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Table: Optimal Matching Distance

	100 KW	Cheap Flight	Game	Map	United	Ups
Distance (User)	8.88 (4.65)	8.72 (4.11)	12.32 (8.37)	22.57 (5.37)	25.10 (8.27)	9.35 (6.50)
Distance (Value-per -click)	10.17 (4.90)	10.06 (4.78)	15.69 (8.83)	16.46 (3.88)	26.96 (7.38)	9.66 (4.49)
Distance Difference	-1.29** (6.76)	-1.34** (6.01)	-3.36 ** (9.06)	6.11** (7.01)	-1.86** (9.11)	-0.31 (5.71)
Distance Difference (%)	-12.7%	-13.3%	-27.3%	37.2%	-6.8%	-3.3%

$**p < 0.05, *p < 0.1$

Conclusions

- Hard to measure long time impact of score ranking rules
- Measure the bias of Yahoo's search engine towards advertisers and/or users at scale
- Analyze the relationship between users' and advertisers' preference
- Caveats:
  - Users' heterogeneity (Keyword shows clear intent)
  - Advertisers' targeting criteria (e.g. geo)
- We did not discuss:
  - Revenue implications
  - Simulate allocation mechanisms (e.g. VCG implementation - Facebook)

Thank You!

Users' Utility

- **Utility-maximizing model** (allow counterfactuals)
- The model accommodates multiple clicks and unobserved correlation across ads within the impression.
- $u_{a(n)}(x)$: Perceived utility of ad a in position n with features x
- f_n : Cost of position n
- Infer $u_{a(n)}(x)$ and f_n $\forall n, a$
- **Markov Decision Process** (alternative logistic model):
  - State: displayed ads in an impression
  - Actions: clicks on ads or conclude search

$$V(\mathcal{C}_t, d_t) = \underbrace{\left(\sum_{n \in \mathcal{C}(t) \cup d_t} u_{a(n)}(x)^{1+R}\right)^{1/(1+R)} - \sum_{n \in \mathcal{C}(t) \cup d_t} f_n}_{\text{Present Reward}} + \underbrace{\beta log[\sum_{d_{t+1} \in D(t+1)} exp[V(\mathcal{C}_{t+1}, d_{t+1})]]}_{\text{Expected Future Reward}}$$

Users' Utility: Estimation

1. For a given value of u, f, α and R compute the continuation value $V(.)$ for all t. In finite-horizon problems the optimal decision rule $\delta^* = (\delta_0, ..., \delta_T)$ is computed by backward induction starting at the terminal period T.
2. Given $V(\cdot)$ for all t and all d_t, compute the probability that users choose action d_t,

$$P(d_t|\mathcal{C}_t) = \frac{exp[V(\mathcal{C}_t, d_t)]}{\sum_{l_t \in D(\mathcal{C}_t)} exp[V(\mathcal{C}_t, l_t)]}$$

3. Iterate in order to find u, f, α and R that maximizes the likelihood function

$$\{\hat{u}, \hat{f}, \hat{\alpha}, \hat{R}\} = argmax_\theta \prod_{k=1}^{K} \prod_{t=1}^{T_k} P(d_t^k|\mathcal{C}_t^k)$$

where K corresponds to the total number of impressions, and T_k is equal to the maximum number of sponsored ads in impression k.

Results: Counterfactual

Table: Counterfactual

	Cheap Flight	Game	Map
Counterfactual: Advertiser			
eCTR	25.32% **	45.21% **	-12% **
User Utility	18.16%*	20.67%	-1.53%
Advertiser Utility	26.35% **	77.29% **	4.42%
Counterfactual: User			
eCTR	43.81% **	73.34% **	6.39% *
User Utility	23.01%**	36.81%	3.26%
Advertiser Utility	13.56%	59.90% **	-8.67%

** $p < 0.05$, * $p < 0.1$