Optimal Real-Time Bidding for Display Advertising

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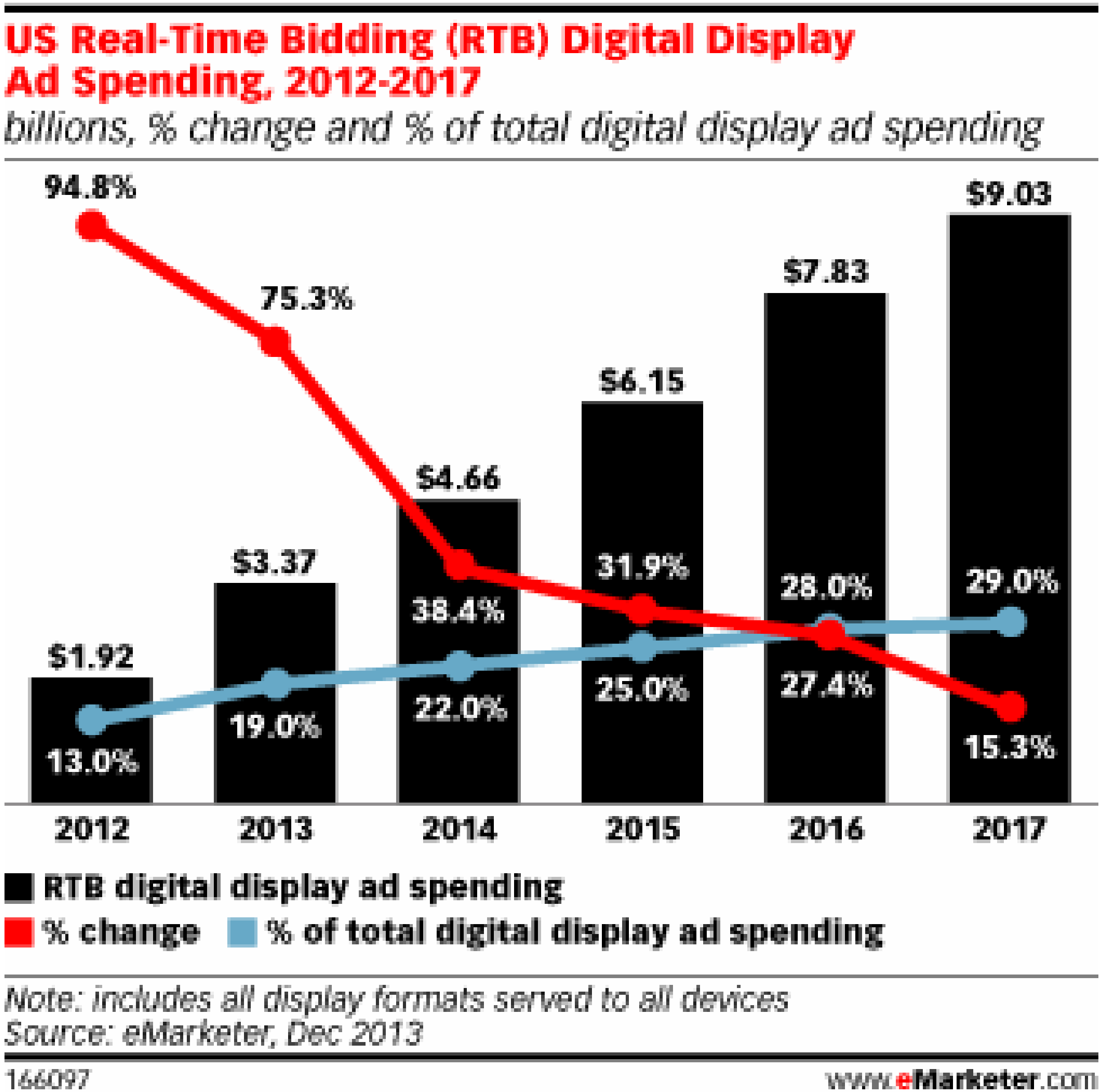
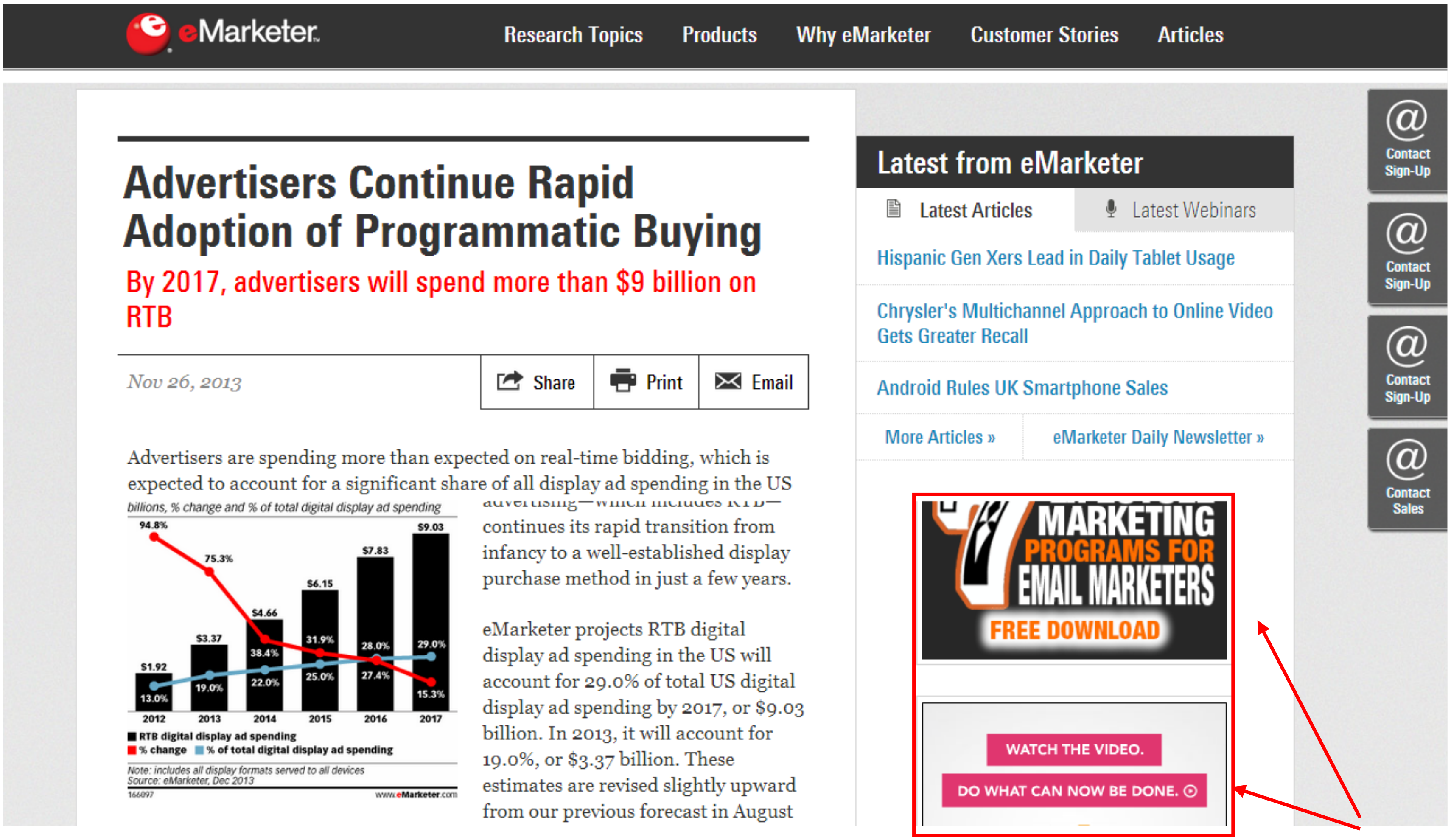

US Real-Time Bidding (RTB) Digital Display Ad Spending, 2012-2017
billions, % change and % of total digital display ad spending
94.8%
75.3%
38.4%
31.9%
28.0%
15.3%
$1.92
$3.37
$4.66
$6.15
$7.83
$9.03
13.0%
19.0%
22.0%
25.0%
27.4%
29.0%
2012
2013
2014
2015
2016
2017
RTB digital display ad spending
% change
% of total digital display ad spending
Note: includes all display formats served to all devices
Source: eMarketer, Dec 2013
166097
www.eMarketer.com

What is Real-Time Bidding?

- Every online **ad impression** can be evaluated, bought, and sold, all **individually**, and all **instantaneously**.
- Instead of buying a bundle of impressions, advertisers are now buying **users** directly.

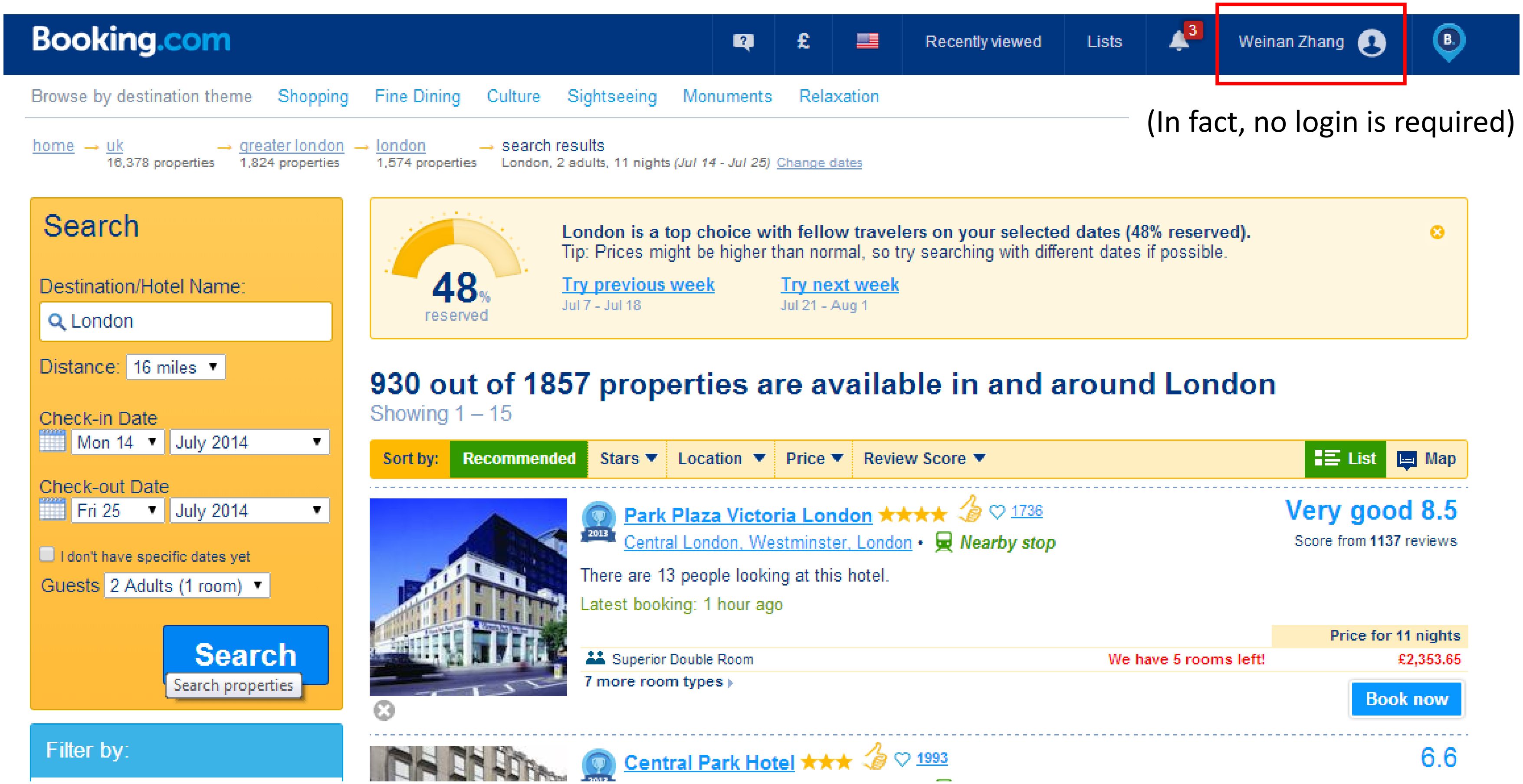
An Example

Weinan regularly reads articles on emarketer.com



Content-related ads

Weinan recently checked the London hotels

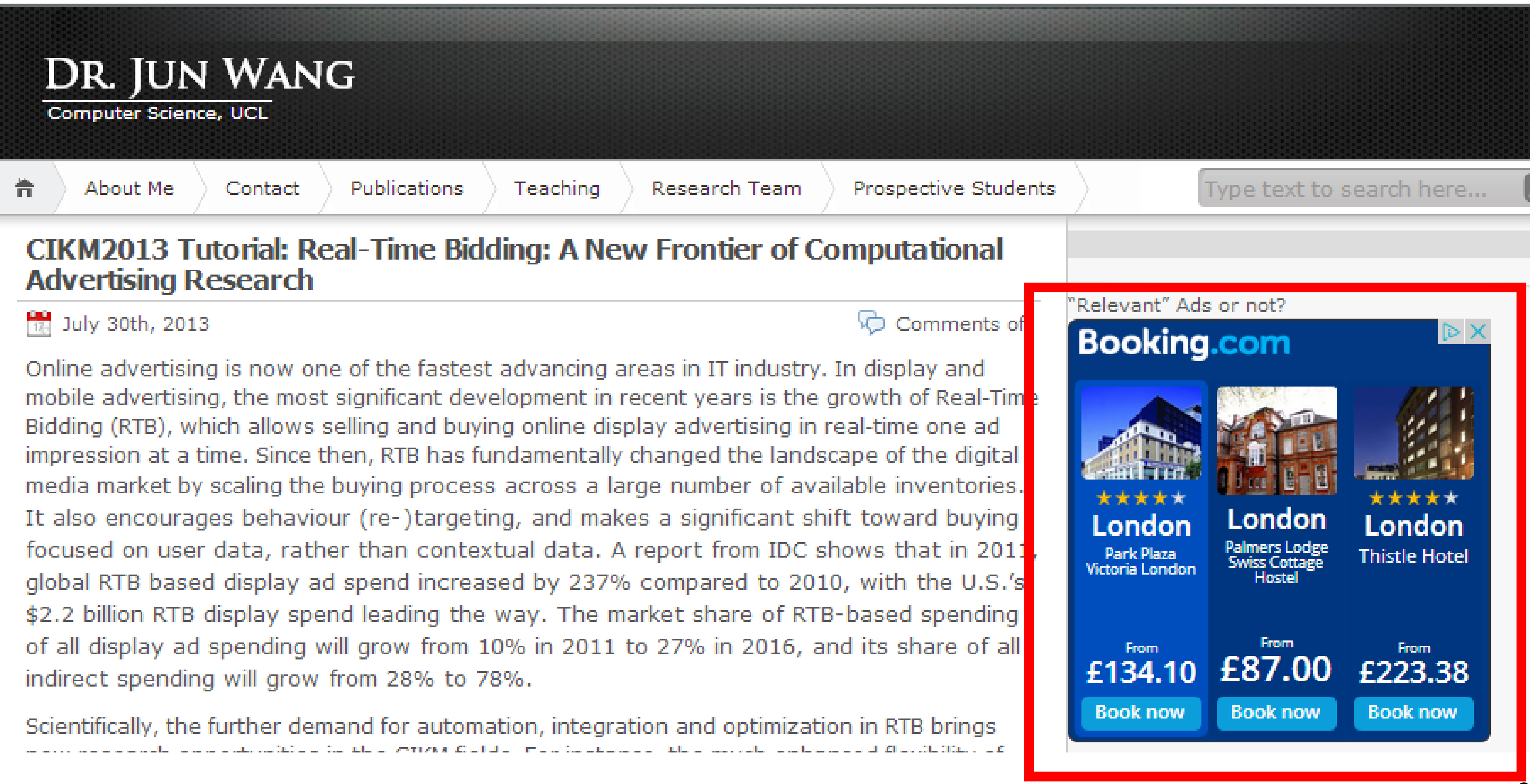


(In fact, no login is required)

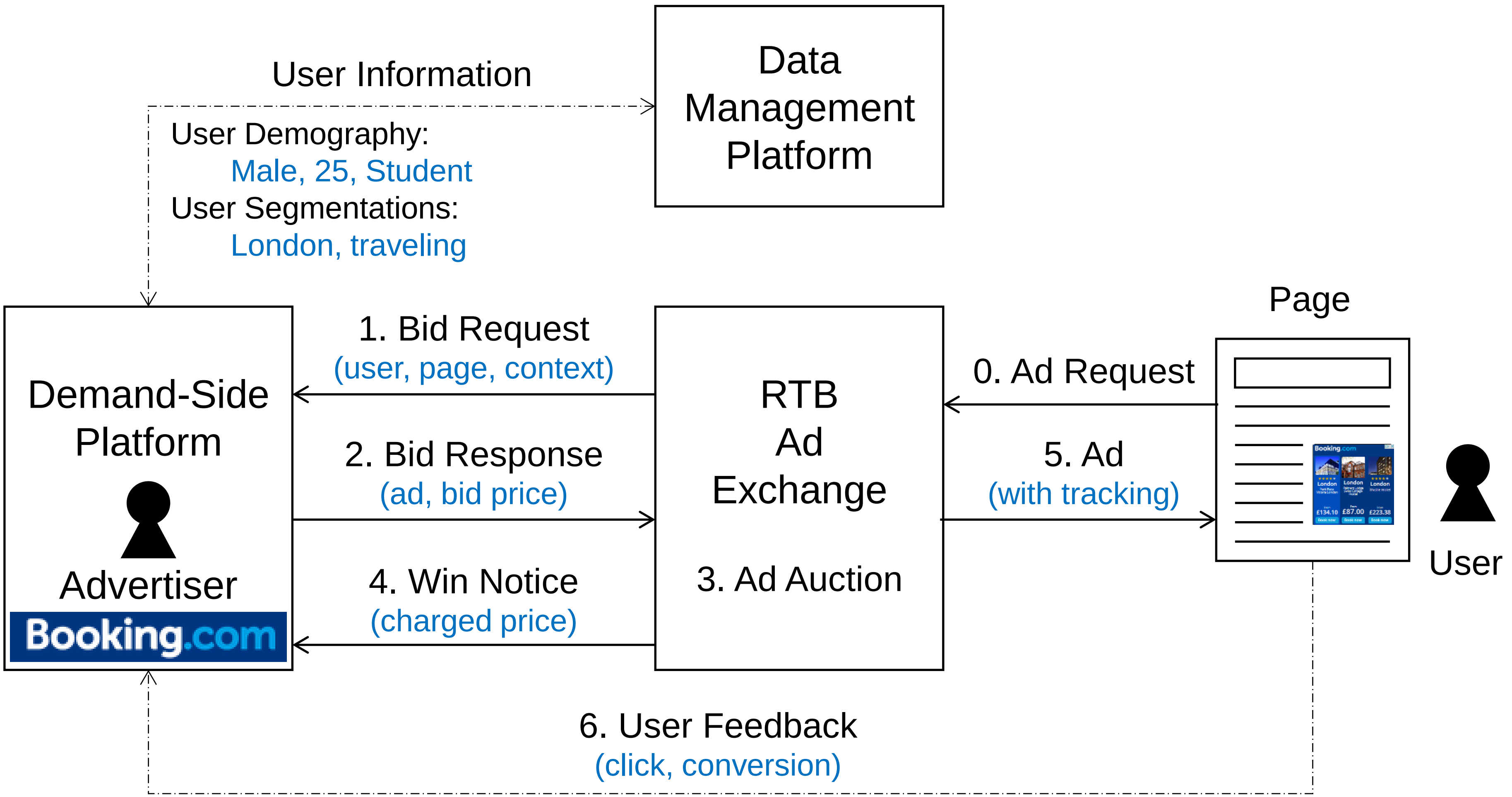
Relevant ads on facebook.com

Even on supervisor’s homepage!

(User targeting dominates the context)



How RTB works



Our Scope

Bid Request → Bidding Strategy → Bid Price

(user, ad, page, context)

- Objective

$$\max_{\text{bidding strategy}} \quad \text{KPI}$$
$$\text{subject to} \quad \text{cost} \leq \text{budget}$$

Campaign's Key Performance Indicator

For example: Expected click number

Optimal bidder: the formulation

- Functional Optimisation Problem

winning function CTR estimation

$$b()_{\mathrm{OI}}\; b()_{\mathrm{ORTB}} = \arg\max_{b()} \; N_T \int_\theta \theta w(b(\theta)) p_\theta(\theta) d\theta \longleftarrow$$

context+ad features

bidding function

$$\text{subject to} \;\; N_T \int_\theta b(\theta) w(b(\theta)) p_\theta(\theta) d\theta \le B \longleftarrow$$

budget

Cost upper bound

- Components
  - x, the bid request, user and ad features
  - $\theta(x)$, the CTR prediction function
  - $b(\theta(x), x)$, the bidding function
  - $w(b, x)$, the win probability function
- Dependency assumption:

Optimal bidder: the formulation

- Functional Optimisation Problem

winning function CTR estimation

$$b()_{\mathrm{OI}}\; b()_{\mathrm{ORTB}} = \arg\max_{b()} \; N_T \int_\theta \theta w(b(\theta)) p_\theta(\theta) d\theta \quad \longleftarrow$$ context+ad features

bidding function

$$\text{subject to} \quad N_T \int_\theta b(\theta) w(b(\theta)) p_\theta(\theta) d\theta \leq B \quad \longleftarrow$$ budget

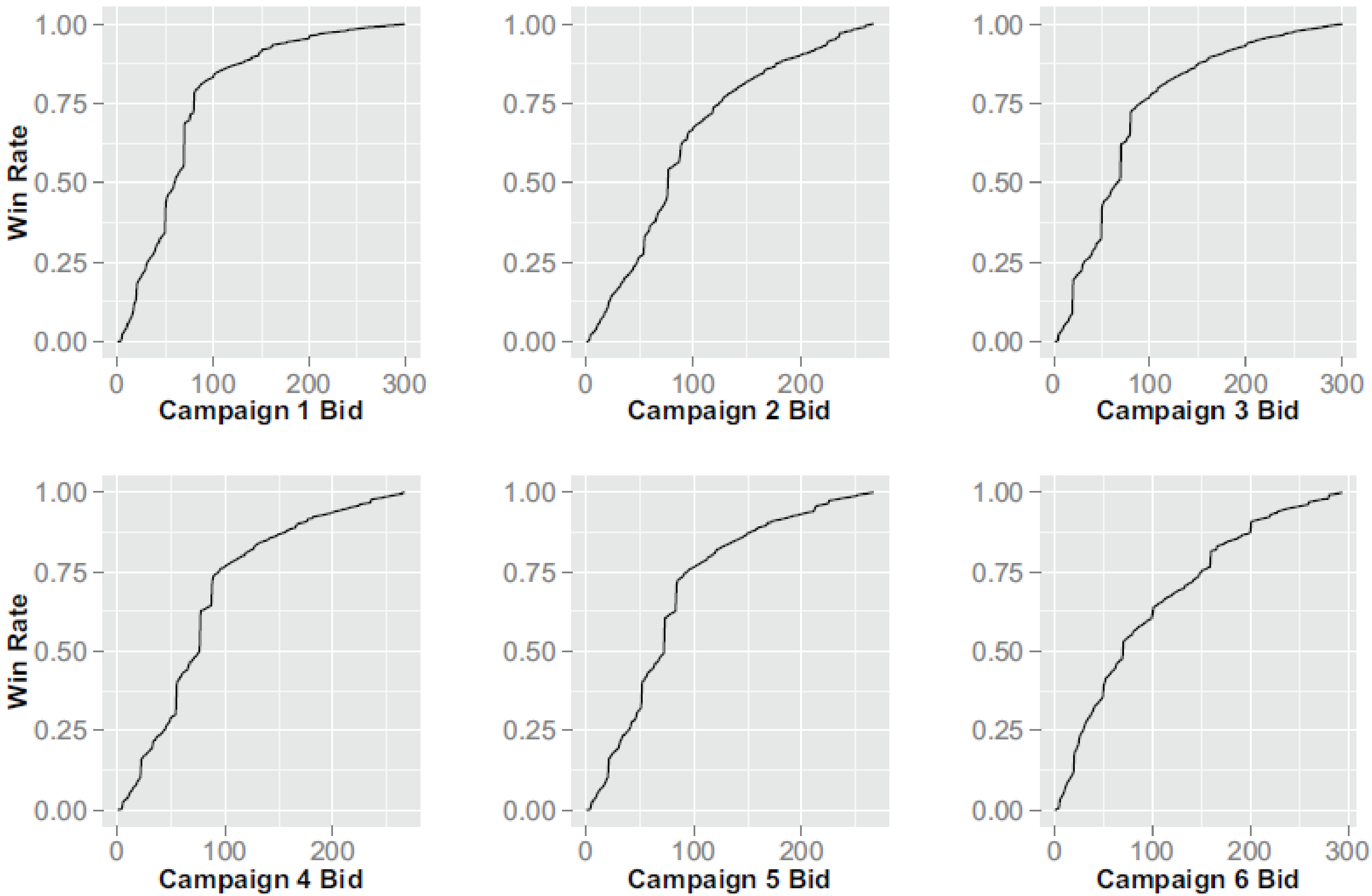
Cost upper bound

- Solution: Calculus of variations

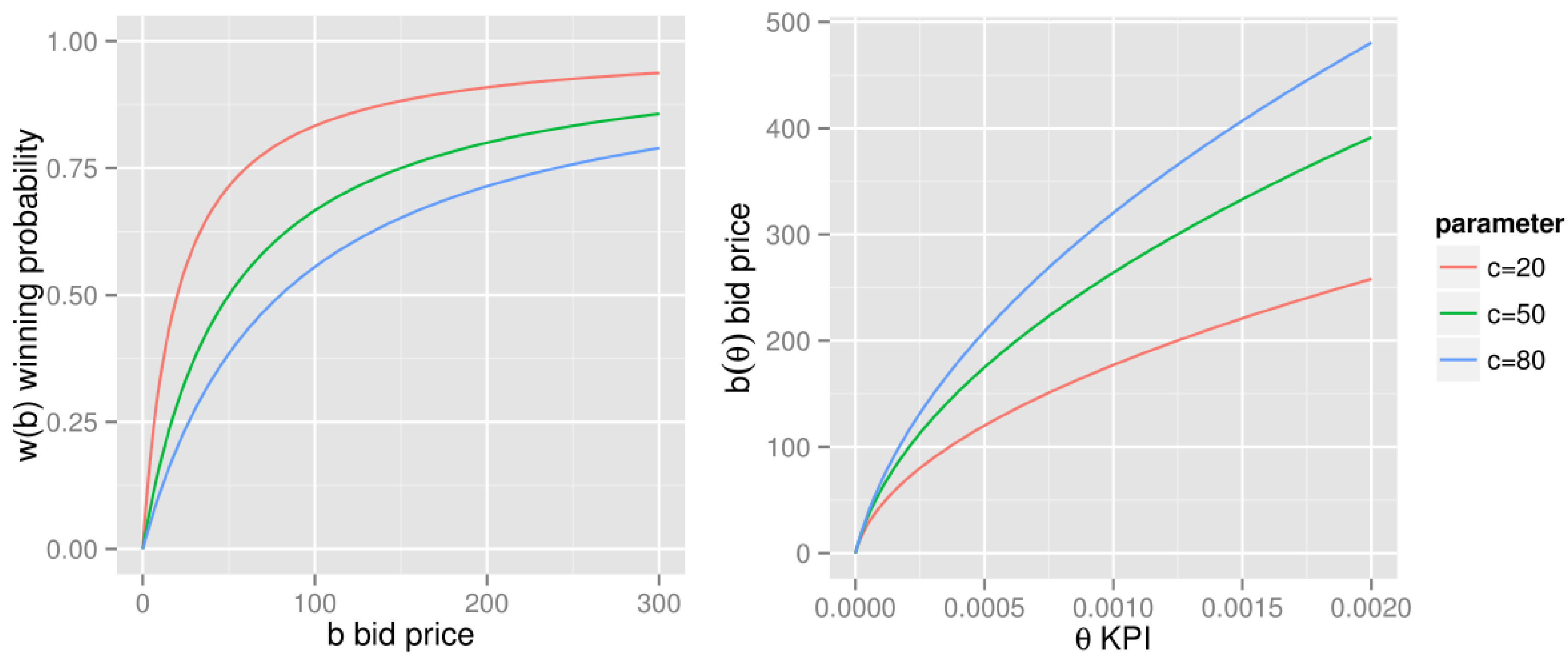
$$\mathcal{L}(b(\theta), \lambda) = \int_\theta \theta w(b(\theta)) p_\theta(\theta) d\theta - \lambda \int_\theta b(\theta) w(b(\theta)) p_\theta(\theta) d\theta + \frac{\lambda B}{N_T}$$

$$\boxed{\lambda w(b(\theta)) = \Big[\theta - \lambda b(\theta)\Big] \frac{\partial w(b(\theta))}{\partial b(\theta)}}$$

Bid Landscape: w(bid)



Optimal bidding strategy: the solution



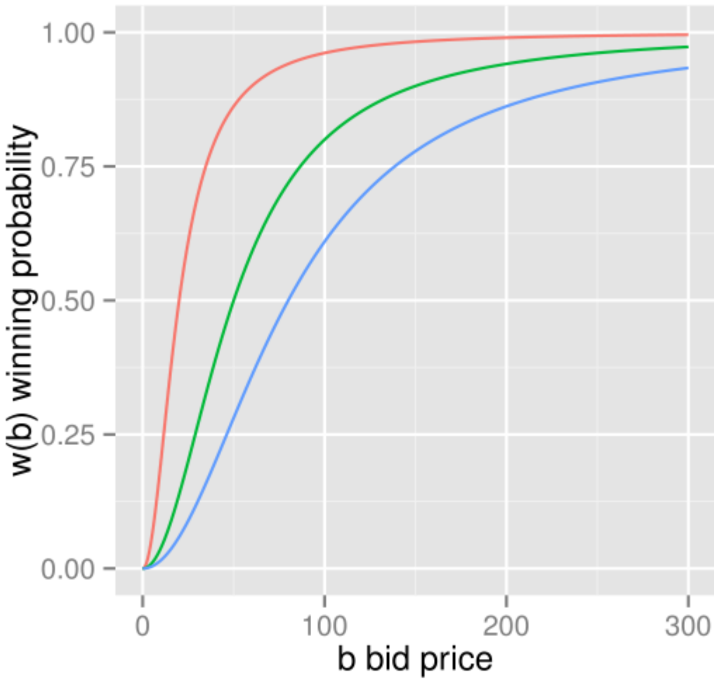
(a) Winning function 1.

(b) Bidding function 1.

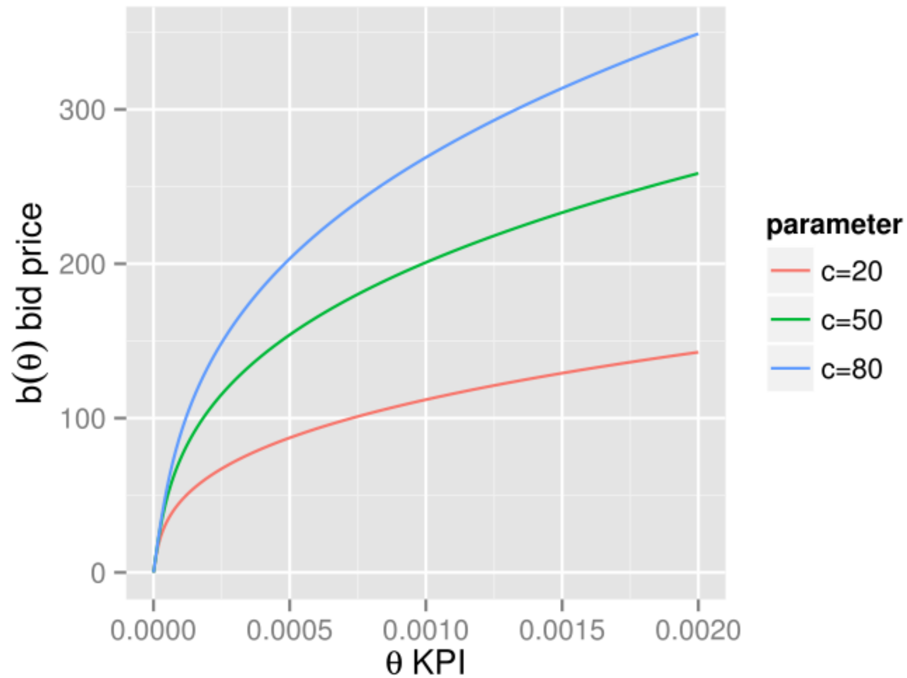
$$w(b(\theta)) = \frac{b(\theta)}{c + b(\theta)} \qquad b_{\mathrm{ORTB1}}(\theta) = \sqrt{\frac{c}{\lambda}\theta + c^2} - c$$

$$\lambda w(b(\theta)) = \left[\theta - \lambda b(\theta)\right] \frac{\partial w(b(\theta))}{\partial b(\theta)}$$

Optimal bidding strategy: the solution



(a) Winning function 2.

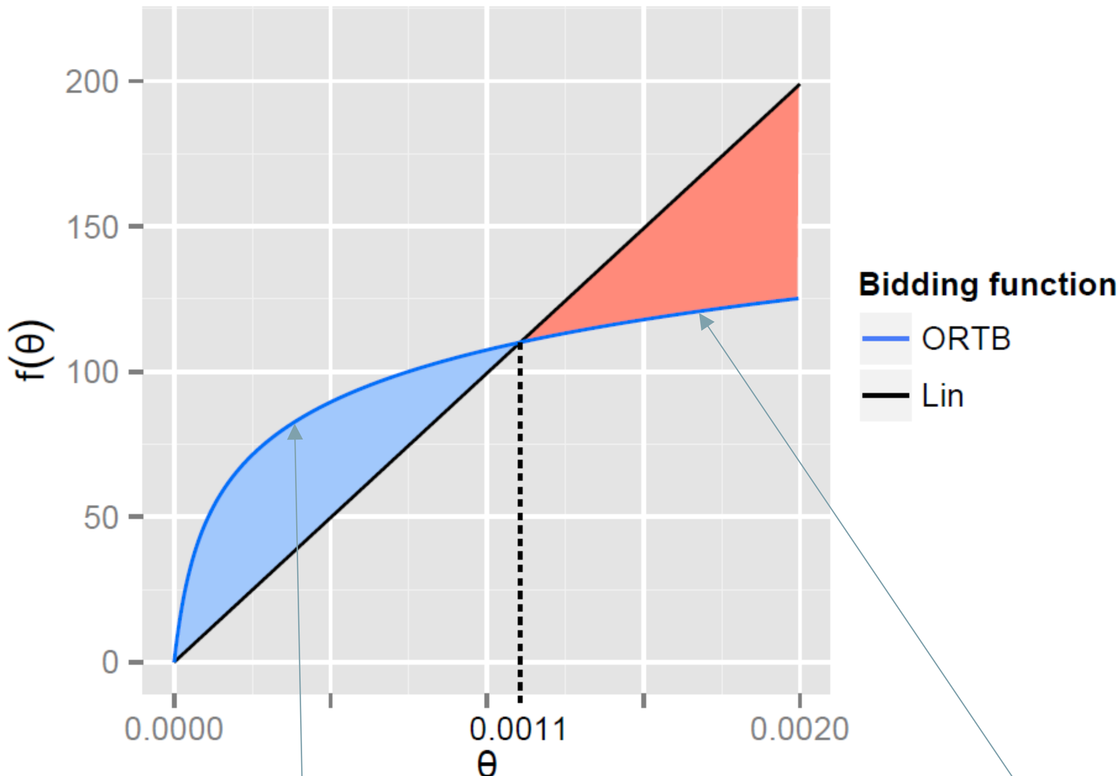


(b) Bidding function 2.

$$w(b(\theta)) = \frac{b^2(\theta)}{c^2 + b^2(\theta)} \qquad b_{\mathrm{ORTB2}}(\theta) = c \cdot \left[\left(\frac{\theta + \sqrt{c^2\lambda^2 + \theta^2}}{c\lambda} \right)^{\frac{1}{3}} - \left(\frac{c\lambda}{\theta + \sqrt{c^2\lambda^2 + \theta^2}} \right)^{\frac{1}{3}} \right]$$

$$\lambda w(b(\theta)) = \Big[\theta - \lambda b(\theta) \Big] \frac{\partial w(b(\theta))}{\partial b(\theta)}$$

Optimal bidding strategy: the solution



Slight increase at low bids is more effective

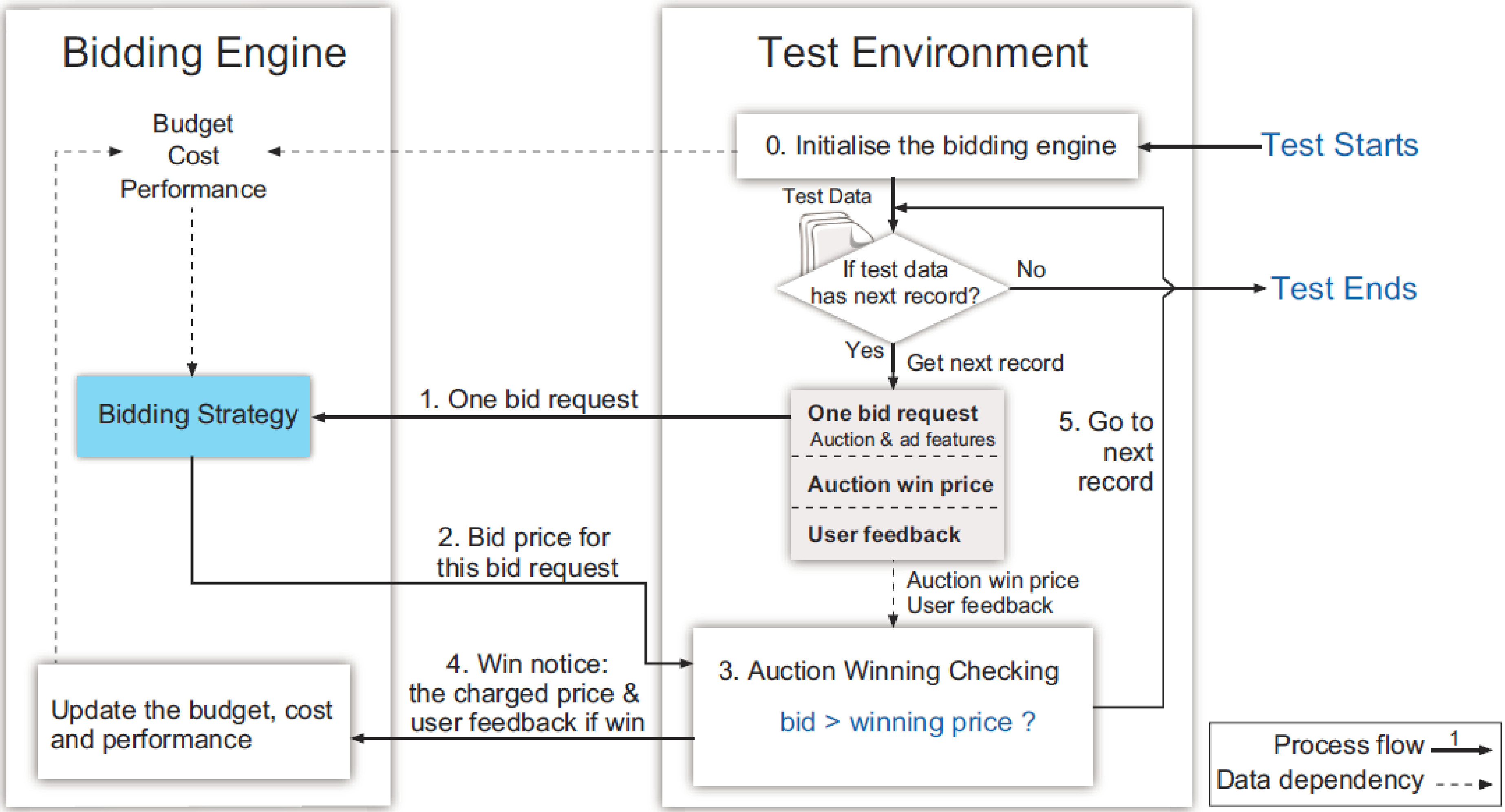
Thus reduce the bids at high CTR or CVR

Experiment

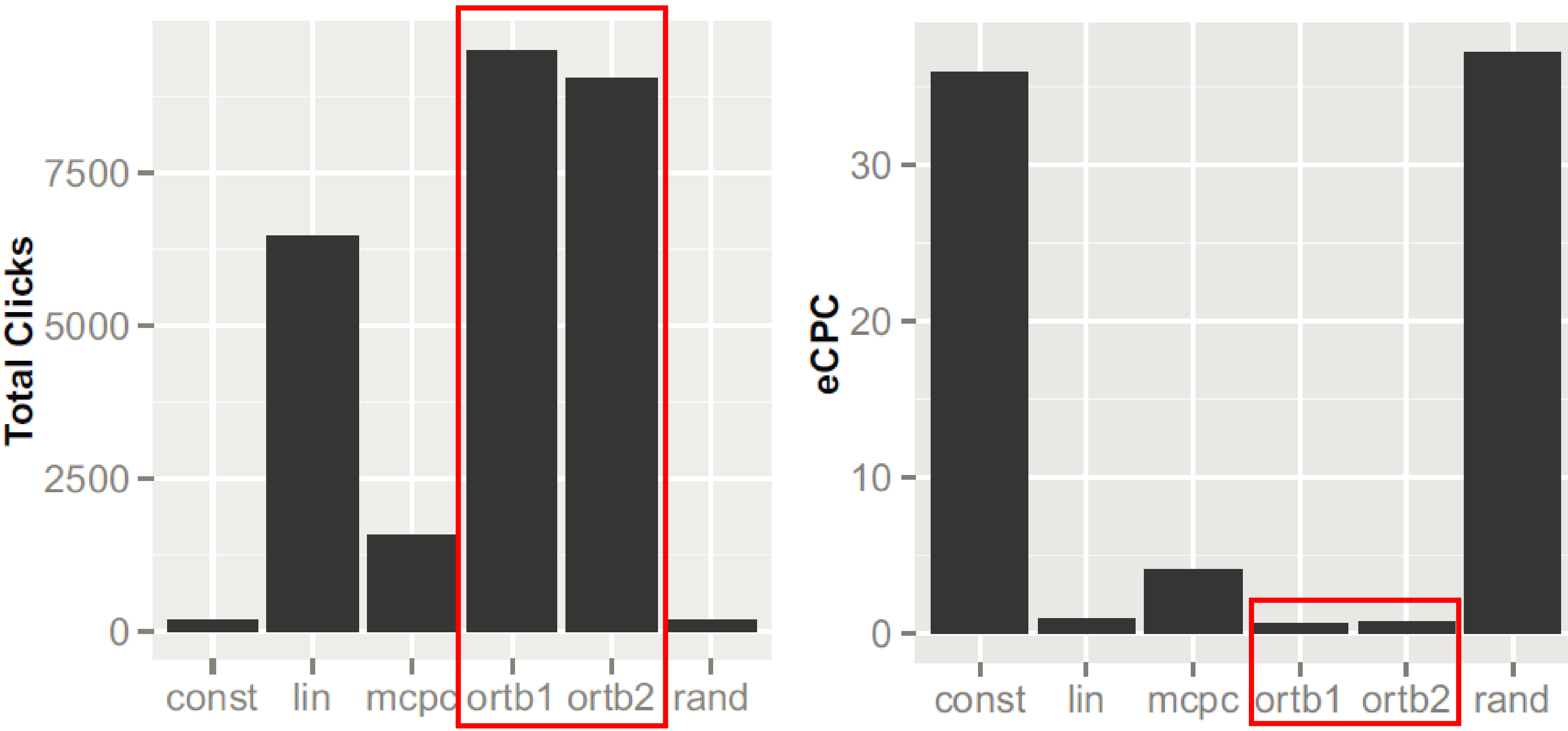
- We used iPinYou's dataset[1]
  - 9 Campaigns, 15M impressions, 11K clicks, 935 conversions
- Evaluated bidding strategies
  - **Const**: Constant
  - **Rand**: Random
  - **Mcpc**: Bidding based on advertiser's given max eCPC [Chen et al. 2011]
  - **Lin**: Linear to pCTR [Perlich et al. 2012]
  - **ORTB1**, **ORTB2**: Optimal bidding strategies with two forms of winning rate functions

1-http://data.computational-advertising.org

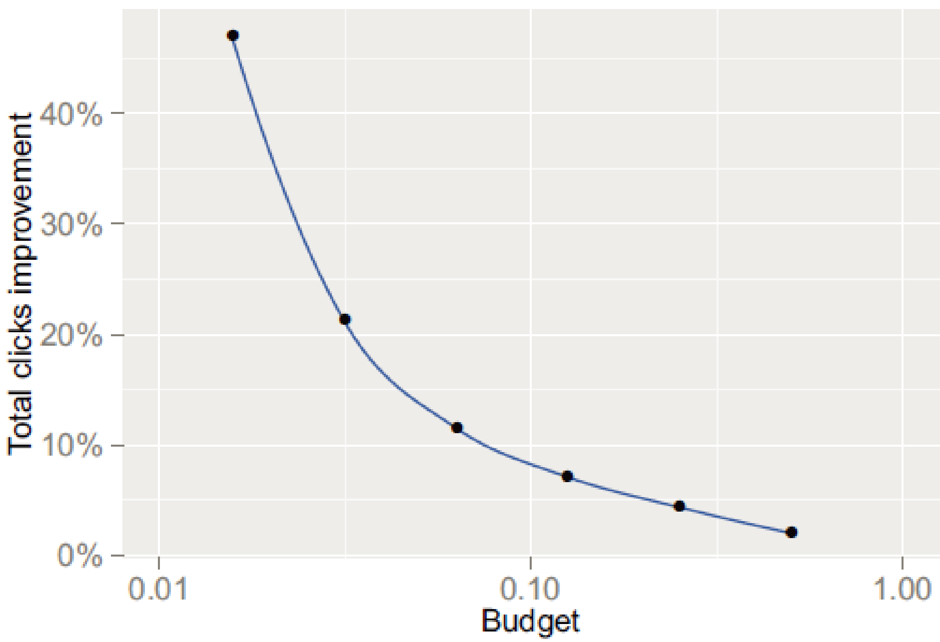
Offline Test Evaluation Flow

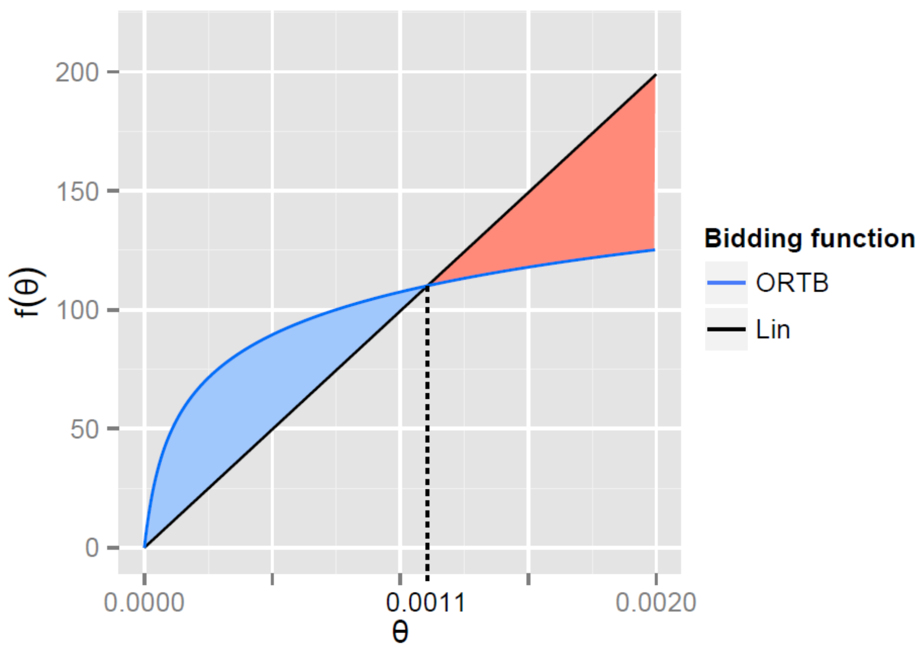


Overall performance – Optimising Clicks

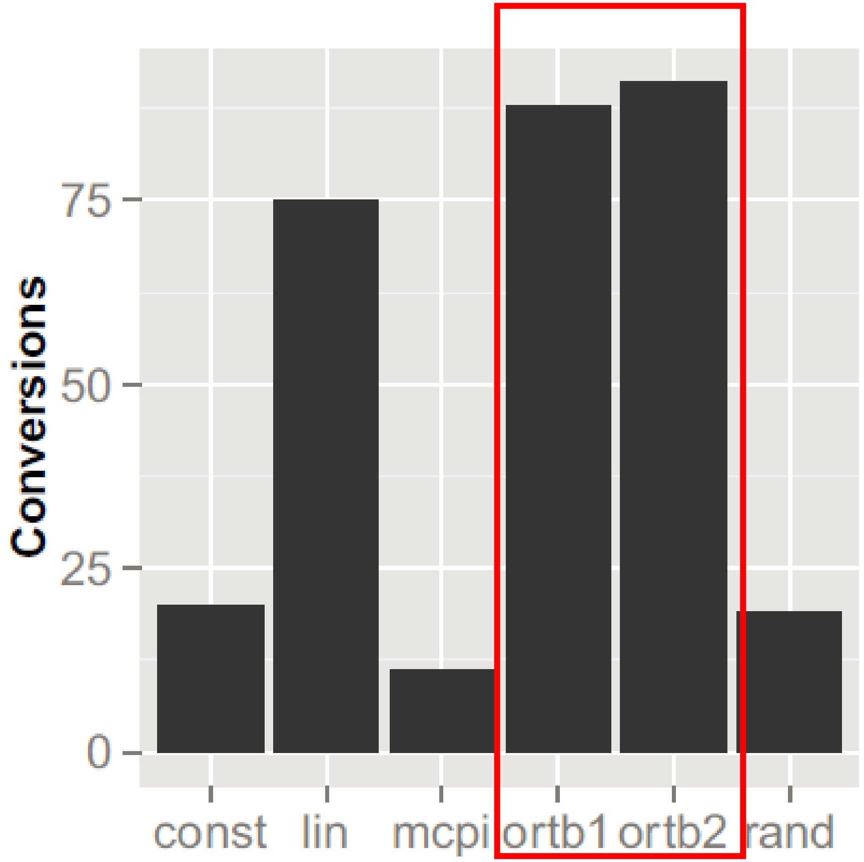


Higher improvement when budget is more limited





Overall performance – Optimising Conversions



Online Evaluation Result of iPinYou Bidding Algorithm Competition Third Season

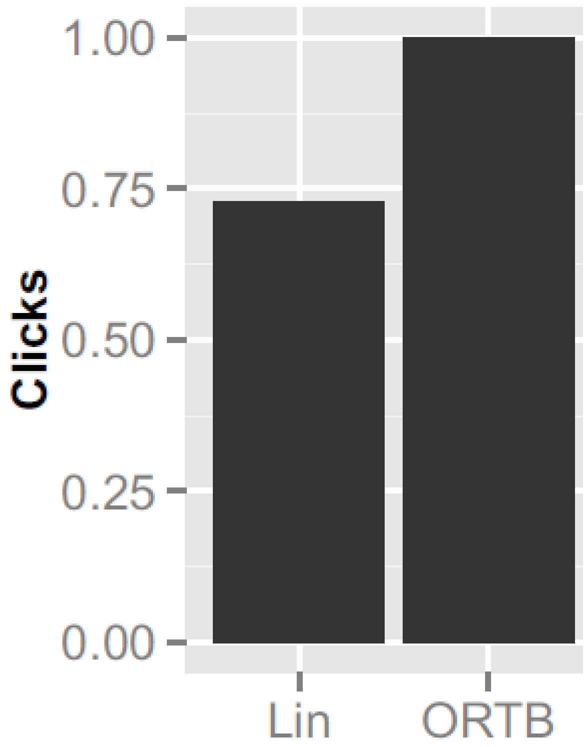
The iPinYou global RTB bidding algorithm competition third and last season has been successfully concluded. The UCL-CA, V_V, PoundsXXX, Run_Fast and Tiger teams have participated in the three-day online finals from Dec 26th,2013 to Dec 28th,2013. The final results, which have been carefully checked by the committee and audited by the jury, are as follows:

rank	team	score
1	UCL-CA	1304
2	V_V	983
3	Run Fast	901
4	PoundsXXX	885
5	Tiger	744

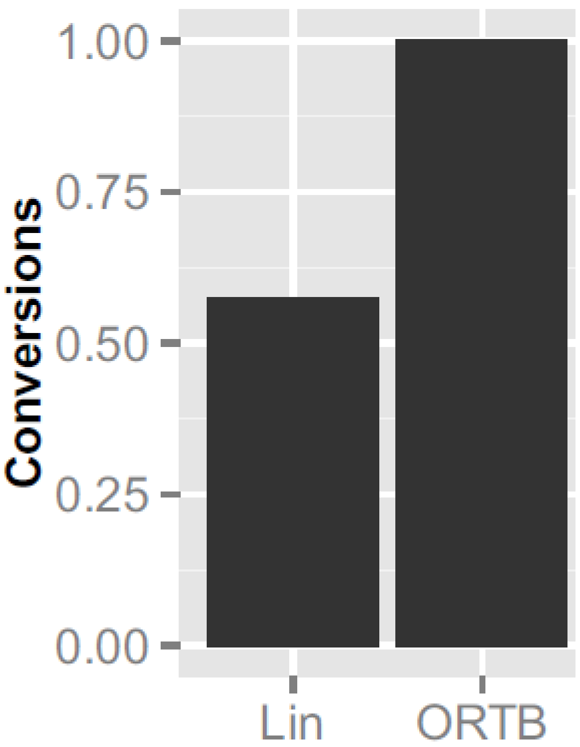
where the final score = clicks + N * reaches, N = 1. The sensible choice of N does not influence the final ranking.

http://contest.ipinyou.com/session-three-online-leaderboard.html

Online Test

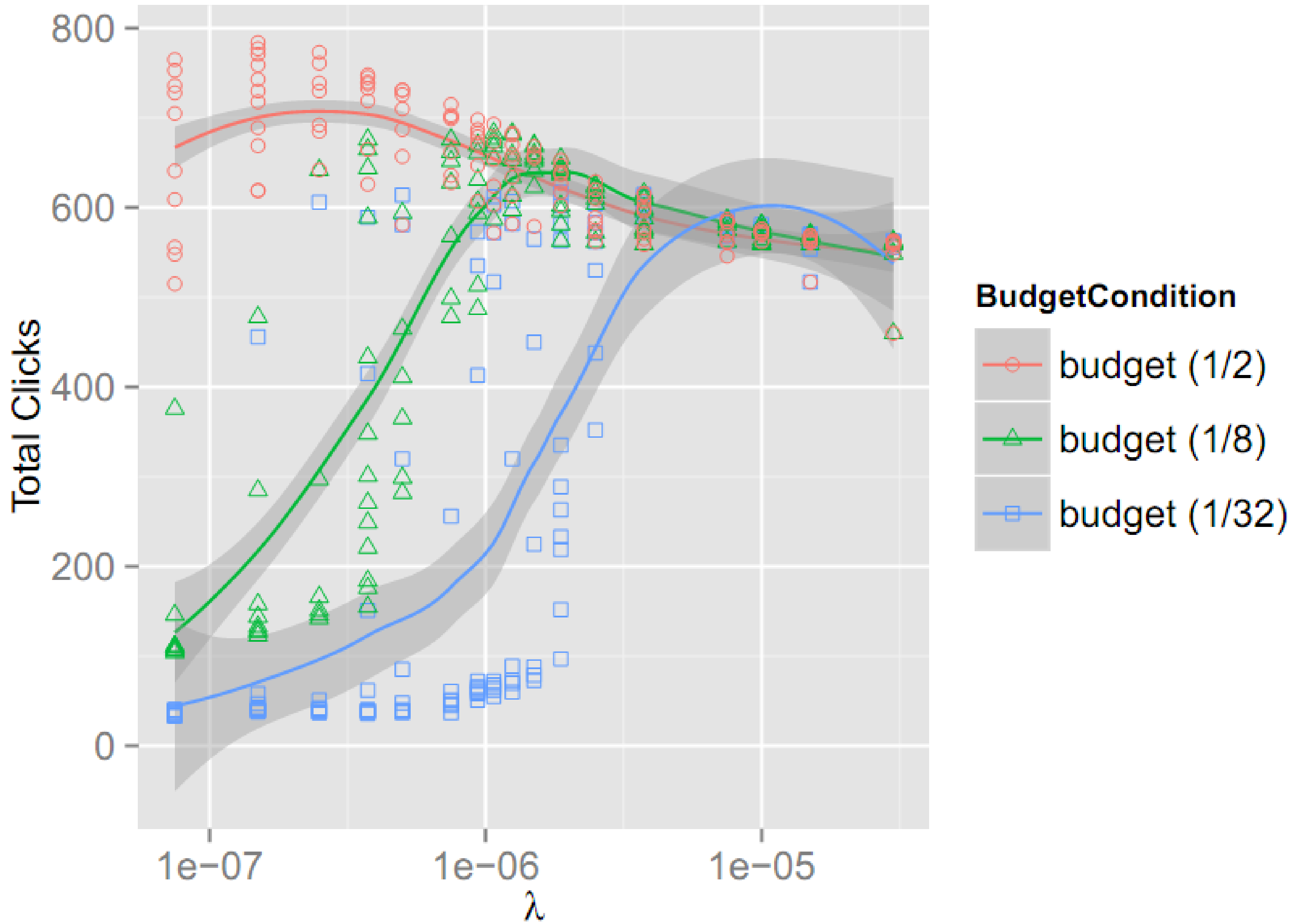


1.00
0.75
0.50
0.25
0.00
Clicks
Lin
ORTB

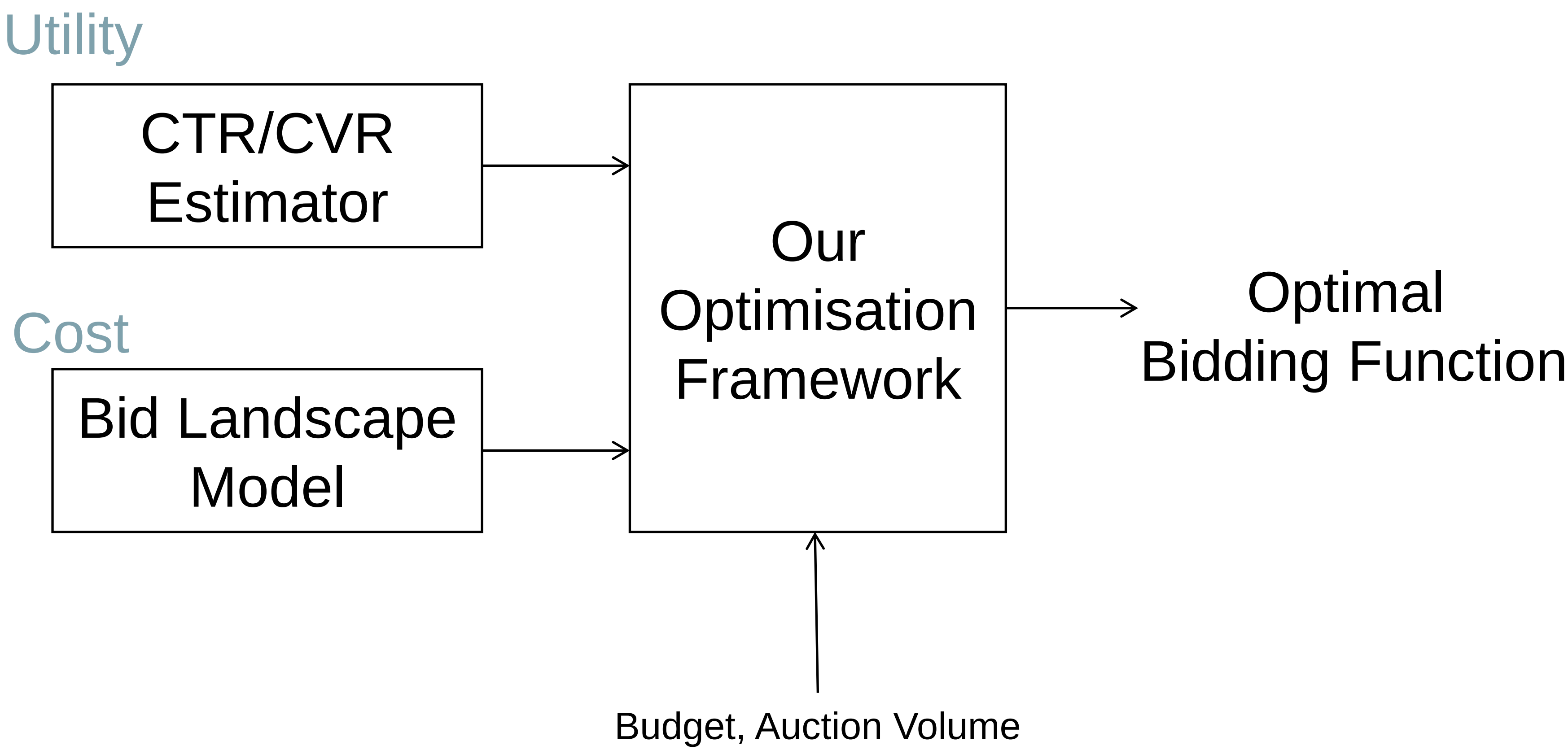


1.00
0.75
0.50
0.25
0.00
Conversions
Lin
ORTB

Parameter tuning – λ for ORTB1



Summary


Utility
CTR/CVR Estimator
Cost
Bid Landscape Model
Our Optimisation Framework
Optimal Bidding Function
Budget, Auction Volume

Future works

- More detailed bid landscape
  - From bid → P(win)   to (bid, features) → P(win)
- Control the dynamics
- Cold start problems

Thank You!
Questions?

See our work on publisher-side optimisation:
Shuai Yuan et al. **An Empirical Study of Reserve Price Optimisation in Real-Time Bidding**
1PM Wednesday, industrial & gov. track