Real-Time Bidding

A New Frontier of
Computational Advertising Research

Jun Wang and Shuai Yuan

University College London

With Invited Speaker

Kaihua Cai

AppNexus

About us

- **Department of Computer Science, University College London**
  - Media future research group
  - Information Retrieval and Computational advertising
- **Dr. Shuai Yuan**
  - Lead Data Scientist, MediaGamma
  - PhD in Computational Advertising
  - Winner of 3rd season of iPinyou Global Bidding Algorithm Competition in 2013 (Weinan Zhang), and the Best Paper Award of ADKDD 2014
- **Dr. Jun Wang**
  - Senior Lecturer (Associate Professor)
  - Information retrieval, collaborative filtering, computational advertising

Invited Talk

AppNexus is one of the largest online advertising exchanges

- Offers one of the most powerful, open and customizable advertising technology platforms for both the buy and sell sides;
- Serves Google AdX, Microsoft Advertising Exchange, Interactive Media (Deutsche Telekom), Collective Exchange, and a lot more

Speaker: Dr. Kaihua Cai

- PhD in Mathematics from Caltech
- Research fellow at MSRI in Berkeley, California and Institute for Advanced Study in Princeton, New Jersey;
- Worked in finance at Chatham Financial, Goral Trading, and IV Capital;
- Joined AppNexus as a Data Scientist in 2012

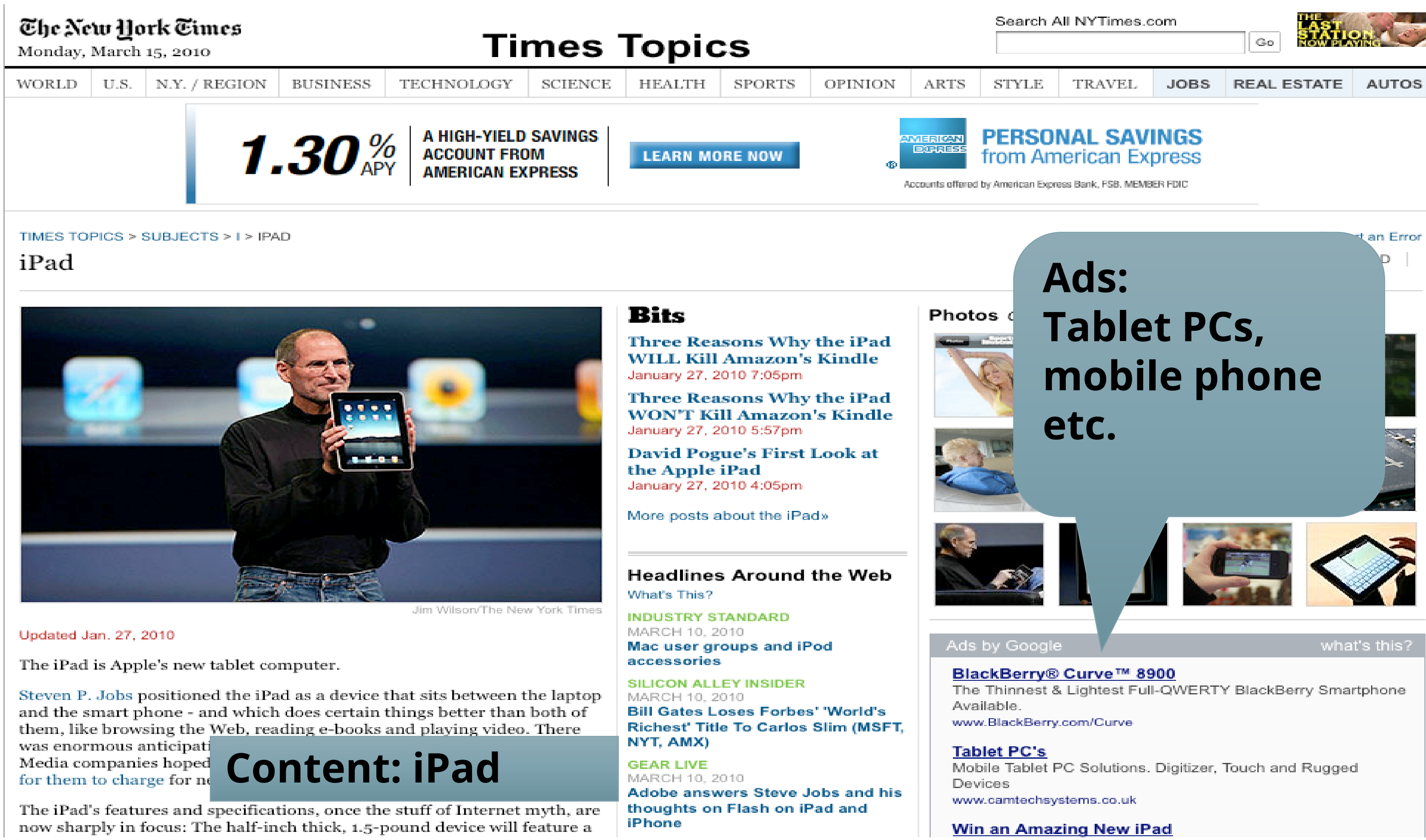
Outline

1. **The background of Computational advertising**
2. **Research problems and techniques**
    1. Bidding strategy Optimisation
    2. Inventory management and floor prices optimisation

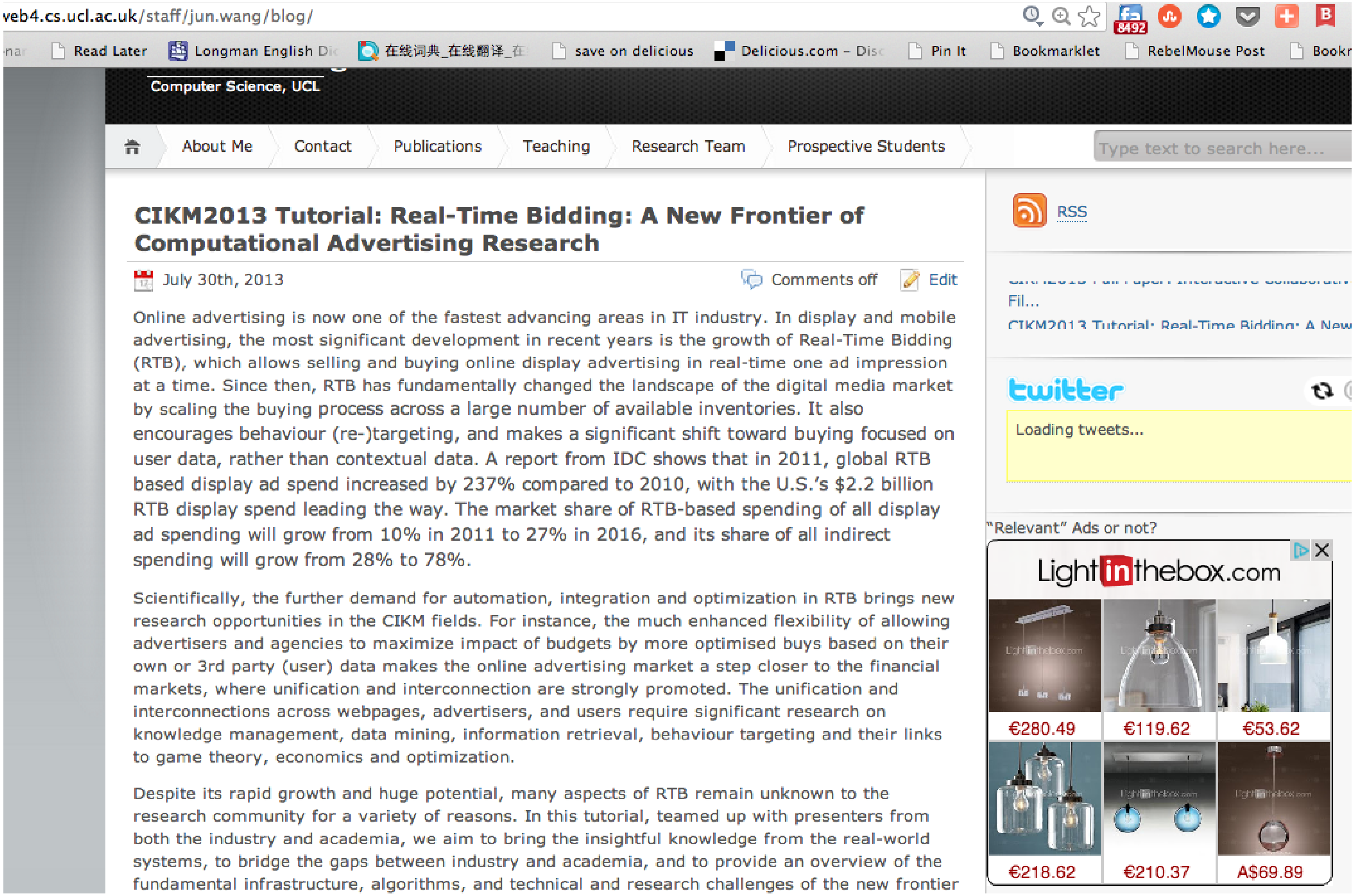
------Break (20min)------

    3. Fighting publisher fraud
    4. Programmatic Guaranteed and Ad Options
3. **Datasets, tools, and platforms**

Contextual ads: relevant to the webpage content

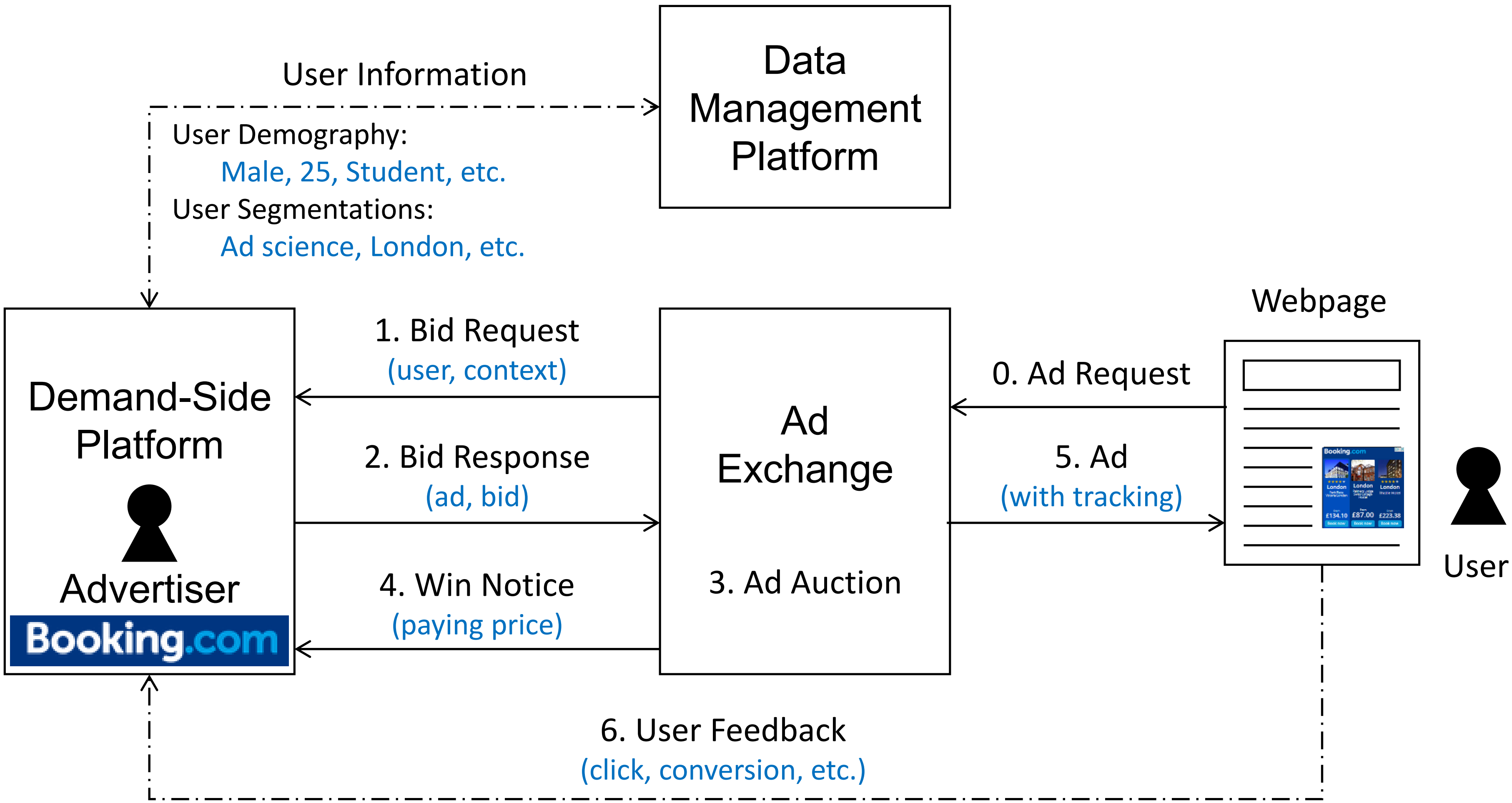


Real-time Advertising:
Selling ad slot per impression targeted to the user



Real-time Advertising:
Selling ad slot per impression targeted to the user

RTB workflow: less than 100ms



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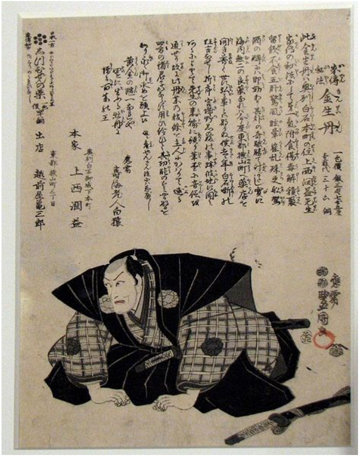
Part 1.1 The background of Computational advertising

- Advertising has a long history
  - Egyptians used papyrus to make sales messages and wall posters (4000 BCE)
  - In the 18th century, ads started to appear in weekly newspapers in England
  - Thomas J. Barratt has been called "the father of modern advertising"



1806	1890
1900	1952

courtesy of Wikipedia

Glossaries

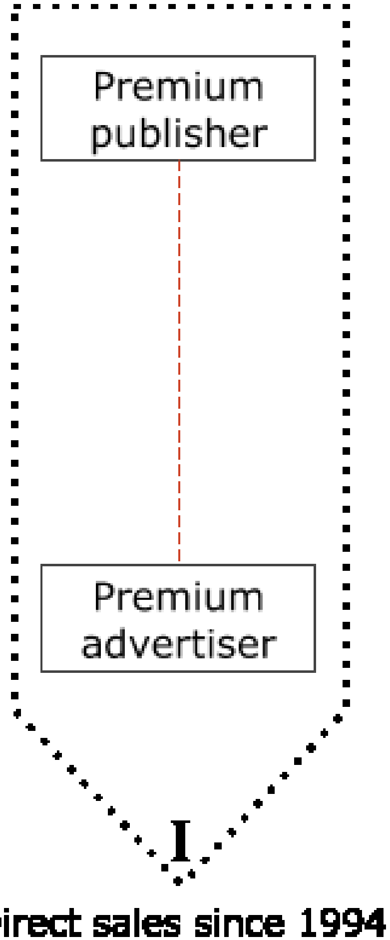
- Real-Time Bidding is an important aspect of Programmatic buying, which is getting more and more popular in Display (related) advertising. Another major part of Online advertising is Sponsored search
- An Impression is an ad display opportunity which generates when a User visits a webpage containing ad Placements
- The Publisher sends a bid request of this impression to an Ad network, or an Ad exchange via his Supply side platform (SSP), then to Demand side platforms (DSP) to reach Advertisers
- Usually, DSPs contact Data management platform (DMP) to check the Segments of the current user, i.e., his intents or interests. Then a bid will be computed for the Campaign
- The payment among these entities is usually in Cost per mille (CPM), but sometimes could be Cost per click (CPC) or Cost per acquisition (CPA)
- If the advertiser wins the impression, his Creative will be displayed to the user

The fundamental challenges

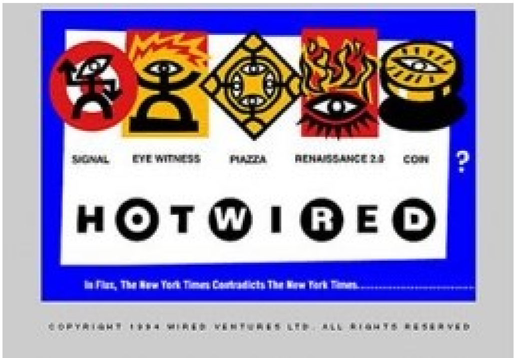
- To find the best match between a given user in a given context and a suitable advertisement?
- To achieve the best campaign performance (e.g., ROI) within the budget constraint?
- To generate the most revenue given the traffic and demand?
- To maintain a healthy environment so that users get less annoyed (both quality and quantity)?

Computational advertising, AZ Border, 2008
Dynamics of bid optimization in online advertisement auctions, C Borges et al. 2007
Dynamic revenue management for online display advertising, G Roels and K Fridgeirsdottir, 2009
Advertising in a pervasive computing environment, A Ranganathan and RH Campbell, 2002

Direct sales (since 1994)



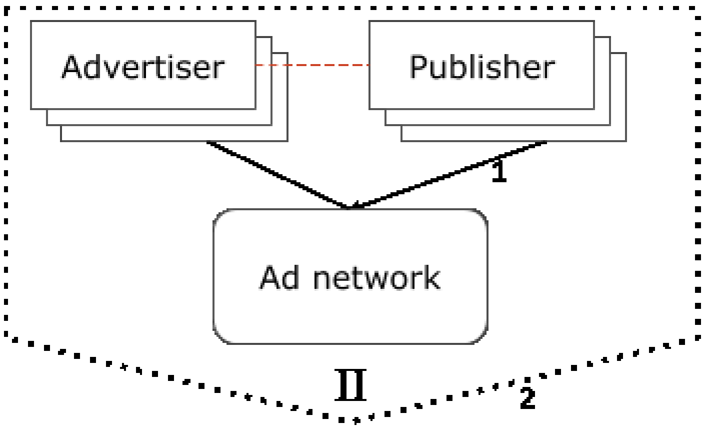
- Advertisers and publishers talk to (4A) agencies
- Still popular in today's marketplace
- Getting back to the market as the Programmatic Guaranteed



27th Oct 1994, AT & T on HotWired.com (78% CTR)

courtesy of Ad Age

Trading in ad networks (since 1996)



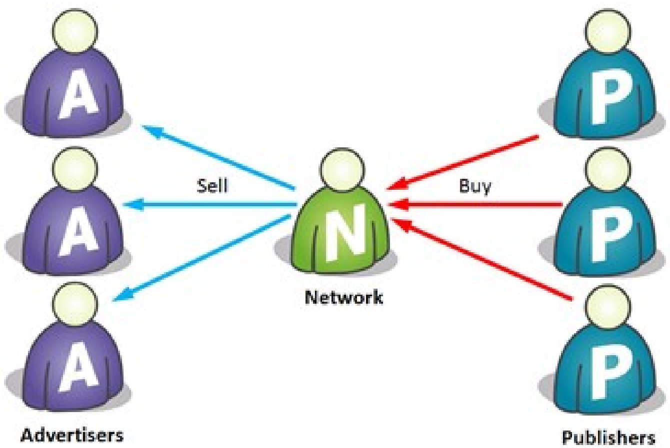
Aggregated demand and supply since 1996

- After direct sales, some impressions will remain unsold (remnants)
- Small publishers cannot find buyers directly

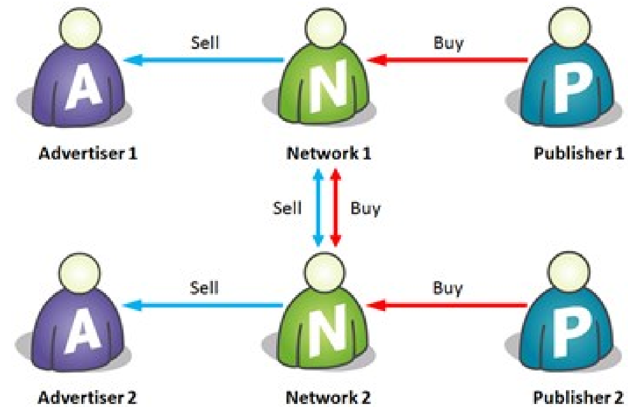
courtesy of Admeld

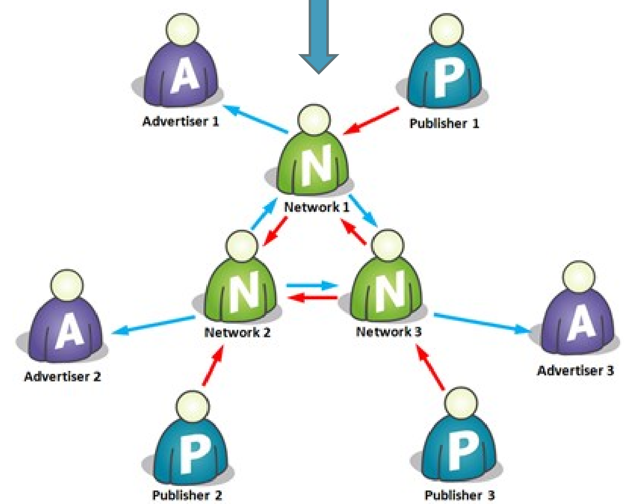
Introducing the ad exchange (since 2009)

single ad network is easy

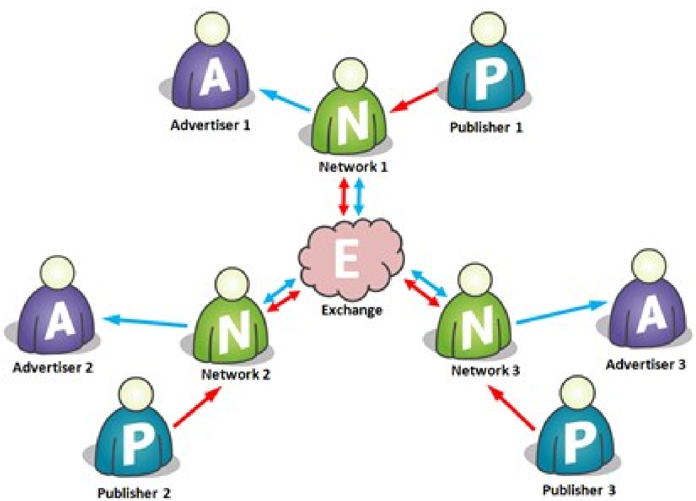


a few ad networks are manageable



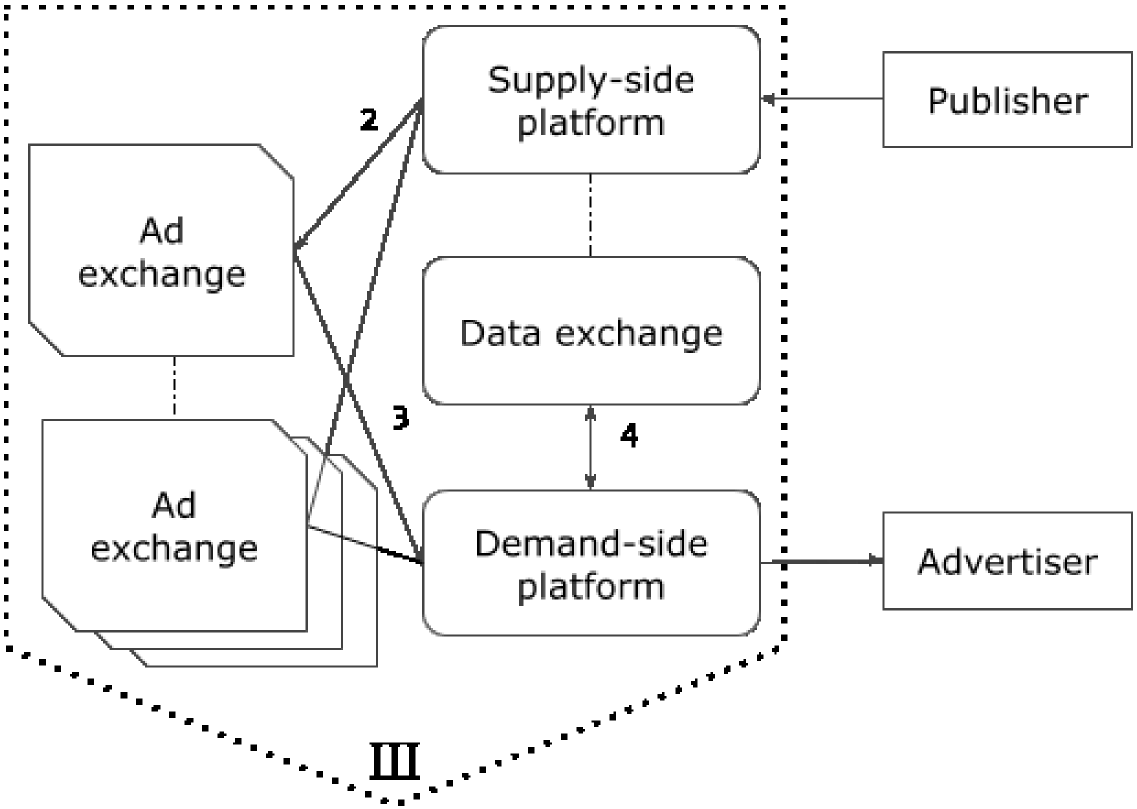


hundreds of ad networks are nightmare



courtesy of www.liesdamnedlies.com

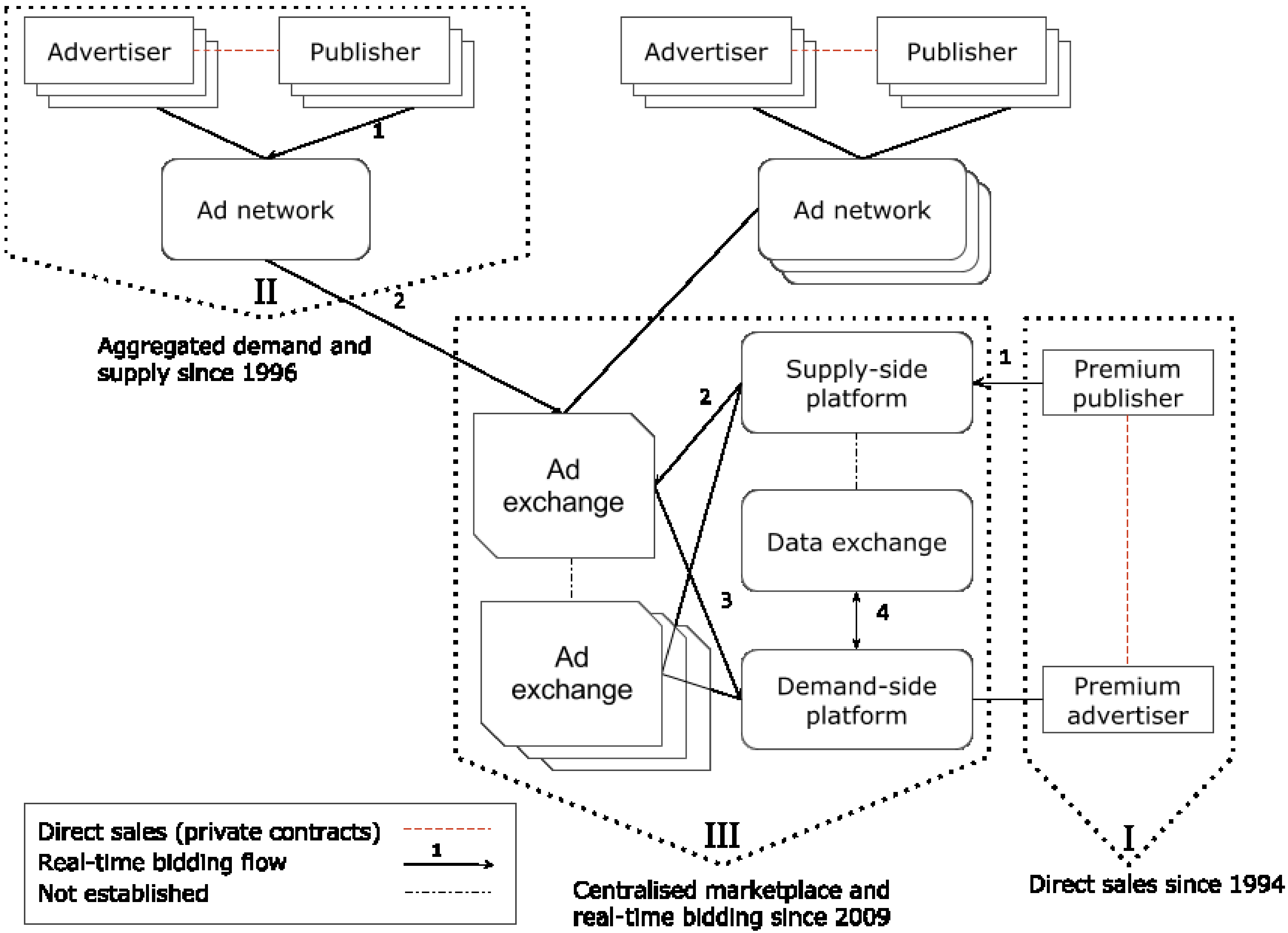
Introducing the ad exchange contd.



Centralised marketplace and real-time bidding since 2009

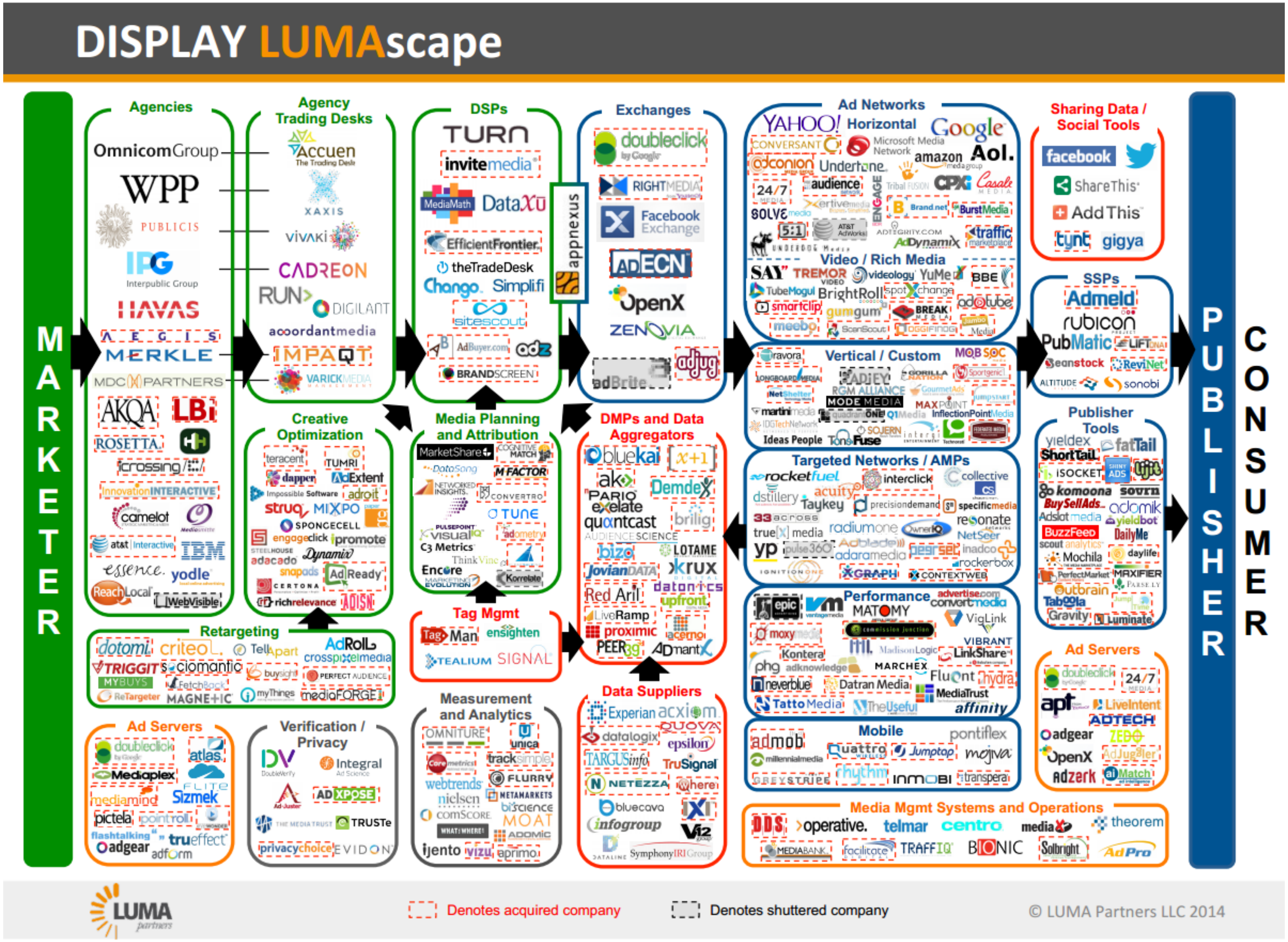
- Ad exchanges are marketplaces
- Advertisers and publishers have to rely on tools to connect
- Real-Time Bidding promotes user-oriented bidding

The simplified history of online (display) advertising



Real-time Bidding for Online Advertising: Measurement and Analysis, S Yuan et al., 2013

The complex display ad eco-system



courtesy of LUMAscape 2014

A great visualisation

Behind the banner

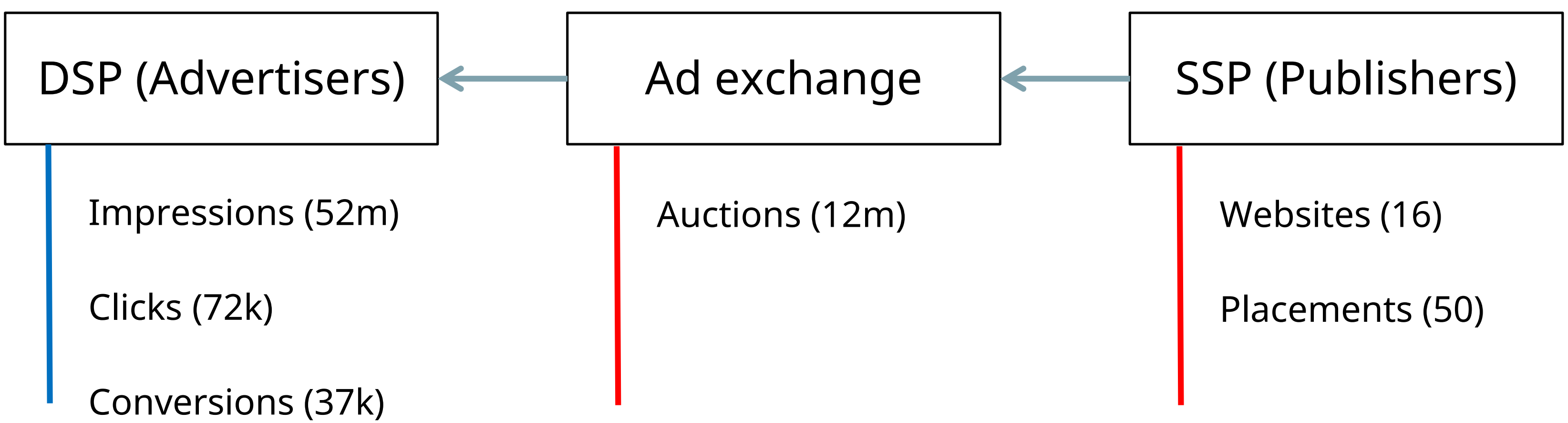
http://o-c-r.org/adcells/

A visualization of the adtech ecosystem, Adobe, 2013

Part 1.2 RTB and an empirical study

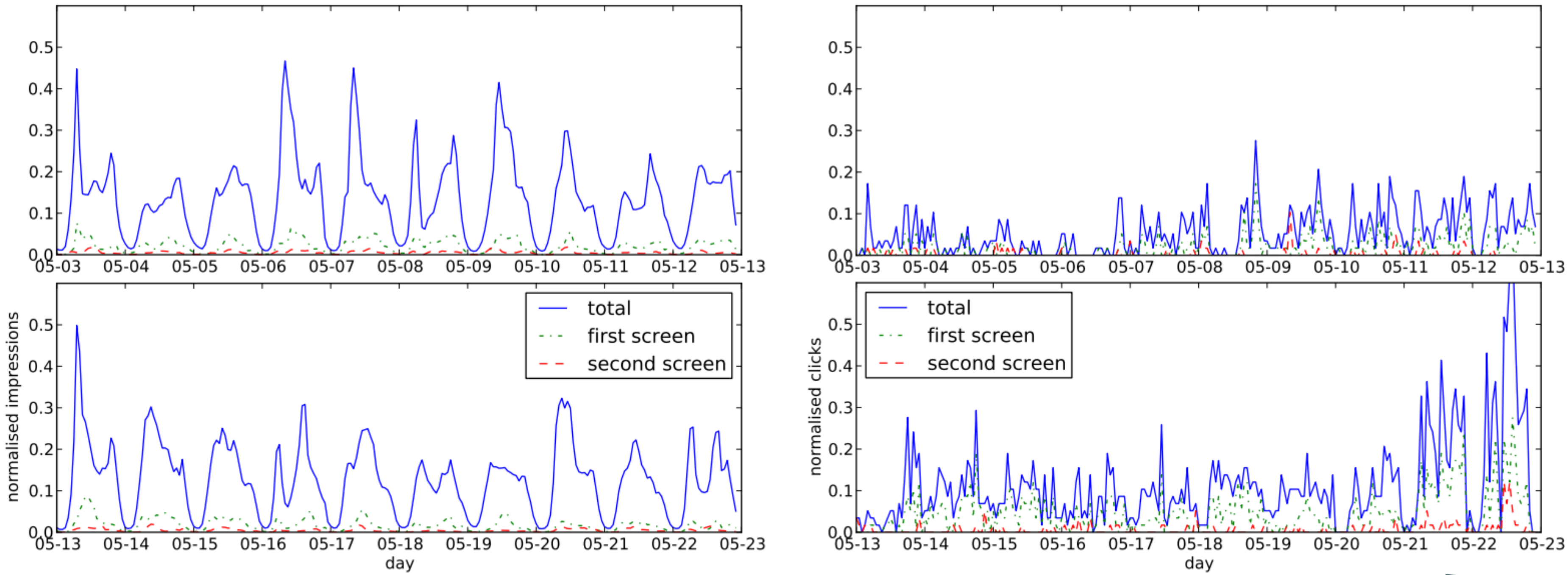
- To understand the bidding behaviours in RTB auctions
- To present some research challenges
- To help to get familiar with RTB in the real-world

- The data is from production DSP & SSP based in UK



Real-time Bidding for Online Advertising: Measurement and Analysis, S Yuan et al., 2013

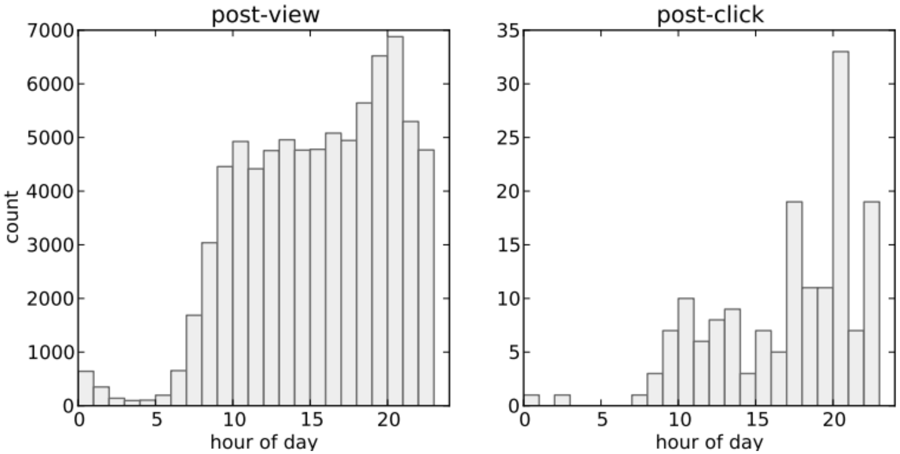
Impressions and clicks

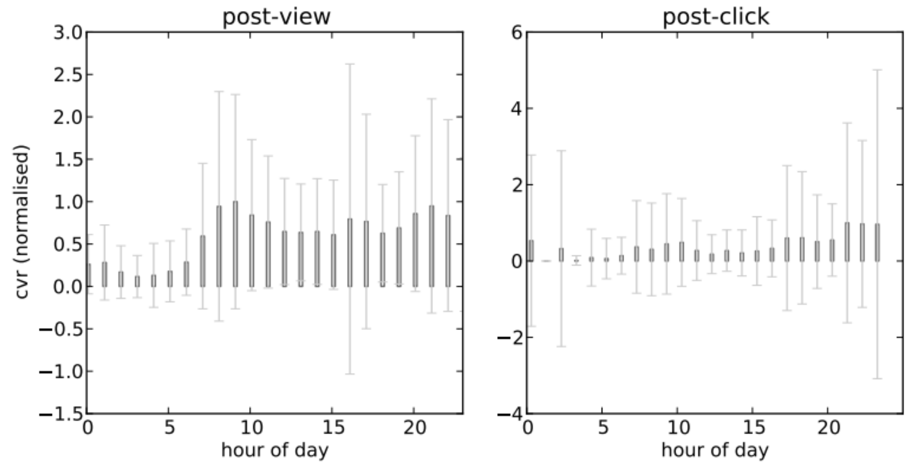


Very noisy

The numbers of imp (left) and click (right) both show strong daily and weak weekly patterns, corresponding to the normal human activity

Conversions

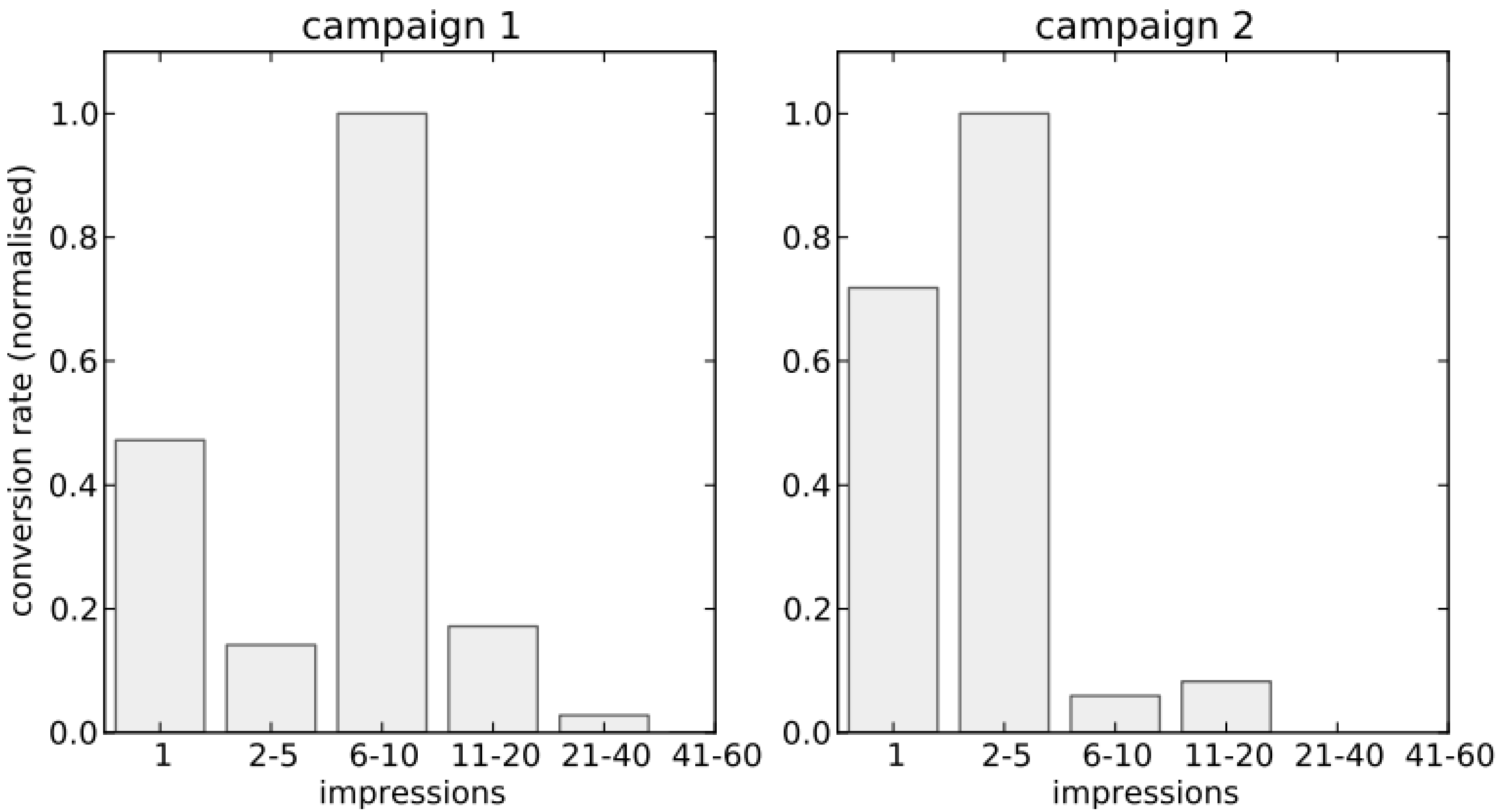




The post-view conversions are NOT negligible

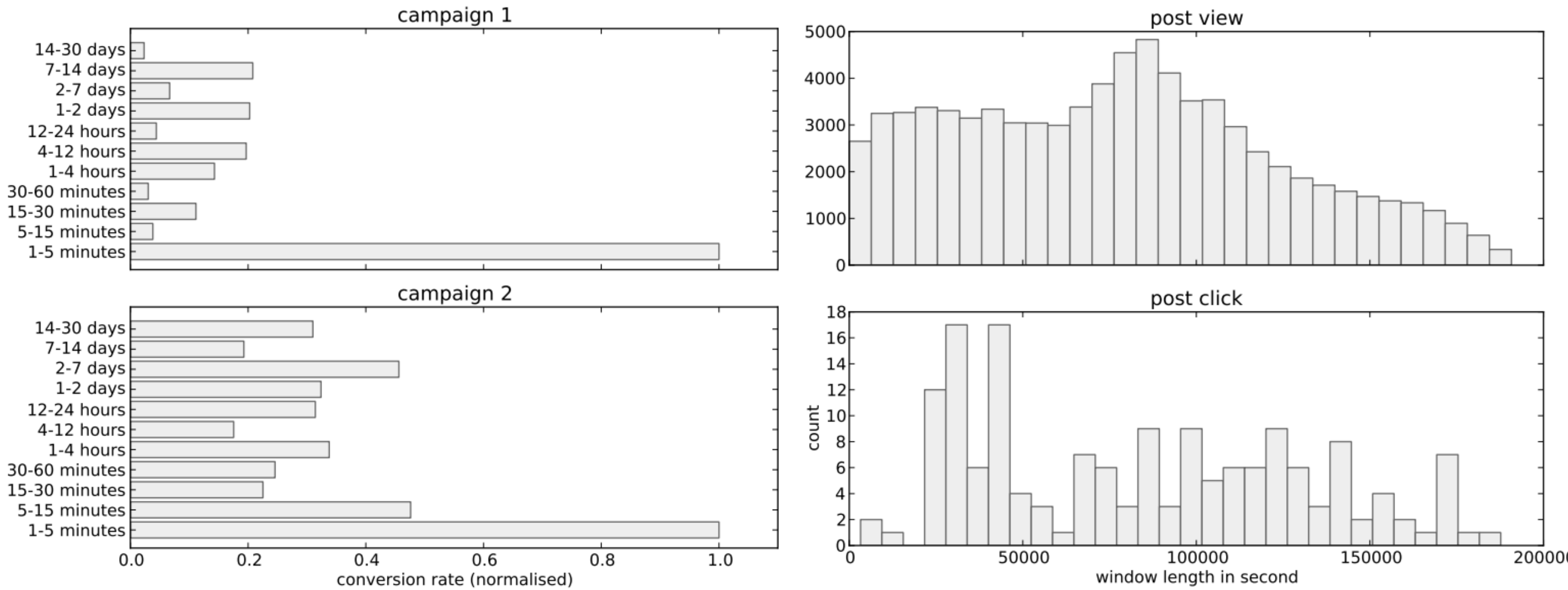
Daily periodic patterns for conv (left) and cvr (right) show that people are less likely to convert during late night

Conversions (Frequency distribution)



The frequency against CVR plot from two different campaigns
Campaign 1 sets a frequency cap of 2-5 -> poor performance
Campaign 2 sets a frequency cap of 6-10 -> waste of budget

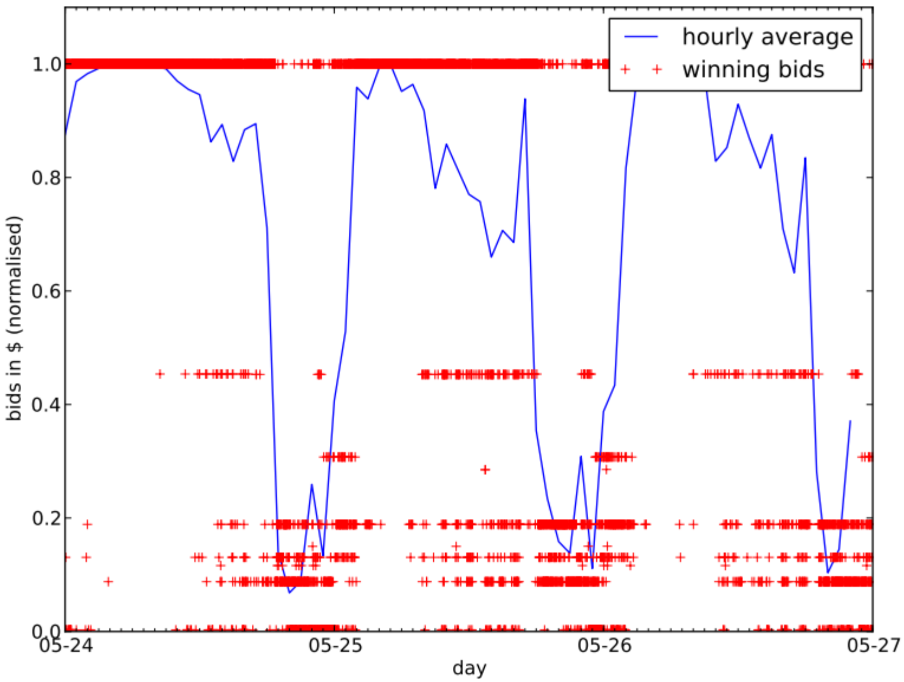
Conversions (Recency distribution)

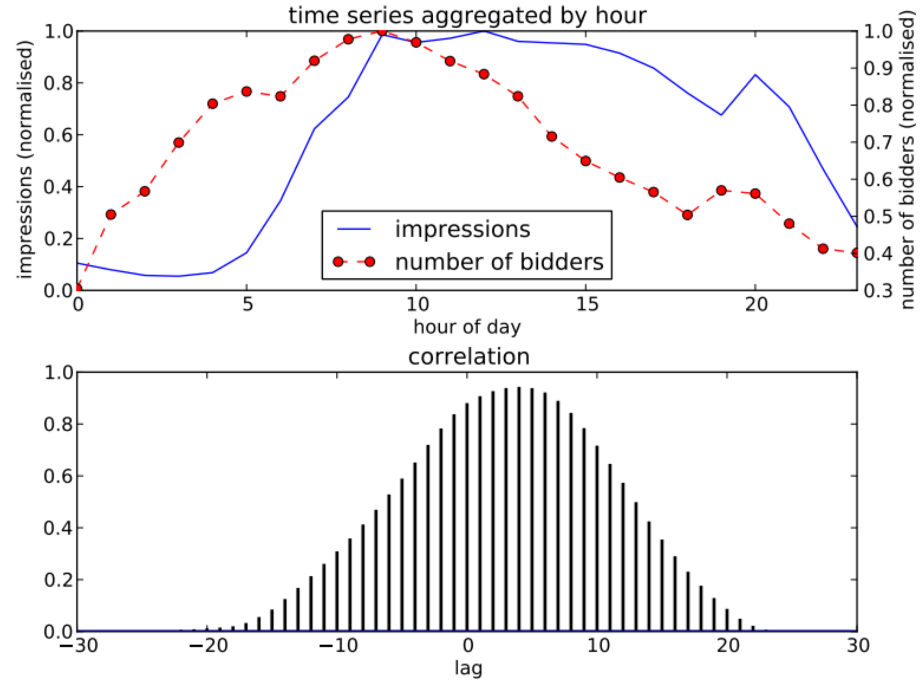


The recency factor affects the CVR (left)
Campaign 1 sets a long recency cap -> waste of budget
Campaign 2 sets a short recency cap -> poor performance

The wide conversion window (right)
challenges attribution models

Auctions (Bidding competition)

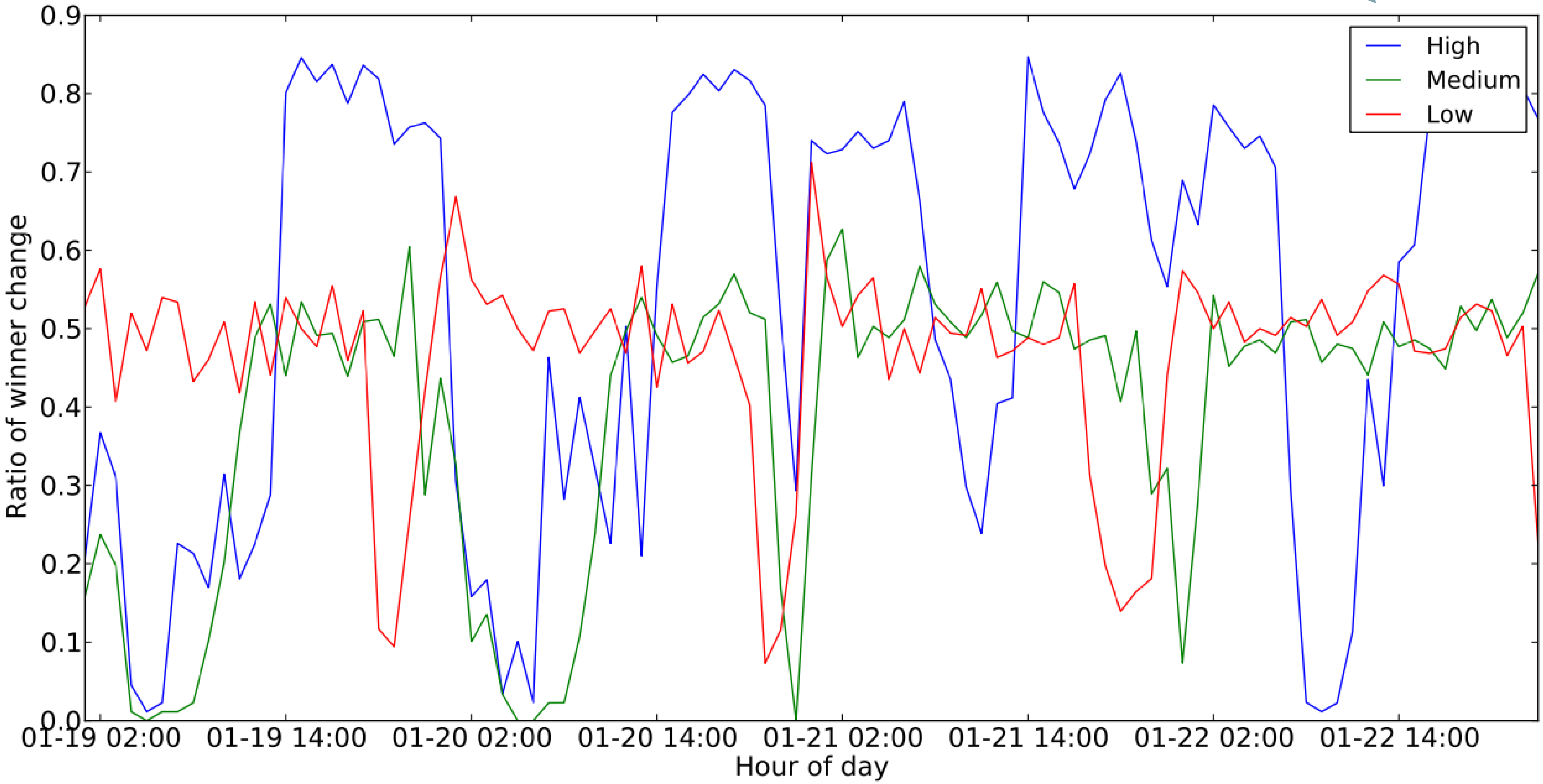




The winning bids peak at 8-10am due to intensive competition

Auctions (Change of winner)

Level of competition
(number of bidders)



The more bidders, the higher chance of winner change

Auctions (Bids' distribution)

	Accepted (p>0.05)	Rejected
AD test per auction	0.343	0.657
AD test per placement	0.000	1.000
CQ test per auction	0.068	0.932

The commonly adopted assumption of Uniform distribution or Log-normal distribution were mostly rejected

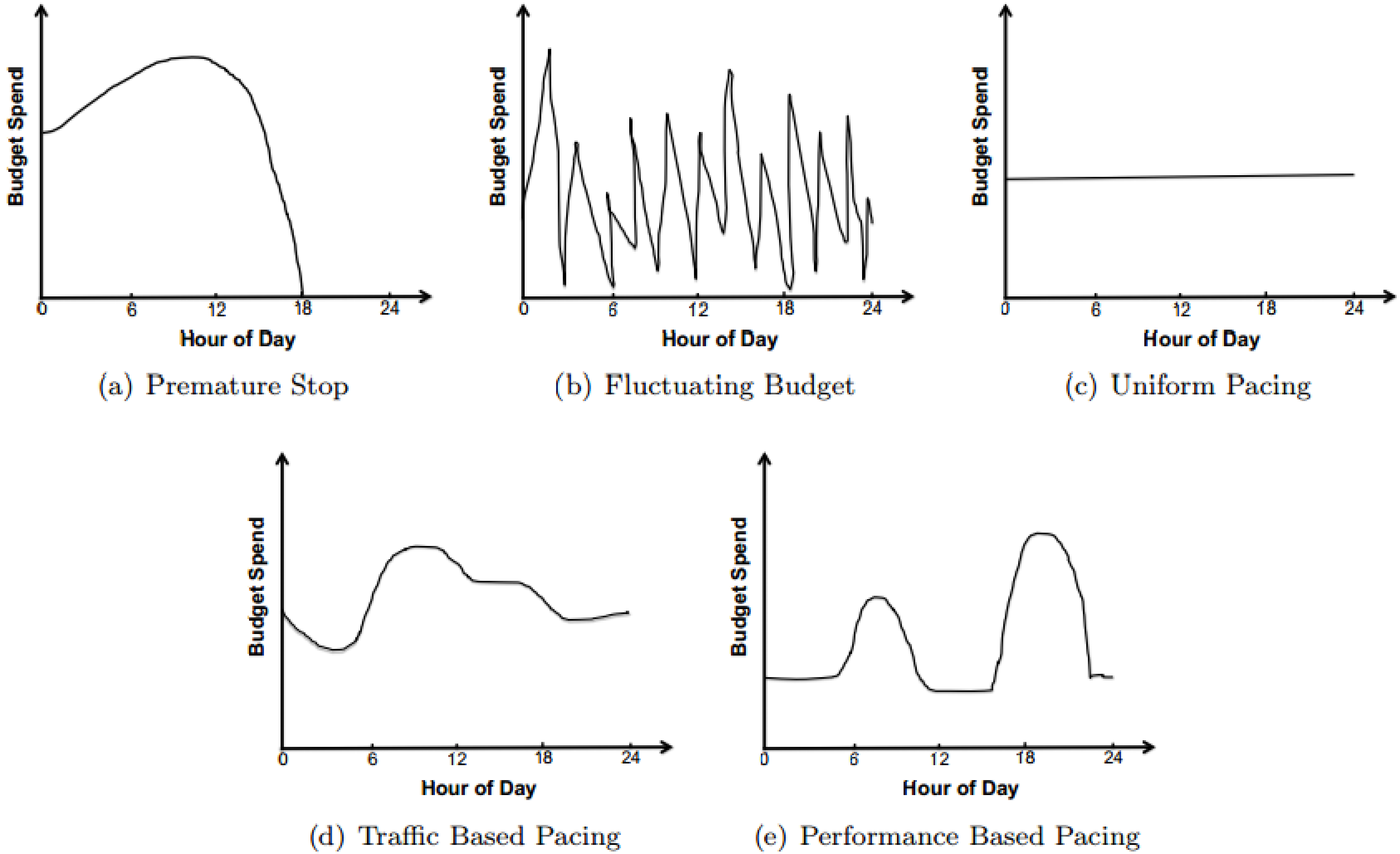
- Anderson-Darling test for Normality
- Chi-squared test for Uniformity

Finding the best fit of bids' distribution is important:

- Optimal reserve price
- Bid landscape forecasting
- etc.

And what's the granularity? (placement, geographical location, time & weekday, etc.)

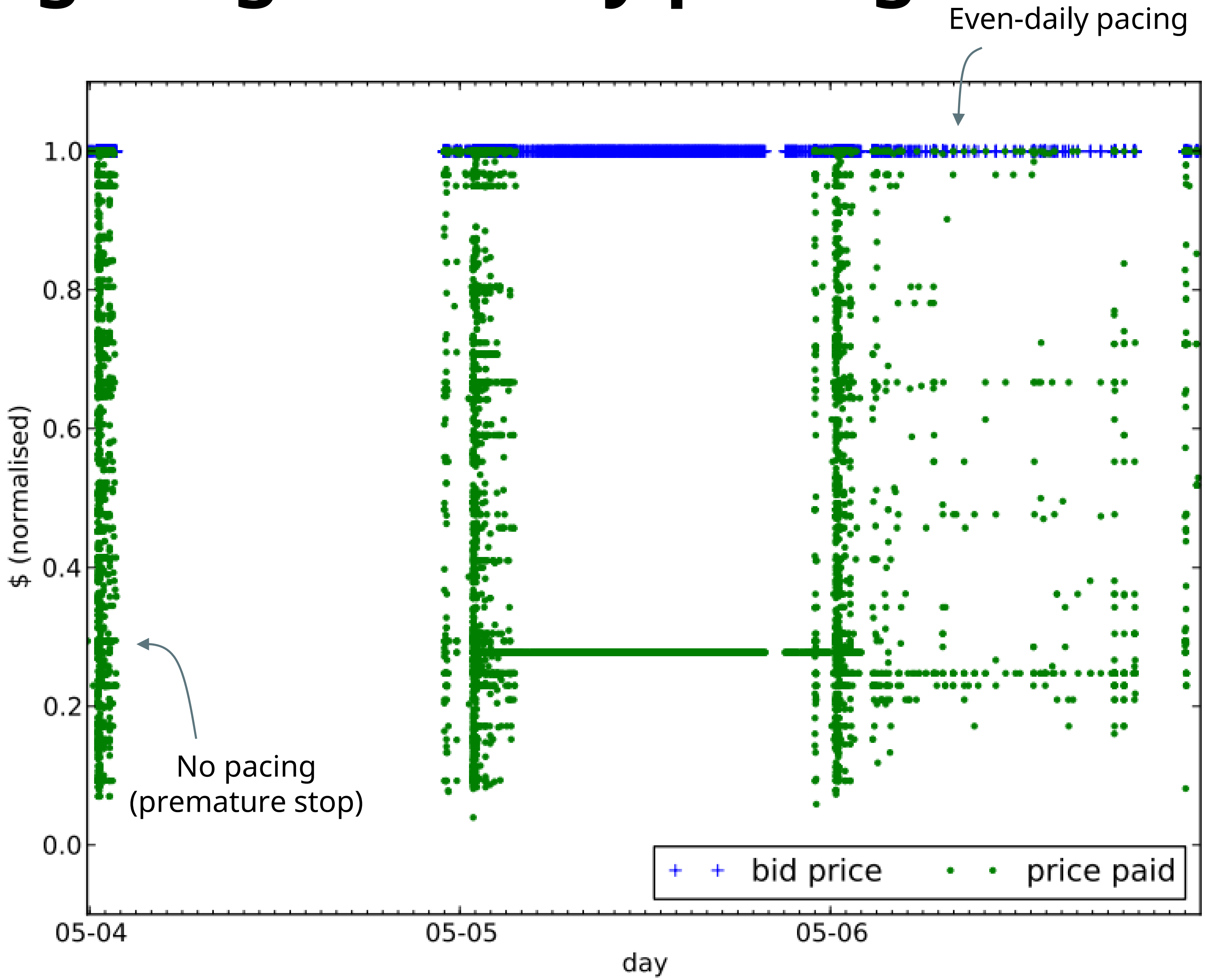
Budgeting and daily pacing



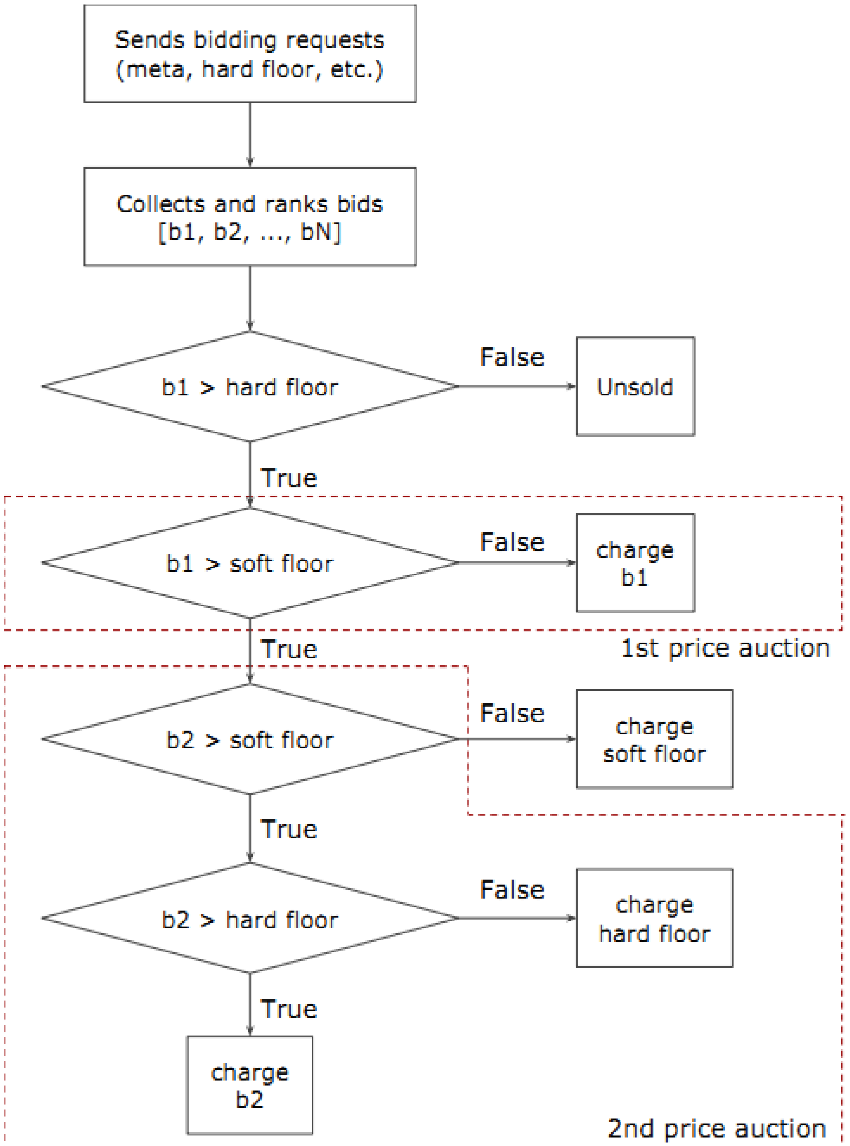
(a) Premature Stop (b) Fluctuating Budget (c) Uniform Pacing (d) Traffic Based Pacing (e) Performance Based Pacing

Real Time Bid Optimization with Smooth Budget Delivery in Online Advertising, KC Lee et al., 2013

Budgeting and daily pacing



A mixture of first and second price auctions



- A high soft floor price can make it first price auction
  (In RTB, floor prices are not always disclosed before auctions)
- In our dataset, 45% first price auctions consumed 55% budgets
- The complicated setting puts advertisers in an unfavourable position and could damage the ad eco-system

Assuming the soft floor can be zero.

References

- The History of Advertising: How Consumers Won the War for Their Attention, HubSpot, 2013
  blog.hubspot.com/the-history-of-advertising-war-for-consumer-attention-slideshare
- How Cluttered Is the Advertising Landscape, Really? HubSpot, 2013
  blog.hubspot.com/how-cluttered-is-advertising-landscape-timeline
- Navigating Planet Ad Tech, MIT Technology Review, 2013
  www.technologyreview.com/view/518551/the-evolution-of-ad-tech/
- Internet Advertising: An Interplay among Advertisers, Online Publishers, Ad Exchanges and Web Users, S Yuan et al., 2013
  arxiv.org/abs/1206.1754
- Ad exchanges: research issues, S Muthukrishnan, 2009
  sites.google.com/site/algoresearch/start2.pdf
- Behind the banner (A visualization of the adtech ecosystem), Adobe, 2013
  cmsummit.com/behindthebanner/

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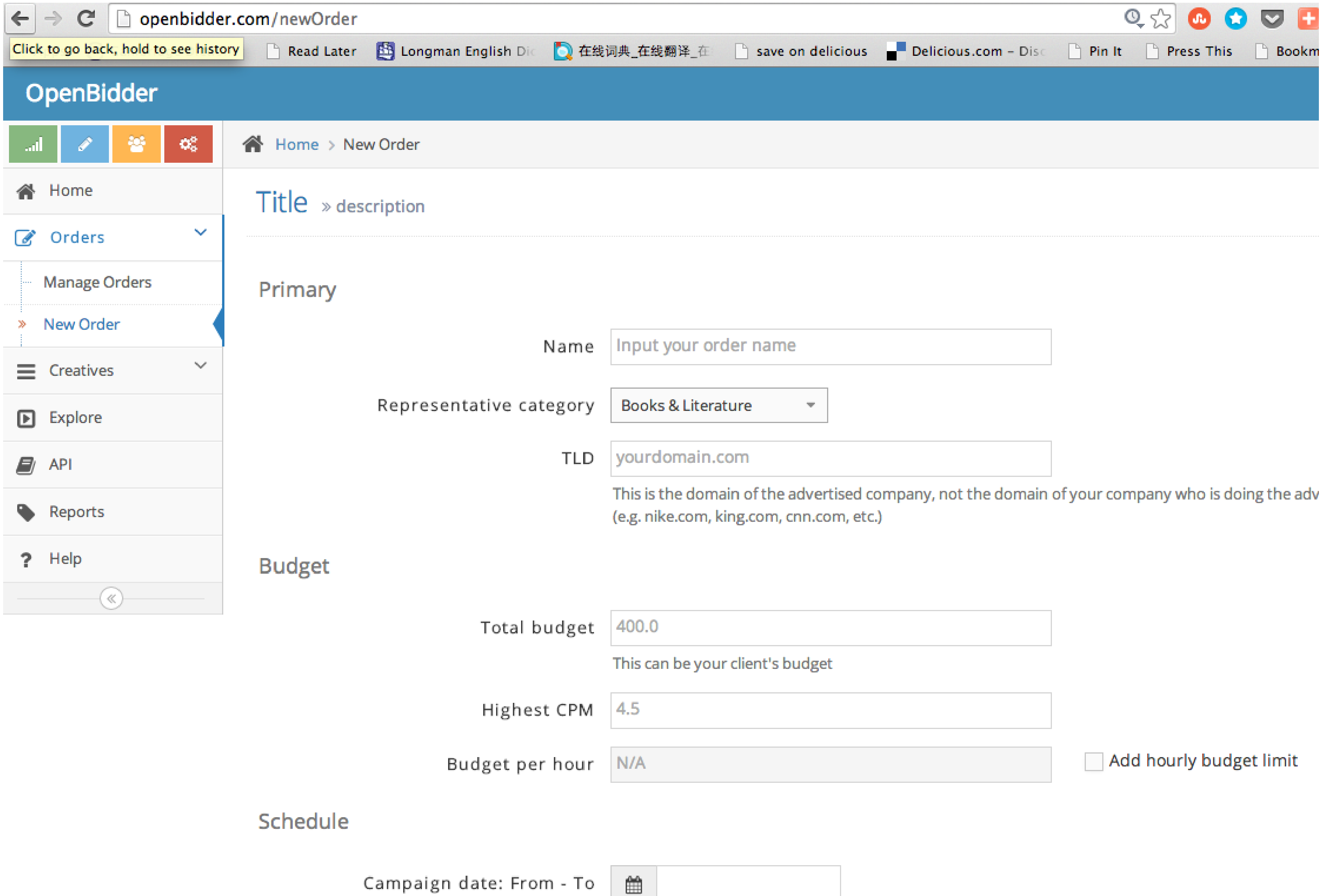
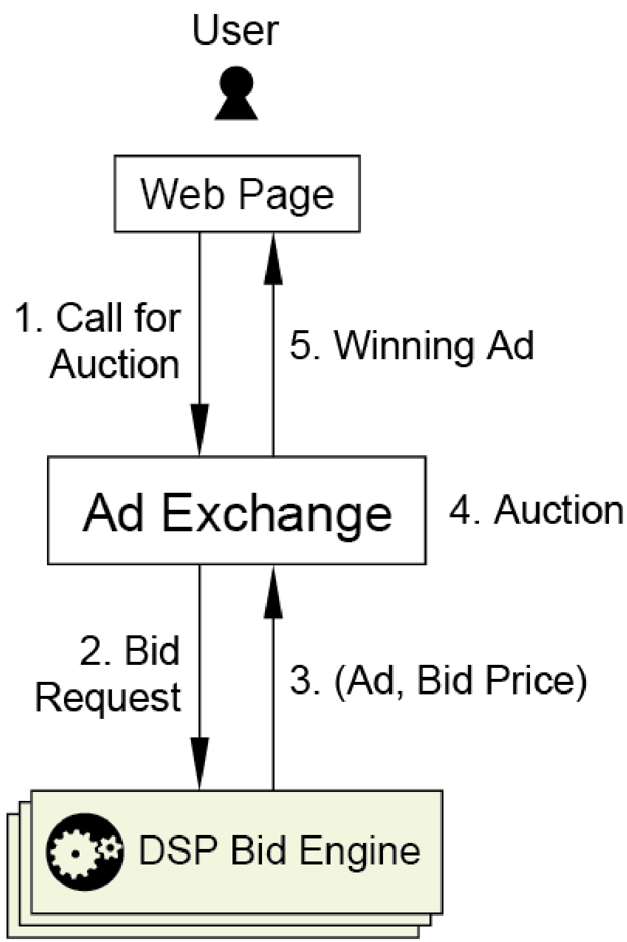
Part 2.1 Bidding strategy

- Bid optimisation methods
  - Introductions
  - CTR predictions
  - Bidders

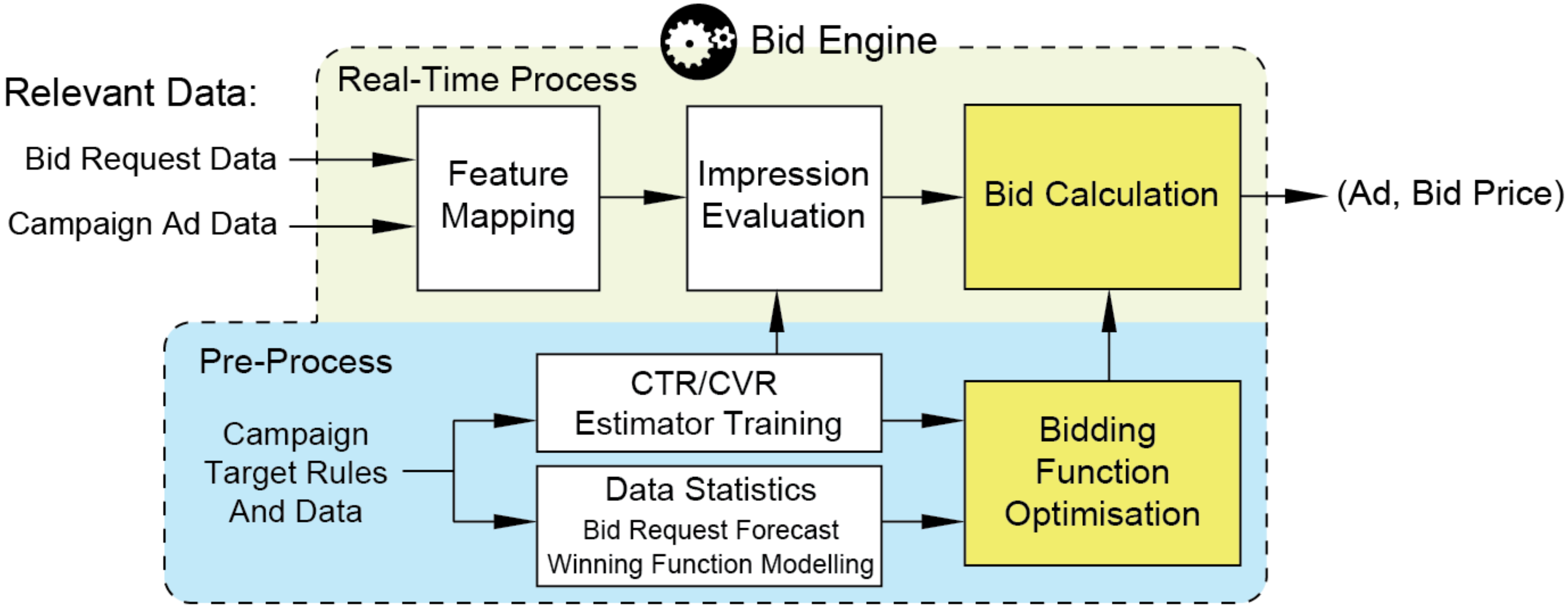
Demand Side Platform (DSP)



Bidder in DSP

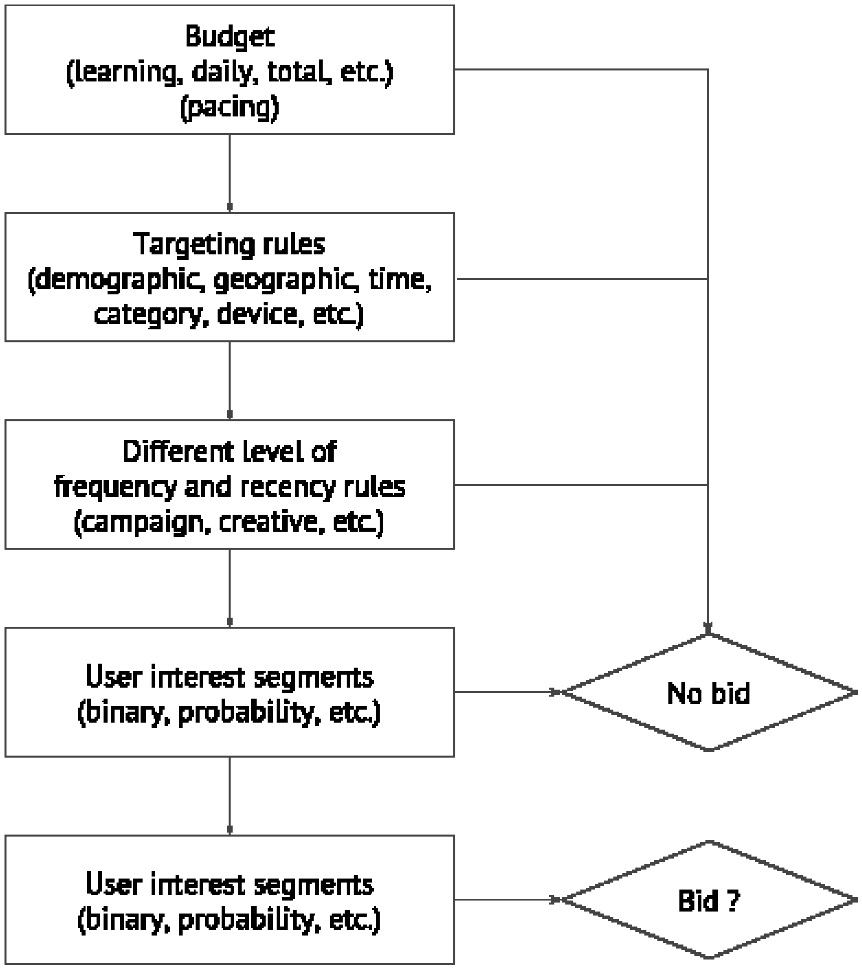


Bidder in DSP



Input-process-output

- Input
  - logs for bid requests, impressions and events (browsing, clicks, conversions)
  - targeting rules
  - budgets and pacing preference
  - internal/external user data
- The Decision Engine
  - regression for effectiveness
  - cost efficiency
- Output
  - bid price



The bidding problem

- Objective
  - Bidding strategy π^*
  - Maximises the KPI (usually $-CPA$)
  - Subject to the constraint $cost \leq budget$
- Components
  - x, the bid request, user and ad features
  - $\theta(x)$, the prediction function (e.g. CTR and CVR)
  - $b(\theta(x), x)$, the bidding function
  - $w(b, x)$, the win function (chances to win the impression)

Typical features example

Col #	Description	Example
*1	Bid ID	015300008...3f5a4f5121
2	Timestamp	20130218001203638
†3	Log type	1
*4	iPinyou ID	35605620124122340227135
5	User-Agent	Mozilla/5.0 (compatible; \ MSIE 9.0; Windows NT \ 6.1; WOW64; Trident/5.0)
*6	IP	118.81.189.*
7	Region	15
8	City	16
*9	Ad exchange	2
*10	Domain	e80f4ec7...c01cd1a049
*11	URL	hz55b00000...3d6f275121
12	Anonymous URL ID	Null
13	Ad slot ID	2147689_8764813
14	Ad slot width	300
15	Ad slot height	250
16	Ad slot visibility	SecondView
17	Ad slot format	Fixed
*18	Ad slot floor price	0
19	Creative ID	e39e178ffd...1ee56bcd
*20	Bidding price	753
*†21	Paying price	15
*†22	Key page URL	a8be178ffd...1ee56bcd
*23	Advertiser ID	2345
*24	User Tags	123,5678,3456

- Optimising from the advertisers’ perspective
  - Ads (creative) known
  - Historical performance known
  - First party audience data available
  - Competition unknown

Predicting CTR or CVR

- Regression
  - Generalised linear regression models (Logistic, Bayesian probit, FTRL-Proximal, etc.)
    - [Richardson2007, Graepel2010, Zhu2010, Chapelle2012, McMahan 2013]
  - Rule based
    - [Dembczynski2008]
  - Tree based models (Random forest, Gradient boosting regression tree, etc.)
    - [Mohan2011]
  - Neural networks and deep learning
    - [Corrado2012]

$$\hat{y}_i = \frac{1}{1 + \exp\{-\boldsymbol{w}^T x_i\}}$$

$$L(\boldsymbol{w}) = \sum_i (-y_i \log(\hat{y}_i) - (1 - y_i)\log(1 - \hat{y}_i)) + \frac{\lambda}{2}\|\boldsymbol{w}\|_2$$

Bidding strategy

- Baseline (constant or random, usually for exploration)
- Linear bidder (proportional to the effect of the inventory)
- Heuristic bidder (linear with capping)
- Multiplicative bidder (a modifier vector applied to basic predictions)
- Uniform bidder (fixed bids based on the bid landscape)
- Optimal bidder (combining prediction with bid landscape)

Linear bidder

- To modify the bid proportional to the effect of the inventory

$$\Phi^* = \frac{p(c|u,i,a)}{E_j[p(c|u,i,a)]}$$

$$B^* = B * \Phi^*$$

- Strategy 2 (aggressive bidding)
  - $\phi < 0.8 \rightarrow \phi = 0$ (not bidding)
  - $0.8 \leq \phi \leq 1.2 \rightarrow \phi = 1$
  - $\phi > 1.2 \rightarrow \phi = 2$

Post-view site visit rate

Campaign	Measure	Str 0	Str 1	Str 2
1	PVSVR	0.00274	0.00294	**0.00333**
2	PVSVR	0.00080	0.00087	**0.00097**
3	PVSVR	0.00031	0.00033	**0.00041**
4	PVSVR	0.00044	0.00047	**0.00053**
5	PVSVR	0.00183	0.00193	**0.00229**
6	PVSVR	0.00037	**0.00041**	0.00040
7	PVSVR	**0.00526**	0.00432	0.00441
8	PVSVR	0.00020	**0.00026**	0.00025
9	PVSVR	0.00185	NA	**0.00205**
10	PVSVR	0.00439	NA	**0.00600**
11	PVSVR	0.00104	NA	**0.00119**
12	PVSVR	0.00889	NA	**0.01088**
13	PVSVR	0.00387	NA	**0.00464**
14	PVSVR	0.00204	NA	**0.00299**
15	PVSVR	0.00292	NA	**0.00319**
1	CPA	**0.4434**	0.5048	0.5640
2	CPA	1.3406	**1.2799**	1.4807
3	CPA	**4.5124**	4.6714	5.2446
4	CPA	**2.3304**	2.5129	2.7400
5	CPA	0.4854	**0.4785**	0.5100
6	CPA	2.7487	**2.6566**	3.3143
7	CPA	**0.1201**	0.1382	0.192
8	CPA	6.1238	**5.6980**	7.9599
9	CPA	0.4764	NA	**0.4261**
10	CPA	**0.1966**	NA	0.2242
11	CPA	**1.1136**	NA	1.5764
12	CPA	**0.1804**	NA	0.2086
13	CPA	**0.3524**	NA	0.4354
14	CPA	0.6074	NA	**0.5497**
15	CPA	**0.4698**	NA	0.6207

C Perlich et al., Bid Optimizing and Inventory Scoring in Targeted Online Advertising, 2012

A heuristic bidder

- To calculate the bid price based on CTR prediction with capping

Predicted CTR

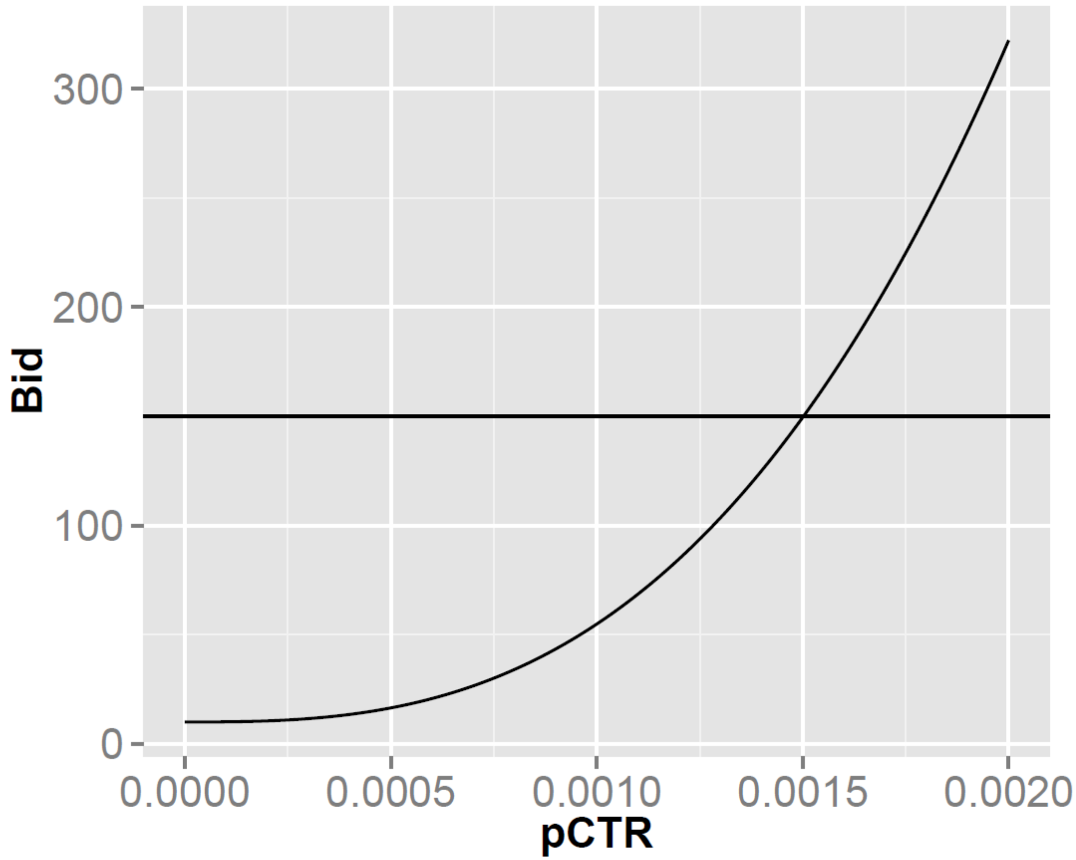
$$b_i = \min\left\{\left(\frac{\hat{y}_i}{y_0}\right)^a y_0 b + c, d\right\}$$

Base (average) CTR

a, b, c, d are empirical parameters
learned from the training dataset

W Zhang et al., Real-Time Bidding Benchmarking with iPinYou Dataset, 2014

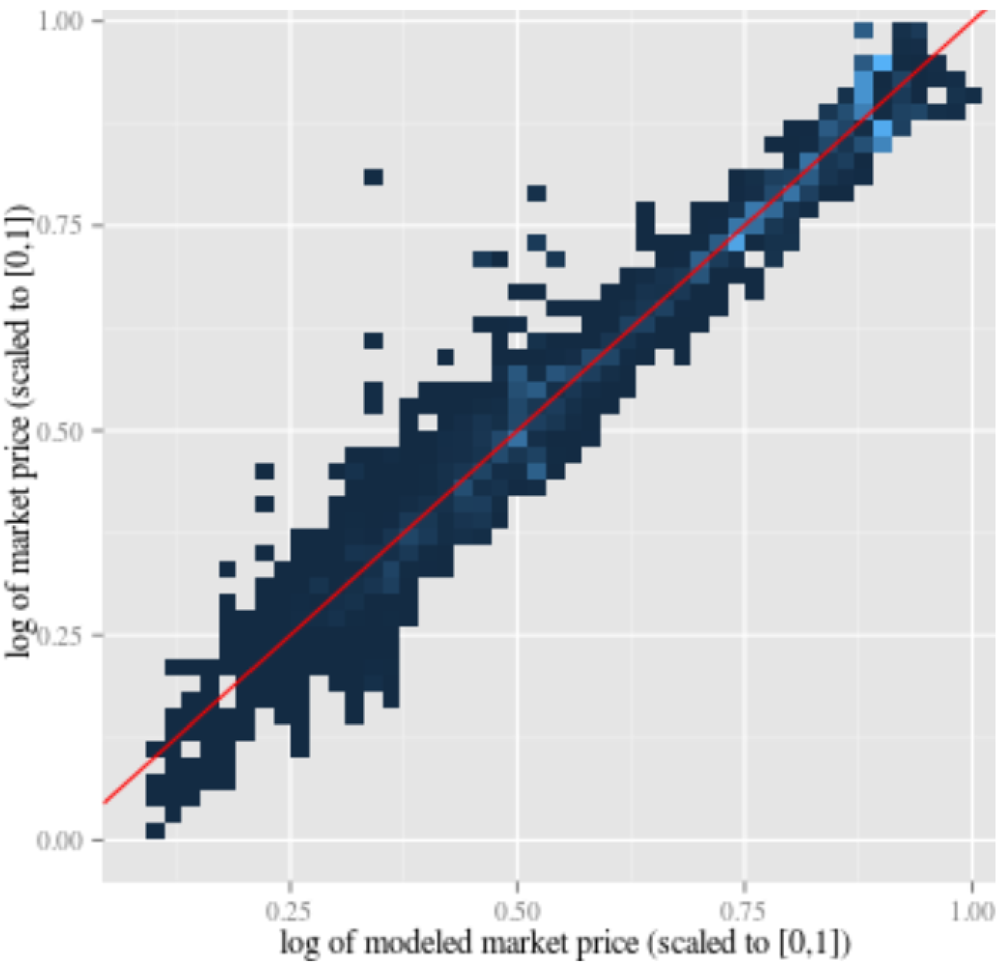
A heuristic bidder



$$y_0 = 10^{-4}$$

$$a = 2.8, b = 0.3, c = 10, d = 150$$

Multiplicative bidder



The market prices can be well represented by the multiplication of two vectors

Features: country & hour of the day

Two bid adjustment dimensions with m and n possible settings

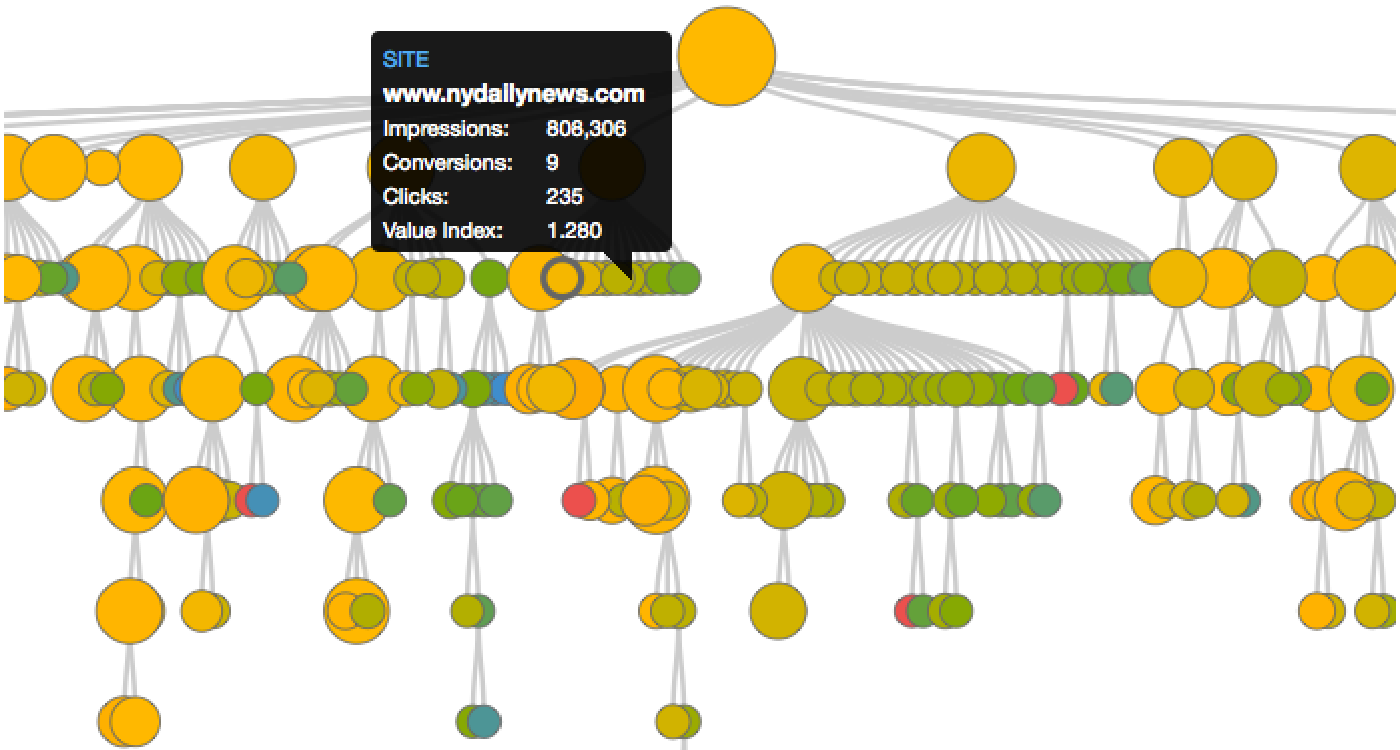
For each entry $(i, j) \in [m] \times [n]$, an advertiser is given a price p_{ij} and value v_{ij}

He is required to specify a bid multiplier r_i for each row i and c_j for each column j

The bid is then $r_i \cdot c_j$

Bateni et al., Multiplicative bidding in online advertising, 2014

An example



Brain algorithm from MediaMath

Advertisers can specify a modifier for a targeting combination

Multiplicative bidder

- A cell (i, j) is captured if $r_i \cdot c_j \geq p_{ij}$
- The budget constraint $\sum p_{ij} \leq B$
- Objective to maximise $\sum v_{ij}$

Algorithm 2: Overview of $O(\log m)$ approximation

Step 1:
Round down all of the p_i's to the nearest powers of 2;
Cluster together rows with the same p_i;
Reorder the clusters in increasing p_i;
Step 2:
Reorder the rows within each cluster in increasing values;
Compute $\mathtt{OPT}(B/4)$, the individual bidding optimum with budget $B/4$;
Step 3:
for h=1,2,...,m **do**
  $\mathtt{ALG}_h \longleftarrow \emptyset$;
  Insert into $\mathtt{ALG}_h$ all height-h towers of $\mathtt{OPT}(B/4)$;
  Insert into $\mathtt{ALG}_h$ all height-h towers in the strips above the ones in the last line;
end
Output the best $\mathtt{ALG}_h$ as $\mathtt{ALG}$

Bateni et al., Multiplicative bidding in online advertising, 2014

Uniform bidder (in sponsored search)

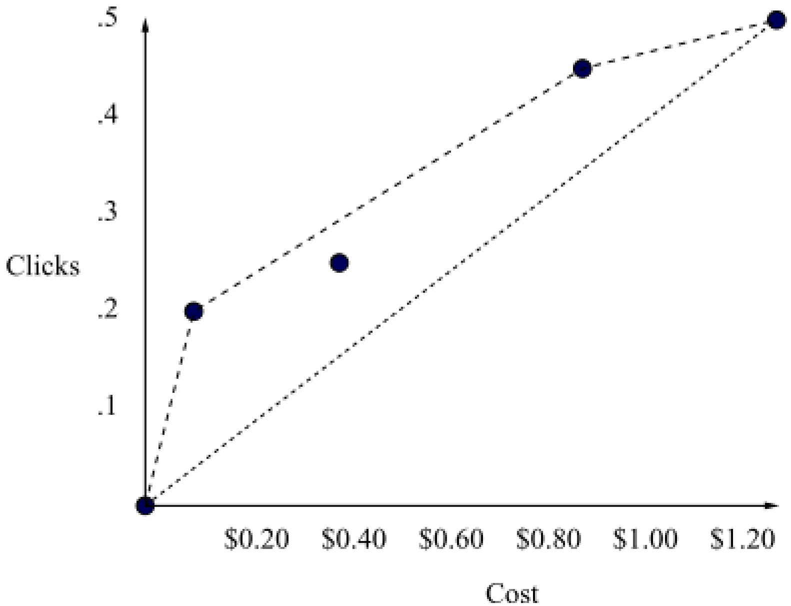
- A bipartite graph G on the two vertex sets K and Q
- Matches of $q \in Q$ are neighbours of q in K
- Click function: $clicks_q(\cdot)$
- Cost function: $cost_q(\cdot)$
- Objective to maximise: $\sum_q clicks_q(b_q)$
- Subject to: $\sum_q cost_q\left(b_q\right) \leq U$

- Nearly all formulation of this optimisation problem is NP-hard

Feldman et al., Budget Optimization in Search-Based Advertising Auctions, 2008

Uniform bidder (in sponsored search)

- An approximation: two-bid uniform strategy
  - To bid b_1 or b_2 on all keywords randomly



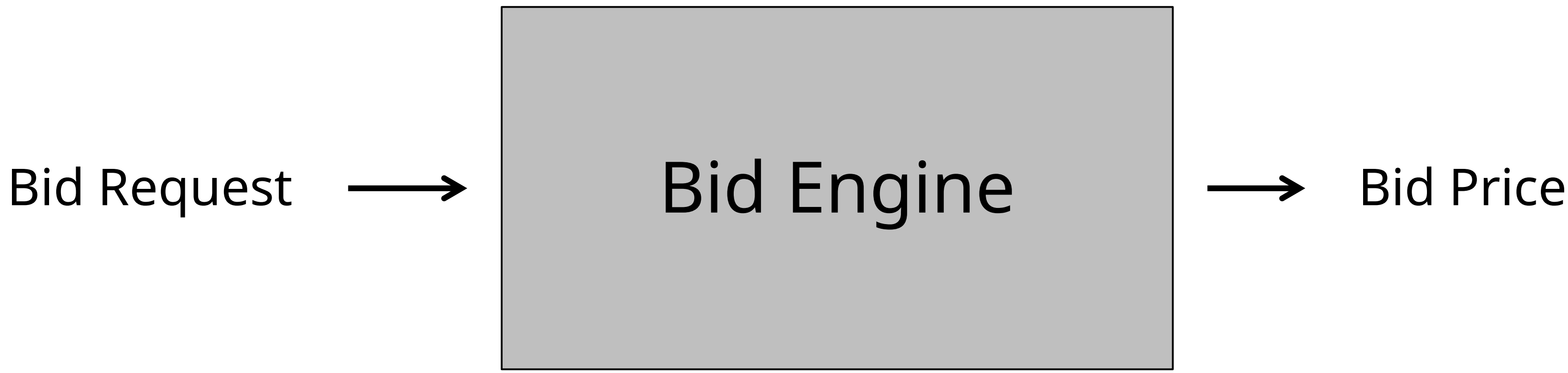
1. Aggregate all the points from the individual query landscapes into a single aggregate landscape.
2. Find the convex hull of the points in the aggregate landscape.
3. Compute the point on the convex hull for the given budget, which is the convex combination of two points α and β.
4. Output the strategy which is the appropriate convex combination of the uniform bid vectors corresponding to α and β.

A bid landscape example, where clicks are plotted as a function of cost;
The effective bids are discrete.

Similarly, a single-bid uniform strategy could be found with worse approximation but better computational complexity.

Feldman et al., Budget Optimization in Search-Based Advertising Auctions, 2008

Optimal Bidder: Problem Definition



Input: bid request include Cookie information (anonymous profile), website category & page, user terminal, location etc
Output: bid price
Considerations: Historic data, CRM (first party data), DMP (3rd party data from Data Management Platform)

What is the optimal bidder given a budget constraint?
e.g., Maximise

$$R=\sum(Clk+Conv*weight)$$

Subject to the budget constraint

Optimal bidder: the formulation

- Functional Optimisation Problem
  - Dependency assumption: $\boldsymbol{x} \rightarrow \theta \rightarrow b \rightarrow w$

winning function

CTR estimation

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

context+ad features

bidding function

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

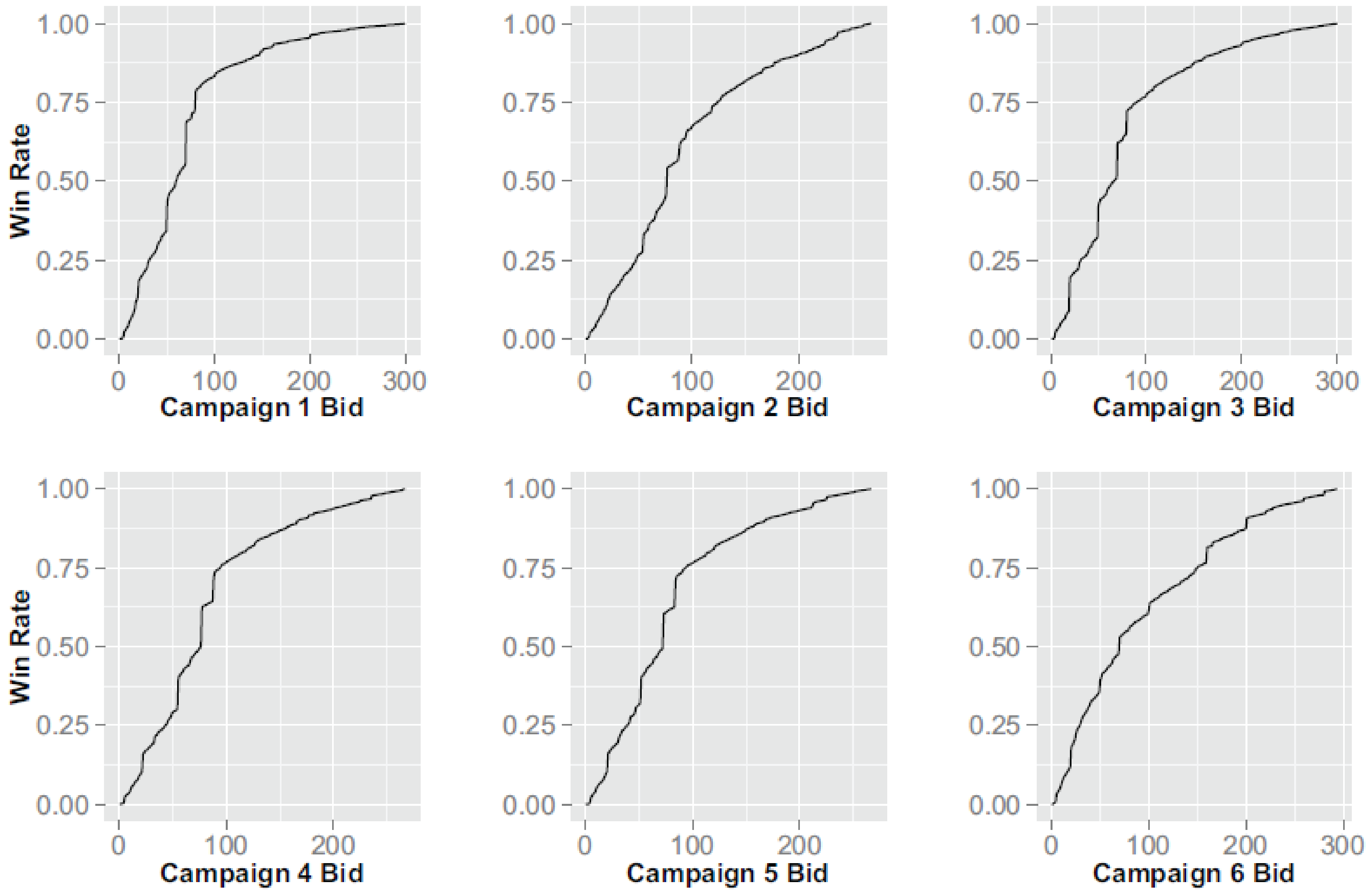
- Solution: Calculus of variations

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

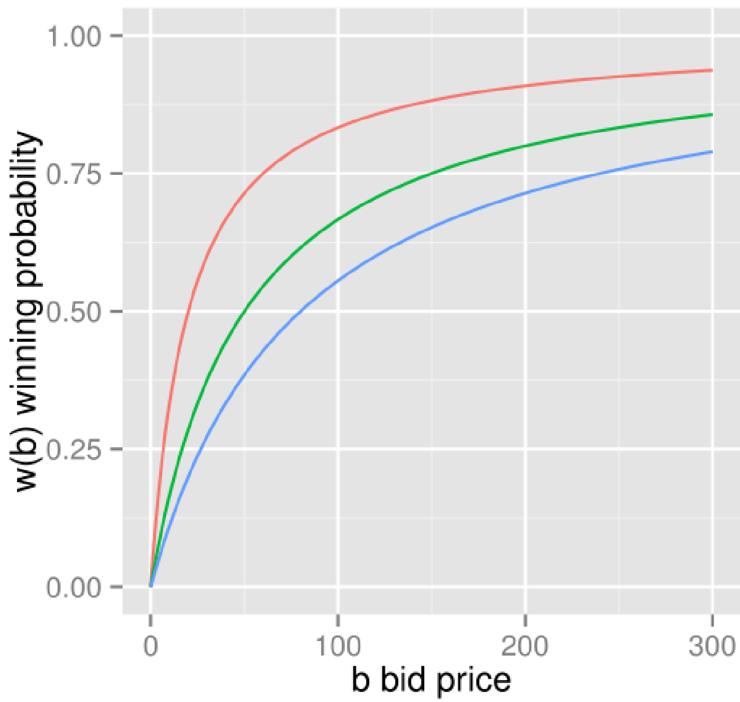
$$\lambda w(b(\theta)) = \Big[\theta - \lambda b(\theta)\Big] \frac{\partial w(b(\theta))}{\partial b(\theta)}$$

W Zhang et al., Optimal Real-Time Bidding for Display Advertising, KDD 2014

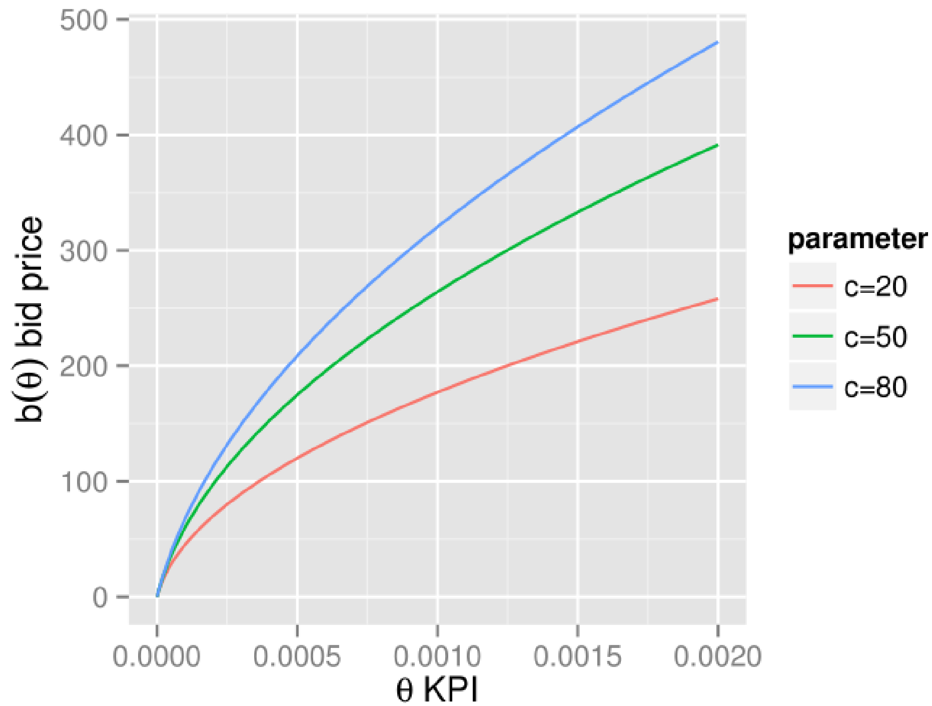
Win function



Optimal bidder: the solution



(a) Winning function 1.



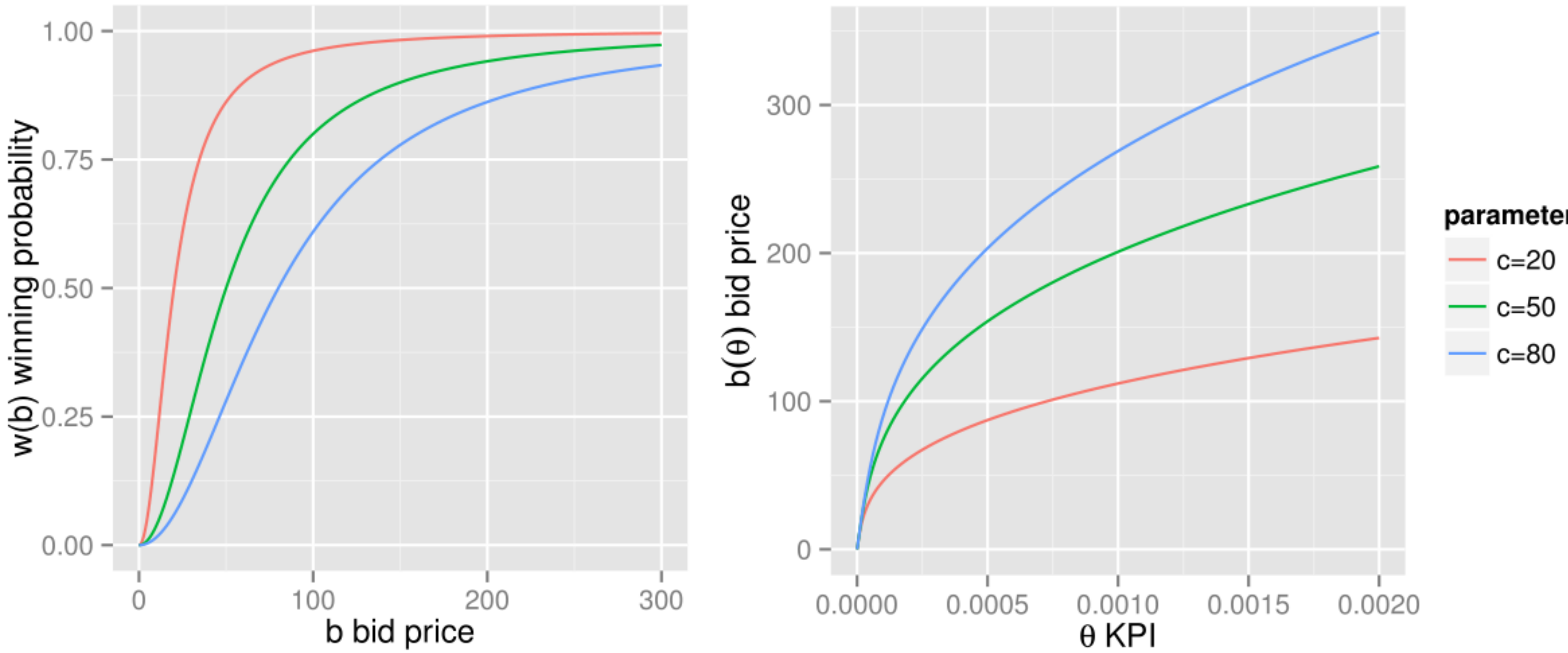
(b) Bidding function 1.

$$w(b(\theta)) = \frac{b(\theta)}{c + b(\theta)}$$

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

W Zhang et al., Optimal Real-Time Bidding for Display Advertising, KDD 2014

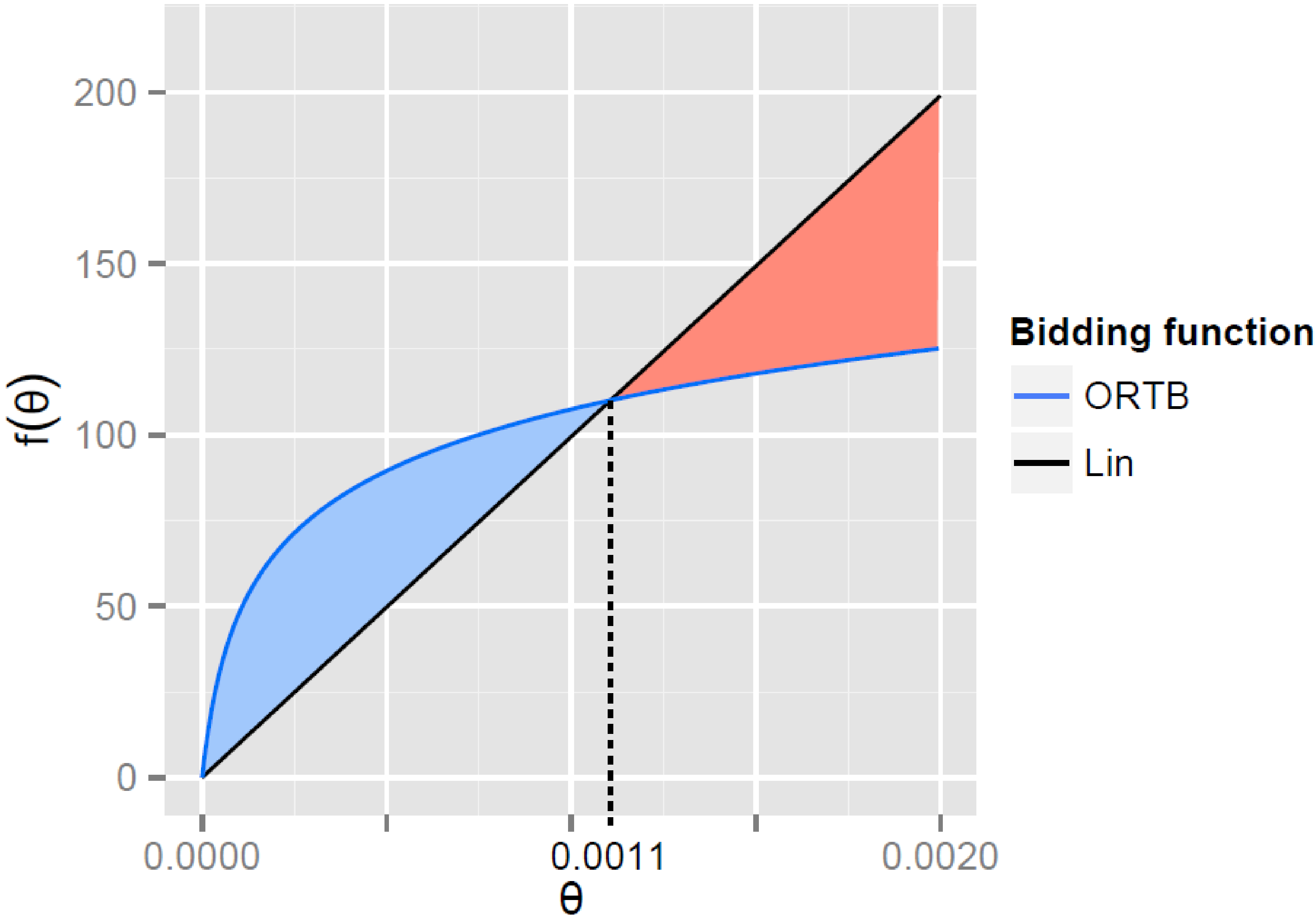
Optimal bidder: the solution



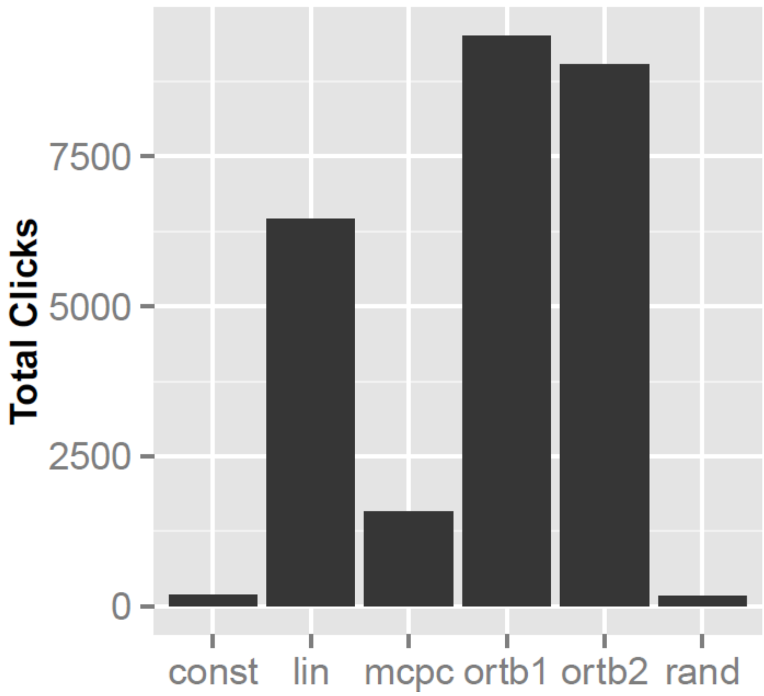
(a) Winning function 2. (b) Bidding function 2.

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

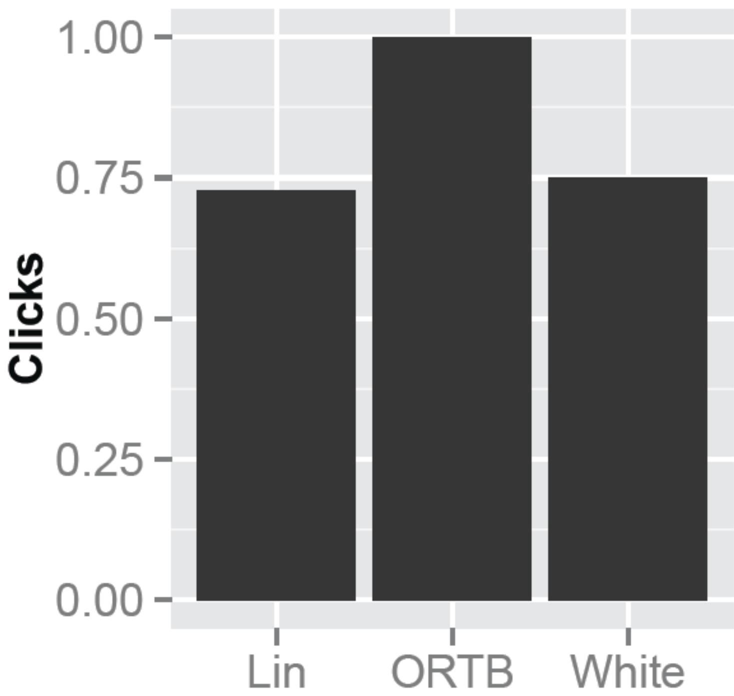
Optimal bidder: the solution



Experiments



Offline



Online

Winner of the first global Real-time Bidding algorithm contest 2013-2014

W Zhang et al., Optimal Real-Time Bidding for Display Advertising, KDD 2014

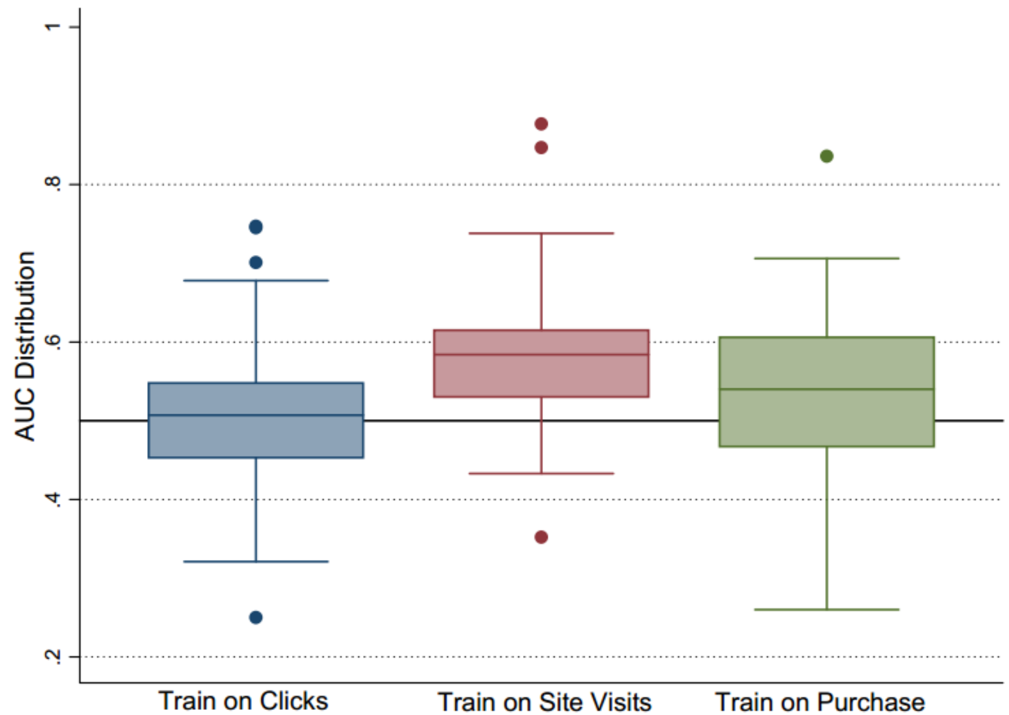
Beyond CTR: Alternative metrics

- Top funnel metrics (to gain brand awareness)
  - brand recall (awareness uplift)
  - branded search
  - direct website traffic
- Mid funnel metrics (to educate and engage the prospects)
  - cost per new website visitor
  - page view & form uplift
- Bottom funnel metrics (to generate value both online and offline)
  - total conversion
  - cost per conversion
  - opportunity contribution (interested but not converted yet)
  - revenue

courtesy of Adexchange

Beyond CTR: Transfer learning

- The Problem
  - CTR is no good metrics but CVR is too low
- Task
  - To train on site visits
- Challenge
  - Which site visits, and weights?
  - Data availability
- Solution
  - Similarity (contextual as a priori, Bayesian)



Dalessandro et al., Evaluating and Optimizing Online Advertising: Forget the Click, But There are Good Proxies, 2012

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- Causal reasoning and learning systems, L Bottou and E Portugaly, 2012
- Ad click prediction: a view from the trenches, HB McMahan et al., 2013
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- Deep learning of representations: looking forward, Y Bengio, 2013

Outline

1. **The background of Computational advertising**
2. **Research problems and techniques**
    1. Bidding strategy Optimisation
    2. Inventory management and floor prices optimisation

------Break (20min)------

    3. Fighting publisher fraud
    4. Programmatic Guaranteed and Ad Options
3. **Datasets, tools, and platforms**

Part 2.2
Inventory management and reserve price optimisation

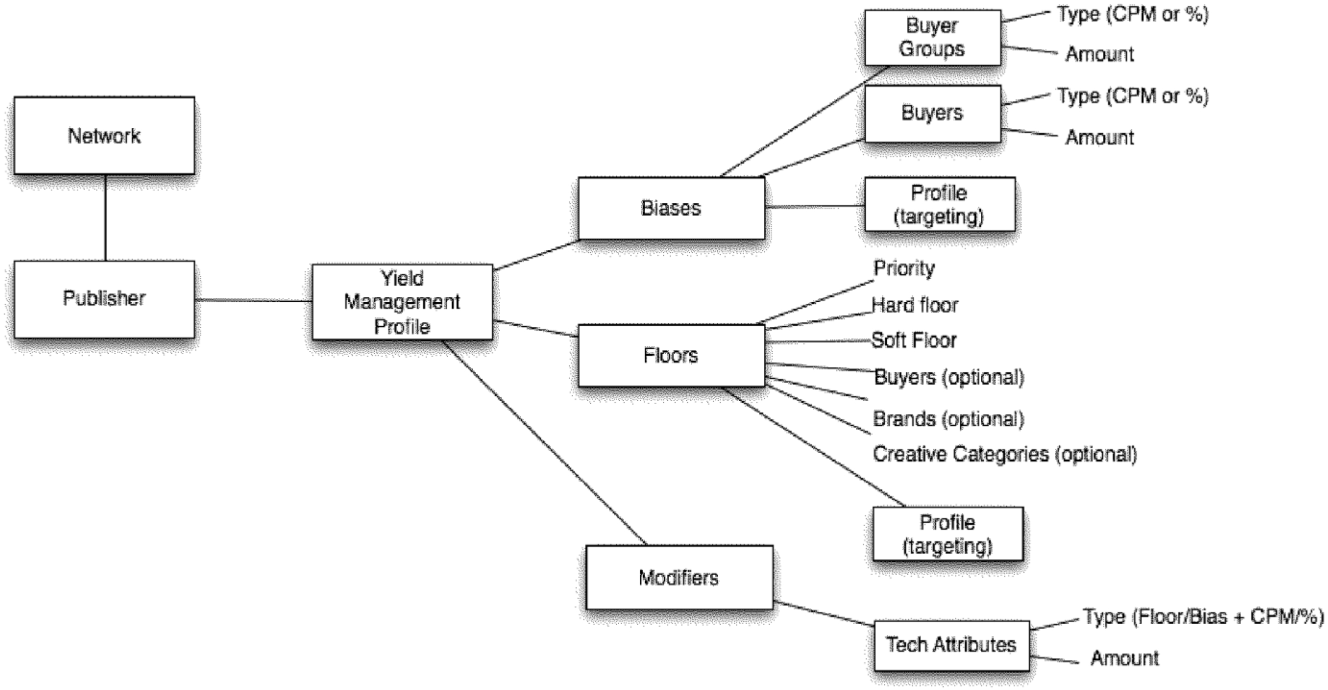
- Typical revenue models
- Ad density optimal control
- Reserve price optimisation

Typical revenue models for the supply side

- Subscription access to content (FT.com)
- Pay Per View access to document (Downloading a paper outside the campus)
- CPM display advertising on site
- CPC advertising on site (Google AdSense)
- Sponsorship of site sections or content types (typically fixed fee for a period)
- Affiliate revenue (Compare shopping, CPA/CPC)

- Subscriber data access for marketing (VISA & MasterCard)
- User contributed data for marketing (Surveys)

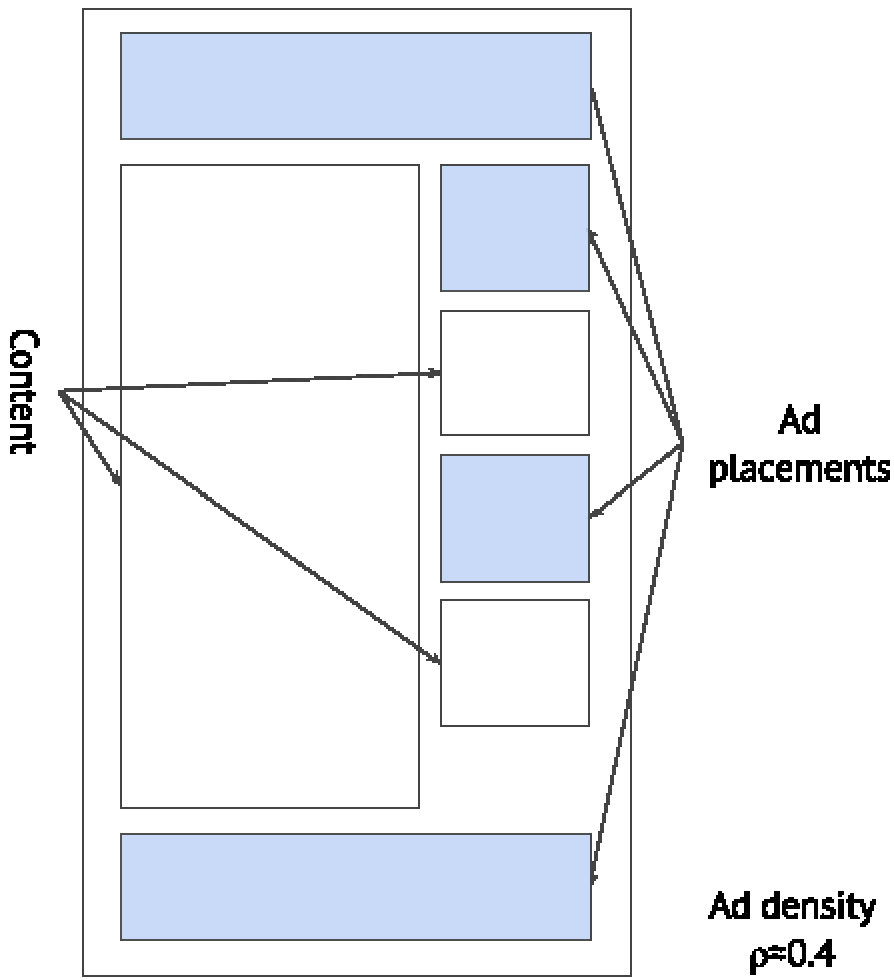
Examples



Yield management tools in AppNexus

A Dilling et al, Advertising bid price modifiers, US Patent 2011

Ad density



The task:

- To find the optimal advertising density (number of ad placements) for a given website

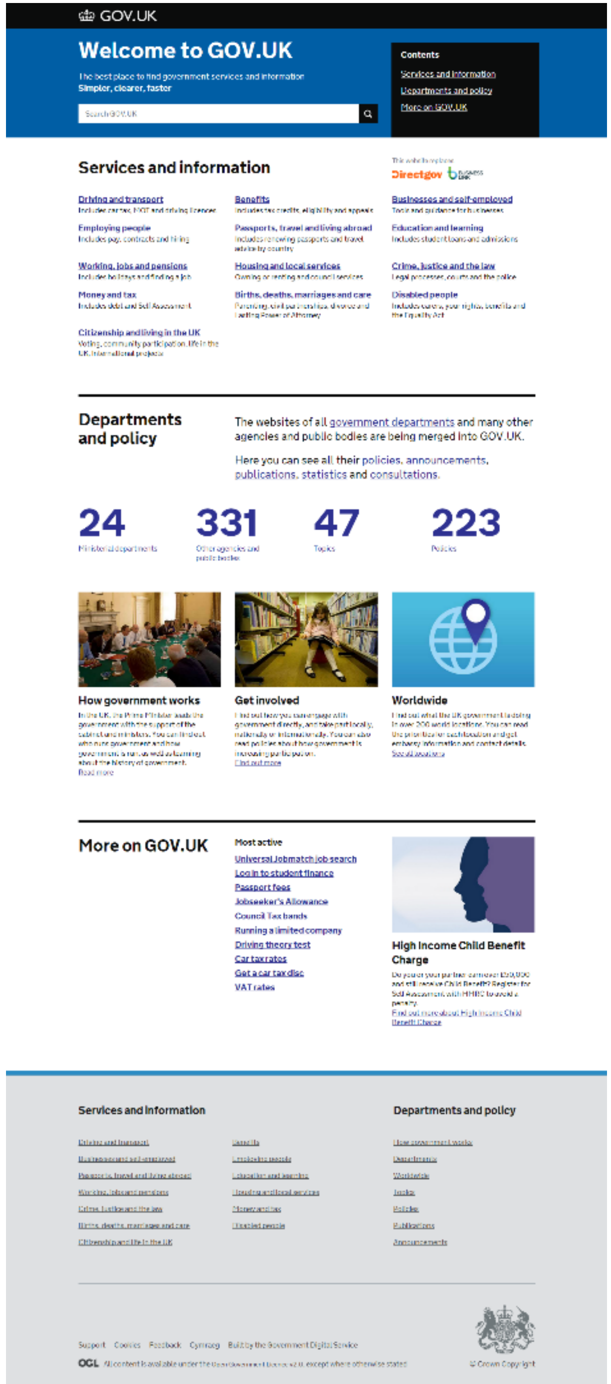
The challenges:

- Users' preference model
- Expected CPM
- Competition

The assumption:

- Using real-time bidding only

No ads

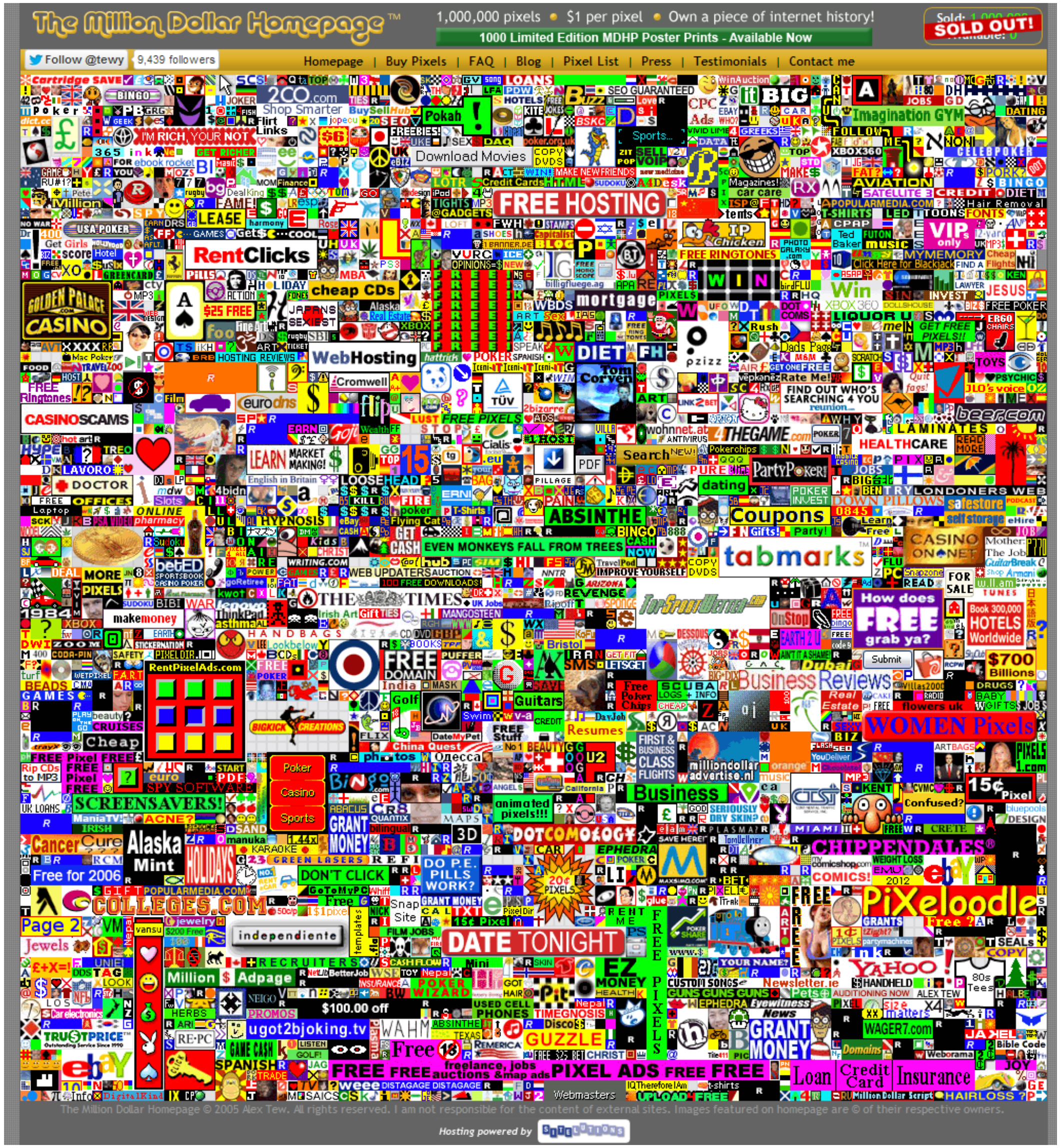


Some websites do not rely on ads to compensate the maintenance cost

- Government
- Education
- Most of .org

courtesy of www.gov.uk

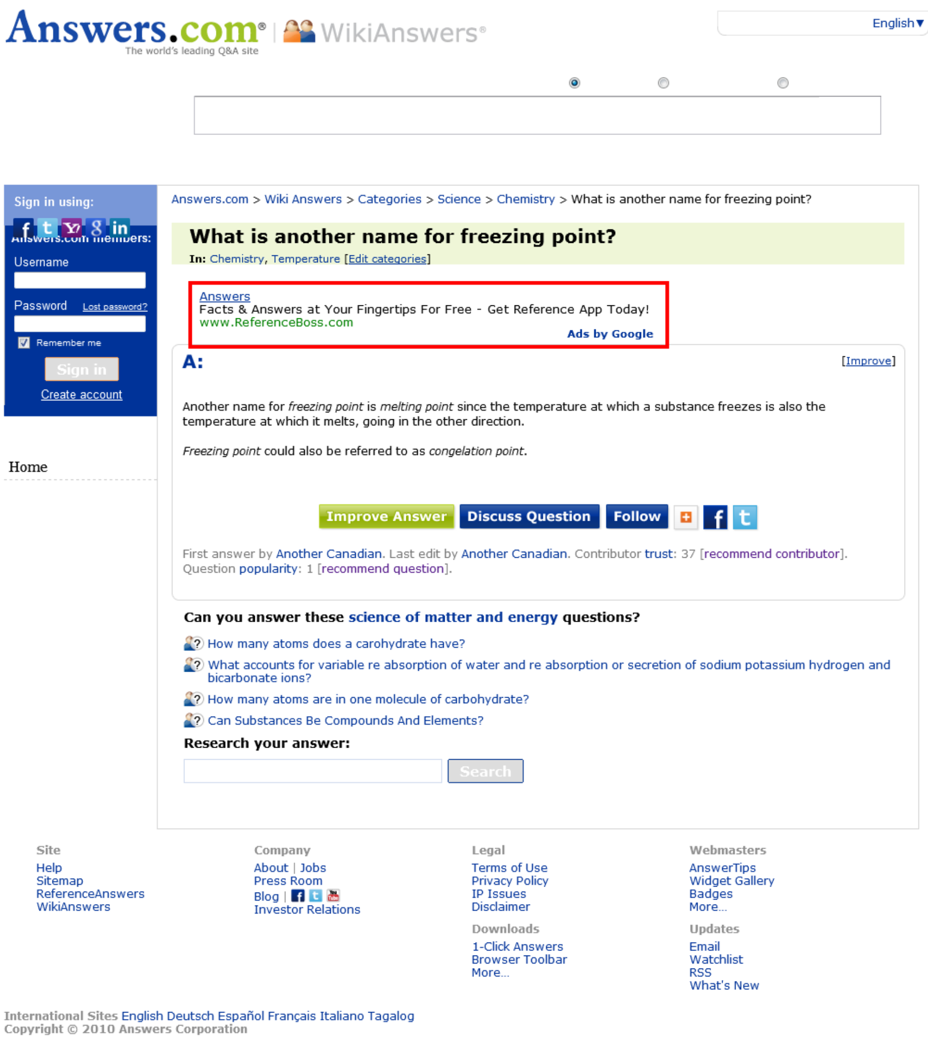
All ads



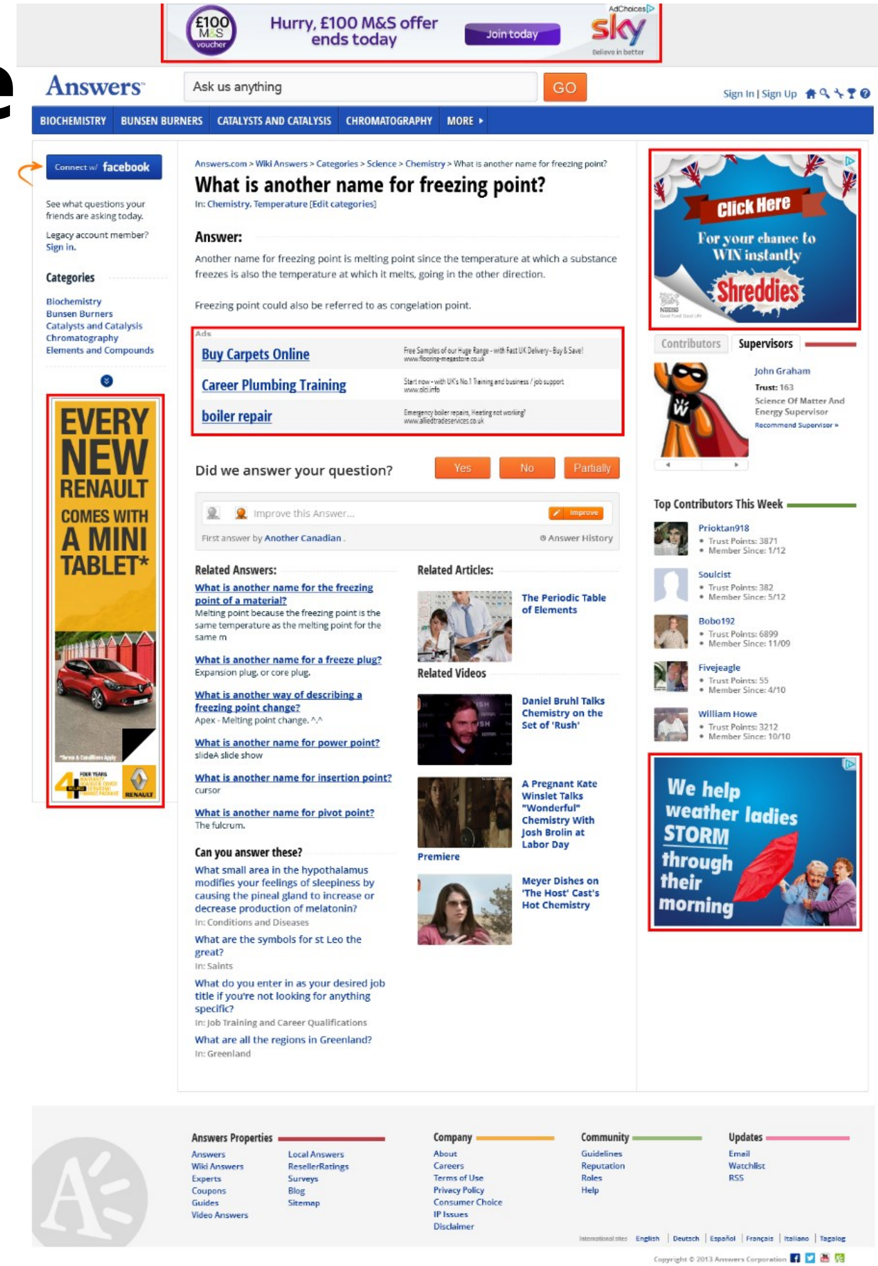
- Created by Alex Tew in 2005
- Selling 100k 100-pixels at $100 each
- Sold out in 4 months
- Almost 0% CTR

courtesy of www.milliondollarhomepage.com

Ad density: example



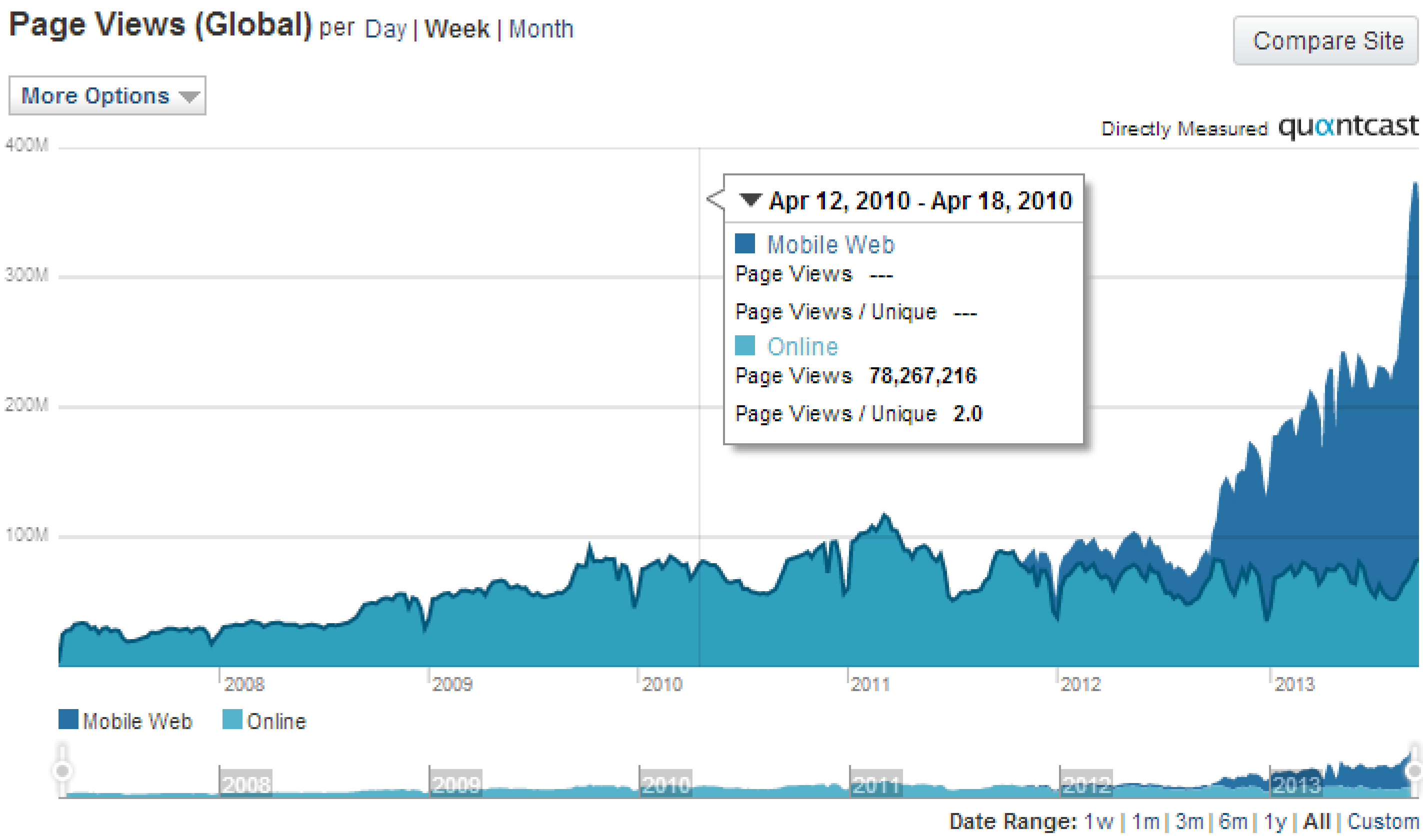
Apr 2010



Sep 2013

courtesy of archive.web.org

Ad density: example



Question: is it reasonable to put on so many more ads?

courtesy of Quantcast

Models and solutions

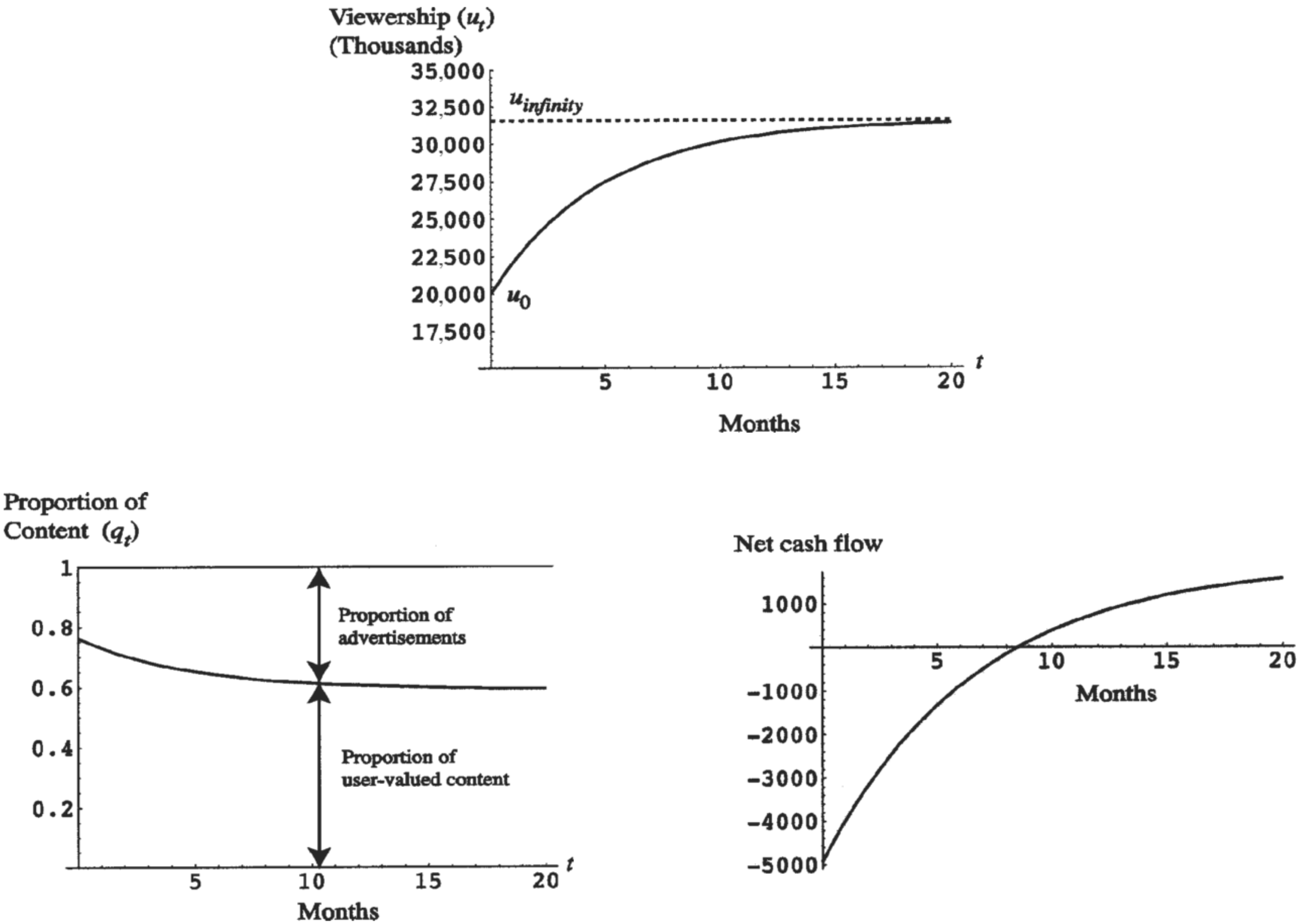
- Assume the following
  - Unit payoff (CPM) c
  - Ad density ρ
  - Impressions x
  - Content cost k
- The cumulative revenue

$$R(T) = \sum_{t}^{T} \left(cx\rho - \frac{k(1-\rho)^2}{2} \right)$$

- The state transition function

$$x(t) = \frac{1}{L-1} \sum_{l}^{L} \rho_l(t) x_l(t) - m\rho_i(t) x_i(t) + h$$

A monopoly case



Dewan et al, Management and valuation of advertisement-supported web sites, 2003

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- Optimal pricing and advertising policies for web services, S Kumar et al., 2004
- Is revamping your web site worthwhile? EY Huang, 2005
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- Dynamic pricing and advertising for web content providers, S Kumar and SP Sethi, 2009
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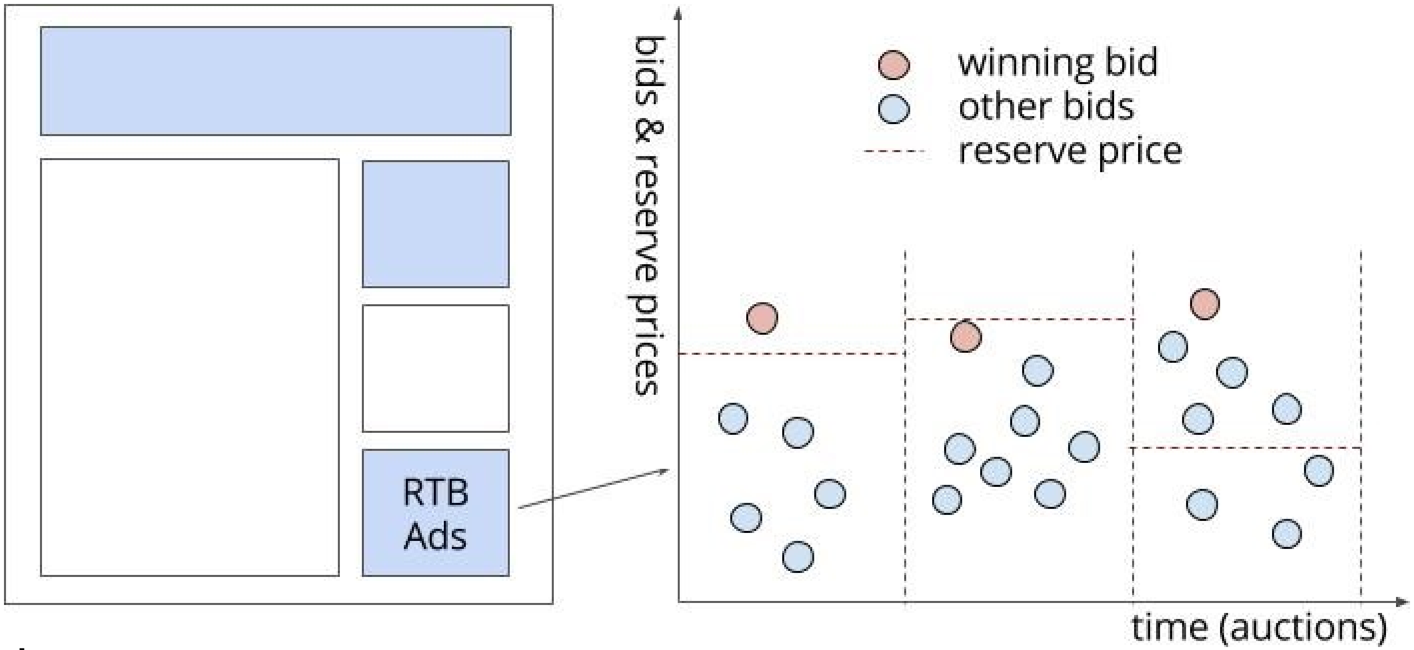
- Dynamic ad layout revenue optimization for display advertising, H Cheng et al., 2012
- Automatic ad format selection via contextual bandits, L Tang et al., 2013

Reserve price optimisation



The task:

- To find the optimal reserve prices

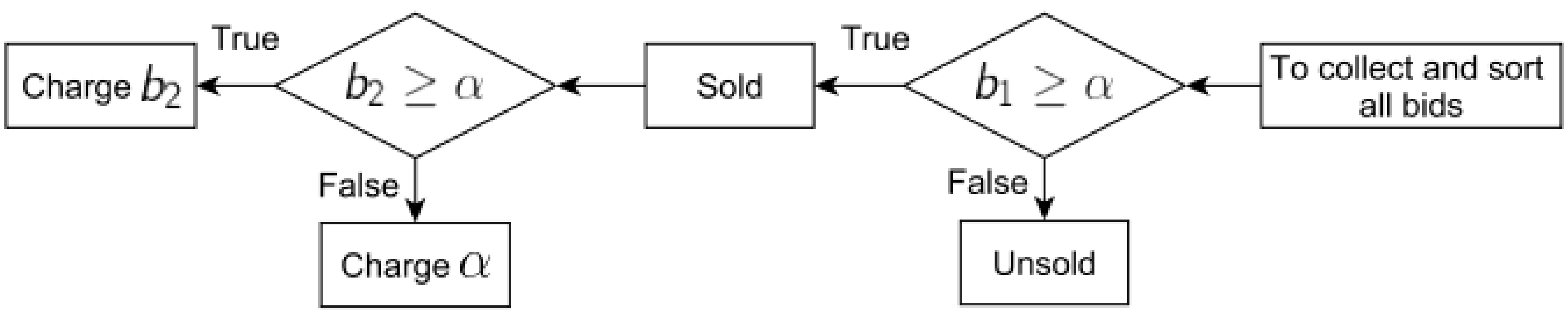
The challenge:

- Practical constraints v.s common assumptions (bids' distribution, bidding private values, etc.)

S Yuan et al., An Empirical Study of Reserve Price Optimisation in Display Advertising, 2014

Why

- Suppose it is second price auction
  - Normal case: $b_2 \geq \alpha$
  - Preferable case: $b_1 \geq \alpha > b_2$ (it increases the revenue)
  - Undesirable case: $\alpha > b_1$ (but there is risk)



An example

- Suppose: two bidders, private values drawn from Uniform[0, 1]
- Without a reserve price (or $a = 0$), the payoff r is:

$$r = E[\min(b_1, b_2)] = 0.33$$

- With $a = 0.2$:

$$r = E[\min(b_1, b_2)\,|b_1 > 0.2, b_2 > 0.2] + 0.32 \times 0.2 = 0.36$$

- With $a = 0.5$:

$$r = E[\min(b_1, b_2)\,|b_1 > 0.5, b_2 > 0.5] + 0.5 \times 0.5 = 0.42$$

- With $a = 0.6$:

$$r = \underbrace{E[\min(b_1, b_2)\,|b_1 > 0.6, b_2 > 0.6]}_{\text{Paying the second highest price}} + \underbrace{(0.6 \times 0.4) \times 2 \times 0.6}_{\text{Paying the reserve price}} = 0.405$$

Ostrovsky and Schwarz , Reserve prices in internet advertising auctions: A field experiment, 2011

The optimal auction theory

- In the second price auctions, advertisers bid their private values $[b_1, \dots, b_K]$
- Private values -> Bids' distributions $F(\boldsymbol{b}) = F_1(b_1) \times \cdots \times F_K(b_K)$
  - Uniform
  - Log-normal
- The publisher also has a private value V_p
- The optimal reserve price is given by:

$$\alpha - \frac{1 - F(\boldsymbol{b})}{F'(\boldsymbol{b})} - V_p = 0$$

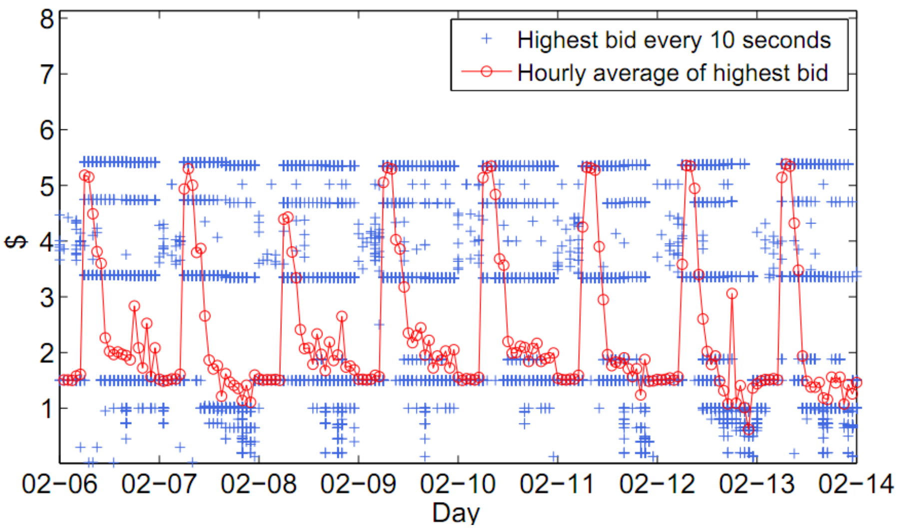
Questions:

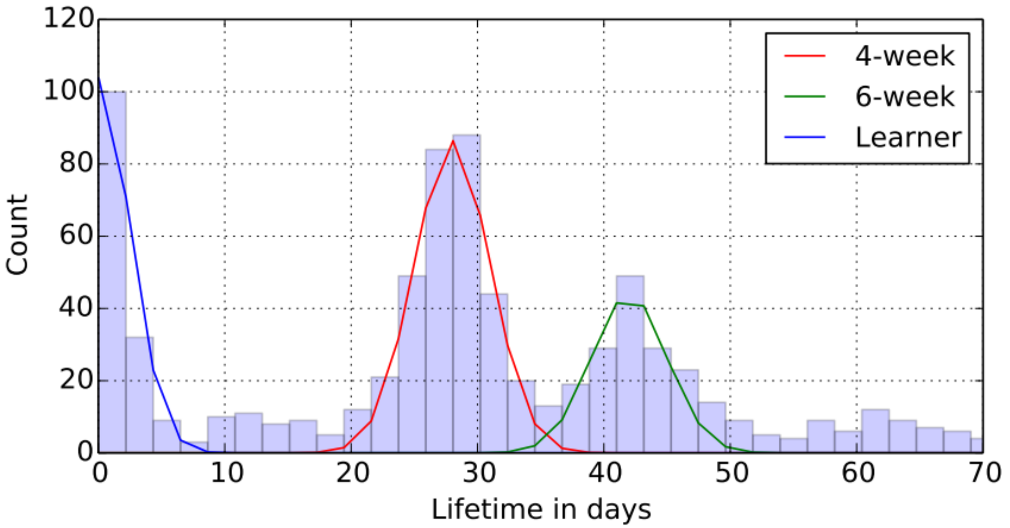
- How are advertisers bidding?
- Does Uniform/Log-normal fit well?

Levin and Smith, Optimal Reservation Prices in Auctions, 1996

Bidding could be irrational

- They usually use a private regression model (No access to publishers)
- Perhaps they don't even know it! (Just try to maximise the ROI)



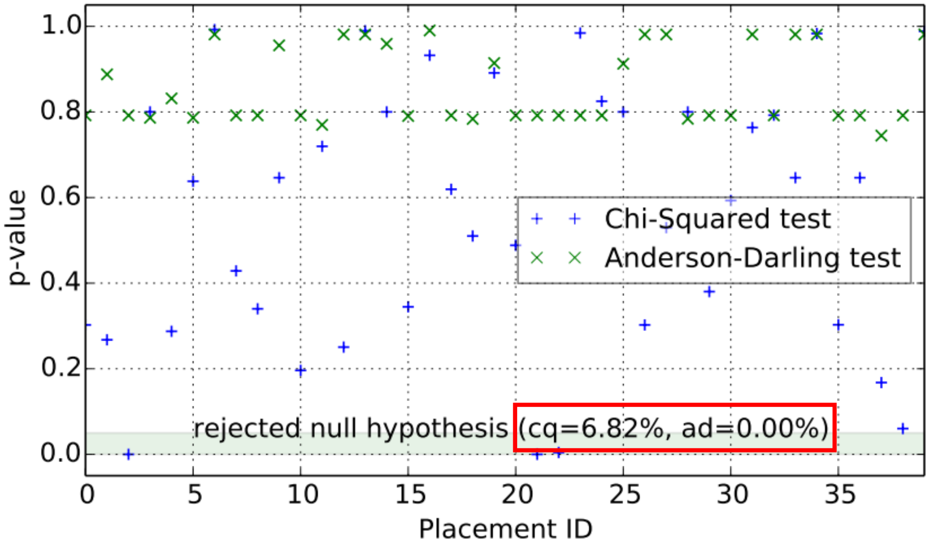


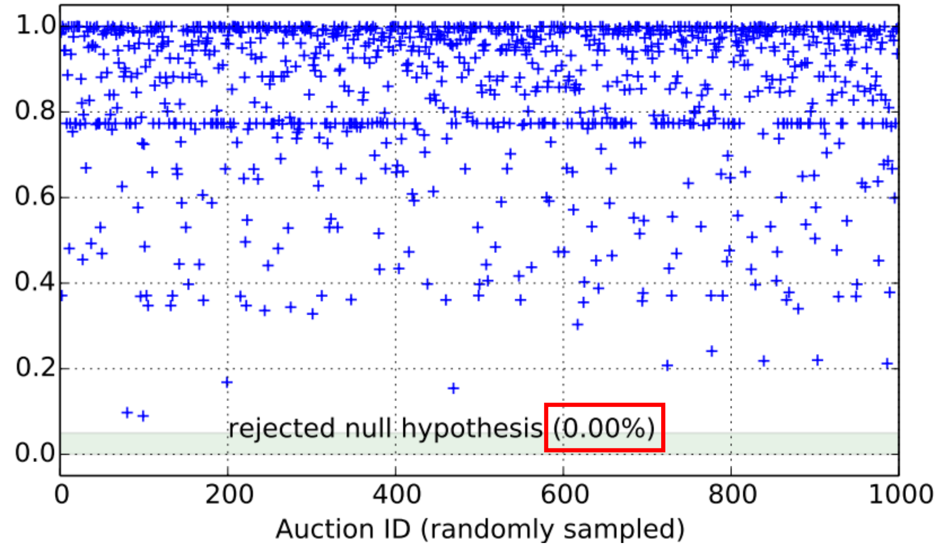
Many advertisers bid at fixed values
(Think about a decision tree)

And they come and go
(with different lifetime span)

S Yuan et al., An Empirical Study of Reserve Price Optimisation in Display Advertising, 2014

Uniform/Log-normal distributions do NOT fit well





Test at the placement level
(because we usually set reserve prices on placements)

Test at the auction level

- Chi-squared test for Uniformity
- Anderson-Darling test for Normality

S Yuan et al., An Empirical Study of Reserve Price Optimisation in Display Advertising, 2014

Results from a field experiment

- On Yahoo! Sponsored search
- Using the Optimal Auction Theory

Table 7: Restricted sample (optimal reserve price < 20¢)

Variable	Value	t-statistic	p-value
Number of keywords (T – treatment group)	222,249		
Number of keywords (C – control group)	11,615		
(Mean change in depth in T)−(mean change in depth in C)	−0.8612	−60.29	< 0.0001
(Mean change in revenue in T)−(mean change in revenue in C)	−11.88%	−2.45	0.0144
Estimated impact of reserve prices on revenues	−9.19%	−11.1	< 0.0001

Mixed results

Table 8: Restricted sample (optimal reserve price ≥ 20¢)

Variable	Value	t-statistic	p-value
Number of keywords (T – treatment group)	216,383		
Number of keywords (C – control group)	11,401		
(Mean change in depth in T)−(mean change in depth in C)	−0.9664	−55.09	< 0.0001
(Mean change in revenue in T)−(mean change in revenue in C)	14.59%	1.79	0.0736
Estimated impact of reserve prices on revenues	3.80%	5.41	< 0.0001

Levin and Smith, Optimal Reservation Prices in Auctions, 1996

Our solution

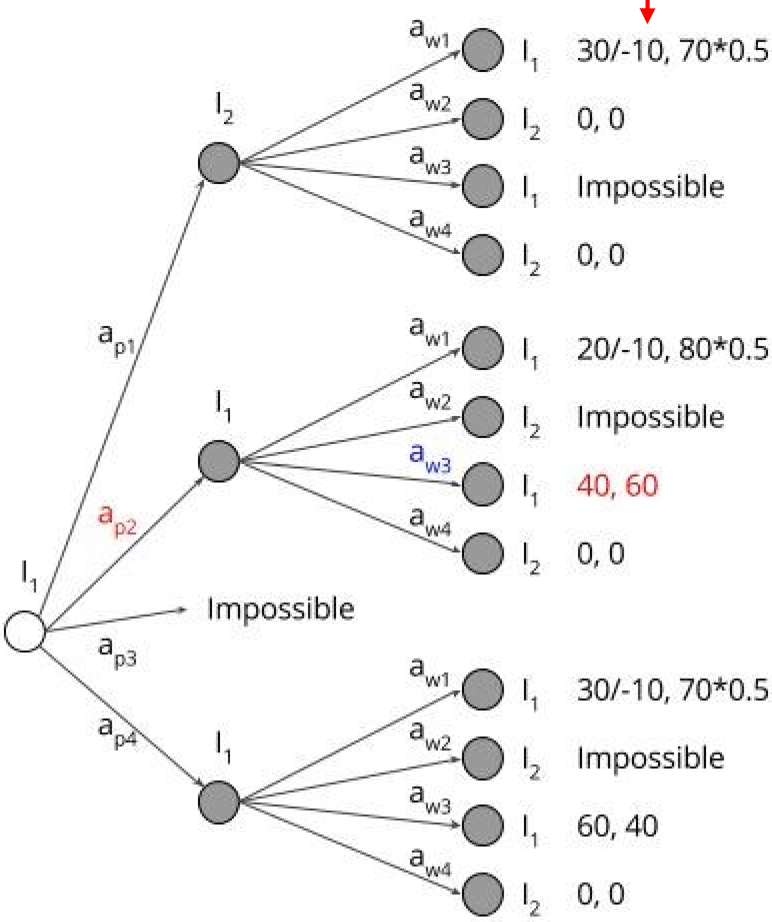
- A dynamic and one-shot game between the winner (w) and the publisher (p)
- Extension form representation
  - Information nodes:
    - I_1: Auction succeeded: the winning bid b_1 is higher
    - I_2: Auction failed: the reserve price α is higher
  - Actions:
    - a_{w1}: to increase b_1 so that $b_1 \geq \alpha$
    - a_{w2}: to increase b_1 so that $b_1 < \alpha$
    - a_{w3}: to decrease b_1 so that $b_1 \geq \alpha$
    - a_{w4}: to decrease b_1 so that $b_1 < \alpha$
    - a_{p1}: to increase α so that $\alpha \geq b_1$
    - a_{p2}: to increase α so that $\alpha < b_1$
    - a_{p3}: to decrease α so that $\alpha \geq b_1$
    - a_{p4}: to decrease α so that $\alpha < b_1$

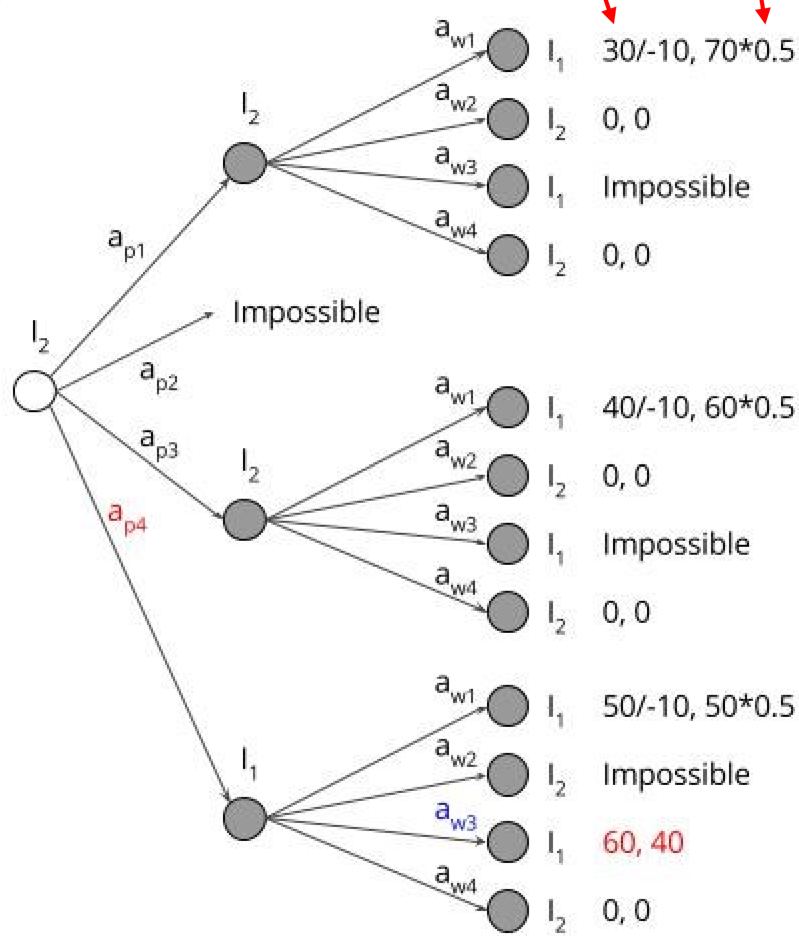
S Yuan et al., An Empirical Study of Reserve Price Optimisation in Display Advertising, 2014

1) Expected payoff of advertiser, publisher

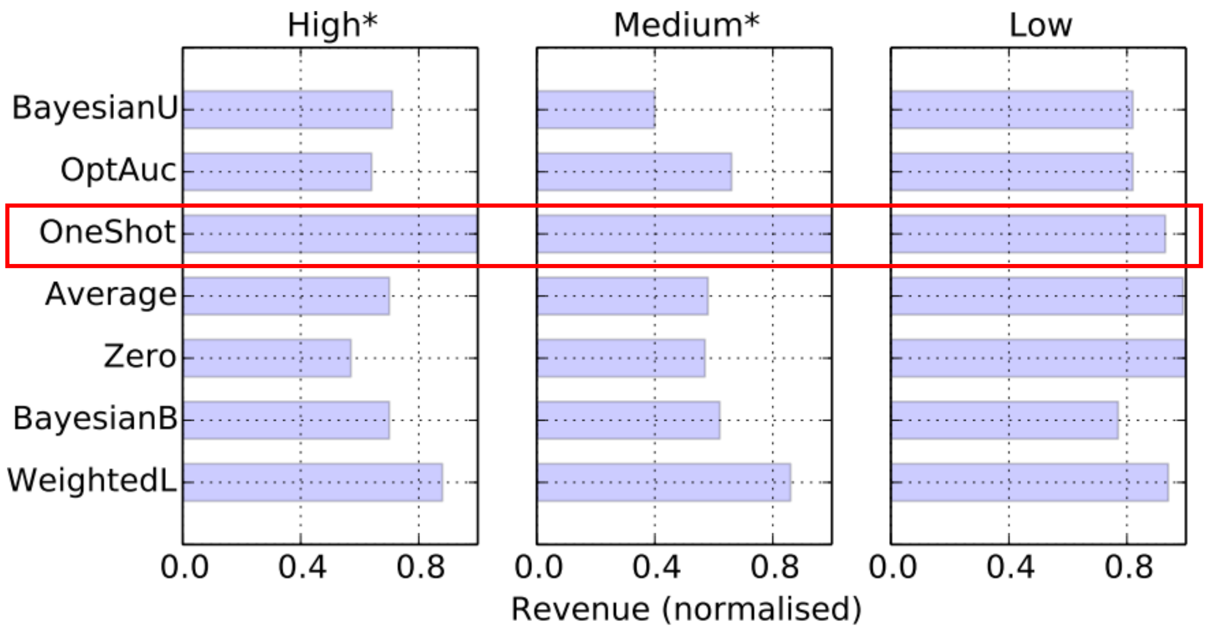
2) Payoff for the advertiser could be negative if one has been bidding the max price
(a_{w1}: to increase b_1 so that $b_1 \geq \alpha$)

3) One won't do that,
so discounted publisher's payoff



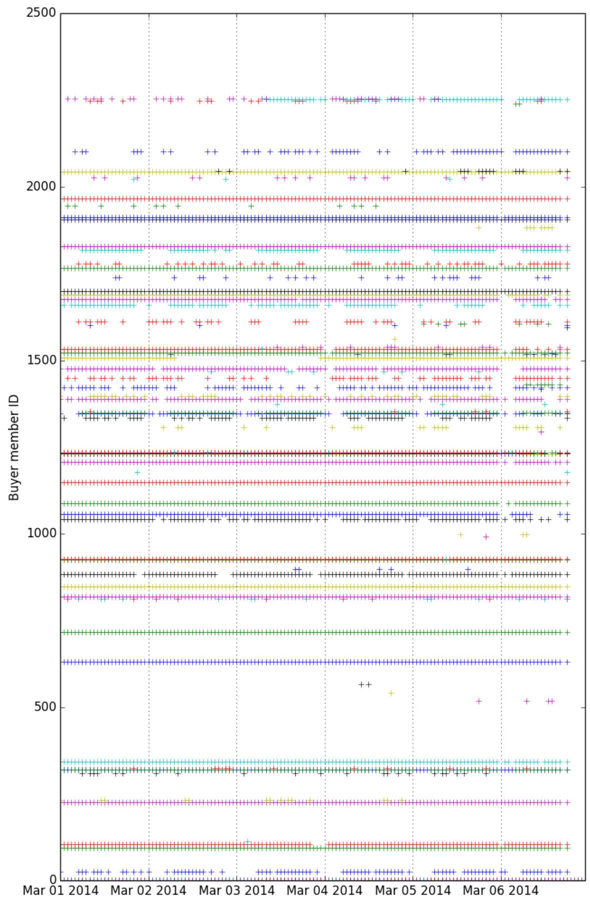


Findings



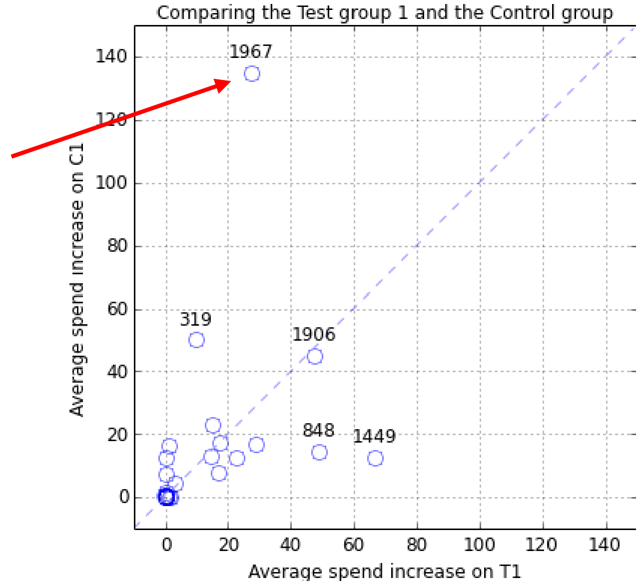
12.3% better than the second best
28.5% better than the optimal auction theory

S Yuan et al., An Empirical Study of Reserve Price Optimisation in Display Advertising, 2014

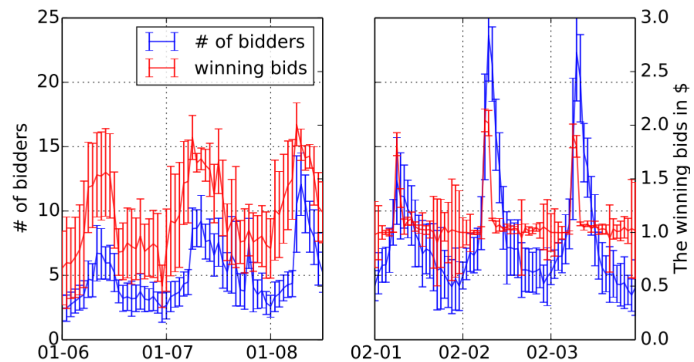


The continuous bidding activity

An outlier
(Triggered by some random action)



The unchanged budget allocation



The unchanged bidding pattern

S Yuan et al., An Empirical Study of Reserve Price Optimisation in Display Advertising, 2014

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Let’s have a break

20min

Outline

1. **The background of Computational advertising**
2. **Research problems and techniques**
    1. Bidding strategy Optimisation
    2. Inventory management and floor prices optimisation

------Break (20min)------

    3. Fighting publisher fraud
    4. Programmatic Guaranteed and Ad Options
3. **Datasets, tools, and platforms**

Part 2.3 Fighting publisher fraud

- Overview
- Detecting fraud
- A classification algorithm
- A graph clustering algorithm

Publisher fraud in Online advertising

- Definition
  - Publisher generates non-human traffic to sell for money
- How to fraud
  - Publisher sets up bots to visit its own websites
  - Publisher installs malware to other’s machine and the malware visits the websites without the machine’s owner knowing it.
- Category
  - Impression fraud
  - Click fraud
- Impact
  - 10% - 30% of RTB impressions estimated to be bot traffic
  - Cost advertisers billions of dollar in 2014

Characteristics of publisher fraud

- Bot is Non-human
    - Bot usually uses old version OS/browser
    - Bot generates traffic 24 hours a day
- Greedy
    - It has to be large scale to be profitable
- Require high liquidity
    - Usually sold cheap: as cheap as $1 for 100K imps
    - Has long daisy chain, deeply embedded
- Little transparency
    - Domain obfuscation

Fighting publisher fraud: the old fashion way

- Put the police on the street
  - Manually eyeball the webpage
  - Verify the address on the Google map
- Follow how the money flows
- This approach just can’t scale and is not sustainable
- Better to hand over this problem to data scientist

Data Scientists’ Toolbox

- Anomaly detection
  - Online algorithm
  - Offline algorithm
- Classification algorithm
  - Human traffic vs. bot traffic
  - Human clicks vs. bot clicks
- Clustering algorithm
  - Bots could display dramatically different behavior.
- Language process technique
  - Fraudulent websites often scrape content from each other or legit websites

Problem set

- What can be fraudulent
  - Cookie ID
  - IP address: both audience IP and web site host IP
  - URL
  - Ad placement
  - Publisher

Features

- Audience-related
- Content-related
- Business-related
- Audience-content interaction
- Audience-business interaction

Applying tools to problems

- Cookie ID
  - Anomaly detection both online and offline
- Audience IP address
  - Anomaly detection both online and offline
- Web site host IP with Cookie ID
  - Bipartite graph, clustering algorithm on graph
  - Both supervised and unsupervised
- URL
  - Outlier detecting against Alexa ranking
- Ad placement, Publisher
  - Classification with SVM or logistic regression

Example #1: Classification on publisher

- Off-the-shelf algorithm
  - For example Python scikit-learn
  - Logistic regression with L1 regularization
  - Support vector machine
- Training data
  - Known good and bad publishers from other algorithms
  - Collect multiple daily data point for each publisher
- Features
  - Cover both impression and clicks
- Performance
  - 96% prediction accuracy

Example #1: Result and Caveat

- SVM performs slightly better than Logistic Regression (LR), but LR is preferred for its transparency.
- Produces quality score for each publisher.
- The power of the algorithm is as good as the training data.
  - Good at combining the strength of individual detection algorithms.
  - Unlikely to find brand-new fraud pattern.
- More scrutiny and manual checking is needed before blacklisting fraudulent publishers.

Example #2: Graph clustering algorithm

- Key observation:
  - Even the major sites only share at most 20% cookie_id within a few hours, let alone those long tail sites.
- Define a graph:
  - Node: site
  - Weighted edge: user overlap ratio of two sites
- Cluster this weighted undirected graph
- Any big cluster with long tail sites are all fraud.
- Main reference for this approach:
  - Using Co-visitation Networks For Classifying Non-Intentional Traffic by six authors at m6d Research

Example #2: algorithm implementation

Cluster nodes on weighted undirected graph

Let e_{ij} be the fraction of weights of edges connecting community i and community j

Define $a_i = \sum_j e_{ij}$ and $Q = \sum_i (e_{ii} - a_i^2)$

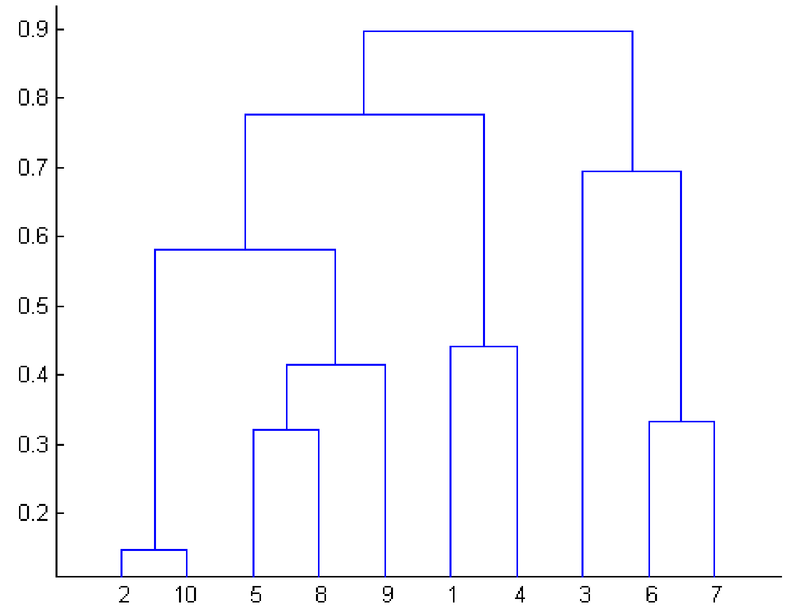
Goal: maximize Q

Note: $a_i a_j = e_{ij}$ on average for random graph

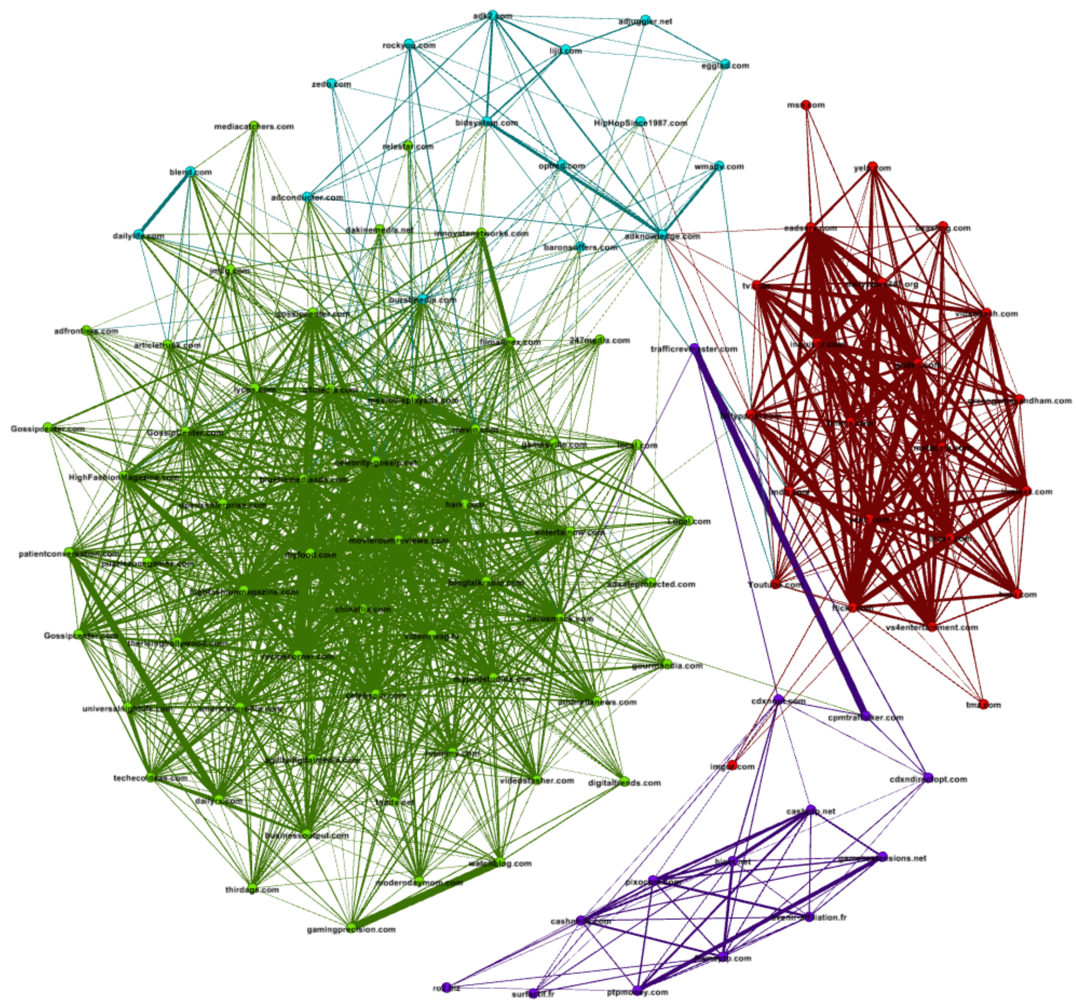
"Fast algorithm for detecting community structure in networks" by M. E. J. Newman

Example #2: How to maximize Q

- A bottom-up greed algorithm starts with each node as its own community.
- At each step, merge two communities which increase Q most
  - The change of Q at each step could be negative
- Pick communities for the maximum of Q
- Result in dendrograph



Example #2: A beautiful picture



Outline

1. **The background of Computational advertising**
2. **Research problems and techniques**
    1. Bidding strategy Optimisation
    2. Inventory management and floor prices optimisation

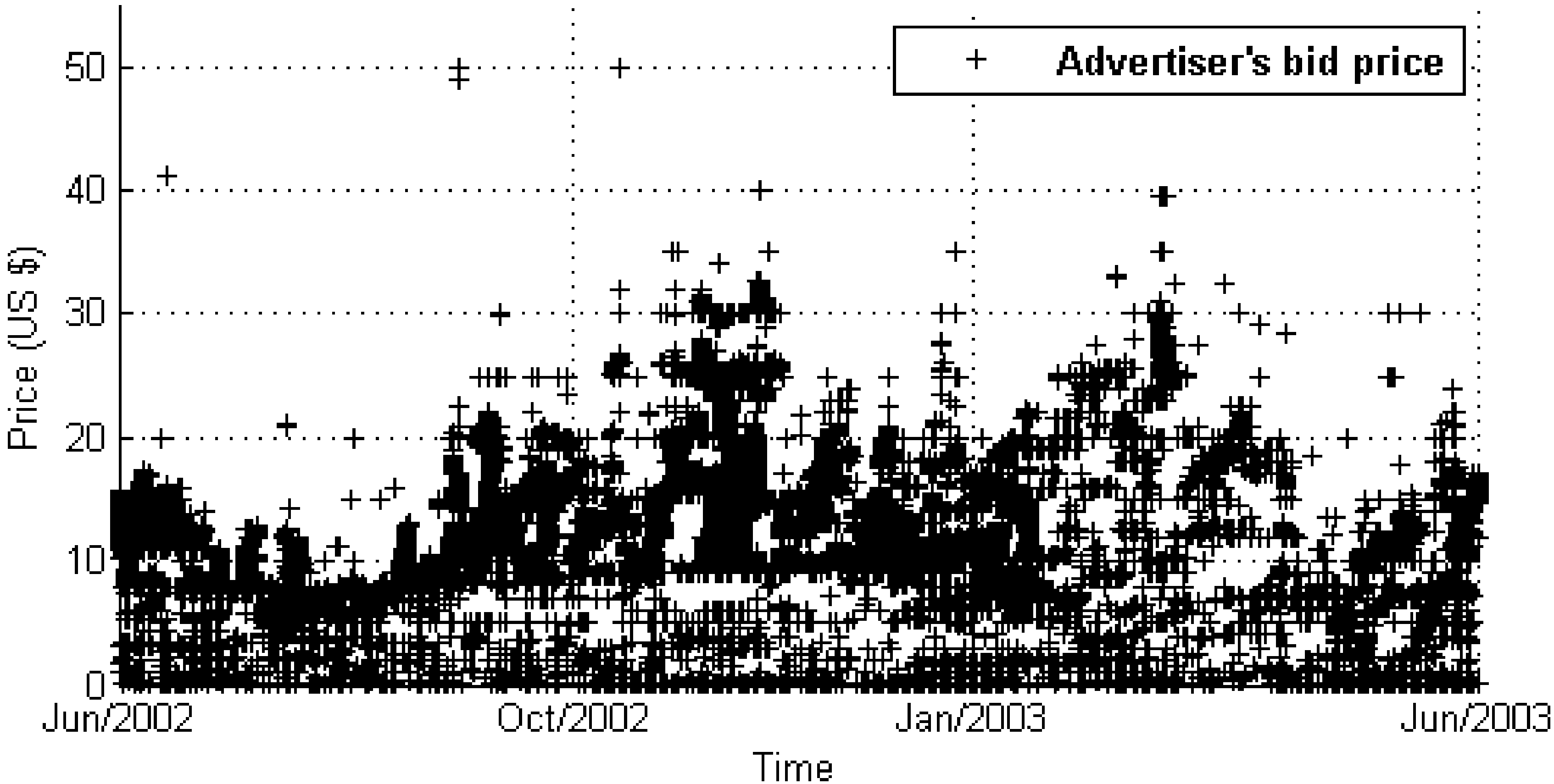
    ------Break (20min)------

    3. Fighting publisher fraud
    4. Programmatic Guaranteed and Ad Options
3. **Datasets, tools, and platforms**

Part 2.4 Programmatic Guaranteed and Ad Options

- RTB
  - Combined with the forward market
  - Combined with the futures & options exchange

(RTB) Ads prices are volatile

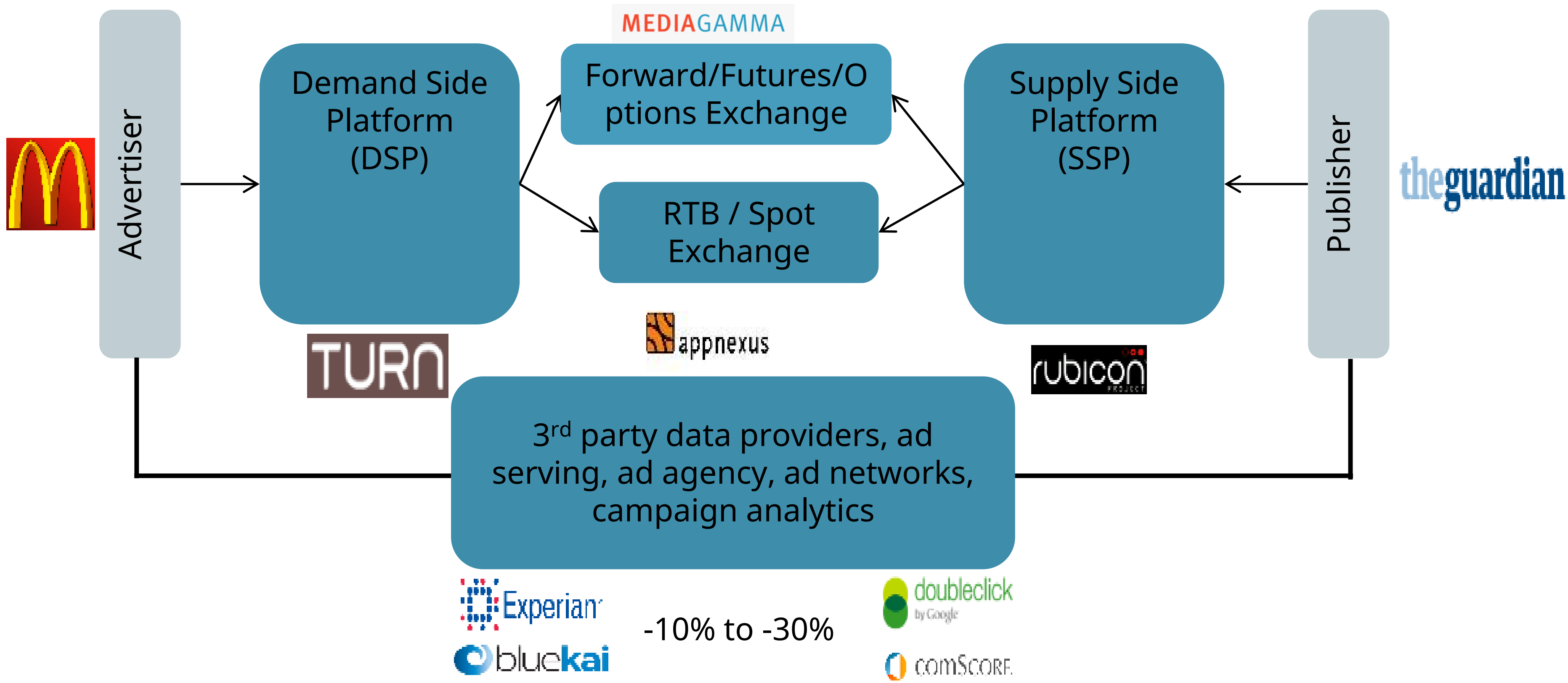


The price movement of a display opportunity from Yahoo! ads data
Under GSP (generalized second price auction)

Hedge the price risk

- Need Ad’s Futures Contract and Risk-reduction Capabilities
  - Technologies are constrained mainly to “spots” markets, i.e., any transaction where delivery takes place right away (in Real-time Advertising and Sponsored Search)
  - No principled technologies to support efficient forward pricing &risk management mechanisms

An analogy with financial markets



Solution 1:

Combine RTB with **Forward Market,** which pre-sell inventories in advance with a fixed price

Solution 2:

If we got **Futures Exchange** or provide **Option Contracts,** advertisers could *lock in* the campaign cost and Publishers could *lock in* a profit in the future

Solution 1:
RTB with Forward Programmatic Guaranteed Market

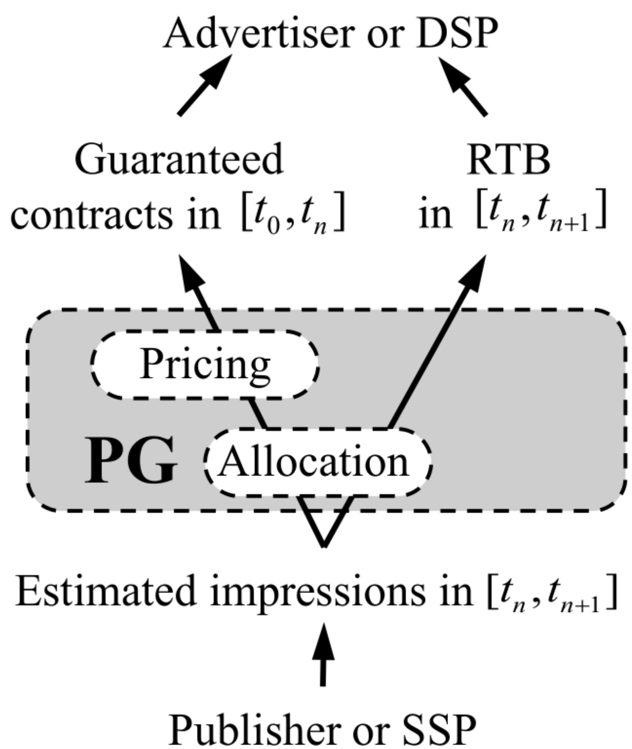


Figure 1: A systematic view of programmatic guarantee (PG) in display advertising: $[t_0, t_n]$ is the time period to sell the guaranteed impressions that will be created in future period $[t_n, t_{n+1}]$.

B Chen et al., A Dynamic Pricing Model for Unifying Programmatic Guarantee and Real-Time Bidding in Display Advertising. Best Paper in ADKDD 2014

Optimization objective

$$\mathbf{max}\left\{\underbrace{\int_0^T (1-\omega\kappa)p(\tau)\theta(\tau,p(\tau))f(\tau)d\tau}_{\substack{G \,=\, \text{Expected total revenue from}\\ \text{guaranted selling minus expected}\\ \text{penalty of failling to delivery}}} + \underbrace{\left(S - \int_0^T \theta(\tau,p(\tau))f(\tau)d\tau\right)\phi(\xi)}_{H \,=\, \text{Expected total revenue from RTB}}\right\}, \quad (1)$$

$$\textbf{s.t.} \quad p(0) = \begin{cases} \phi(\xi) + \lambda\psi(\xi), & \text{if } \pi(\xi) \geq \phi(\xi) + \lambda\psi(\xi) \\ \pi(\xi), & \text{if } \pi(\xi) < \phi(\xi) + \lambda\psi(\xi), \end{cases} \quad (2)$$

where

$$\xi = \frac{\text{Remaining demand in } [t_n, t_{n+1}]}{\text{Remaining supply in } [t_n, t_{n+1}]} = \frac{Q - \int_0^T \theta(\tau,p(\tau))f(\tau)d\tau}{S - \int_0^T \theta(\tau,p(\tau))f(\tau)d\tau}.$$

B Chen et al., A Dynamic Pricing Model for Unifying Programmatic Guarantee and Real-Time Bidding in Display Advertising. Best Paper in ADKDD 2014

Optimised pricing scheme

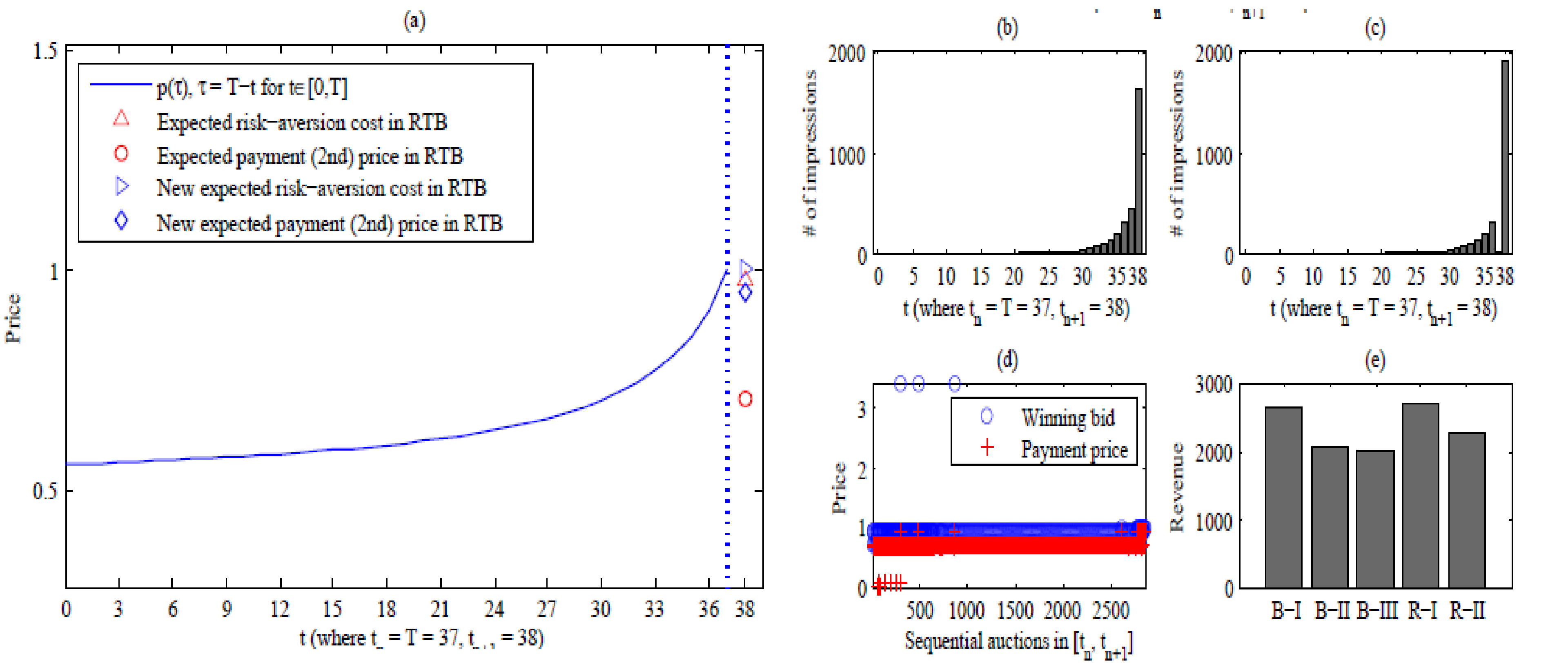


Figure 9: An empirical example of AdSlot14: (a) the optimal dynamic guaranteed prices; (b) the estimated daily demand; (c) the daily demand calculated based on the actual bids in RTB on the delivery date; (d) the winning bids and payment price in RTB on the delivery date; (e) the comparison of revenues [see Table 8 for summary of notations B-I, B-II, B-III, R-I, R-II]. The parameters are: $Q = 17691; S = 2847; \alpha = 2.0506; \beta = 0.2; \zeta = 442; \eta = 0.2; \omega = 0.05; \kappa = 1; \gamma = 0.4240; \lambda = 2$.

B Chen et al., A Dynamic Pricing Model for Unifying Programmatic Guarantee and Real-Time Bidding in Display Advertising. Best Paper in ADKDD 2014

Solution 2: Ad Option Contract

An Ad Option is a contract in which the option publisher grants the advertiser the right but not the obligation to enter into a transaction either buy or sell an underlying ad slot at a specified price on or before a specified date.

The specified pre-agreed price is called strike price and the specified date is called expiration date. The option seller grants this right in exchange for a certain amount of money at the current time is called option price.

J Wang and B Chen, Selling futures online advertising slots via option contracts, WWW 2012.

Ad options: Benefits

Advertisers	▪ secure impressions delivery ▪ reduce uncertainty in auctions ▪ cap cost
Publishers	▪ sell the inventory in advance ▪ have a more stable and predictable revenue over a long-term period ▪ increase advertisers' loyalty

Ad options contd.

t = T

t = 0

Pays £5 upfront option price to obtain the option.

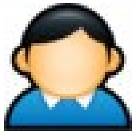
Submits a request of guaranteed ad delivery for the keywords ‘MSc Web Science’, ‘MSc Big Data Analytics’ and ‘Data Mining’ for the future 3 month term [0, T], where T = 0.25.

Sells a list of ad keywords via a multi-keyword multi-click option

multi-keyword multi-click option (3 month term)		
upfront fee (m = 100)	keywords list	fixed CPCs
£5	‘MSc Web Science’	£1.80
	‘MSc Big Data Analytics’	£6.25
	‘Data Mining’	£8.67

Timeline

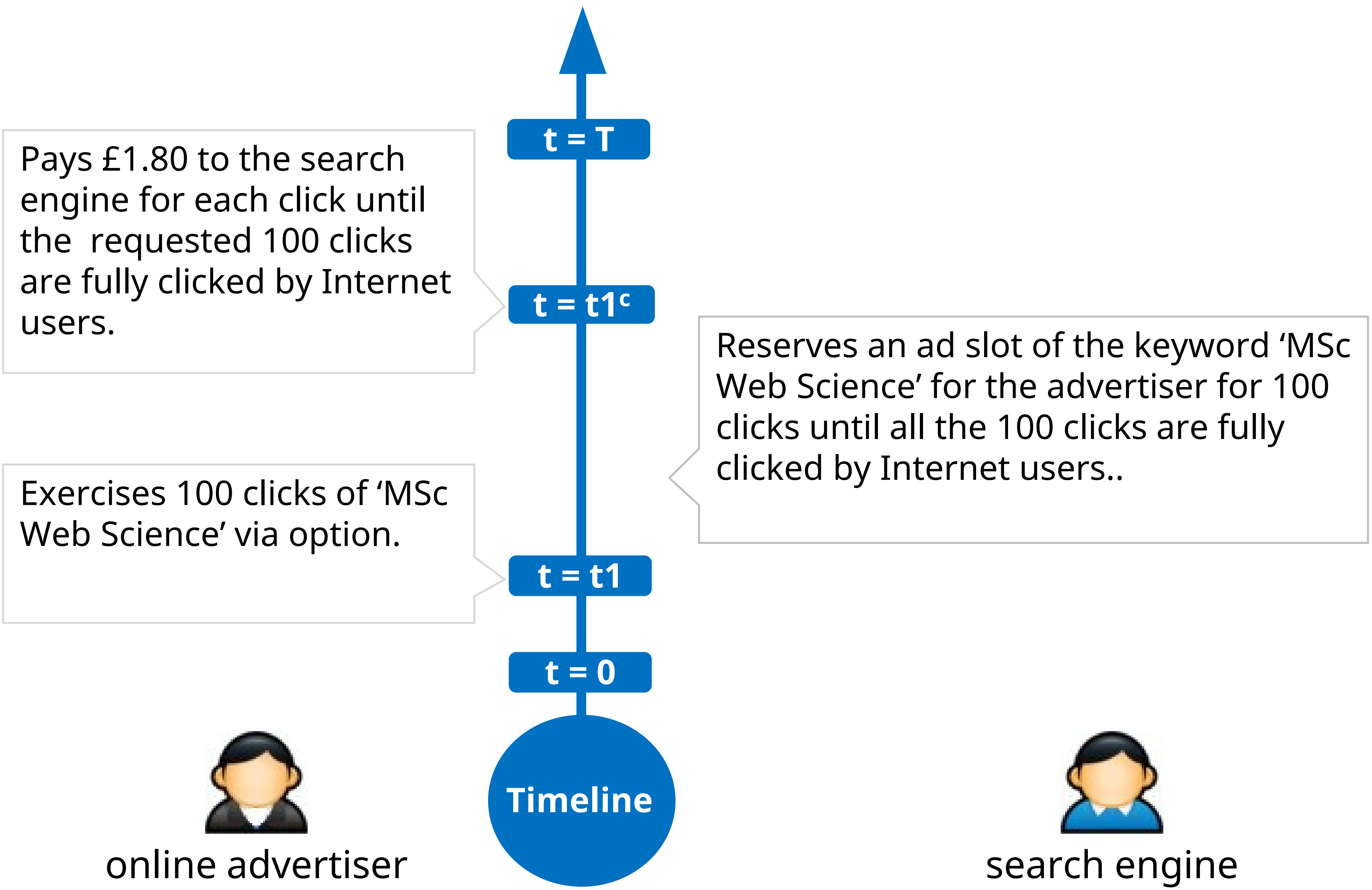
online advertiser



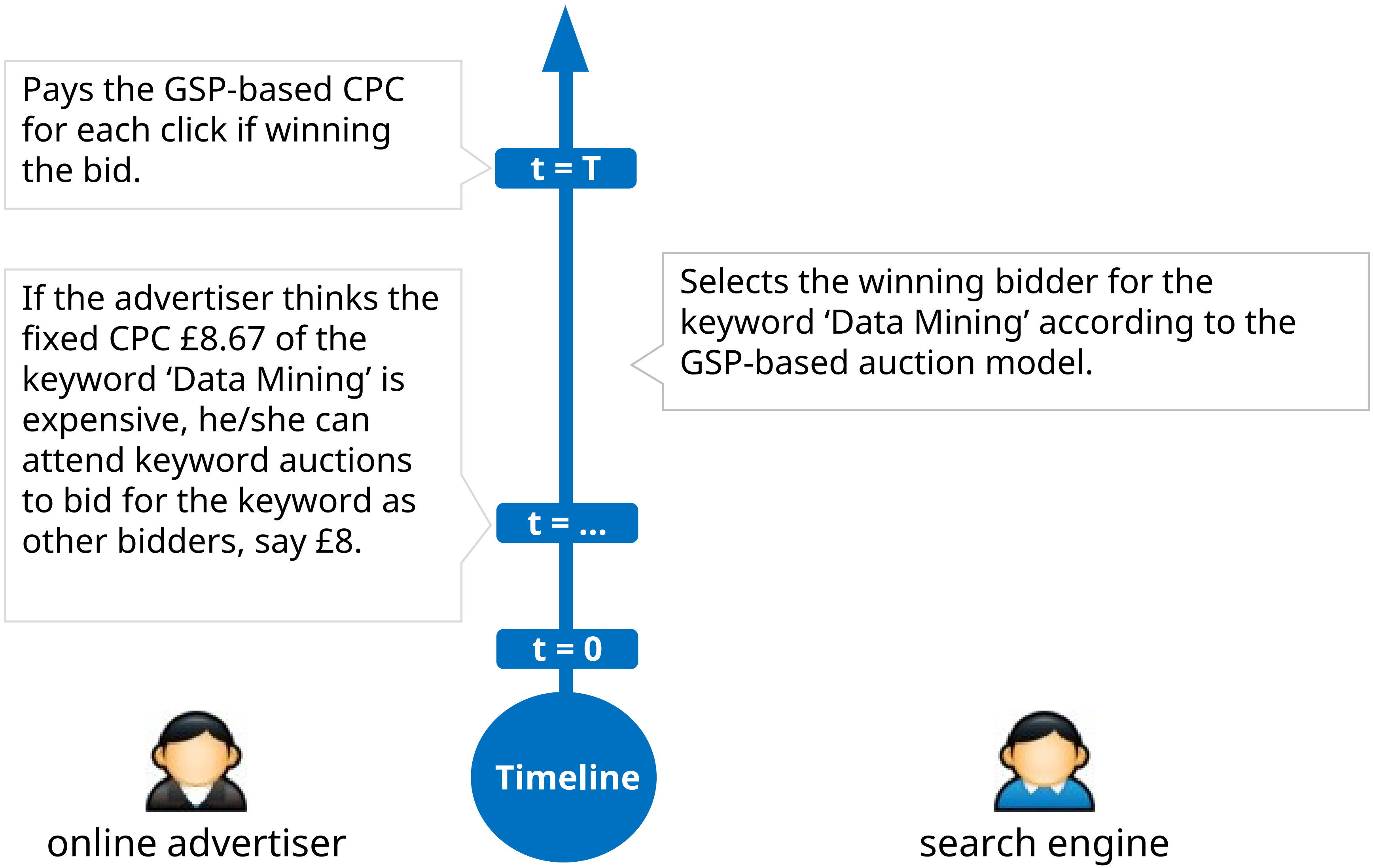
search engine

B Chen et al., Multi-Keyword Multi-Click Advertisement Option Contract for Sponsored Search, 2013

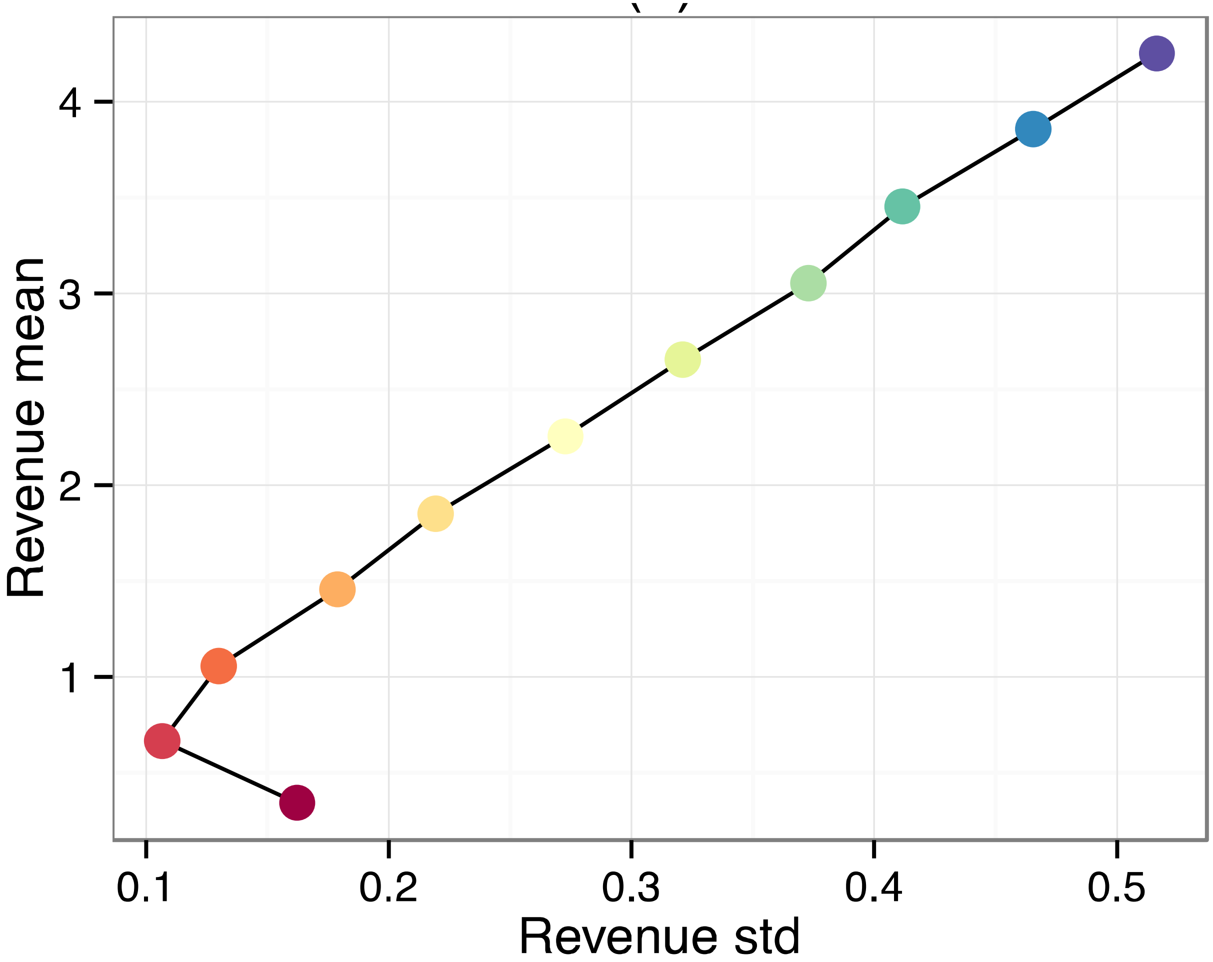
Exercising the option



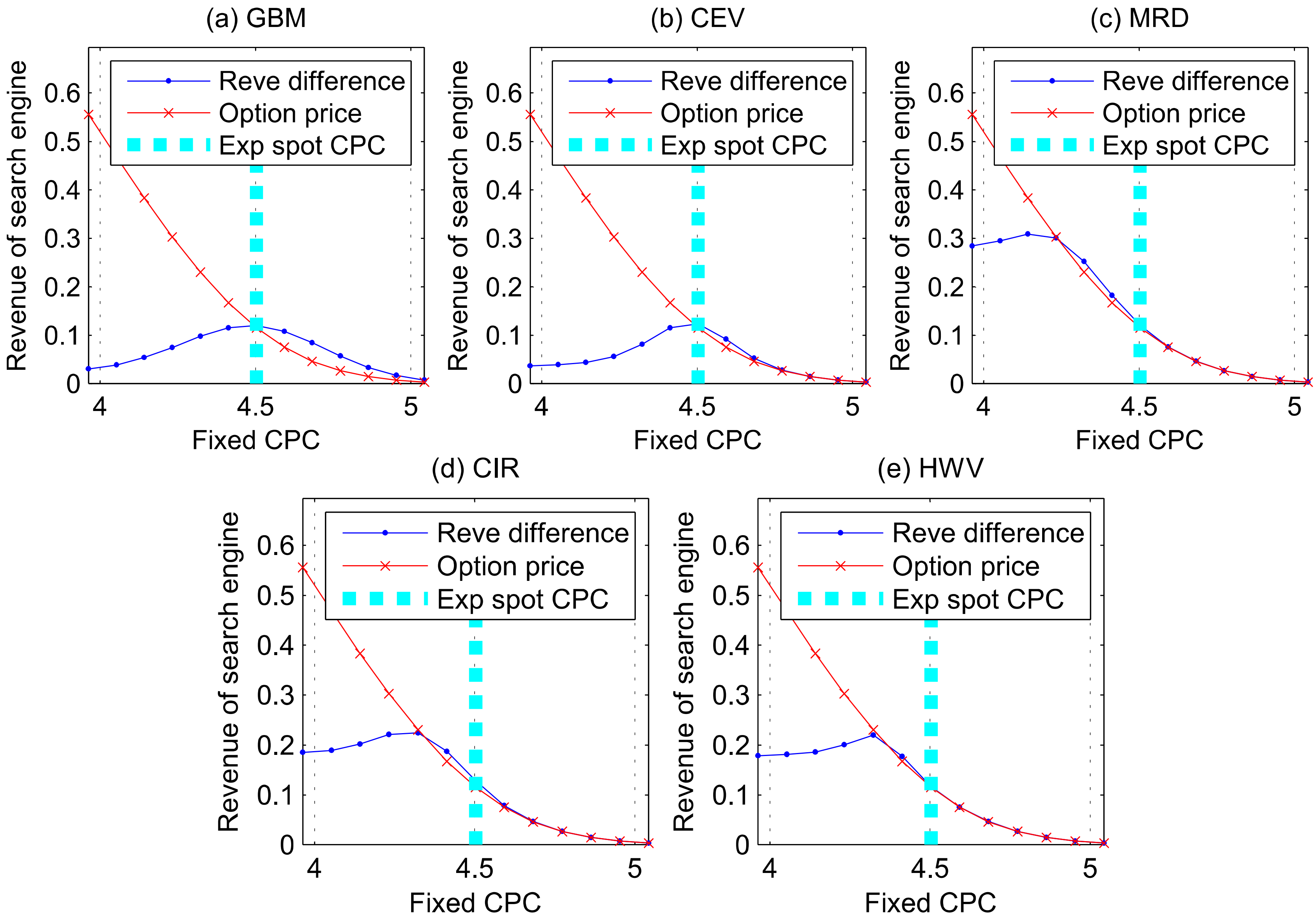
Not exercising the option



Risk Hedge when Ad Options and RTB spot are combined



B Chen and J Wang, A Lattice Framework for Pricing Display Ad Options with the Stochastic Volatility Underlying Model, Technical Report, 2014



An empirical example of search engine's revenue for the keyword *equity loans*

B Chen et al. Multi-Keyword Multi-Click Option Contracts for Sponsored Search Advertising, Technical Report, 2013

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- The economics of the online advertising industry, DS Evans, 2008
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- The arrival of real-time bidding, Google, 2011

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- Estimating conversion rate in display advertising from past erformance data, K Lee et al,. 2012
- Handling forecast errors while bidding for display advertising, KJ Lang et al., 2012
- Marketing campaign evaluation in targeted display advertising, J Barajas et al., 2012
- Ad exchange-proposal for a new trading agent competition game, M Schain and Y Mansour, 2012
- Auctions for online display advertising exchanges: approximations and design, S Balseiro et al., 2012
- Real-time bidding for online advertising: measurement and analysis, S Yuan et al., 2013

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- Impression fraud in on-line advertising via pay-per-view networks, K Springborn and P Barford, 2013
- An overview of computational challenges in online advertising, RE Chatwin, 2013
- Competition and yield optimization in ad exchanges, SR Balseiro, 2013
- Internet advertising revenue report, IAB and PwC

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Part 3.1 Datasets

- iPinYou Real-Time Bidding Dataset
  - data.computational-advertising.org
  - 5.87GB
  - Bid requests, impressions, clicks, conversions
- Criteo conversion logs
  - labs.criteo.com/2014/08/criteo-release-public-datasets
  - O Chapelle, Modeling Delayed Feedback in Display Advertising, 2014
  - 534MB
  - Conversion logs

Datasets

- Criteo - Kaggle Display Advertising Challenge Dataset
  - labs.criteo.com/downloads/2014-kaggle-display-advertising-challenge-dataset
  - 4.3G
  - CTR prediction
- Avazu – Kaggle CTR Prediction Challenge
  - www.kaggle.com/c/avazu-ctr-prediction
  - Deadline: 9th Feb 2015
- Open advertising dataset
  - code.google.com/p/open-advertising-dataset
  - Data from Google AdWords

Datasets

- Internet Advertisements Data Set
  - archive.ics.uci.edu/ml/datasets/Internet+Advertisements
  - Display ads, webpage and ad context
- Farm Ads Data Set
  - archive.ics.uci.edu/ml/datasets/Farm+Ads
  - Ad creative and landing pages

Datasets

- Webscope from Yahoo!
  - webscope.sandbox.yahoo.com
  - Sponsored search, CTR prediction
- KDD CUP 2012 Track 2
  - www.kddcup2012.org/c/kddcup2012-track2/data
  - Tencent search engine, sponsored search, CTR prediction

Part 3.2 Tools

- OpenRTB API specification
  - openrtb.github.io/OpenRTB
  - A good description of protocols and data exchanges
- RTBKit
  - rtbkit.org
  - An open source Real-time bidding framework
  - No (intelligent) bidding algorithms included
  - Production level design and implementation
  - Takes effort to setup

Tools

- Revive Adserver
  - www.revive-adserver.com
  - An open source Ad server
  - Formerly known as OpenX Source
- Orbit Open Ad Server
  - orbitopenadserver.com
  - An open source Ad server
- mAdserver
  - www.madserve.org
  - An open source mobile Ad server
  - No longer being developed