



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

The New York Times
Monday, March 15, 2010

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TIMES TOPICS > SUBJECTS > I > IPAD

iPad



Jim Wilson/The New York Times

Updated Jan. 27, 2010

The iPad is Apple's new tablet computer.

Steven P. Jobs positioned the iPad as a device that sits between the laptop and the smart phone - and which does certain things better than both of them, like browsing the Web, reading e-books and playing video. There was enormous anticipation. Media companies hoped for them to charge for no

Content: iPad

The iPad's features and specifications, once the stuff of Internet myth, are now sharply in focus: The half-inch thick, 1.5-pound device will feature a

Bits

Three Reasons Why the iPad WILL Kill Amazon's Kindle
January 27, 2010 7:05pm

Three Reasons Why the iPad WON'T Kill Amazon's Kindle
January 27, 2010 5:57pm

David Pogue's First Look at the Apple iPad
January 27, 2010 4:05pm

More posts about the iPad»

Headlines Around the Web
What's This?

INDUSTRY STANDARD
MARCH 10, 2010
Mac user groups and iPod accessories

SILICON ALLEY INSIDER
MARCH 10, 2010
Bill Gates Loses Forbes' 'World's Richest' Title To Carlos Slim (MSFT, NYT, AMX)

GEAR LIVE
MARCH 10, 2010
Adobe answers Steve Jobs and his thoughts on Flash on iPad and iPhone

Photos 

Ads:
Tablet PCs, mobile phone etc.

Ads by Google

BlackBerry® Curve™ 8900
The Thinnest & Lightest Full-QWERTY BlackBerry Smartphone Available.
www.BlackBerry.com/Curve

Tablet PC's
Mobile Tablet PC Solutions. Digitizer, Touch and Rugged Devices
www.camtechsystems.co.uk

Win an Amazing New iPad

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

veb4.cs.ucl.ac.uk/staff/jun.wang/blog/

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CIKM2013 Tutorial: Real-Time Bidding: A New Frontier of Computational Advertising Research

July 30th, 2013 Comments off Edit

Online advertising is now one of the fastest advancing areas in IT industry. In display and mobile advertising, the most significant development in recent years is the growth of Real-Time Bidding (RTB), which allows selling and buying online display advertising in real-time one ad impression at a time. Since then, RTB has fundamentally changed the landscape of the digital media market by scaling the buying process across a large number of available inventories. It also encourages behaviour (re-)targeting, and makes a significant shift toward buying focused on user data, rather than contextual data. A report from IDC shows that in 2011, global RTB based display ad spend increased by 237% compared to 2010, with the U.S.'s \$2.2 billion RTB display spend leading the way. The market share of RTB-based spending of all display ad spending will grow from 10% in 2011 to 27% in 2016, and its share of all indirect spending will grow from 28% to 78%.

Scientifically, the further demand for automation, integration and optimization in RTB brings new research opportunities in the CIKM fields. For instance, the much enhanced flexibility of allowing advertisers and agencies to maximize impact of budgets by more optimised buys based on their own or 3rd party (user) data makes the online advertising market a step closer to the financial markets, where unification and interconnection are strongly promoted. The unification and interconnections across webpages, advertisers, and users require significant research on knowledge management, data mining, information retrieval, behaviour targeting and their links to game theory, economics and optimization.

Despite its rapid growth and huge potential, many aspects of RTB remain unknown to the research community for a variety of reasons. In this tutorial, teamed up with presenters from both the industry and academia, we aim to bring the insightful knowledge from the real-world systems, to bridge the gaps between industry and academia, and to provide an overview of the fundamental infrastructure, algorithms, and technical and research challenges of the new frontier

RSS

CIKM2013 Tutorial: Real-Time Bidding: A New Frontier of Computational Advertising Research

July 30th, 2013

Comments off Edit

Relevant Ads or not?

Lightinthebox.com

Lighting Fixtures	Price
Lamp	€280.49
Lamp	€119.62
Lamp	€53.62
Lamp	€218.62
Lamp	€210.37
Lamp	A\$69.89

Real-time Advertising:

Selling ad slot per impression targeted to the user

DR. JUN WANG
Computer Science, UCL

About Me Contact Publications Teaching Research Team Prospective Students Type text to search here... 

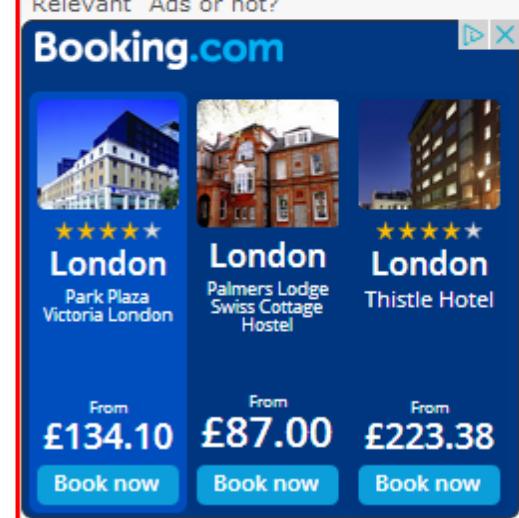
CIKM2013 Tutorial: Real-Time Bidding: A New Frontier of Computational Advertising Research

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Online advertising is now one of the fastest advancing areas in IT industry. In display and mobile advertising, the most significant development in recent years is the growth of Real-Time Bidding (RTB), which allows selling and buying online display advertising in real-time one ad impression at a time. Since then, RTB has fundamentally changed the landscape of the digital media market by scaling the buying process across a large number of available inventories. It also encourages behaviour (re-)targeting, and makes a significant shift toward buying focused on user data, rather than contextual data. A report from IDC shows that in 2011, global RTB based display ad spend increased by 237% compared to 2010, with the U.S.'s \$2.2 billion RTB display spend leading the way. The market share of RTB-based spending of all display ad spending will grow from 10% in 2011 to 27% in 2016, and its share of all indirect spending will grow from 28% to 78%.

Scientifically, the further demand for automation, integration and optimization in RTB brings

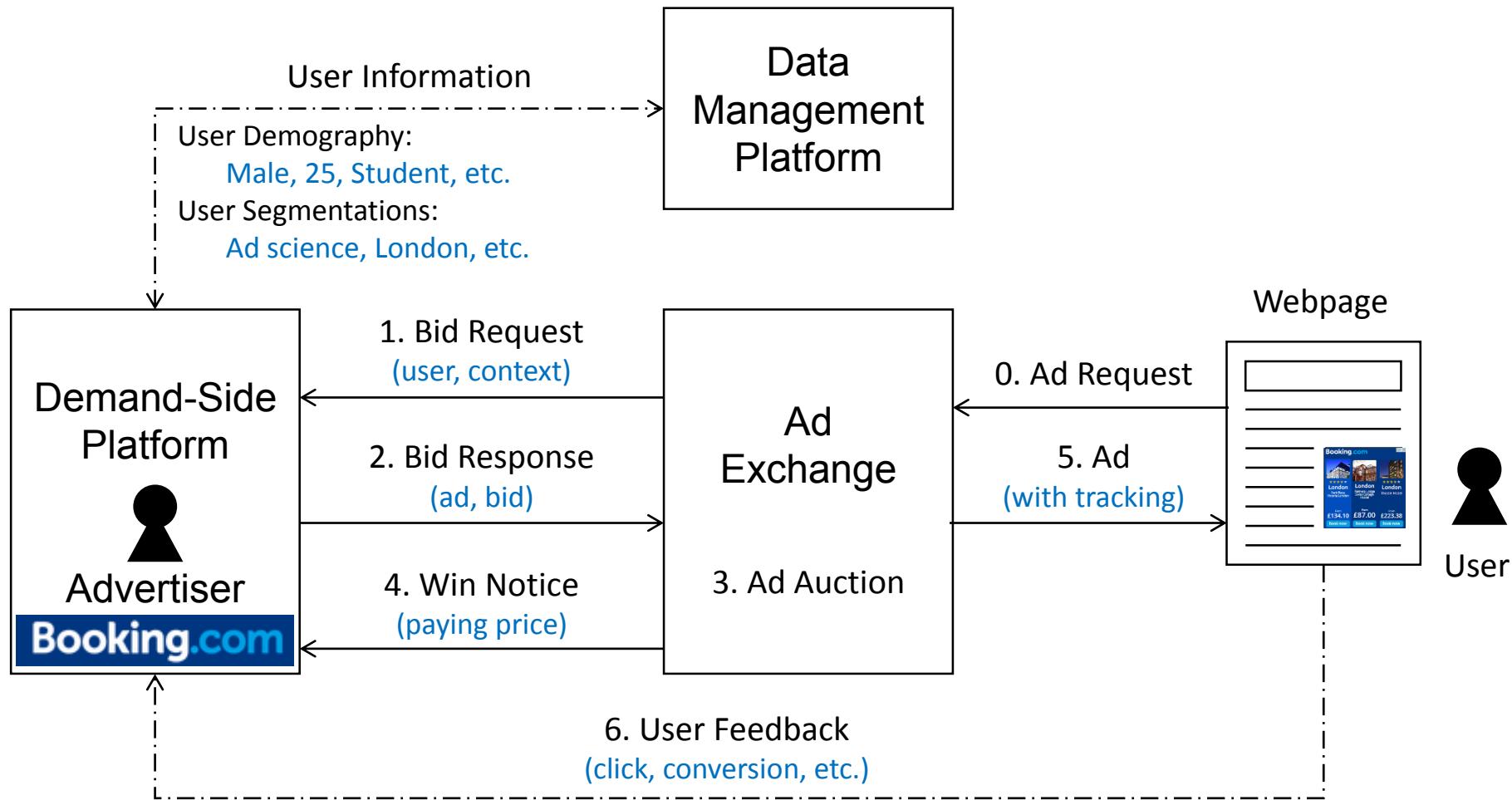
"Relevant" Ads or not?



The advertisement is for Booking.com, featuring four hotel options in London:

- Park Plaza Victoria London: From £134.10, Book now
- Palmers Lodge Swiss Cottage Hostel: From £87.00, Book now
- Thistle Hotel: From £223.38, Book now

RTB workflow: less than 100ms



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)-----

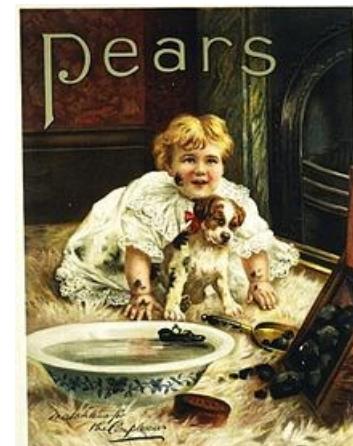
3. Fighting publisher fraud

4. Programmatic Guaranteed and Ad Options

3. Datasets, tools, and platforms

Part 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

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)?

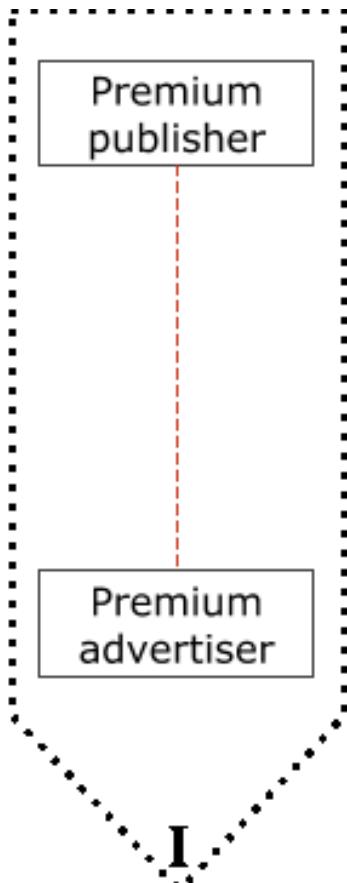
Computational advertising, AZ Border, 2008

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

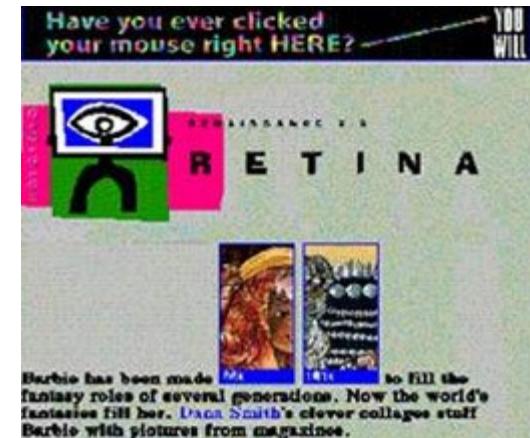
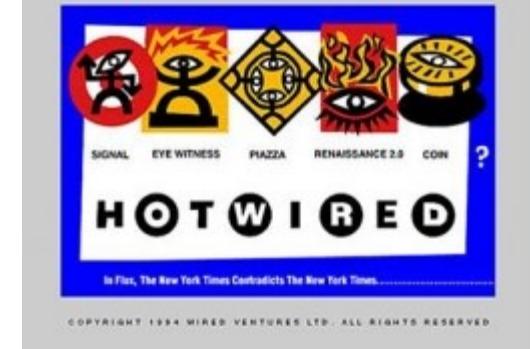
Advertising in a pervasive computing environment, A Ranganathan and RH Campbell, 2002

Direct sales (since 1994)



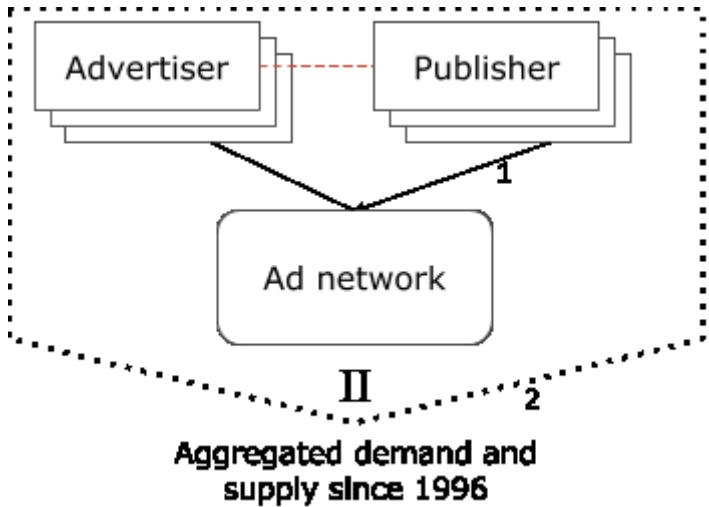
- Advertisers and publishers talk to (4A) agencies
- Still popular in today's marketplace
- Getting back to the market as the **Programmatic Guaranteed**

Direct sales since 1994



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

Trading in ad networks (since 1996)

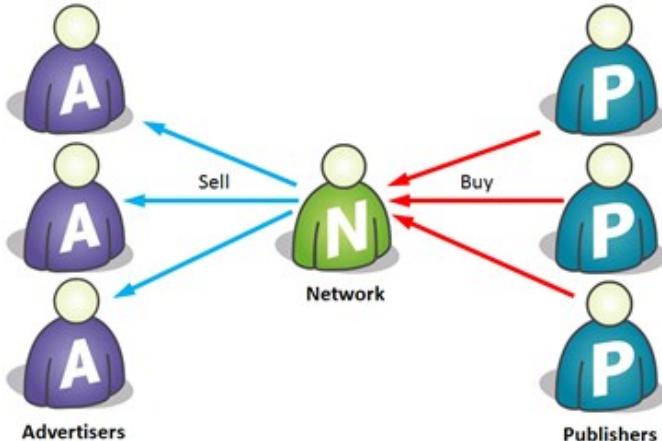


- After direct sales, some impressions will remain unsold (remnants)
- Small publishers cannot find buyers directly

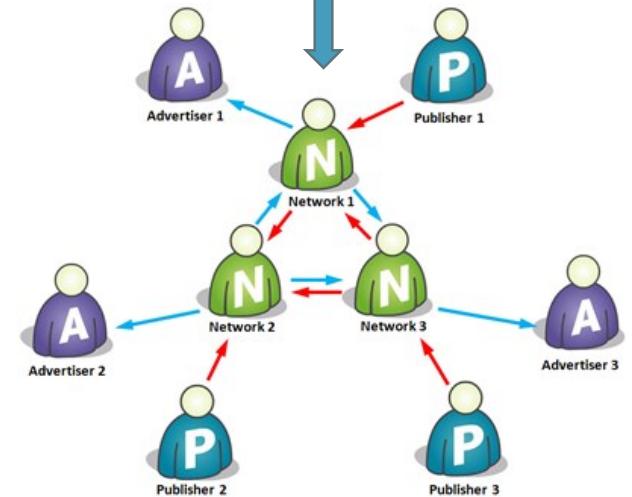
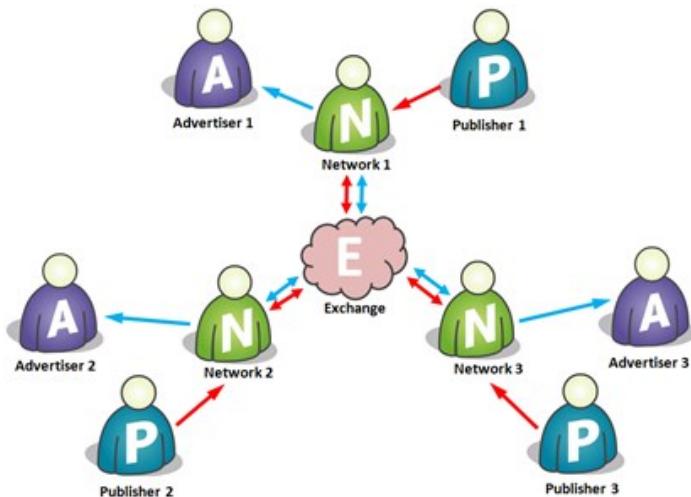
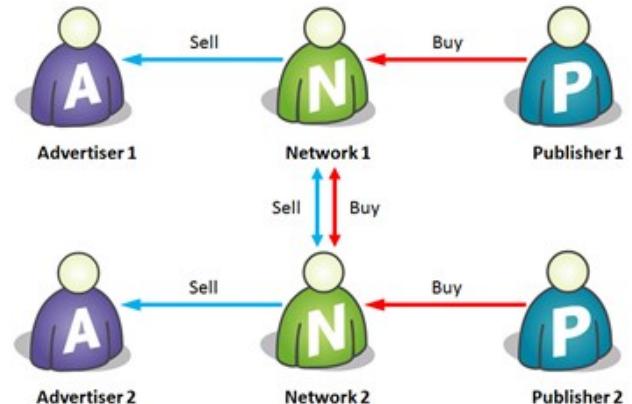


Introducing the ad exchange (since 2009)

single ad network is easy

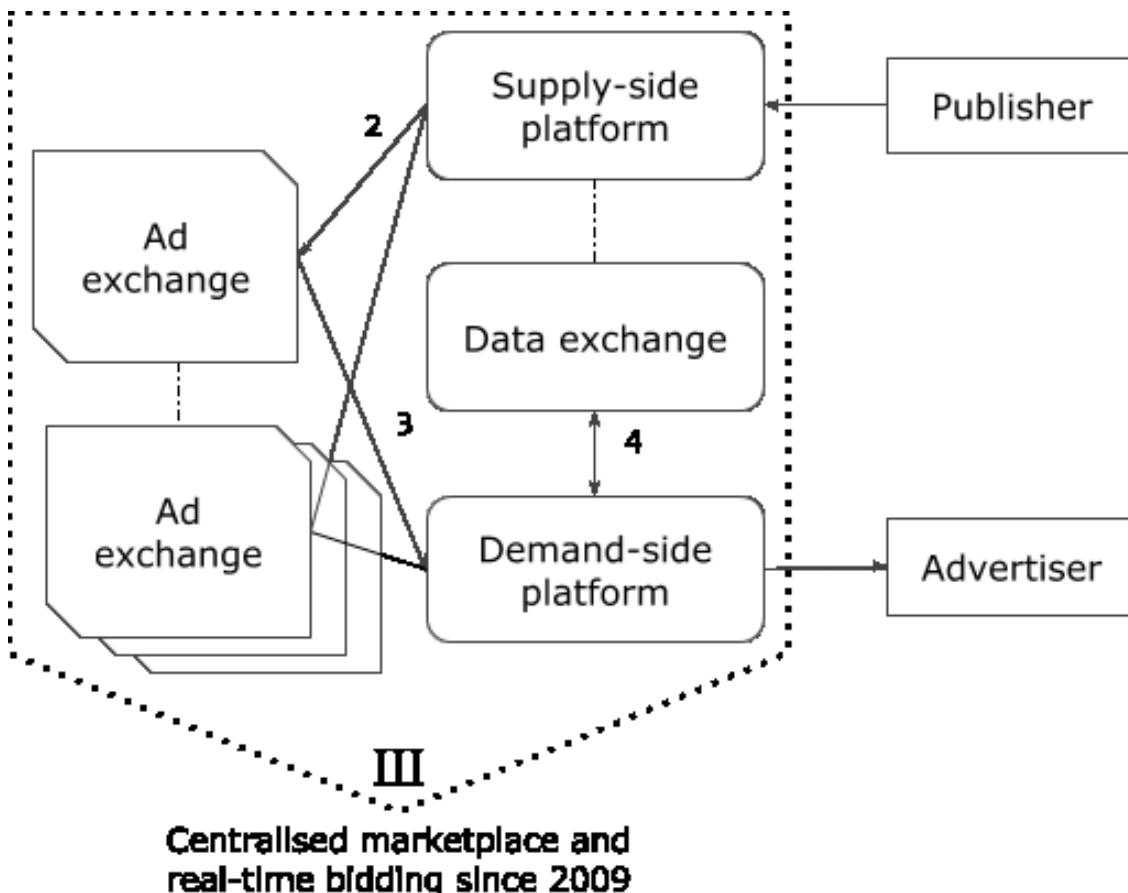


a few ad networks are manageable



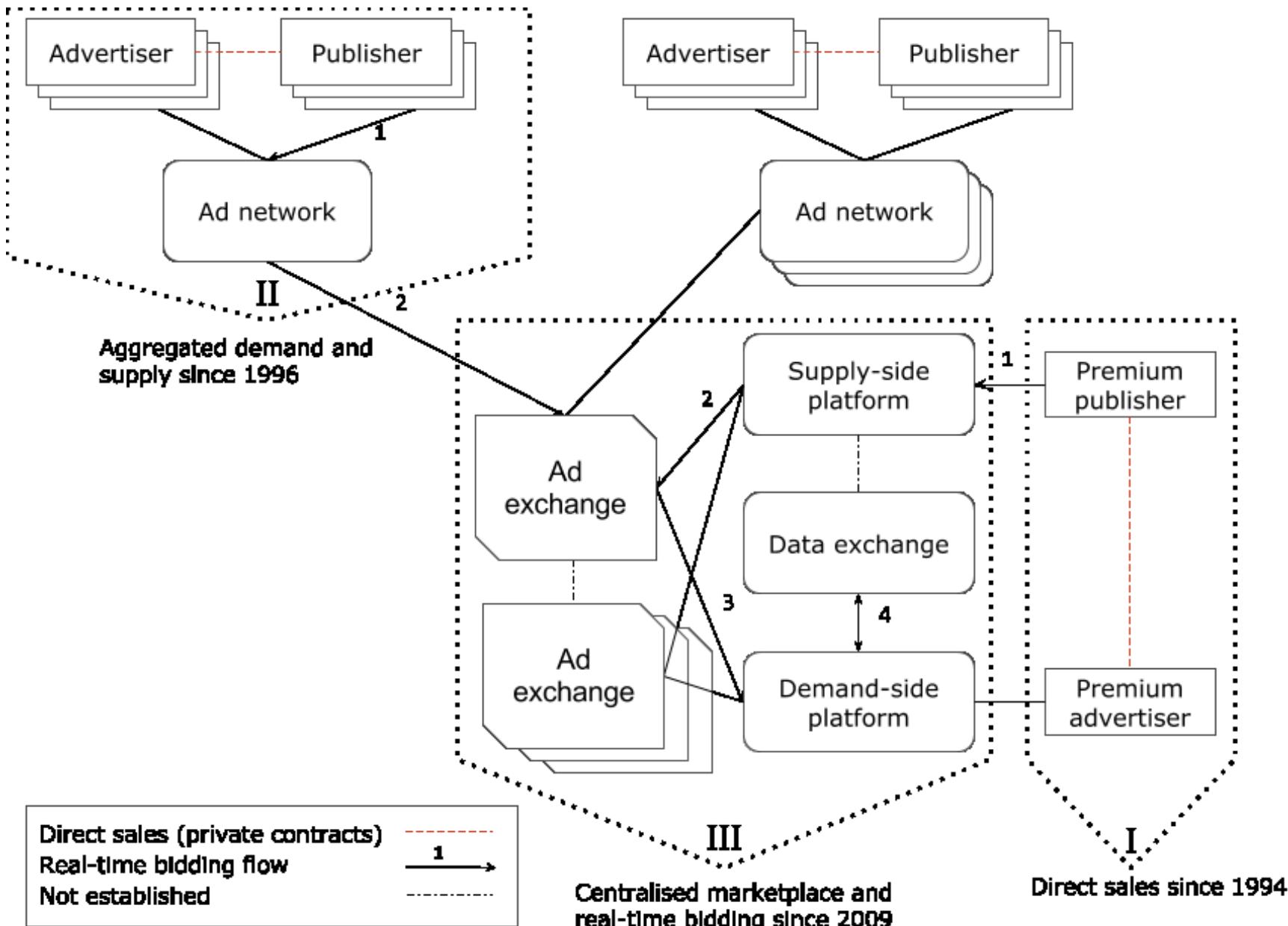
hundreds of ad networks are nightmare

Introducing the ad exchange contd.



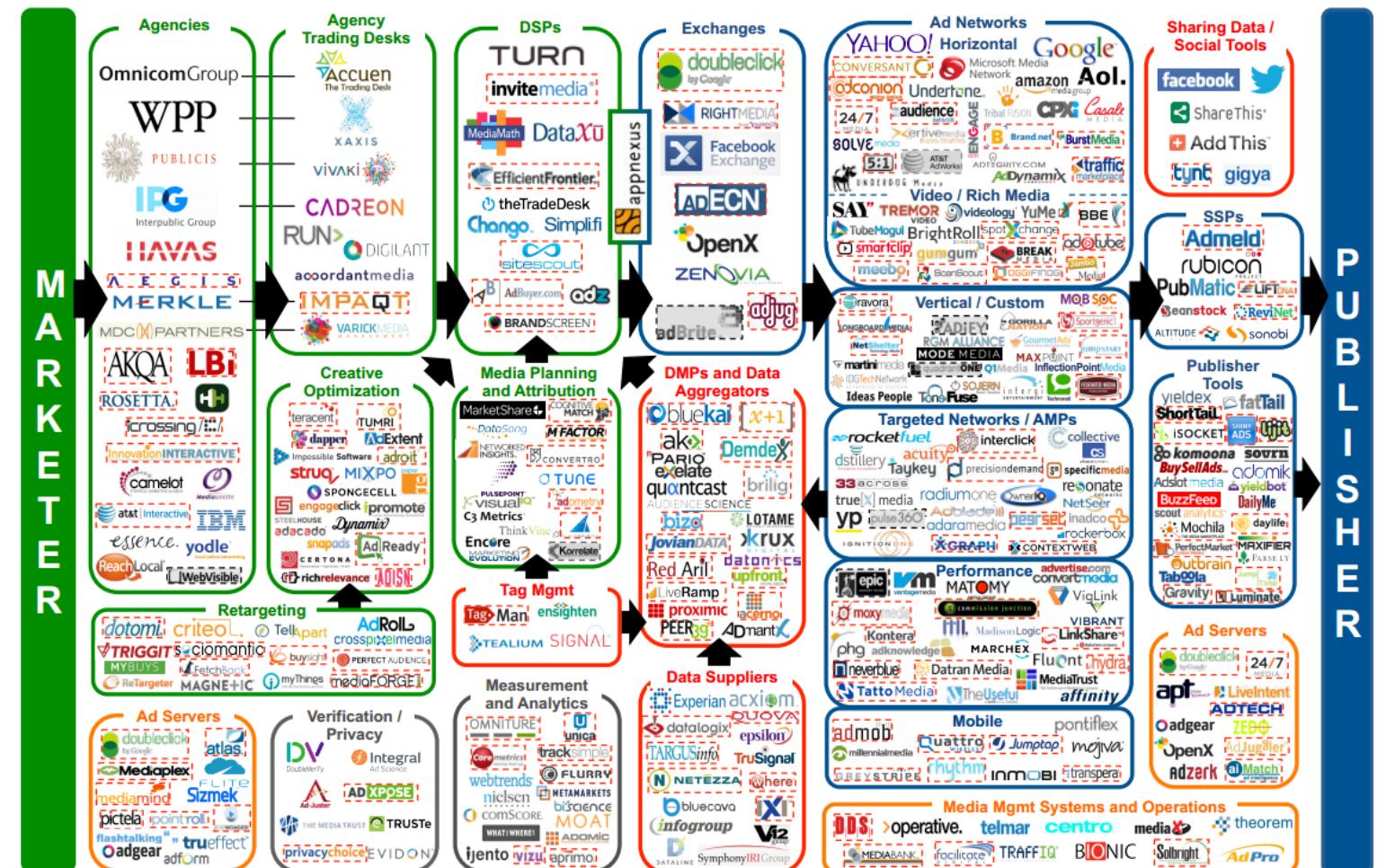
- Ad exchanges are marketplaces
- Advertisers and publishers have to rely on tools to connect
- Real-Time Bidding promotes user-oriented bidding

The simplified history of online (display) advertising



The complex display ad eco-system

DISPLAY LUMAscape



The logo for LUMA partners, featuring the word "LUMA" in a bold, sans-serif font with an orange sunburst icon to the left, and "partners" in a smaller, italicized, lowercase font below it.

 Denotes acquired company

Denotes shuttered company

© LUMA Partners LLC 2014

A great visualisation

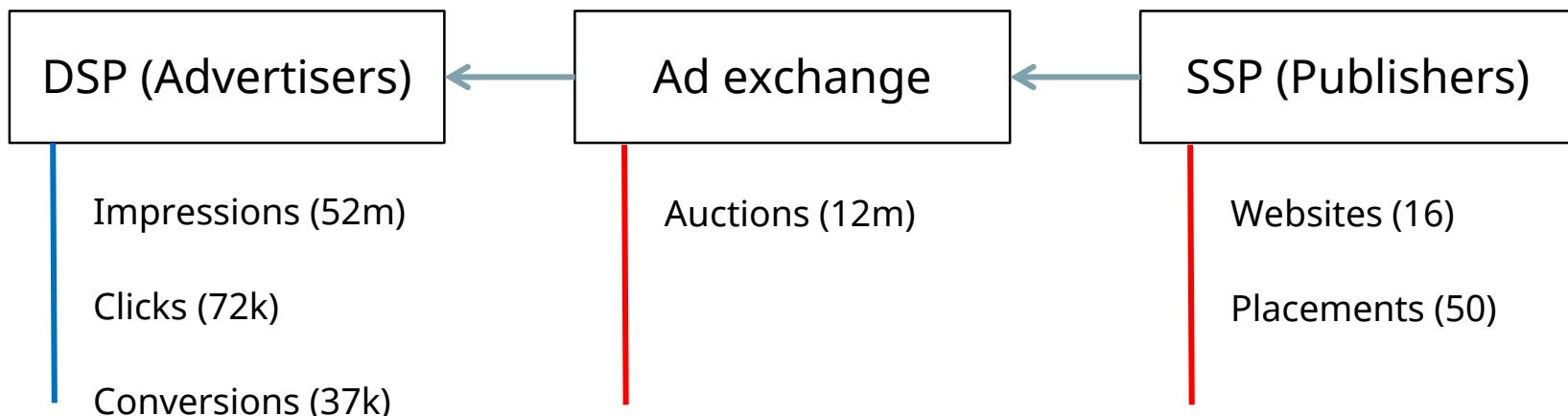
Behind the banner

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

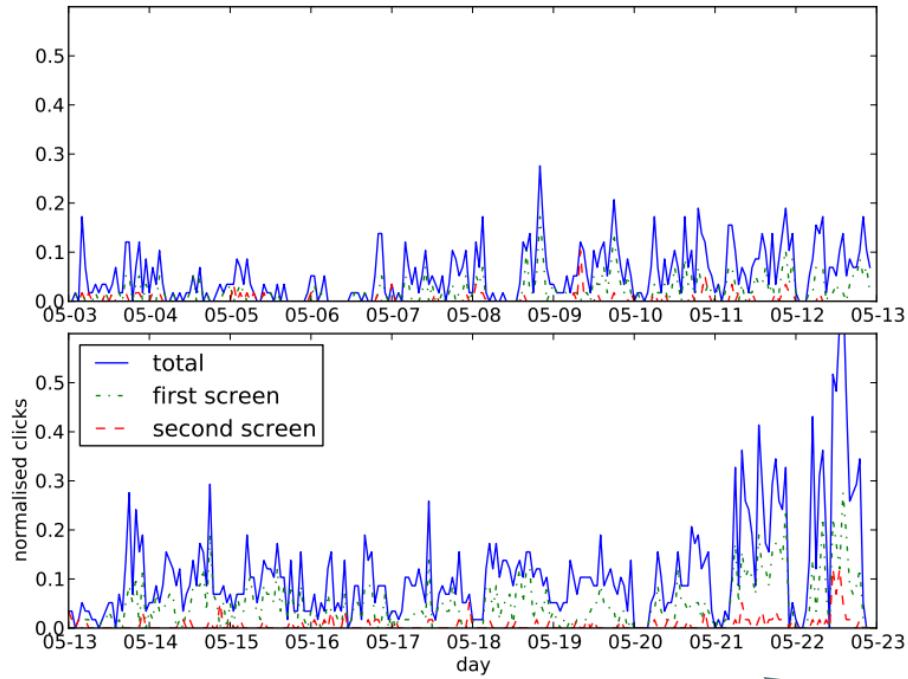
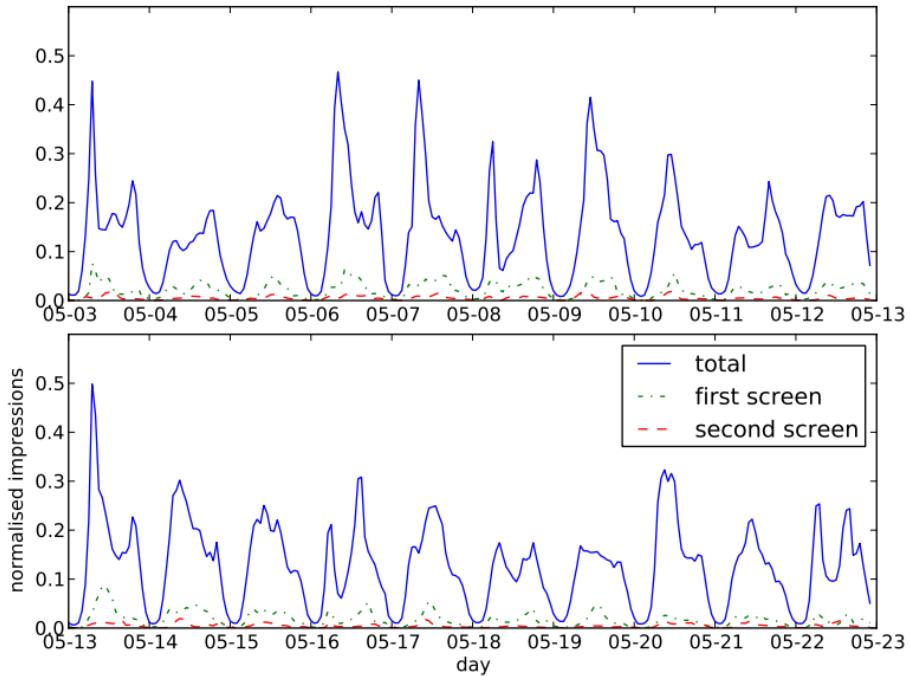
A visualization of the adtech ecosystem, Adobe, 2013

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



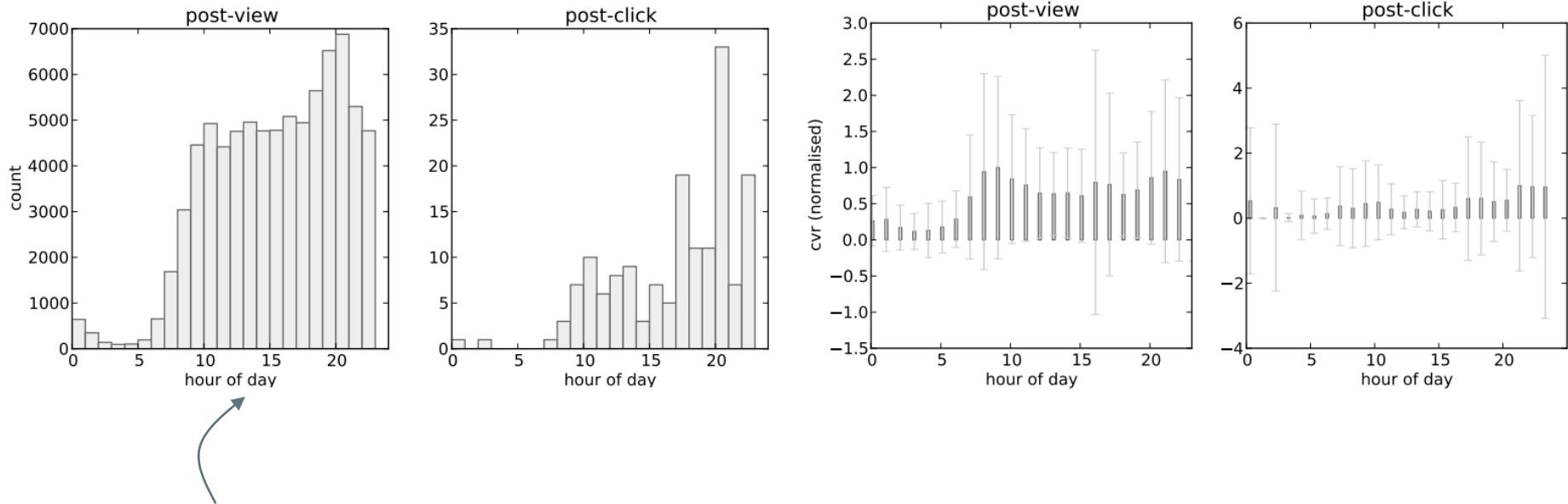
Impressions and clicks



Very noisy

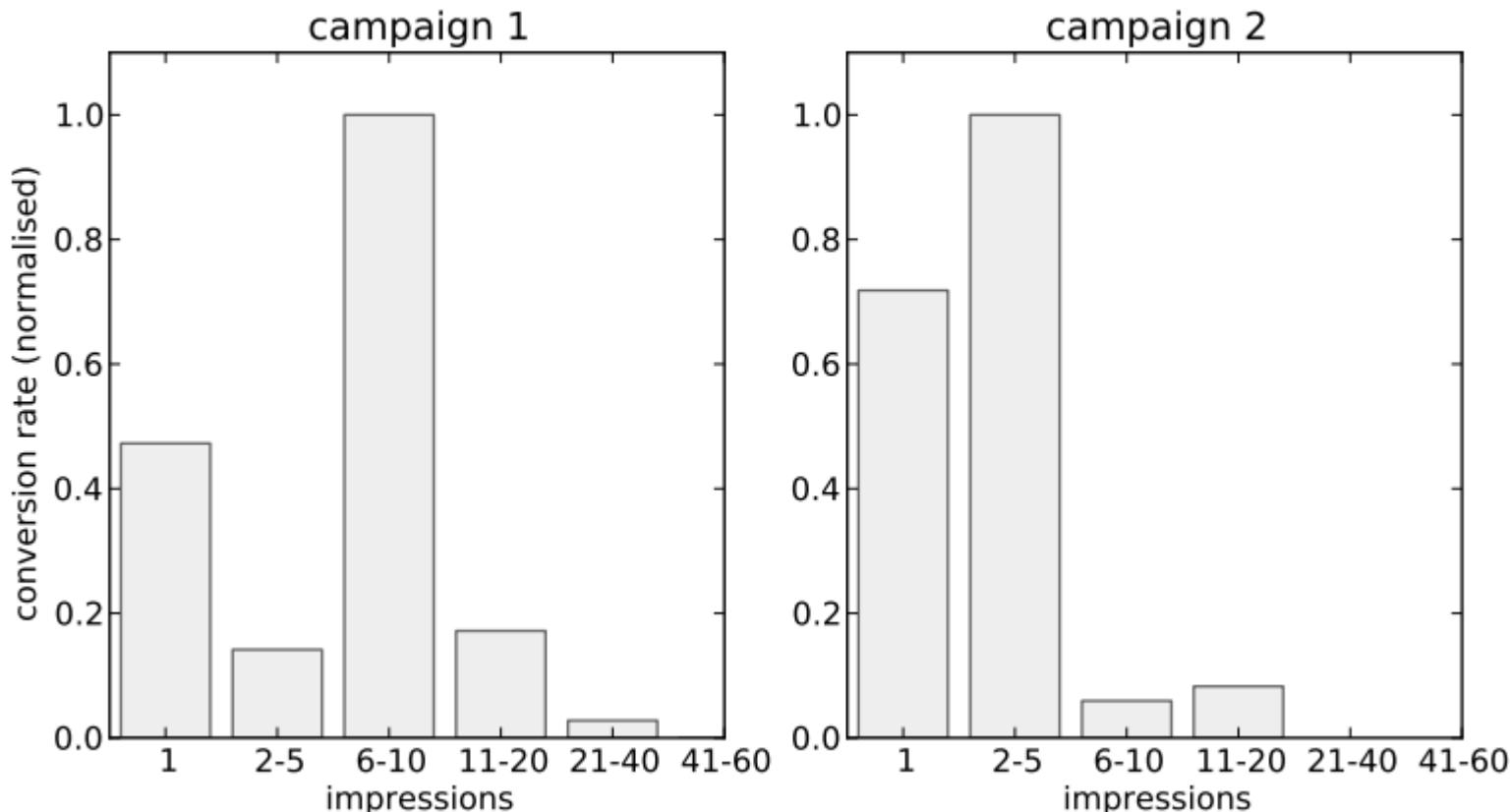
The numbers of imp (left) and click (right) both show strong daily and weak weekly patterns, corresponding to the normal human activity

Conversions



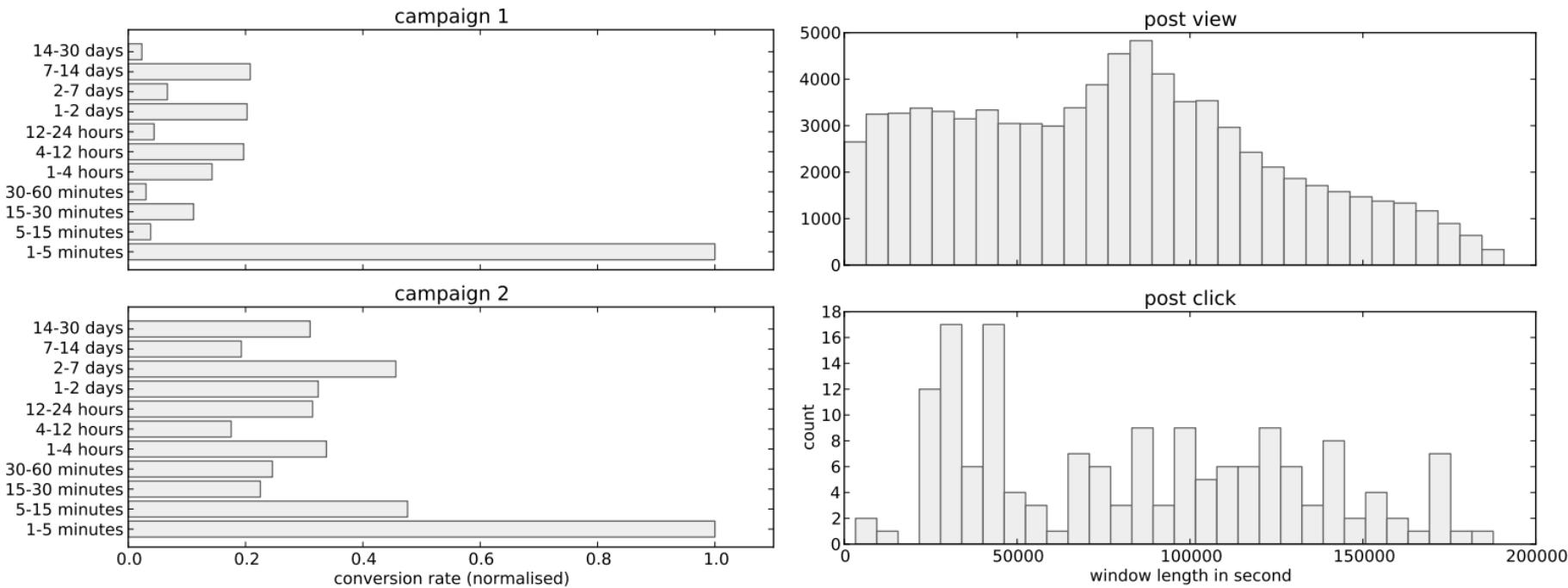
Daily periodic patterns for conv (left) and cvr (right) show that people are less likely to convert during late night

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)

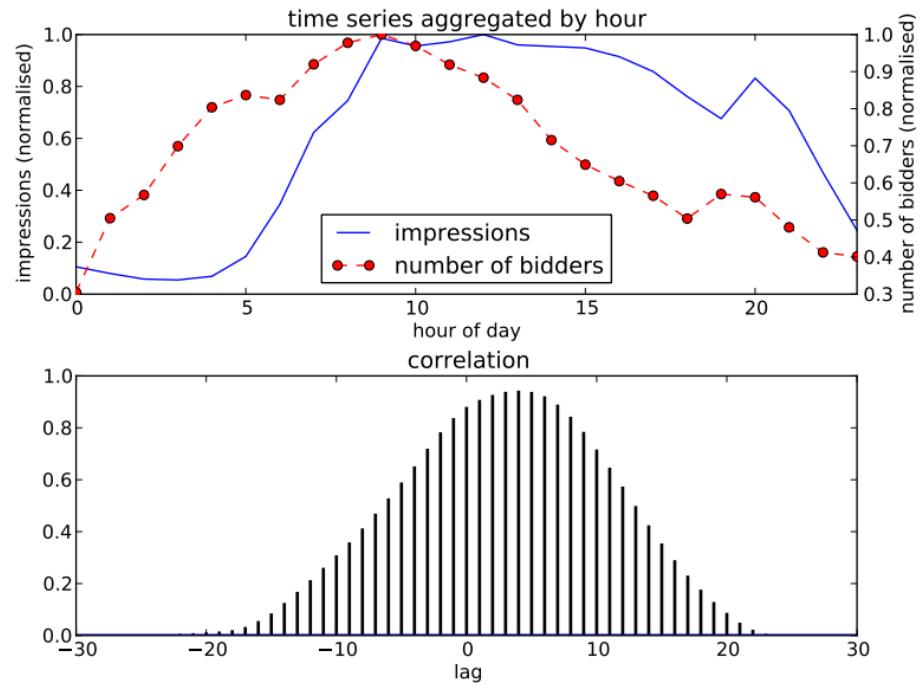
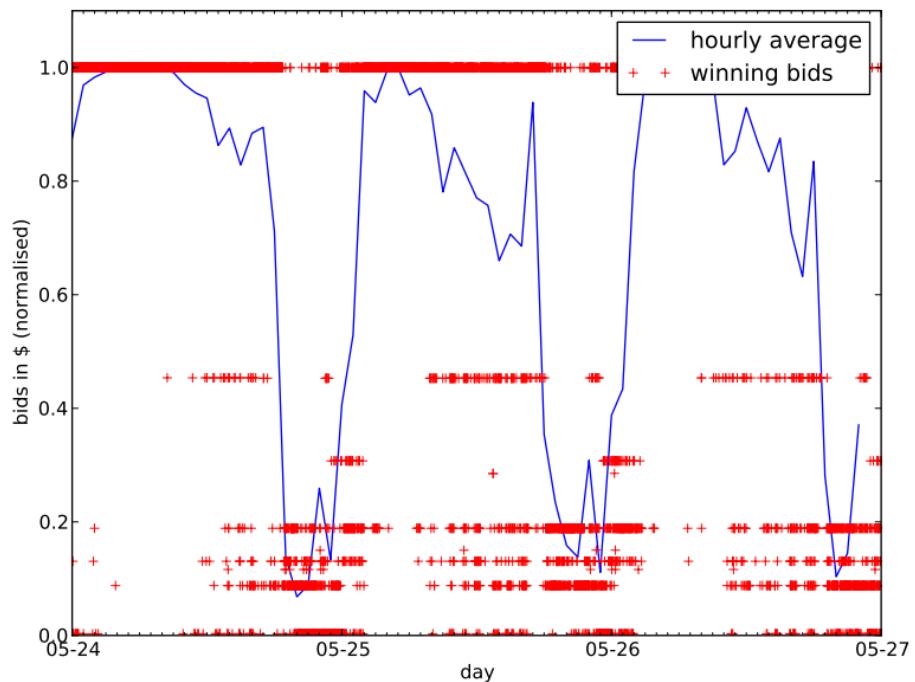
Campaign 1 sets a long recency cap -> waste of budget

Campaign 2 sets a short recency cap -> poor performance

The wide conversion window (right)
challenges attribution models



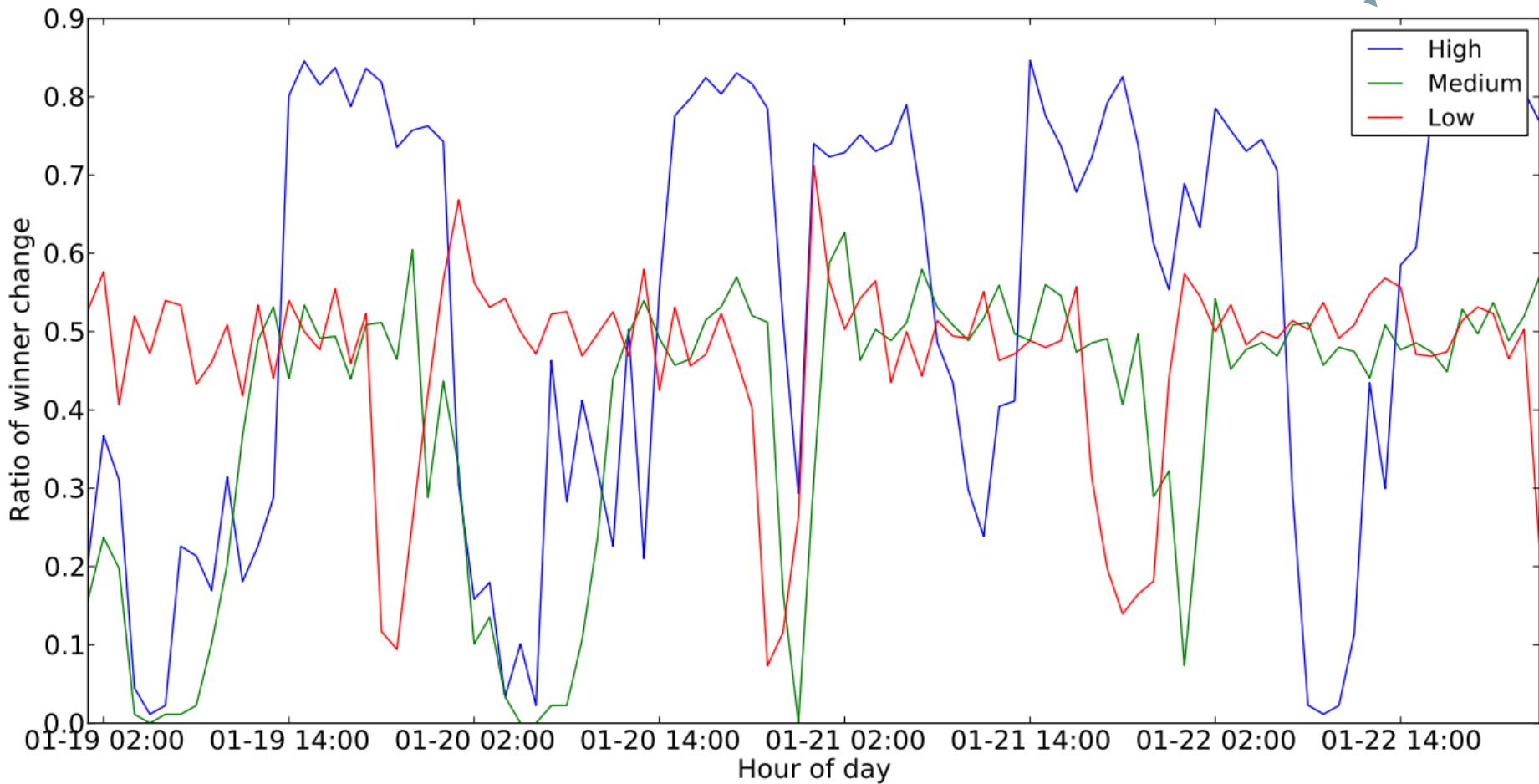
Auctions (Bidding competition)



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

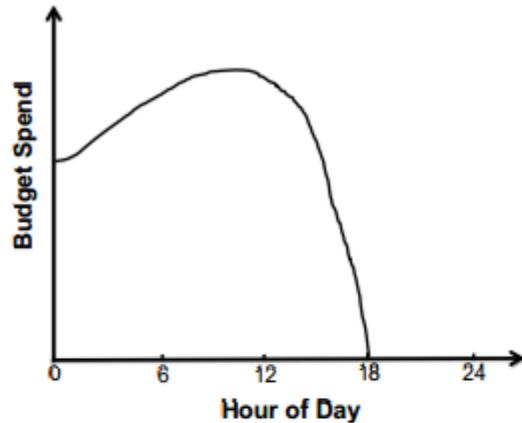
- Anderson-Darling test for Normality
- Chi-squared test for Uniformity

Finding the best fit of bids' distribution is important:

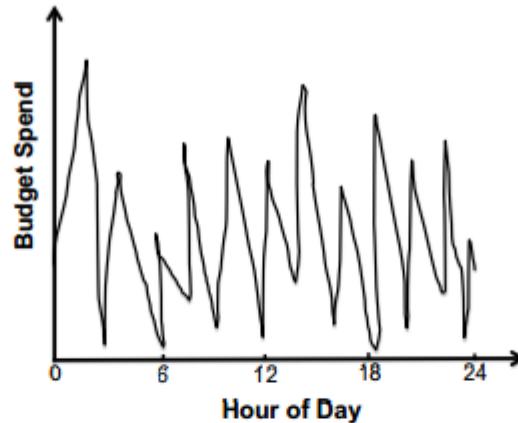
- Optimal reserve price
- Bid landscape forecasting
- etc.

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

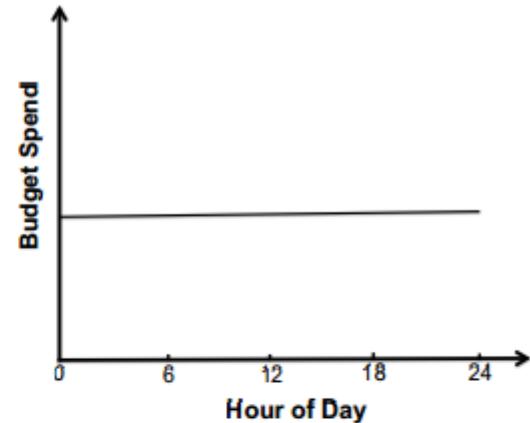
Budgeting and daily pacing



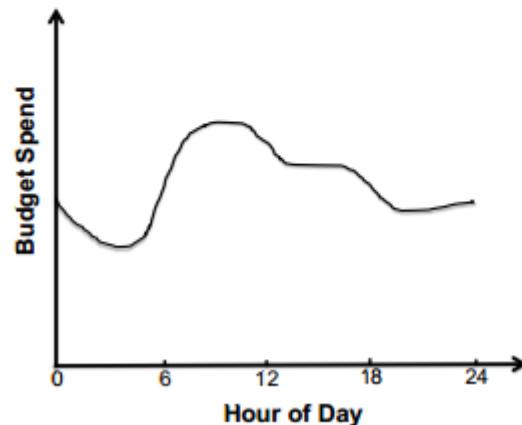
(a) Premature Stop



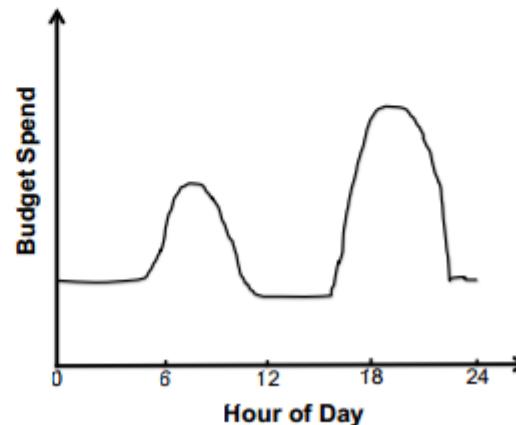
(b) Fluctuating Budget



(c) Uniform Pacing

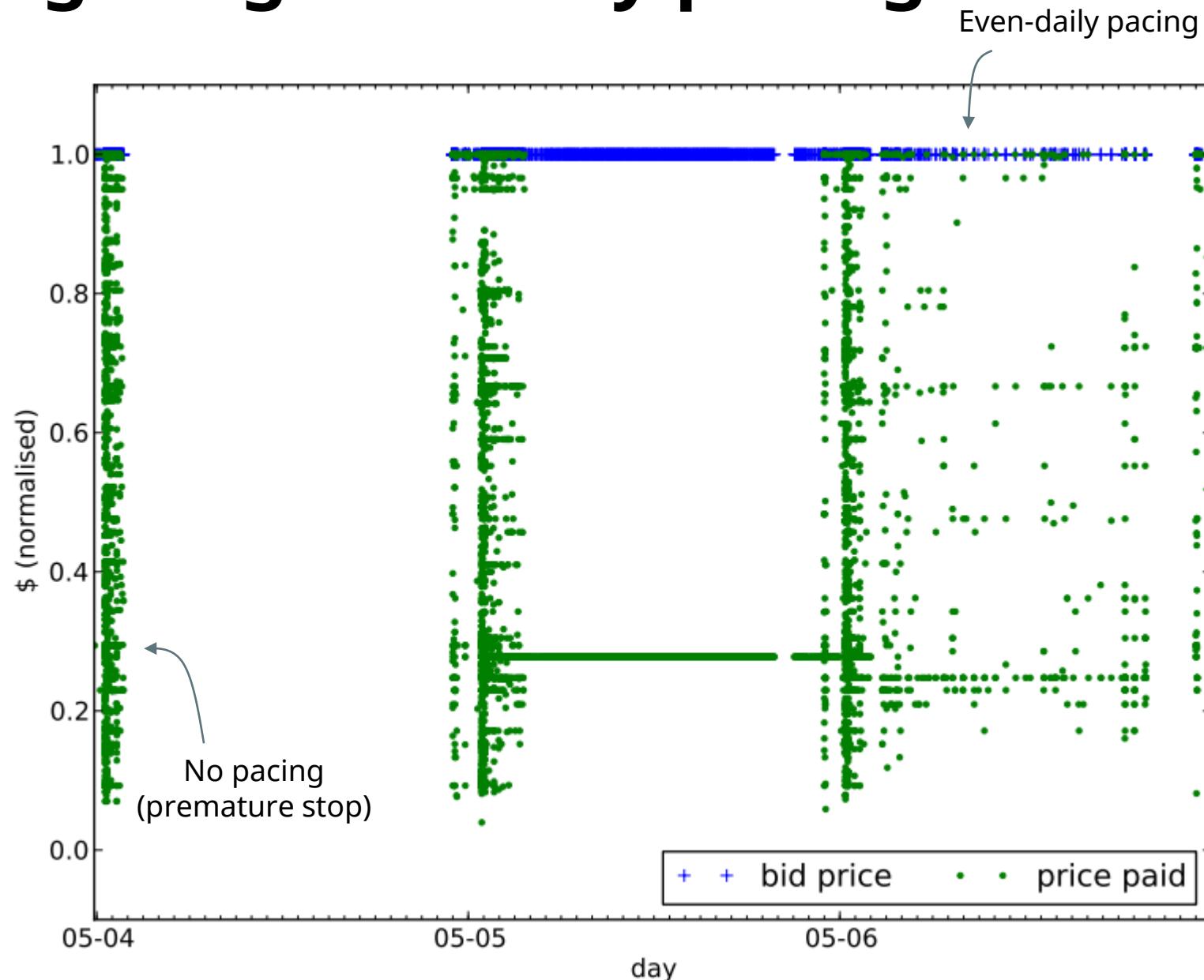


(d) Traffic Based Pacing

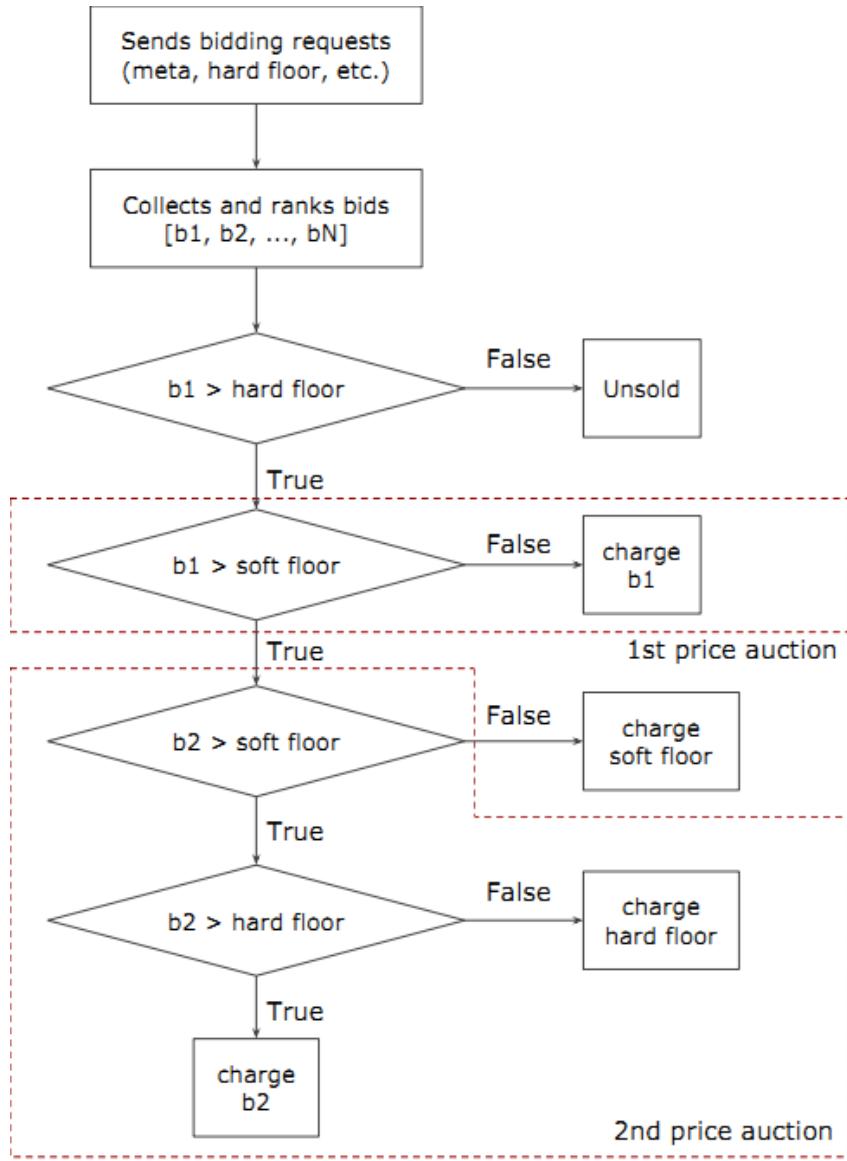


(e) Performance Based Pacing

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

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Part 2.1 Bidding strategy

- Bid optimisation methods
 - Introductions
 - CTR predictions
 - Bidders

Demand Side Platform (DSP)

The screenshot shows the OpenBidder.com interface for creating a new order. The left sidebar has a navigation menu with Home, Orders (selected), Manage Orders, New Order (highlighted in blue), Creatives, Explore, API, Reports, and Help.

Primary

- Name: Input your order name
- Representative category: Books & Literature
- TLD: yourdomain.com

This is the domain of the advertised company, not the domain of your company who is doing the adv (e.g. nike.com, king.com, cnn.com, etc.)

Budget

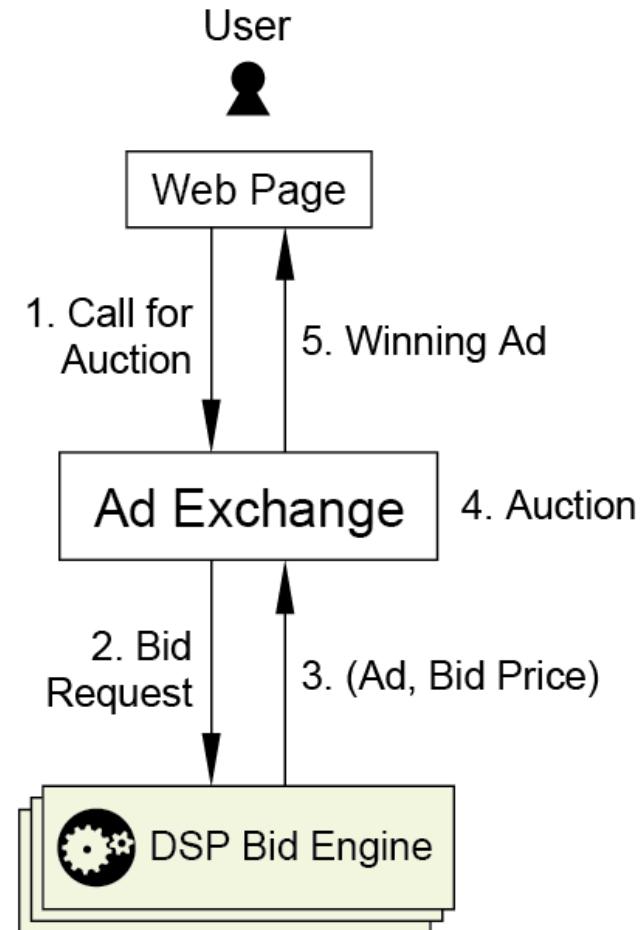
- Total budget: 400.0
- This can be your client's budget
- Highest CPM: 4.5
- Budget per hour: N/A

Add hourly budget limit

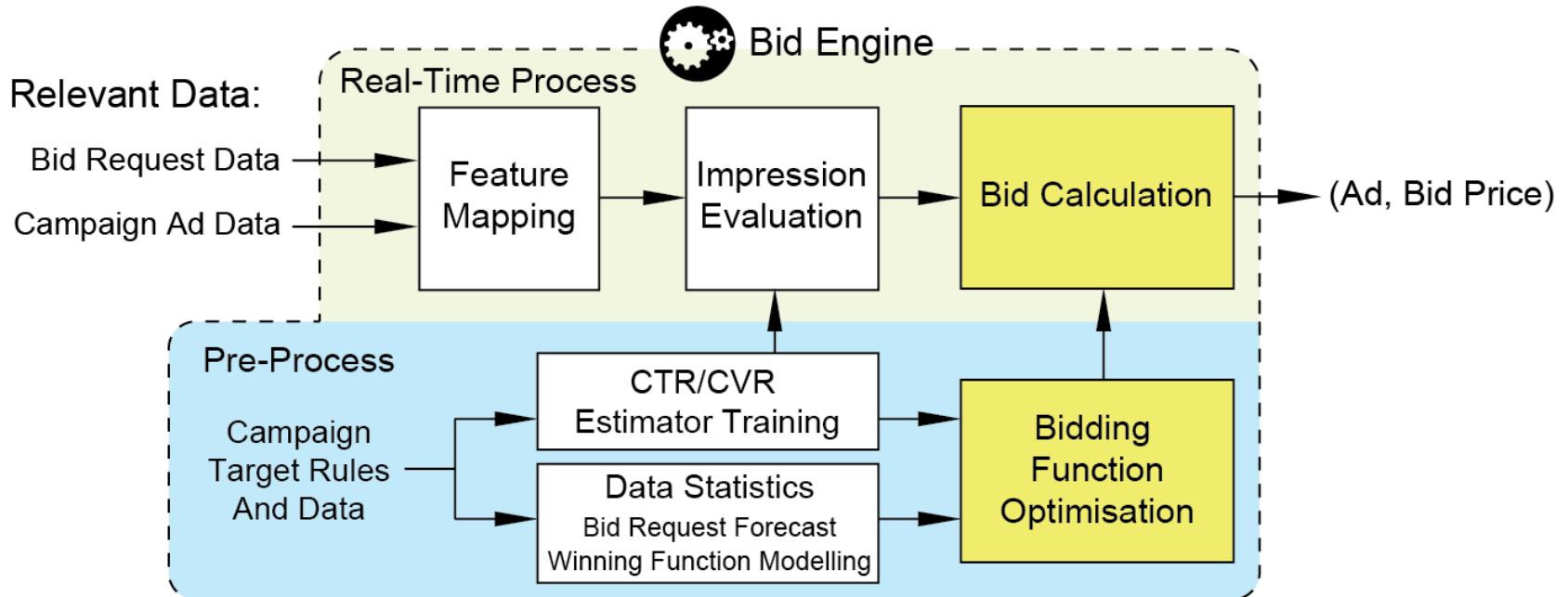
Schedule

Campaign date: From - To

Bidder in DSP

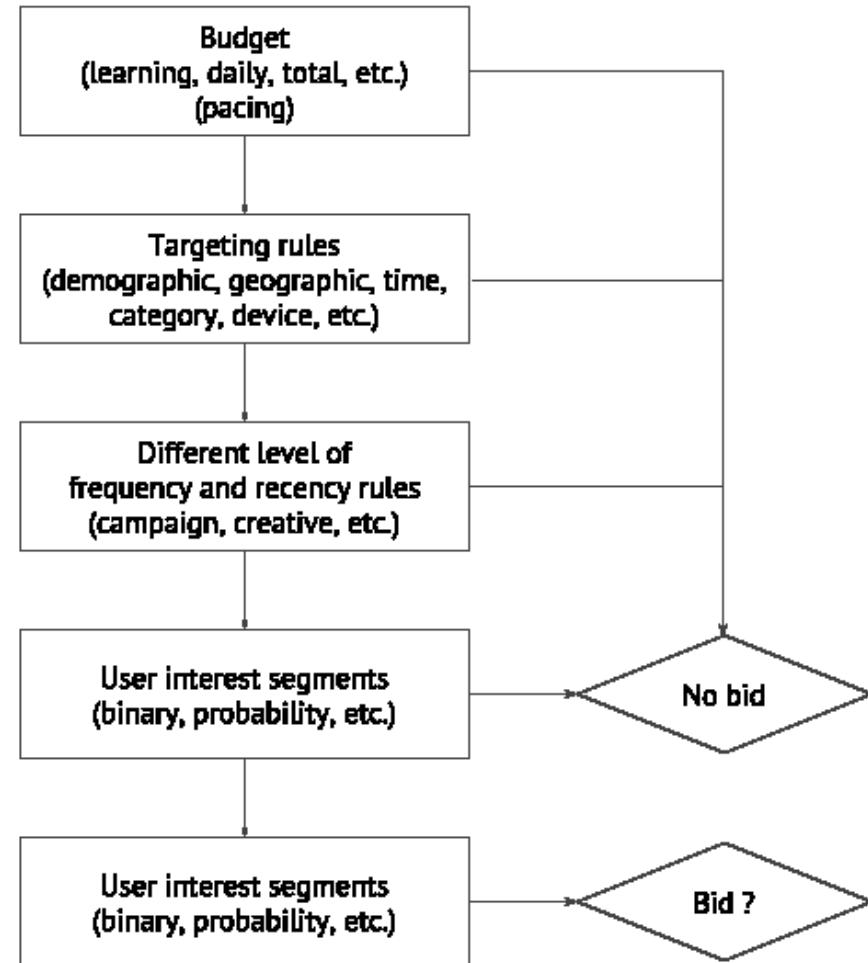


Bidder in DSP



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]

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

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

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

A heuristic bidder

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

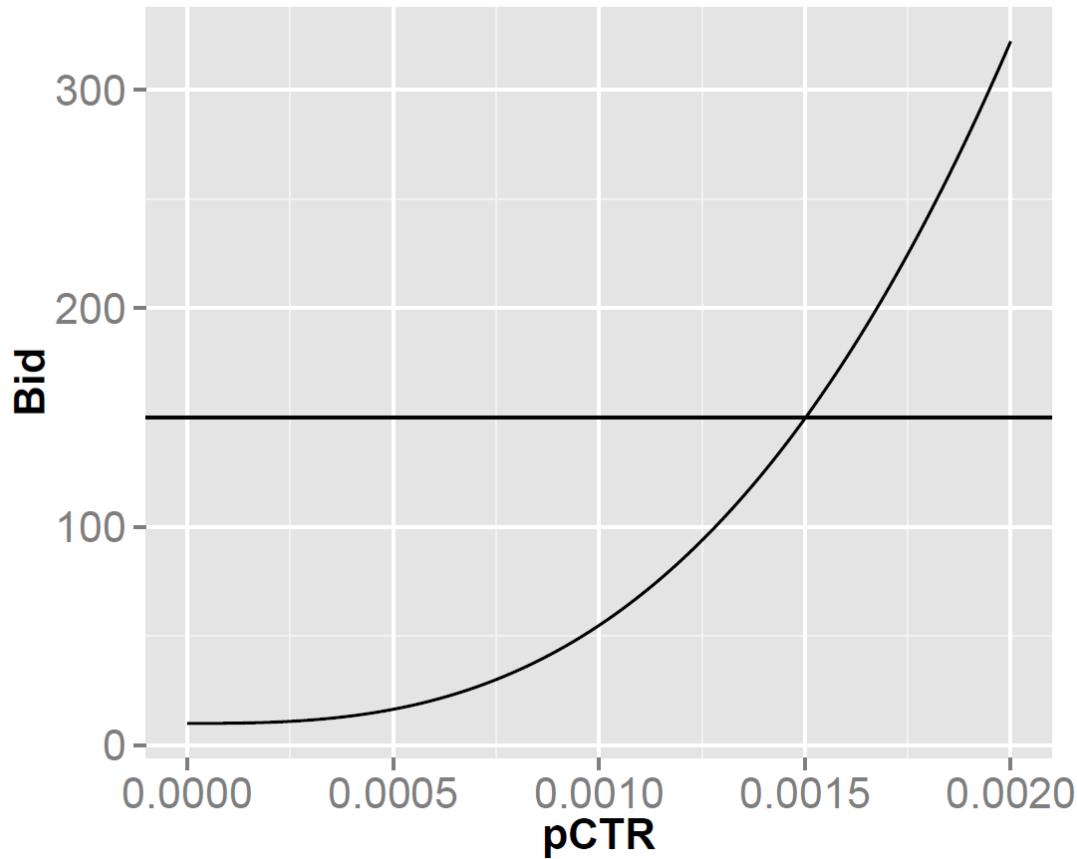
$$b_i = \min \left\{ \left(\frac{\hat{y}_i}{y_0} \right)^a y_0 b + c, d \right\}$$

↑
Base (average) CTR

↓
Predicted CTR

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

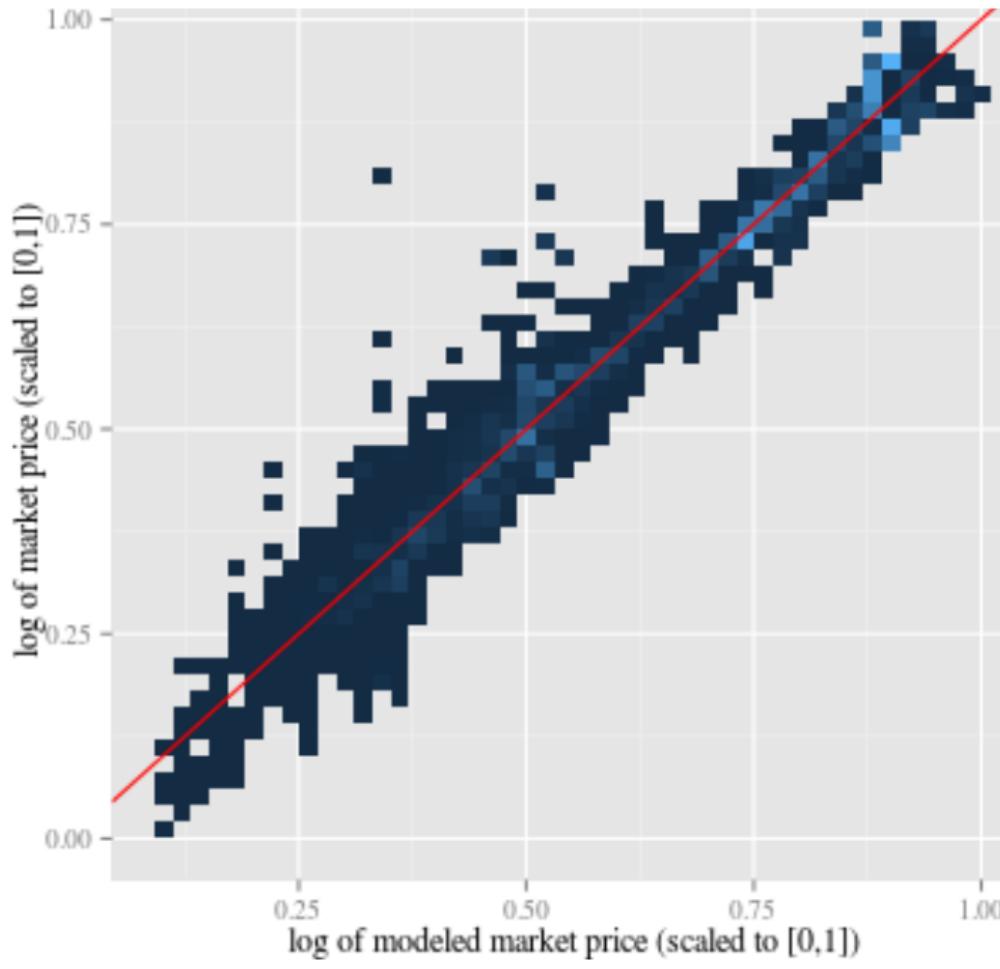
A heuristic bidder



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

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

Multiplicative bidder



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

Features: country & hour of the day

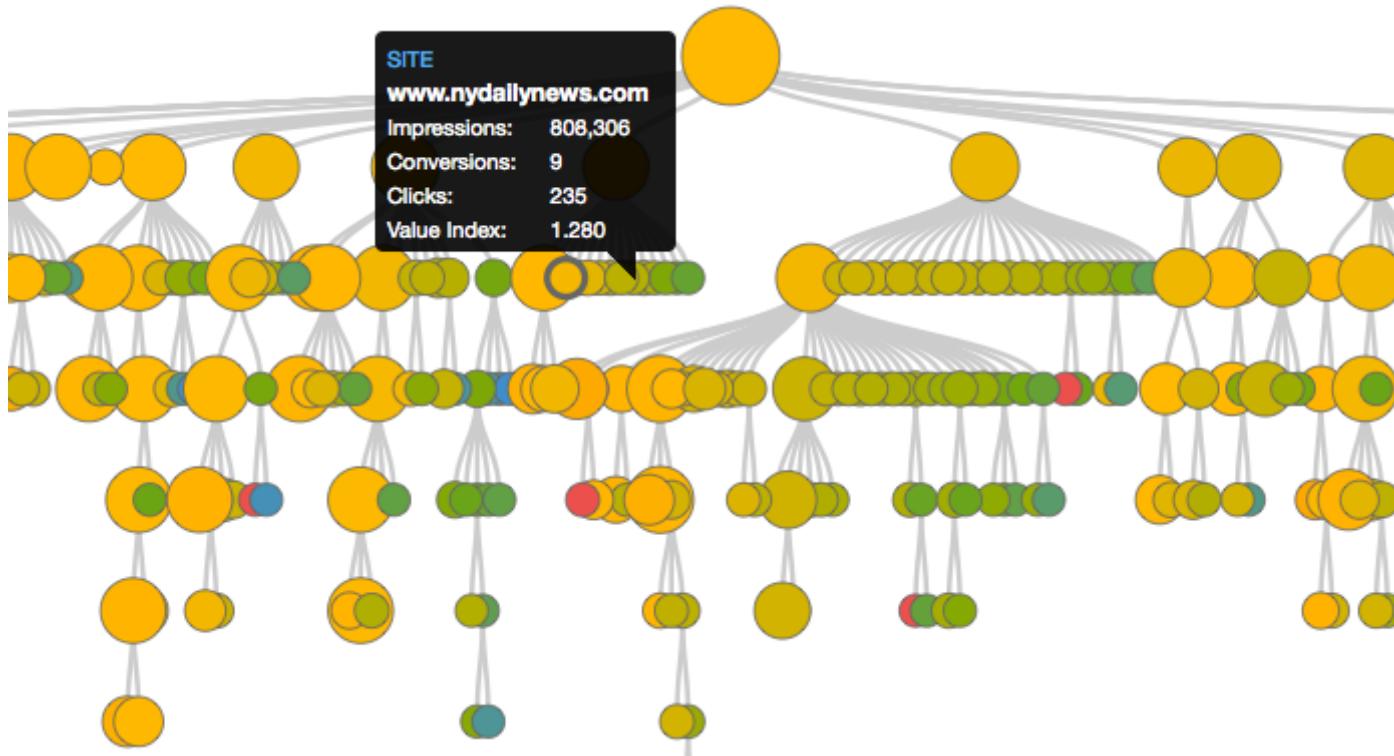
Two bid adjustment dimensions with m and n possible settings

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 $r_i \cdot c_j$

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 $\text{OPT}(B/4)$, the individual bidding optimum with budget $B/4$;

Step 3:

for $h=1,2,\dots,m$ **do**

$\text{ALG}_h \leftarrow \emptyset$;

 Insert into ALG_h all height- h towers of $\text{OPT}(B/4)$;

 Insert into ALG_h all height- h towers in the strips above the ones in the last line;

end

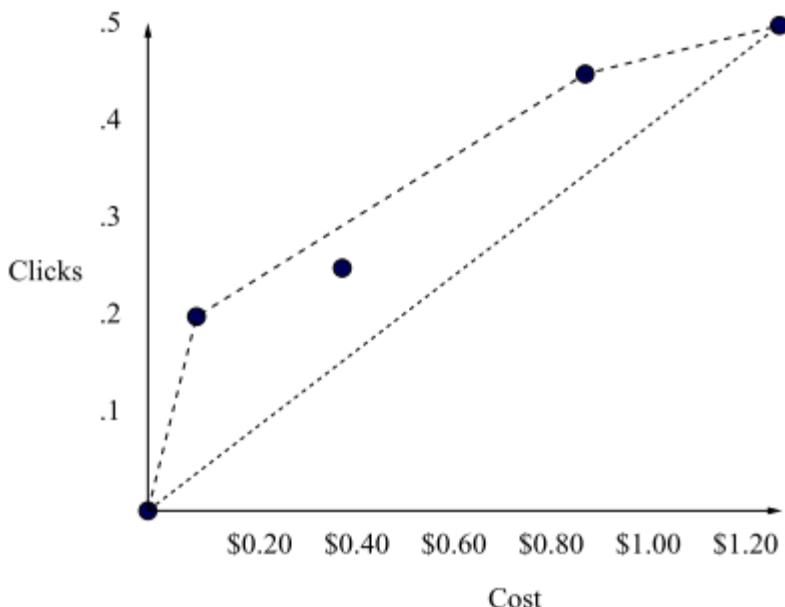
Output the best ALG_h as ALG

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: $\text{clicks}_q(\cdot)$
- Cost function: $\text{cost}_q(\cdot)$
- Objective to maximise: $\sum_q \text{clicks}_q(b_q)$
- Subject to: $\sum_q \text{cost}_q(b_q) \leq U$
- Nearly all formulation of this optimisation problem is NP-hard

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.

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: $x \rightarrow \theta \rightarrow b \rightarrow w$

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

← context+ad features

bidding function

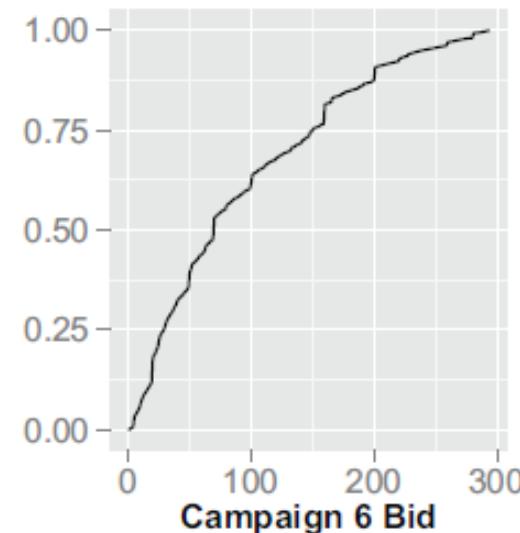
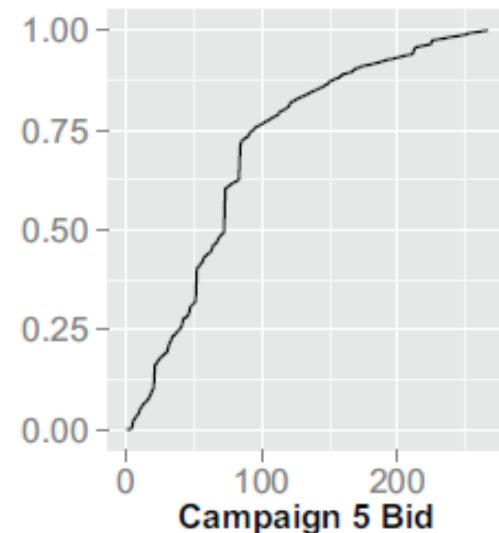
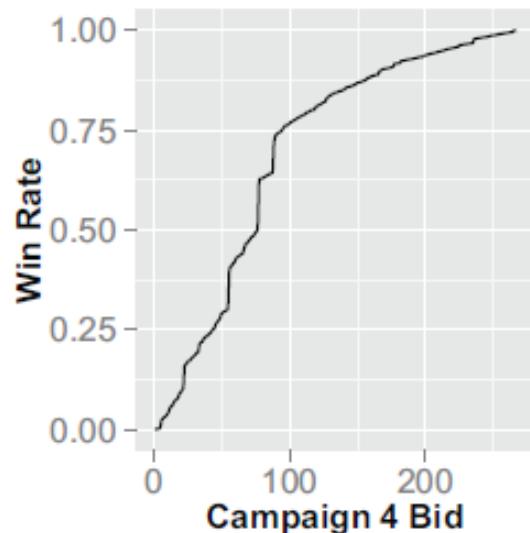
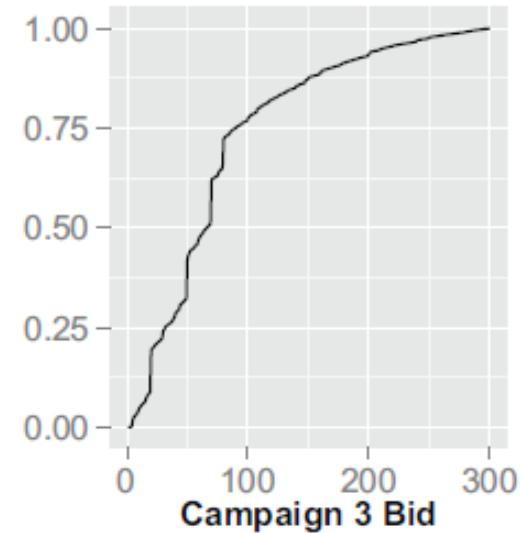
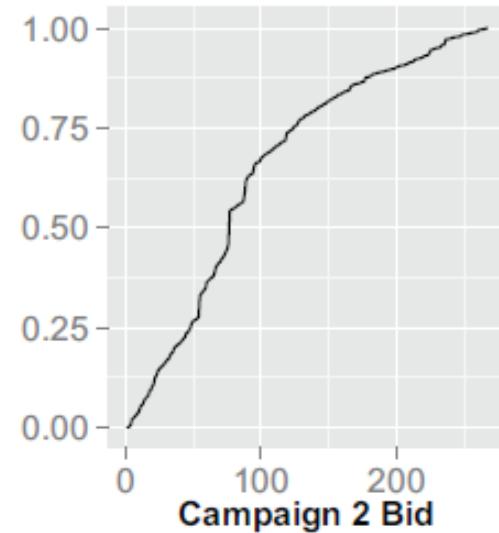
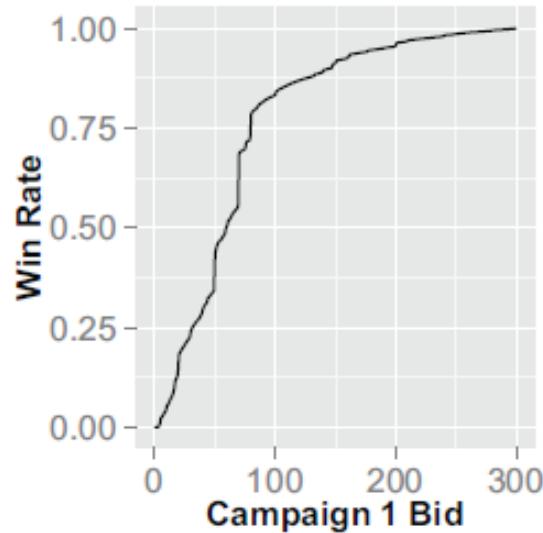
subject to $N_T \int_{\theta} b(\theta) w(b(\theta)) p_{\theta}(\theta) d\theta \leq B \leq B^*$

- Solution: Calculus of variations

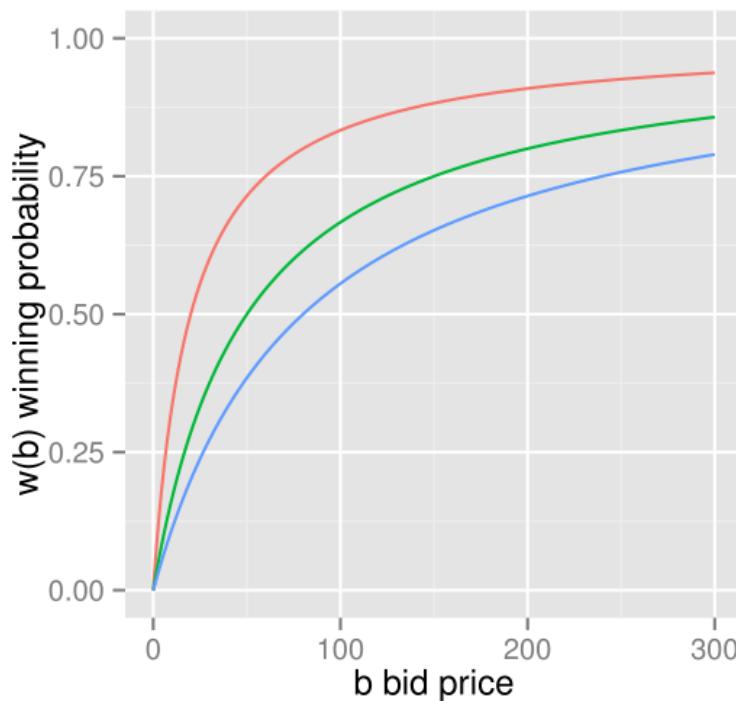
$$\mathcal{L}(b(\theta), \lambda) = \int_{\theta} \theta w(b(\theta)) p_{\theta}(\theta) d\theta - \lambda \int_{\theta} b(\theta) w(b(\theta)) p_{\theta}(\theta) d\theta + \frac{\lambda B}{N_T}$$

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

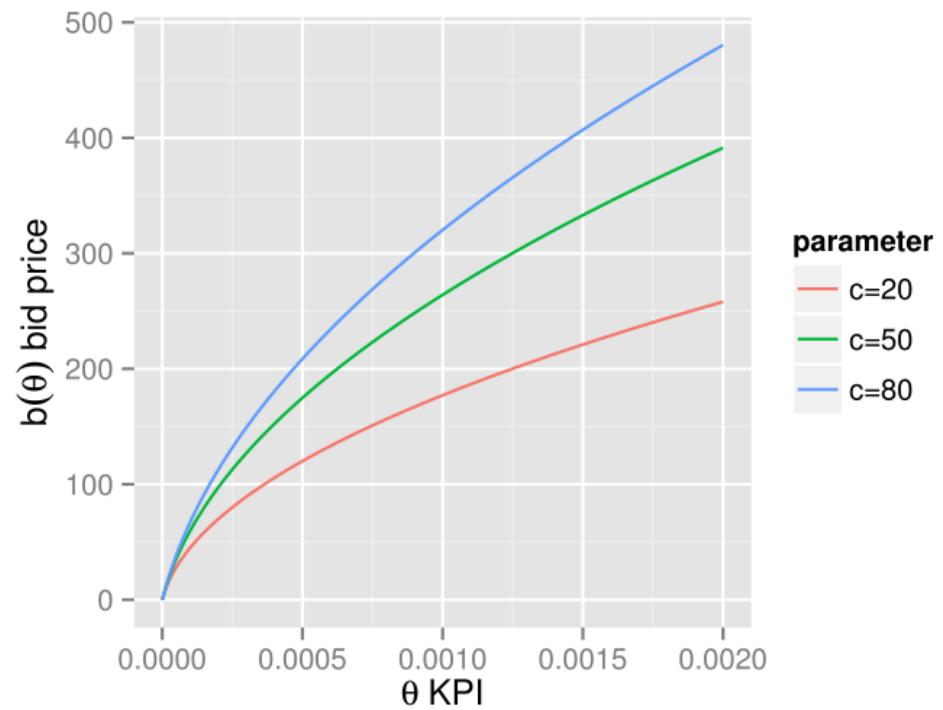
Win function



Optimal bidder: the solution



(a) Winning function 1.

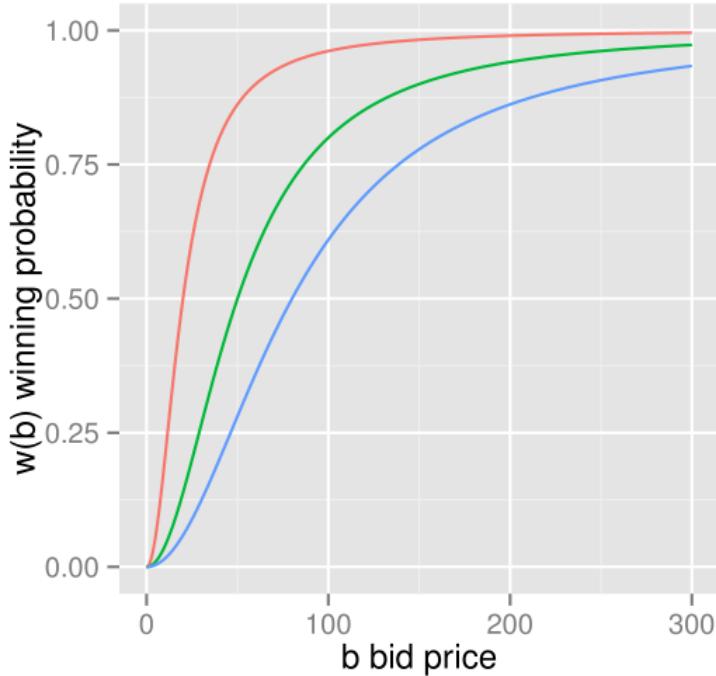


(b) Bidding function 1.

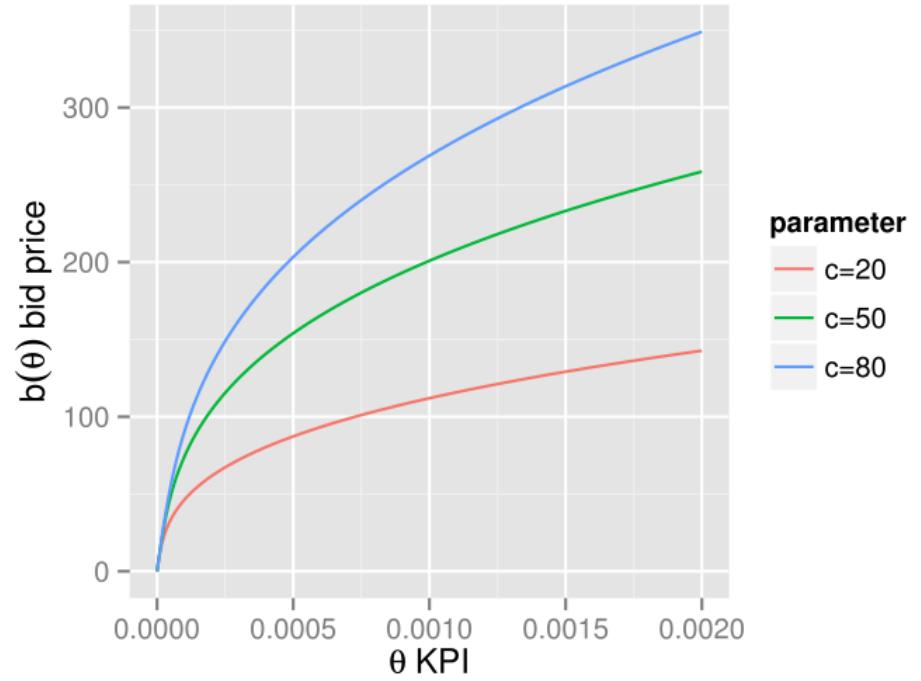
$$w(b(\theta)) = \frac{b(\theta)}{c + b(\theta)}$$

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

Optimal bidder: the solution



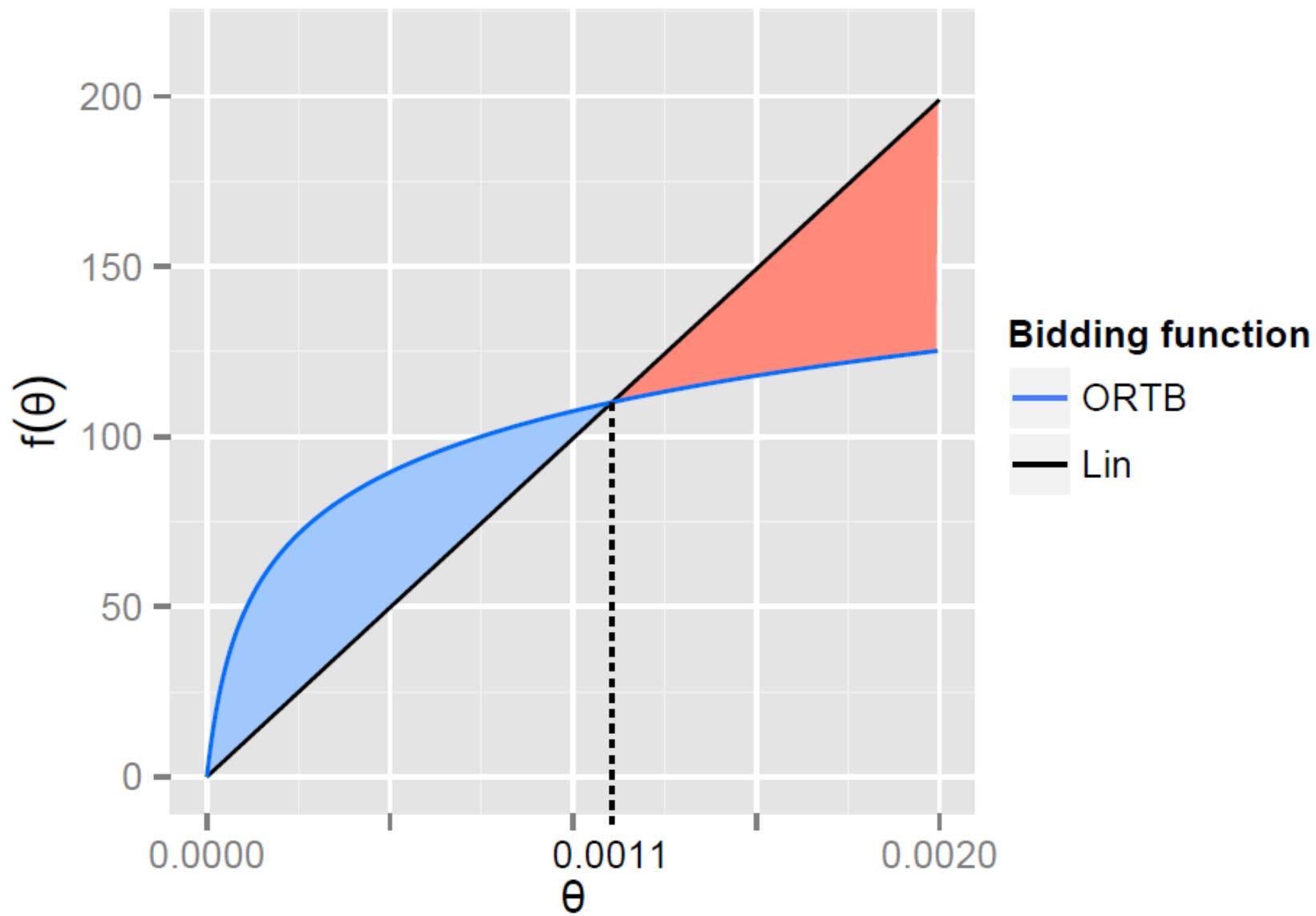
(a) Winning function 2.



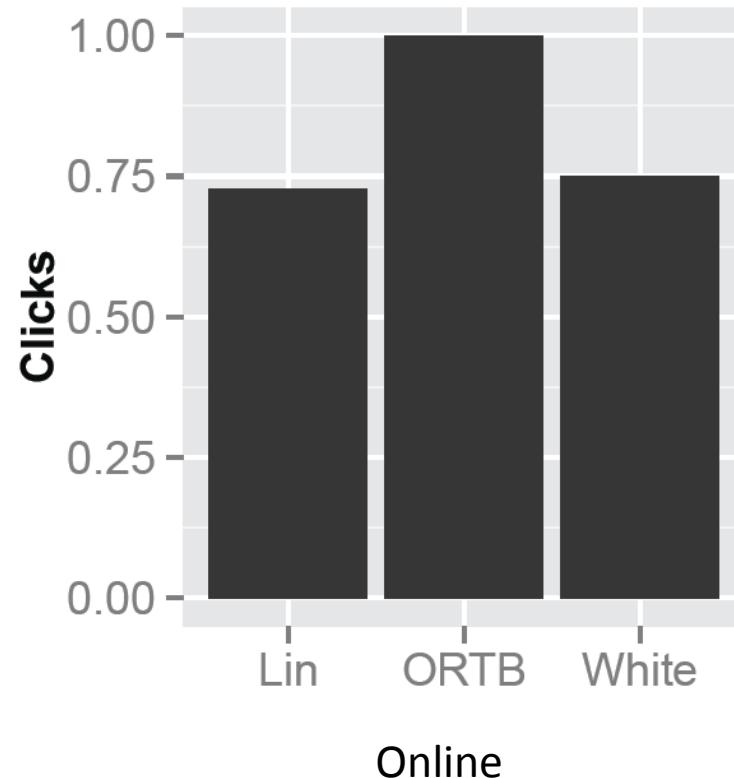
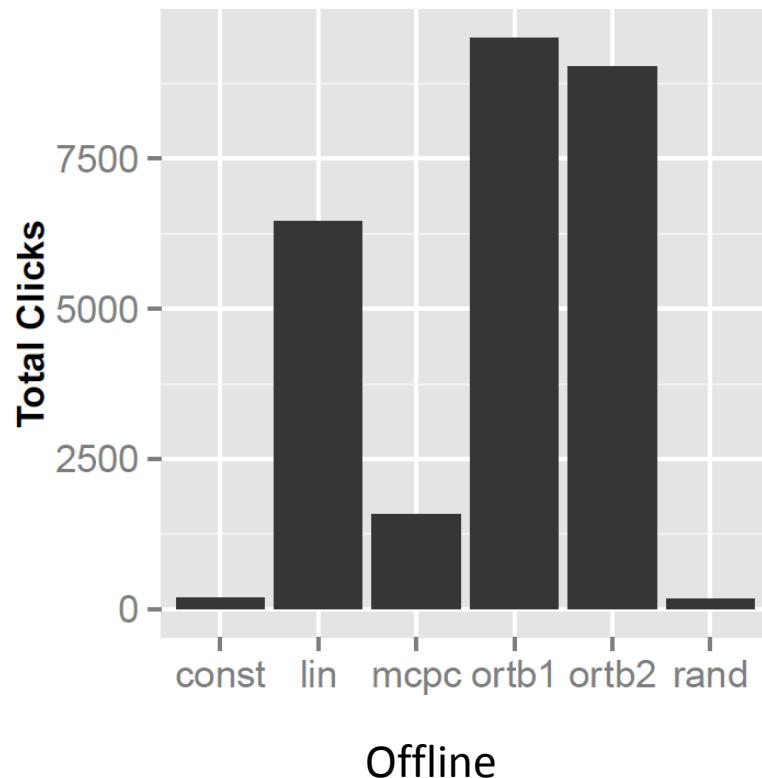
(b) Bidding function 2.

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

Optimal bidder: the solution



Experiments



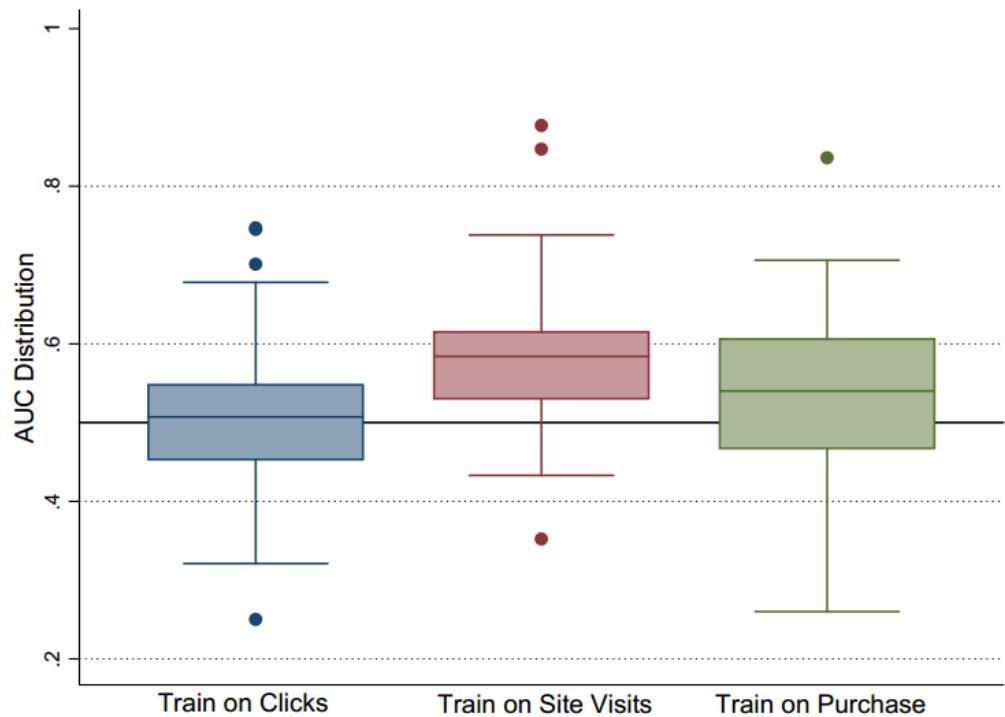
Winner of the first global Real-time Bidding algorithm contest 2013-2014

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

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)



References

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- A novel click model and its applications to online advertising, ZA Zhu et al., 2010.
- Web-search ranking with initialized gradient boosted regression trees, A Mohan et al., 2011
- A Gentle introduction to random forests, ensembles, and performance metrics in a commercial system, D Benyamin, 2012, goo.gl/XpbkDY
- Deep networks for predicting ad click through rates, G Corrado, 2012
- Click modeling for display advertising, O Chapelle, 2012, goo.gl/fNpZHv
- Causal reasoning and learning systems, L Bottou and E Portugaly, 2012
- Ad click prediction: a view from the trenches, HB McMahan et al., 2013
- Deep learning, yesterday, today, and tomorrow, K Yu et al., 2013
- 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

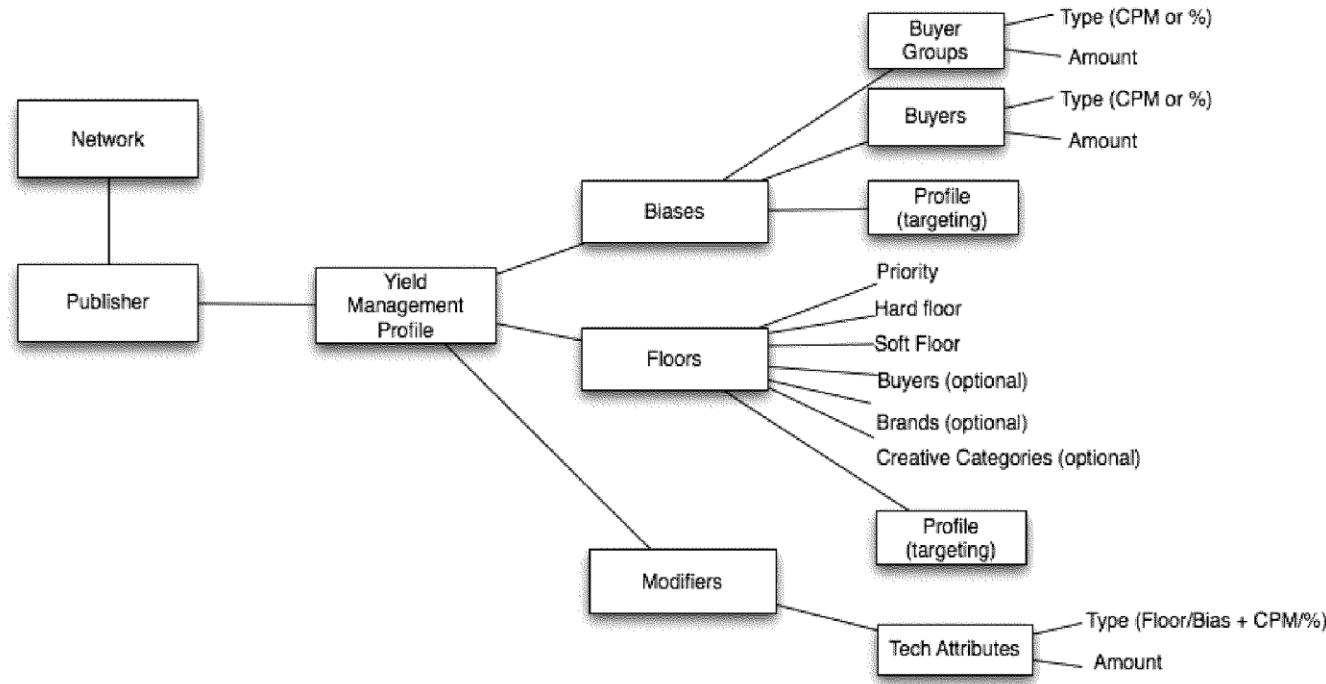
- Typical revenue models
- Ad density optimal control
- Reserve price optimisation

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)

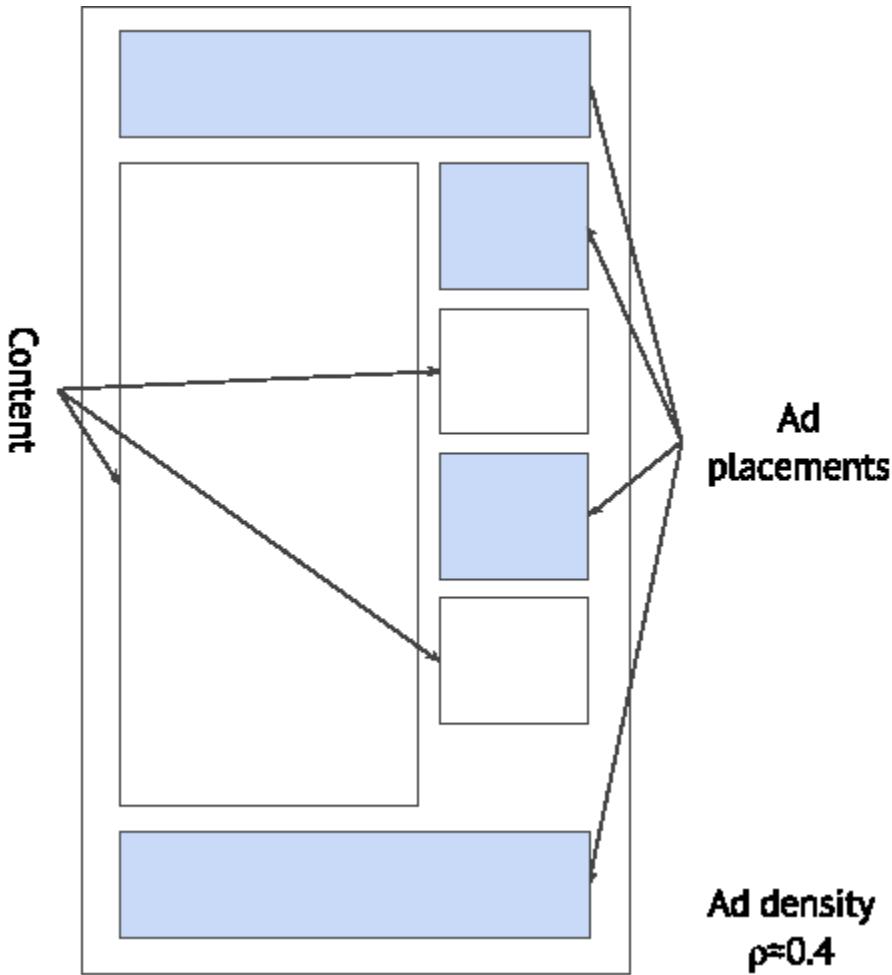
- Subscriber data access for marketing (VISA & MasterCard)
- User contributed data for marketing (Surveys)

Examples



Yield management tools in AppNexus

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

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Departments and policy
More on GOV.UK

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Includes car, road and cycling issues

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Includes pay, contracts and hiring

Working, jobs and pensions
Includes work, training and benefits

Money and tax
Includes debt and self assessment

Citizenship and living in the UK
Voting, community participation, life in the UK, international projects

Benefits
Includes credit, welfare, eligibility and appeals

Passports, travel and living abroad
Includes renewing passports and travel advice by country

Housing and local services
Planning, building regulations and care

Helping you access advice and getting more information

Businesses and self-employed
Tools and guidance for business

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Includes schools and admissions

Crime, justice and the law
Legal processes, crime and the justice system

Disability
Includes care, your rights, condition and mobility issues

Directgov 

Departments and policy

The websites of all government departments and many other agencies and public bodies are being merged into GOV.UK.

Here you can see all their policies, announcements, publications, statistics and consultations.

24 Ministerial departments

331 Other agencies and public bodies

47 Topics

223 Policies

How government works
Find out how the UK's public sector works, from the government's role in the economy through to its role in the community, and how it provides services to citizens and businesses.

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Find out how you can get involved with government directly, whether that's through your local authority or Parliament. You can also find out how you can help government to increase its accountability.

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Jobseeker's Allowance
Council Tax bands
Running a limited company
Driving theory test
Car tax discs
Get a car tax disc
VAT rates

High Income Child Benefit Charge
Do you earn more than £50,000 a year? If so, you may have to pay extra tax on the SSI payments you receive if you're a parent.
Find out more about High Income Child Benefit Charge

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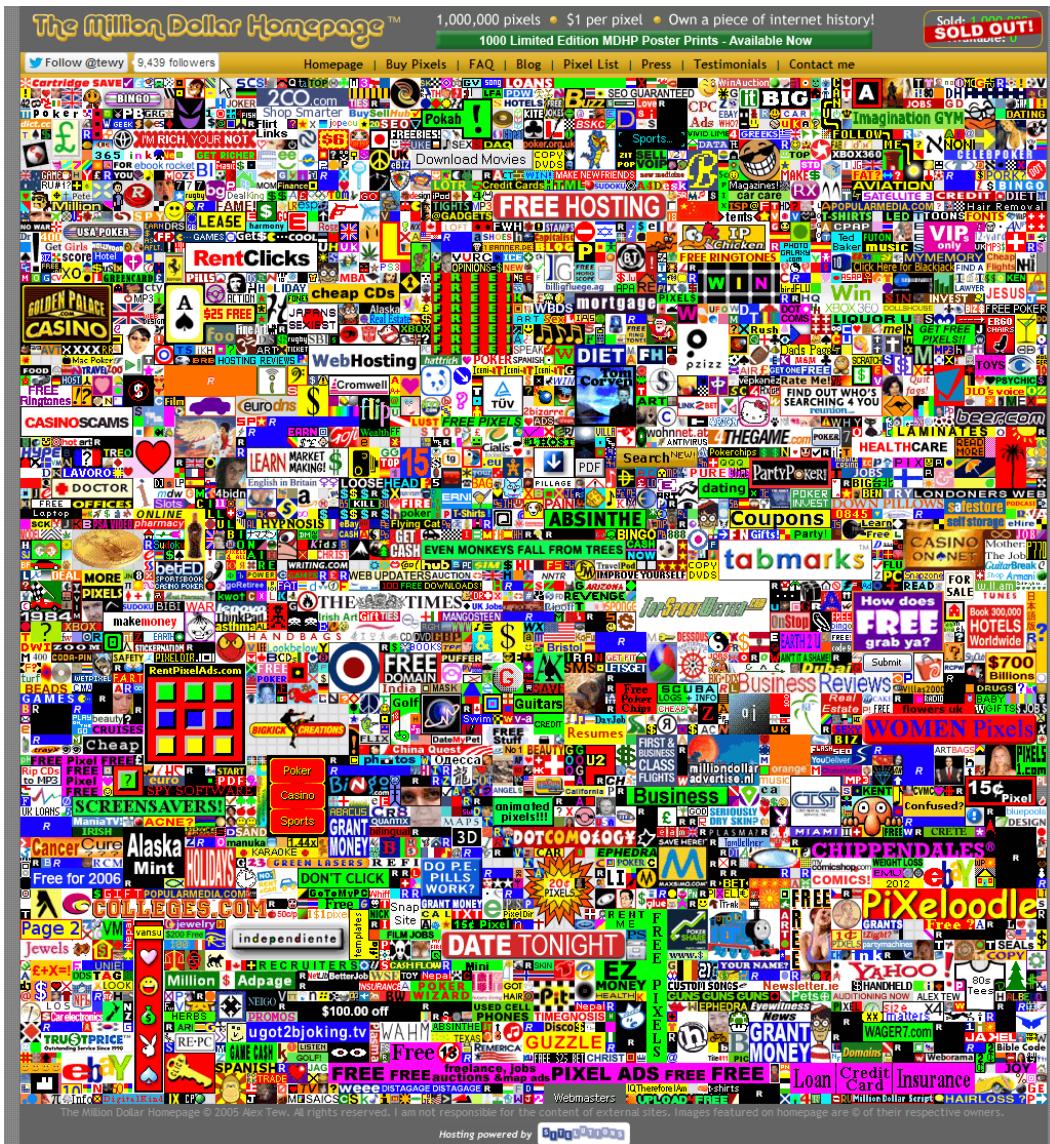
Support | Cookies | Facebook | Cymraeg | Built by the Government Digital Service

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

- Government
- Education
- Most of .org

All ads



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

Ad density: example

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What is another name for freezing point?

In: Chemistry, Temperature [[Edit categories](#)]

Answers
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A:

Another name for *freezing point* is *melting point* since the temperature at which a substance freezes is also the temperature at which it melts, going in the other direction.

Freezing point could also be referred to as *congelation point*.

[Improve Answer](#) [Discuss Question](#) [Follow](#)   

First answer by [Another Canadian](#). Last edit by [Another Canadian](#). Contributor trust: 37 [recommend contributor]. Question popularity: 1 [recommend question].

Can you answer these science of matter and energy questions?

-  How many atoms does a carbohydrate have?
-  What accounts for variable re absorption of water and re secretion of sodium potassium hydrogen and bicarbonate ions?
-  How many atoms are in one molecule of carbohydrate?
-  Can Substances Be Compounds And Elements?

Research your answer:

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Answers.com > Wiki Answers > Categories > Science > Chemistry > What is another name for freezing point?

What is another name for freezing point?
In: Chemistry, Temperature [[Edit categories](#)]

Answer:
Another name for freezing point is melting point since the temperature at which a substance freezes is also the temperature at which it melts, going in the other direction.

Freezing point could also be referred to as congelation point.

Ads

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boiler repair
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Did we answer your question? [Yes](#) [No](#) [Partially](#)

 Improve this Answer... 

First answer by [Another Canadian](#).  Answer History

Related Answers:
What is another name for the freezing point of a material?
Melting point because the freezing point is the same temperature as the melting point for the same m

What is another name for a freeze plug?
Expansion plug, or core plug.

What is another way of describing a freezing point change?
Apex - Melting point change. ^.^

What is another name for power point?
slide-a-slide show

What is another name for insertion point?
cursor

What is another name for pivot point?
The fulcrum.

Can you answer these?
What small area in the hypothalamus modifies your feelings of sleepiness by causing the pineal gland to increase or decrease production of melatonin?
In: Conditions and Diseases

What are the symbols for st Leo the great?
In: Saints

What do you enter in as your desired job title if you're not looking for anything specific?
In: Job Training and Career Qualifications

What are all the regions in Greenland?
In: Greenland

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• Member Since: 11/09

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• Member Since: 4/10

William Howe
• Trust Points: 3212
• Member Since: 10/10

Top Contributors This Week

The Periodic Table of Elements

Daniel Bruhl Talks Chemistry on the Set of 'Rush'

A Pregnant Kate Winslet Talks "Wonderful" Chemistry With Josh Brodin at Labor Day

Meyer Dishes on 'The Host' Cast's Hot Chemistry

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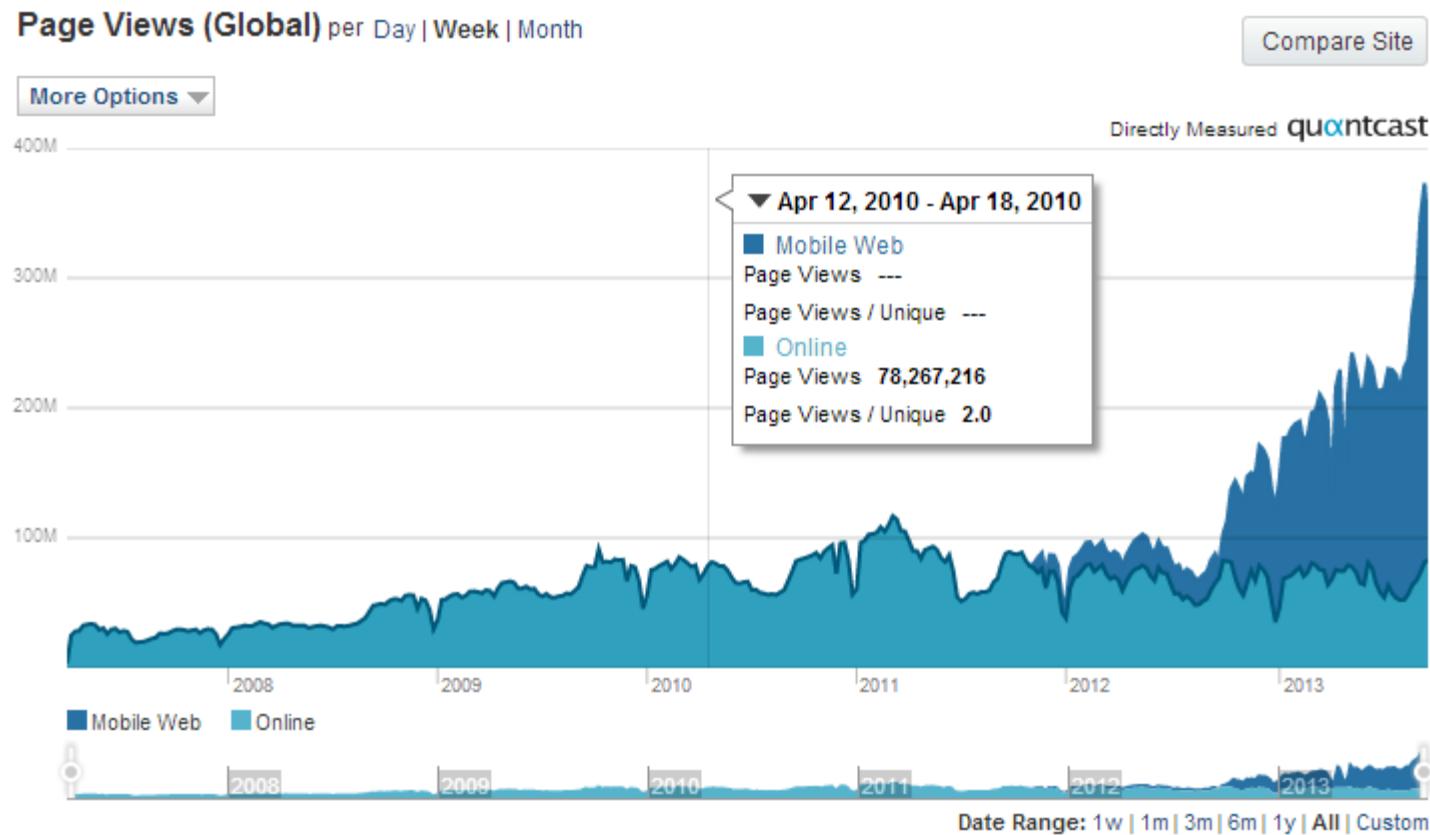
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Ad density: example



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

Models and solutions

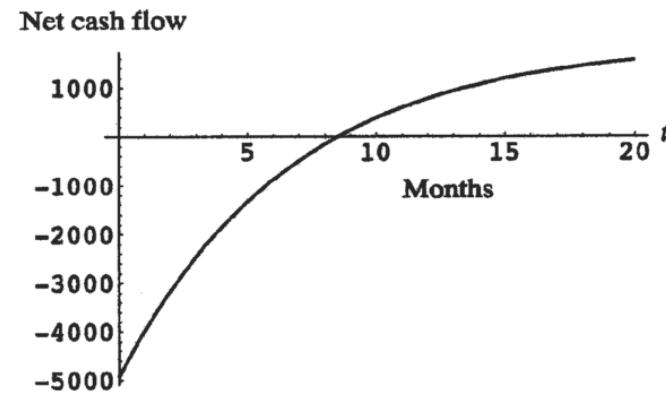
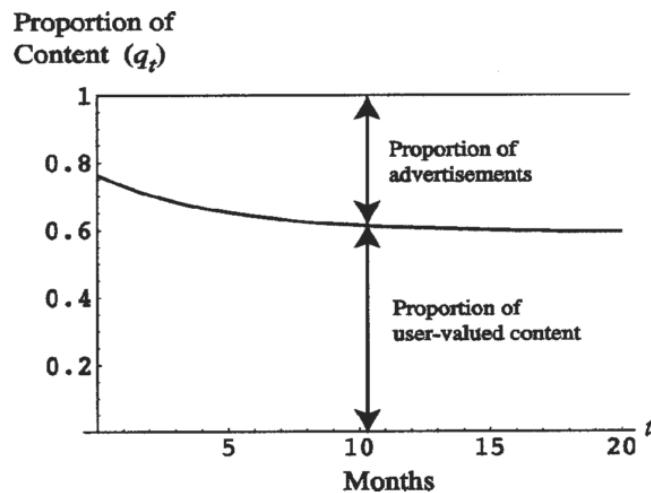
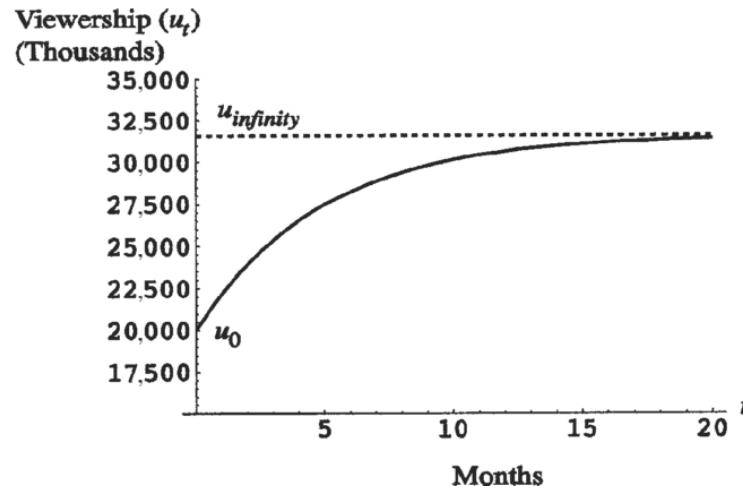
- Assume the following
 - Unit payoff (CPM) c
 - Ad density ρ
 - Impressions x
 - Content cost k
- The cumulative revenue

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

- The state transition function

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

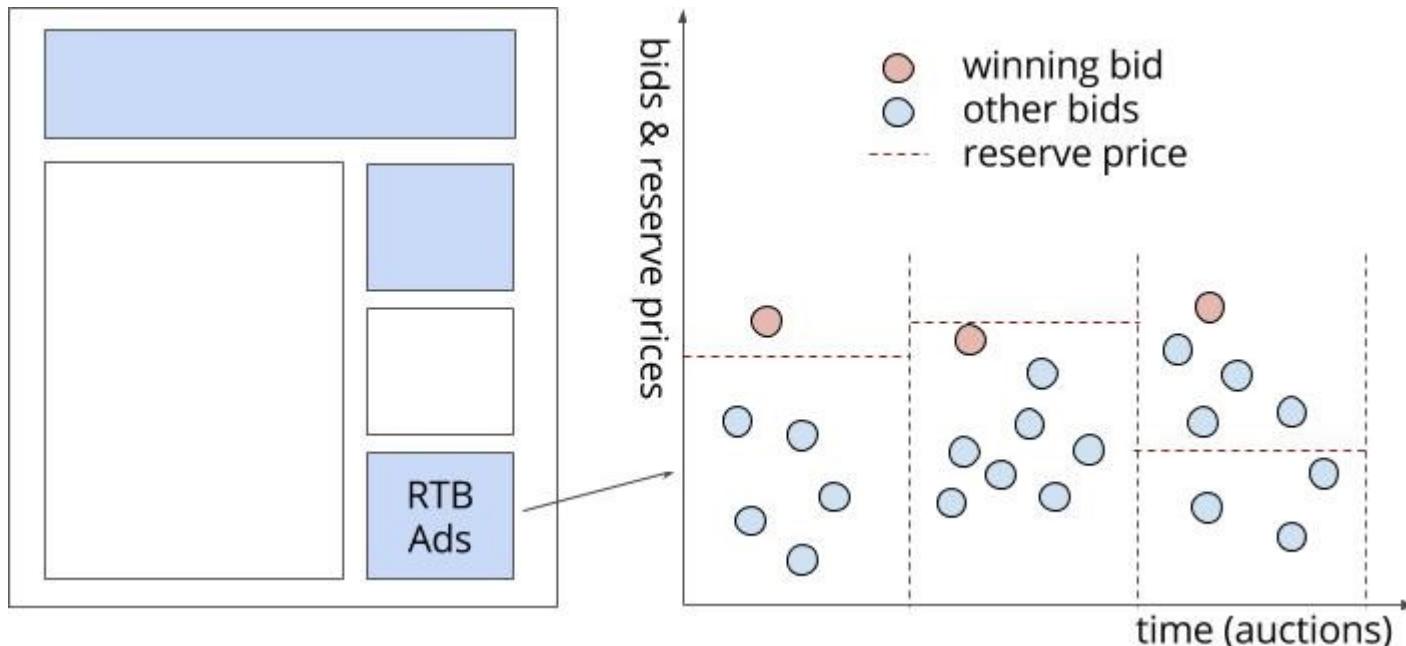
A monopoly case



Reference

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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
- An economic analysis of ad-supported software, BJ Jiang, 2007
- 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:

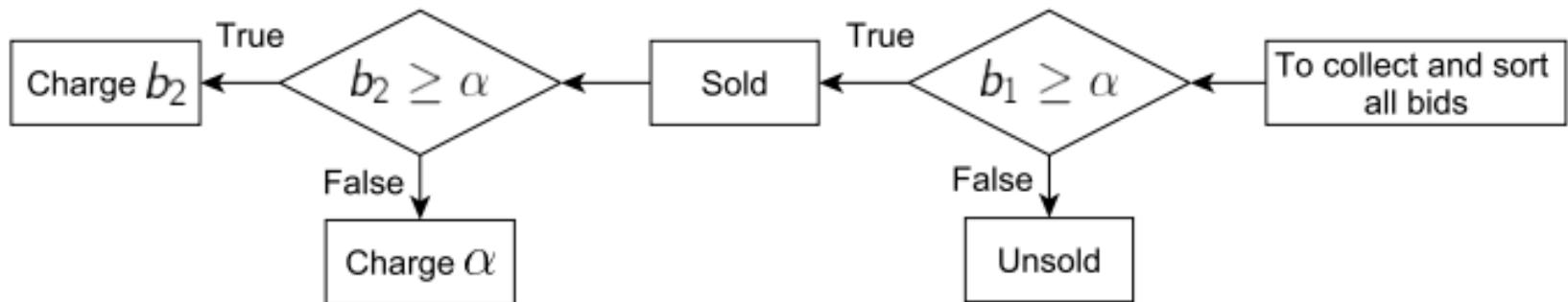
- To find the optimal reserve prices

The challenge:

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

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 $a = 0.6$:

$$r = E[\min(b_1, b_2) | b_1 > 0.6, b_2 > 0.6] + \frac{(0.6 \times 0.4) \times 2 \times 0.6}{}$$



Paying the second highest price Paying the reserve price

The optimal auction theory

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

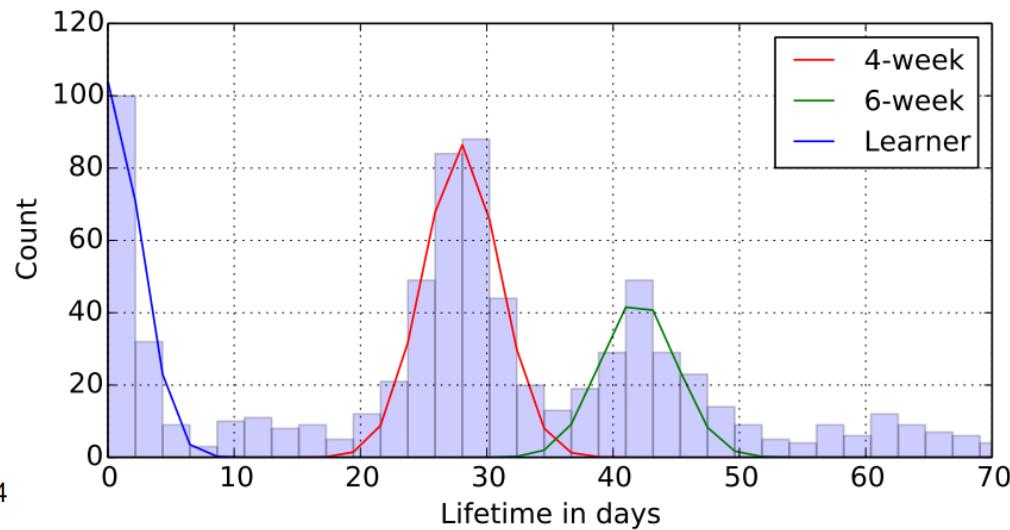
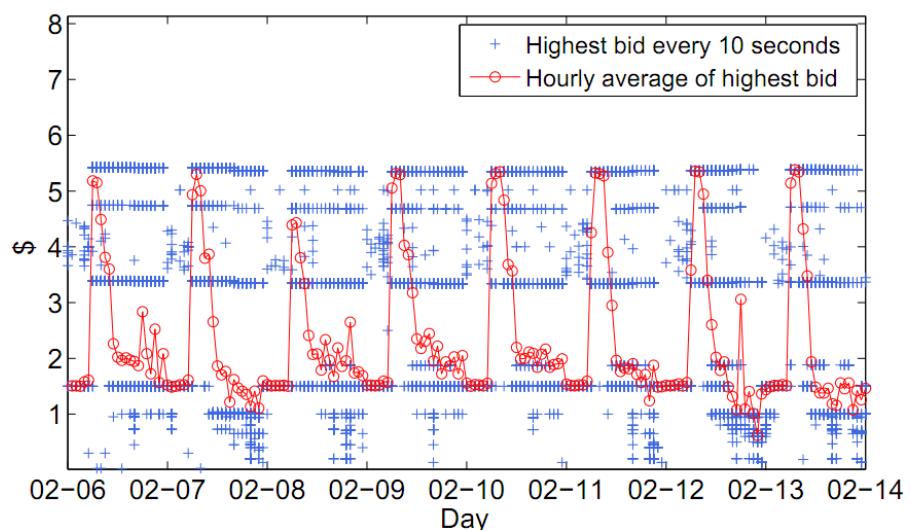
$$\alpha - \frac{1 - F(\mathbf{b})}{F'(\mathbf{b})} - V_p = 0$$

Questions:

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

Bidding could be irrational

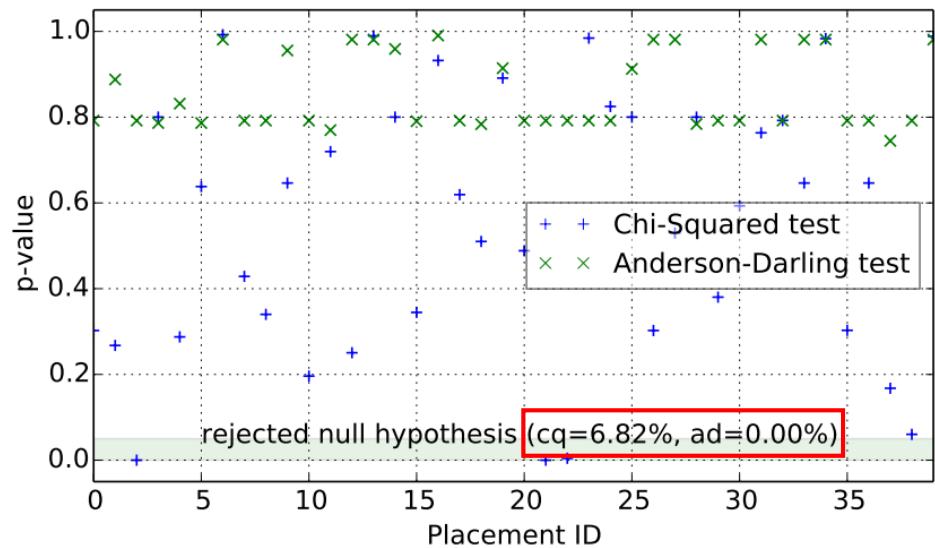
- They usually use a private regression model (No access to publishers)
- Perhaps they don't even know it! (Just try to maximise the ROI)



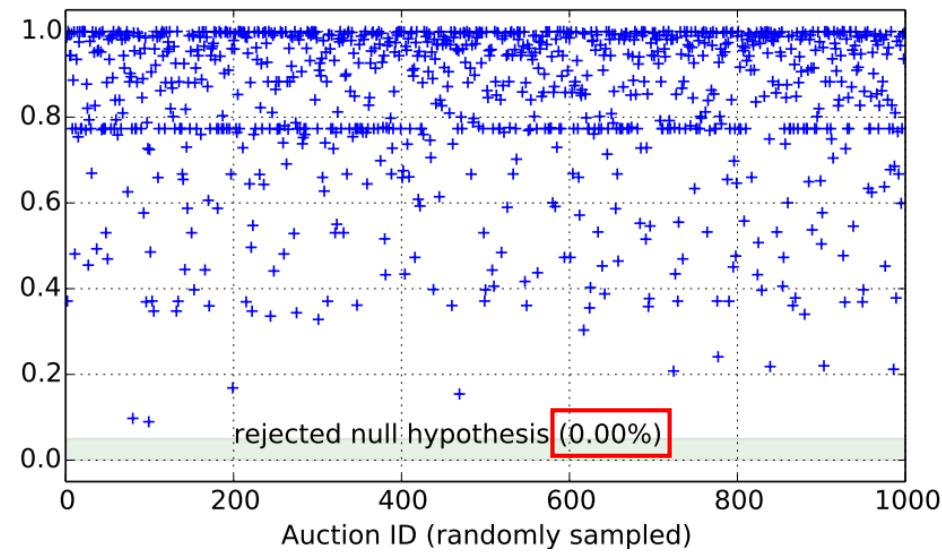
Many advertisers bid at fixed values
(Think about a decision tree)

And they come and go
(with different lifetime span)

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

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 \geq 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

Our solution

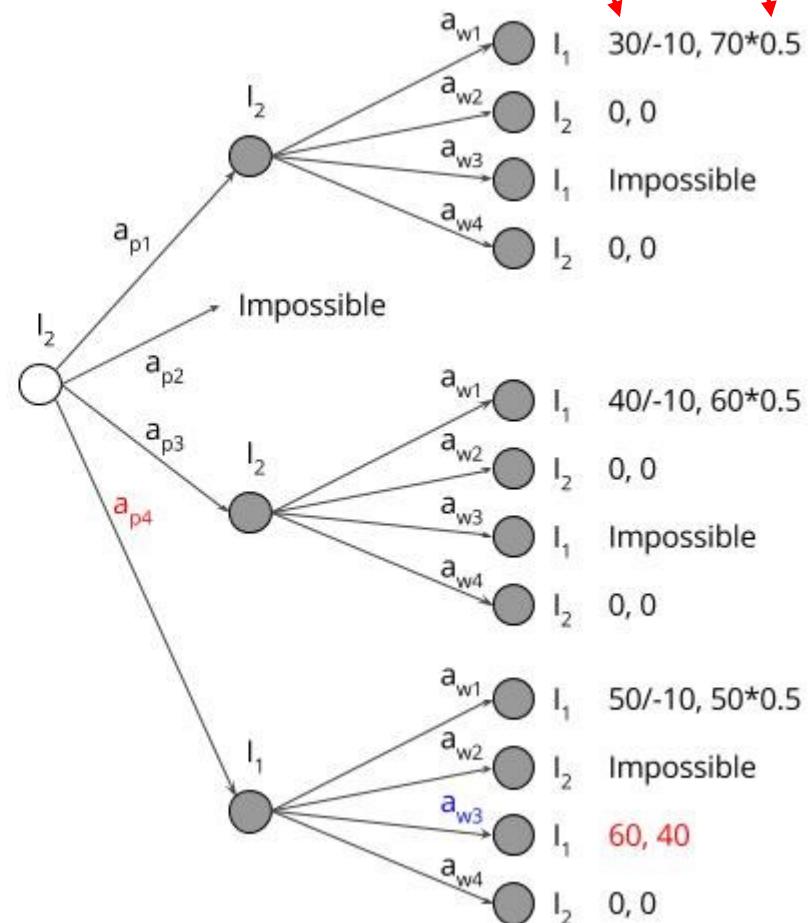
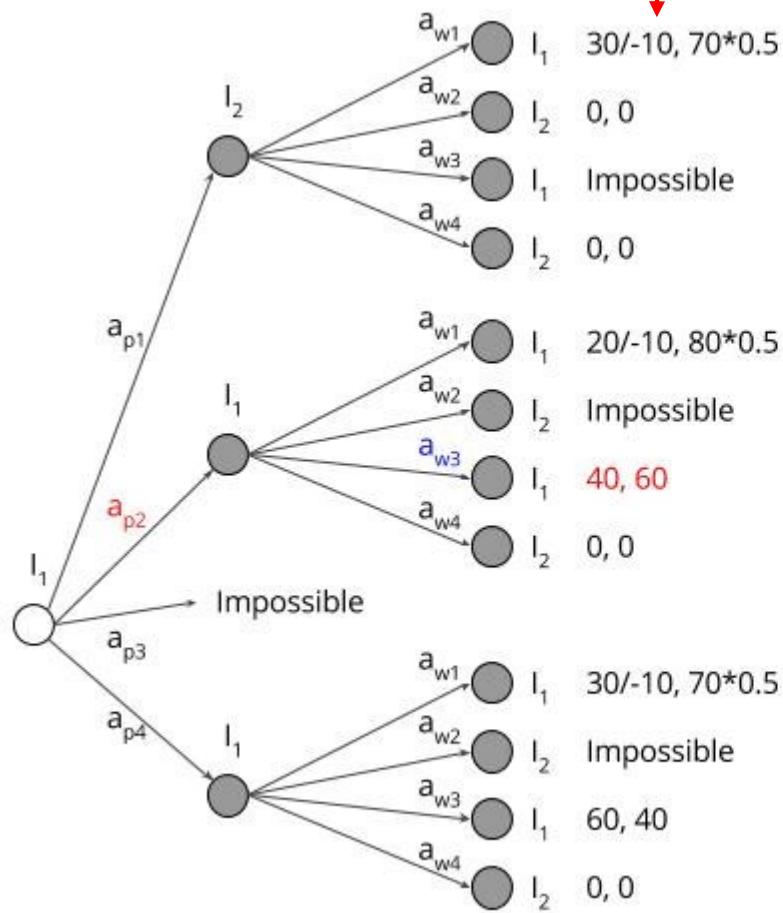
- A dynamic and one-shot game between the winner (w) and the publisher (p)
- Extension form representation
 - Information nodes:
 - I_1 : Auction succeeded: the winning bid b_1 is higher
 - I_2 : Auction failed: the reserve price α is higher
 - Actions:
 - a_{w1} : to increase b_1 so that $b_1 \geq \alpha$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

1) Expected payoff of advertiser, publisher

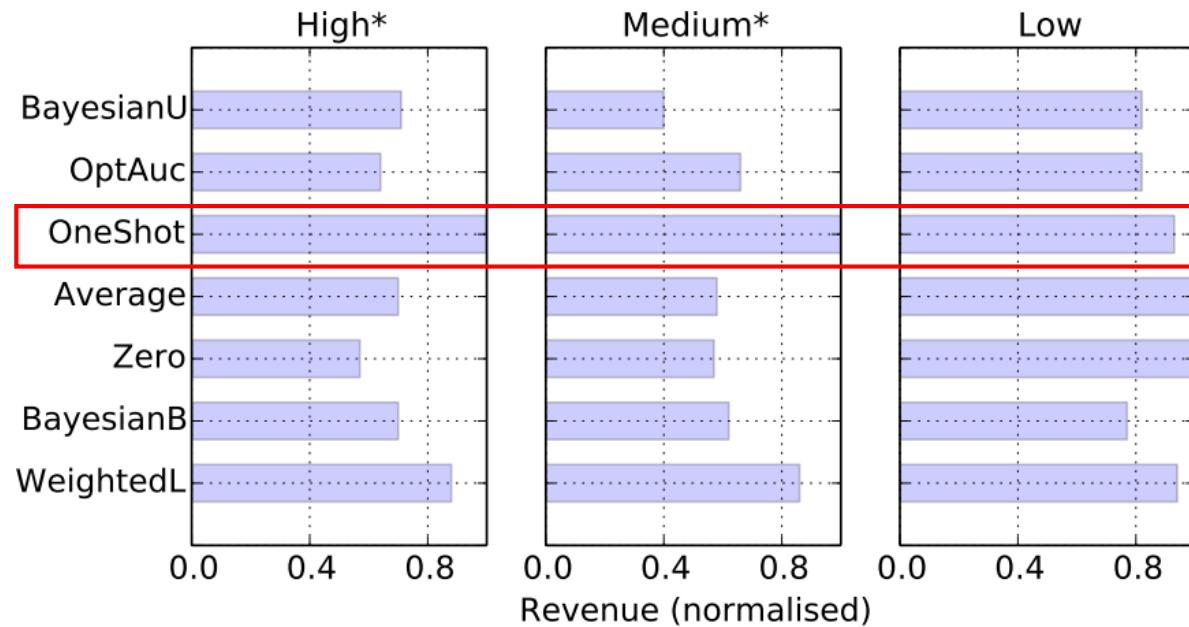
2) Payoff for the advertiser could be negative if one

has been bidding the max price
 $(a_{w1}$: to increase b_1 so that $b_1 \geq \alpha$)

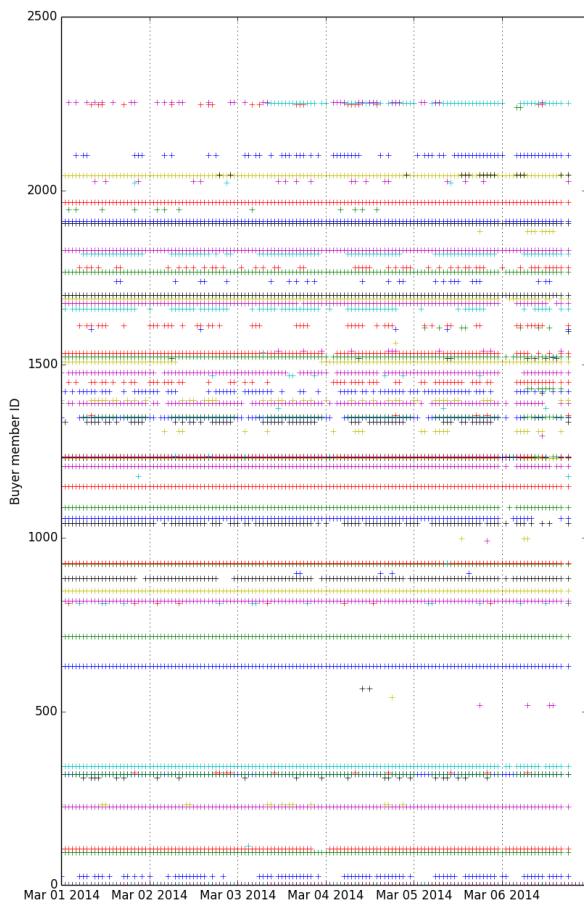
3) One won't do that,
 so discounted publisher's payoff



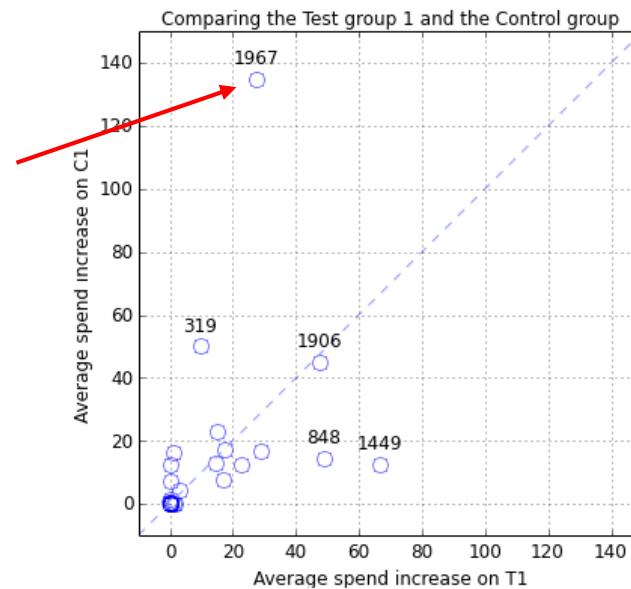
Findings



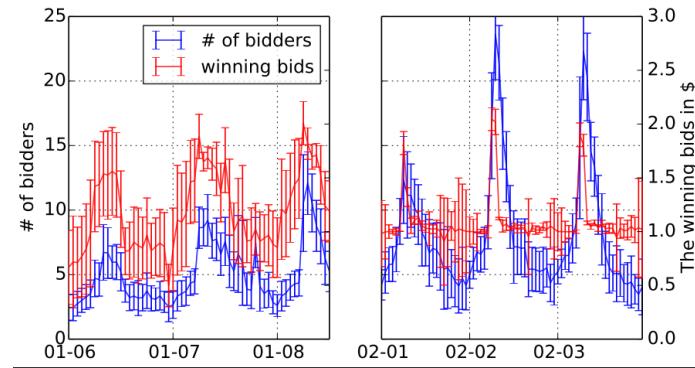
12.3% better than the second best
28.5% better than the optimal auction theory



An outlier
(Triggered by some random action)



The unchanged budget allocation



The unchanged bidding pattern

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- Optimal reservation prices in auctions, Levin and Smith, 1996
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- Auction theory 2nd edition, Krishna, 2009
- Optimal reserve price for the generalized second-price auction in sponsored search advertising, Xiao et al., 2009
- Optimal auction design and equilibrium selection in sponsored search auctions, Edelman and Schwarz, 2010
- Optimal auction design in two-sided markets, R Gomes, 2011

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 $Q = \sum_i (e_{ii} - a_i^2)$

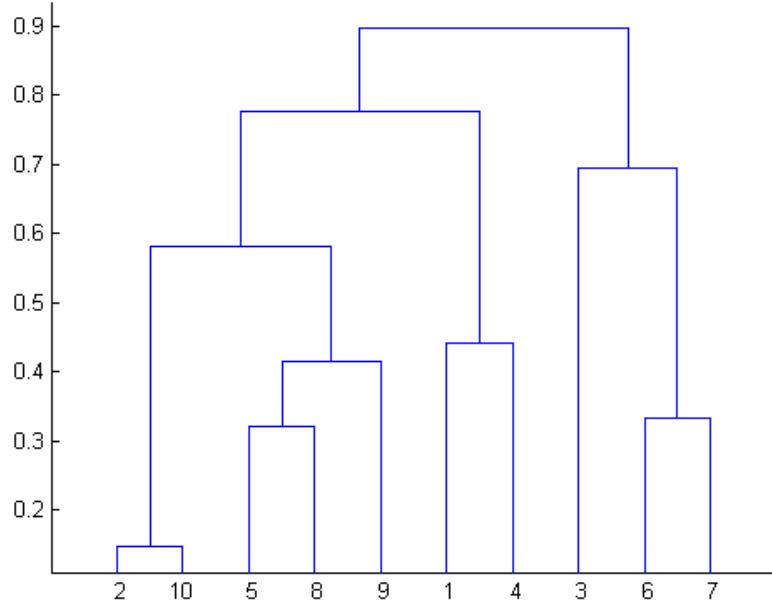
Goal: maximize Q

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

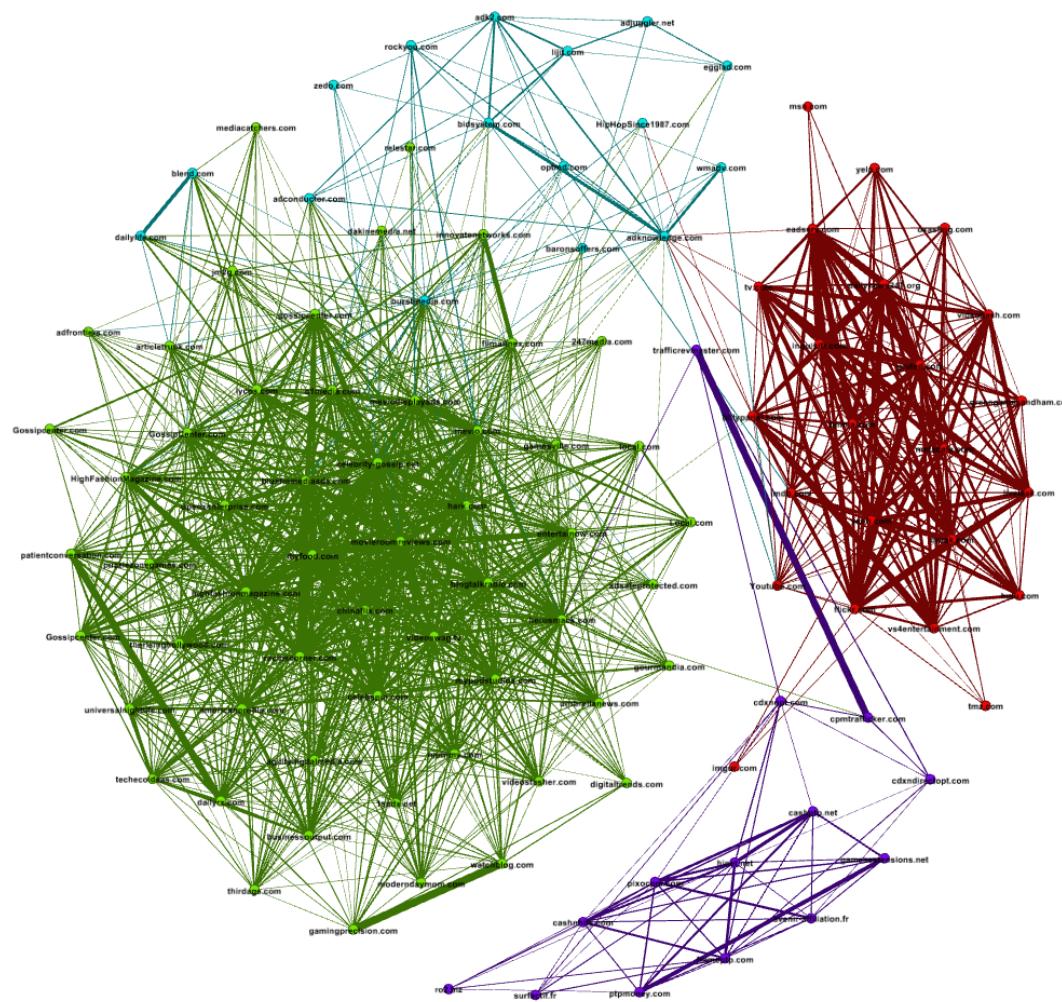
"Fast algorithm for detecting community structure in networks" by M. E. J. Newman

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 dendrogram



Example #2: A beautiful picture



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

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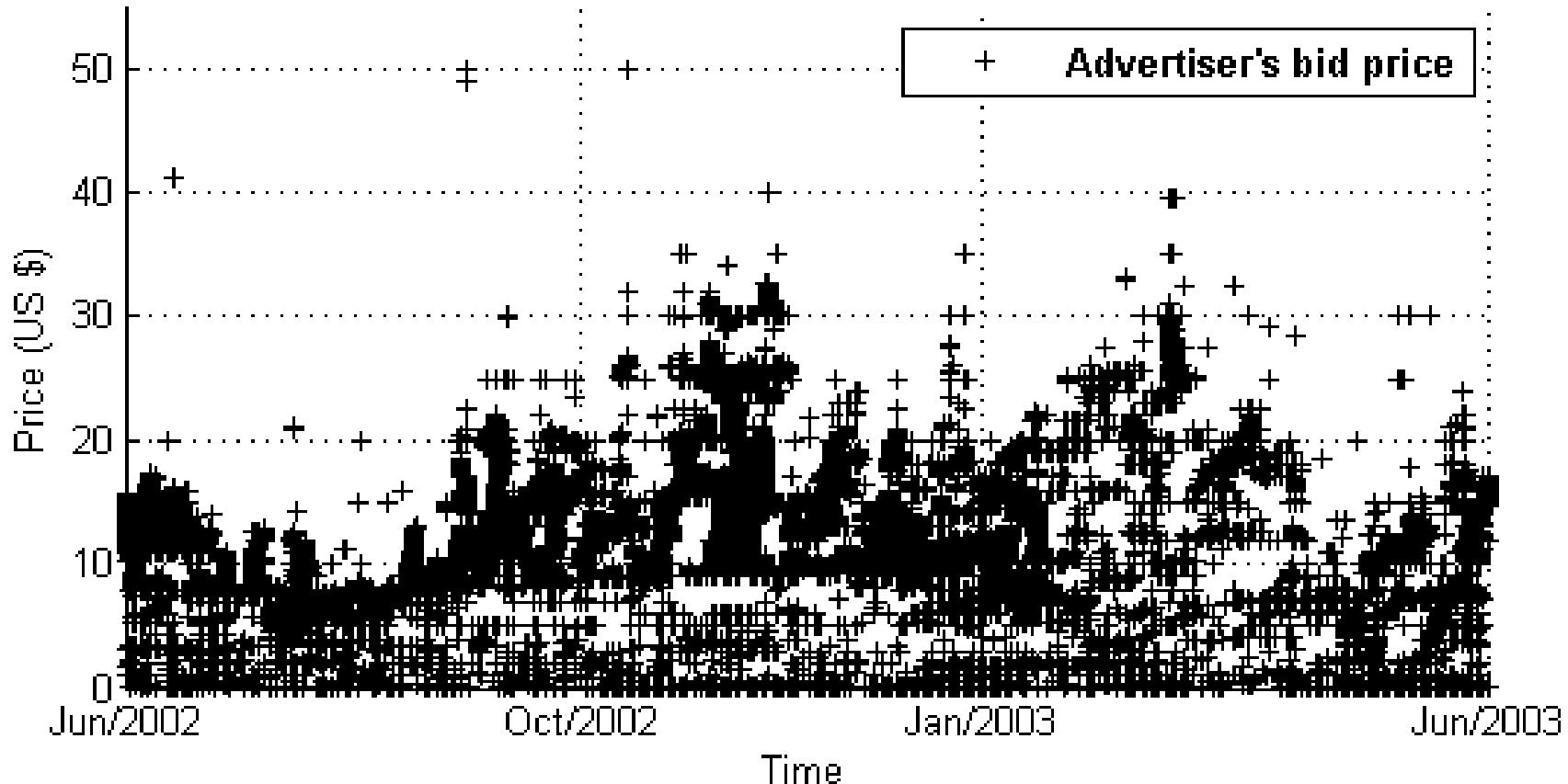
4. Programmatic Guaranteed and Ad Options

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

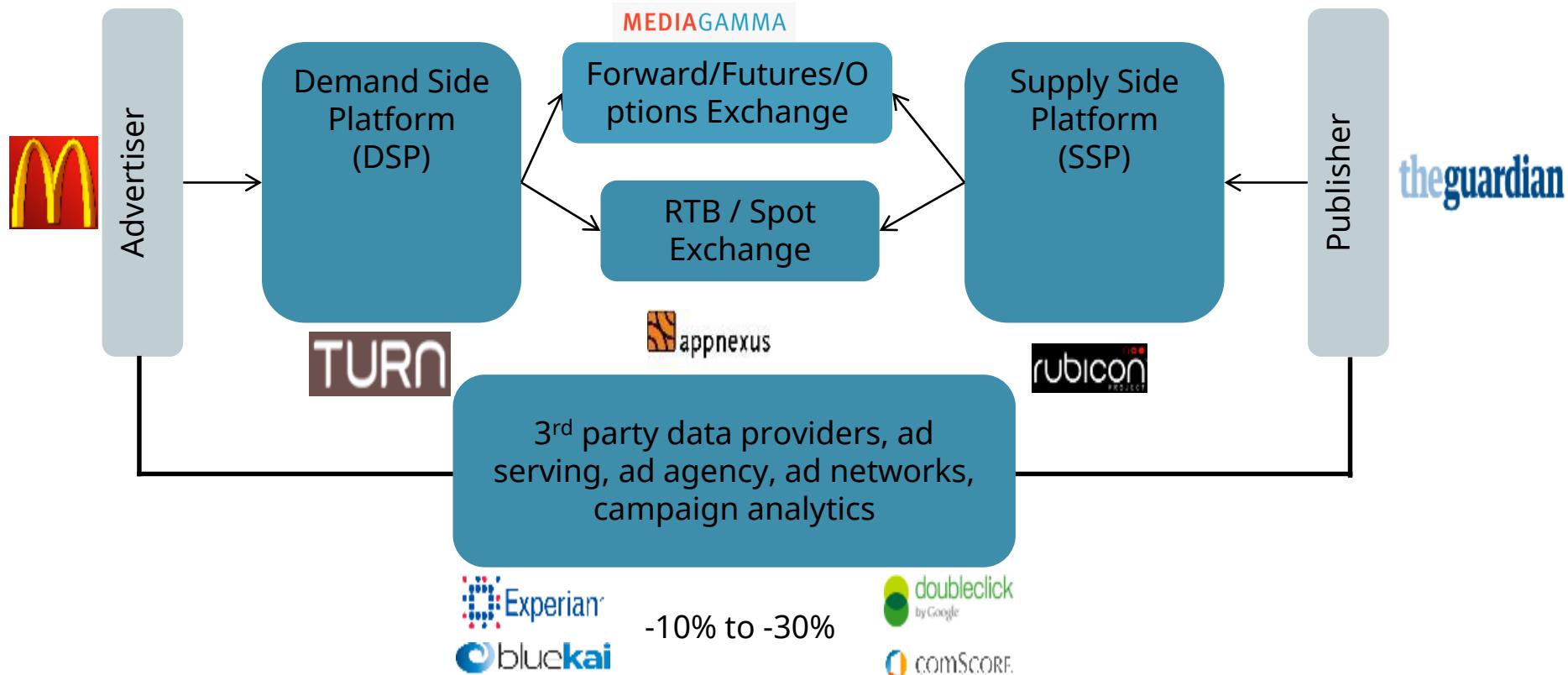


The price movement of a display opportunity from Yahoo! ads data
Under GSP (generalized second price auction)

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

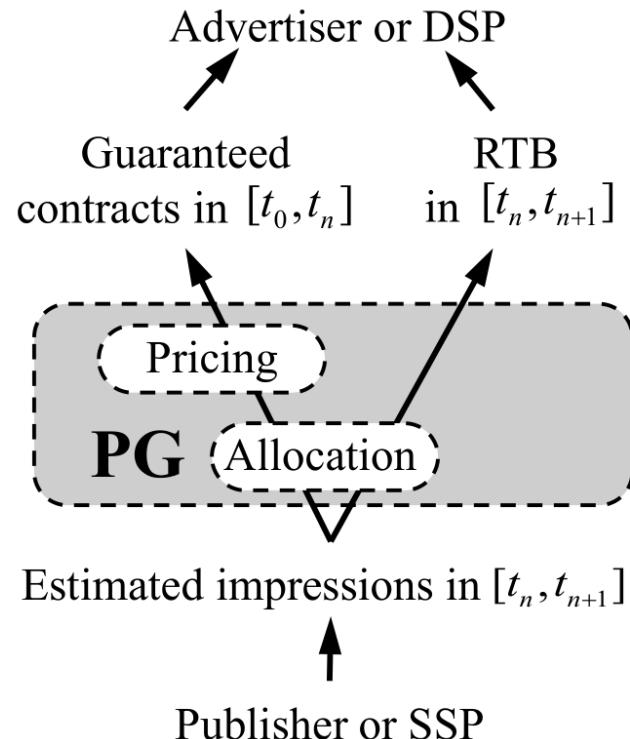


Figure 1: A systematic view of programmatic guarantee (PG) in display advertising: $[t_0, t_n]$ is the time period to sell the guaranteed impressions that will be created in future period $[t_n, t_{n+1}]$.

Optimization objective

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

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

where

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

Optimised pricing scheme

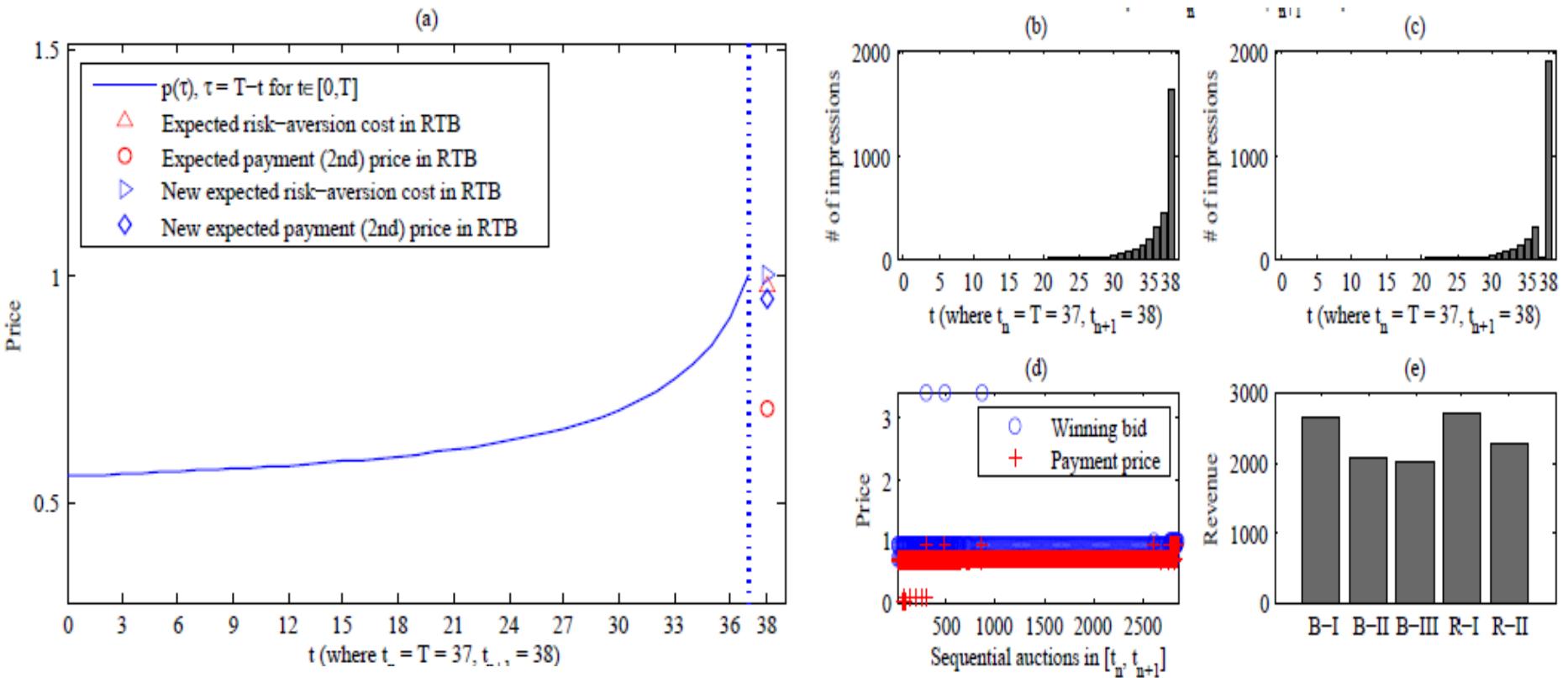


Figure 9: An empirical example of AdSlot14: (a) the optimal dynamic guaranteed prices; (b) the estimated daily demand; (c) the daily demand calculated based on the actual bids in RTB on the delivery date; (d) the winning bids and payment price in RTB on the delivery date; (e) the comparison of revenues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

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**.

Ad options: Benefits

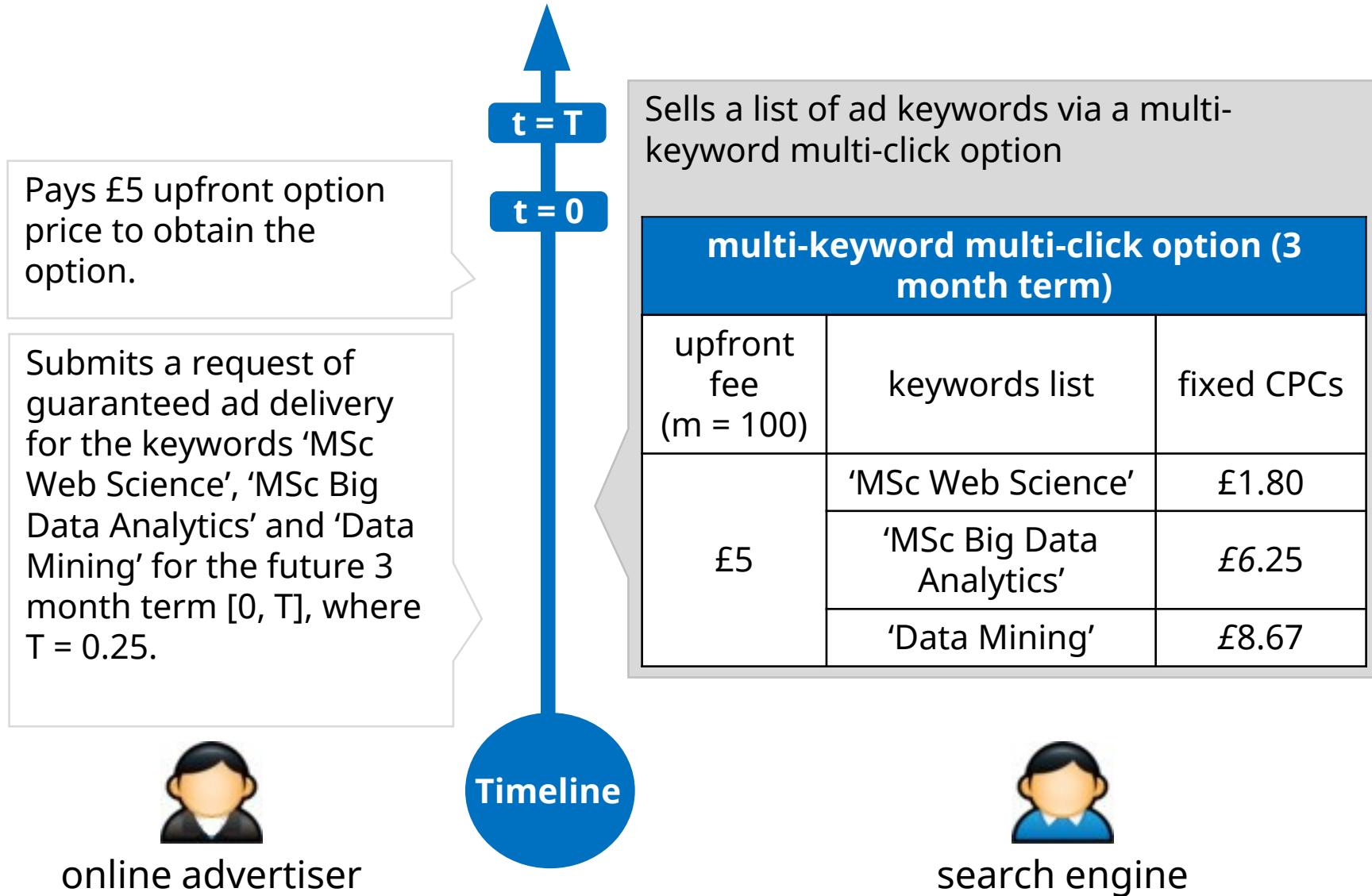
Advertisers

- secure impressions delivery
- reduce uncertainty in auctions
- cap cost

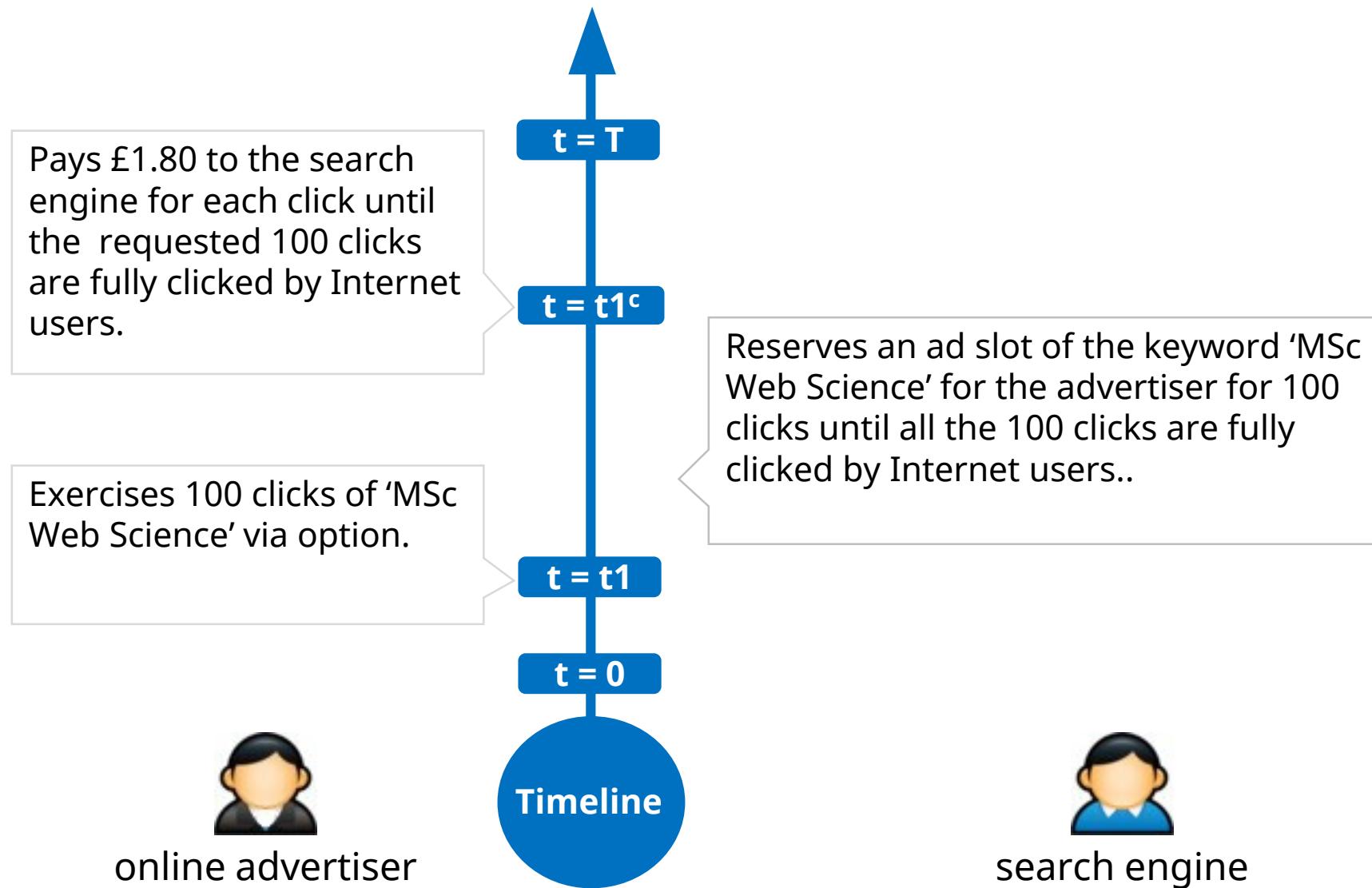
Publishers

- sell the inventory in advance
 - have a more stable and predictable revenue over a long-term period
 - increase advertisers' loyalty
-

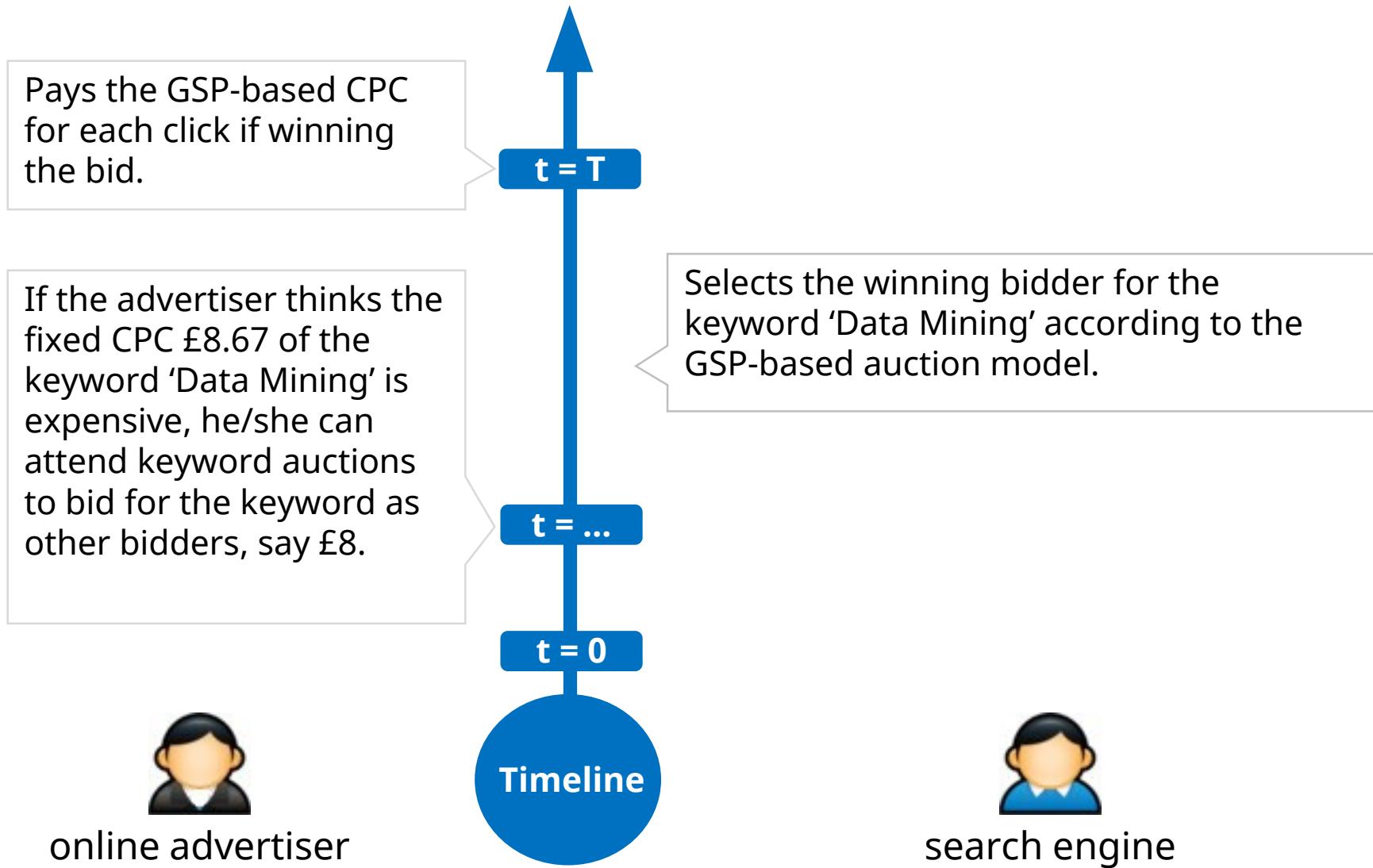
Ad options contd.



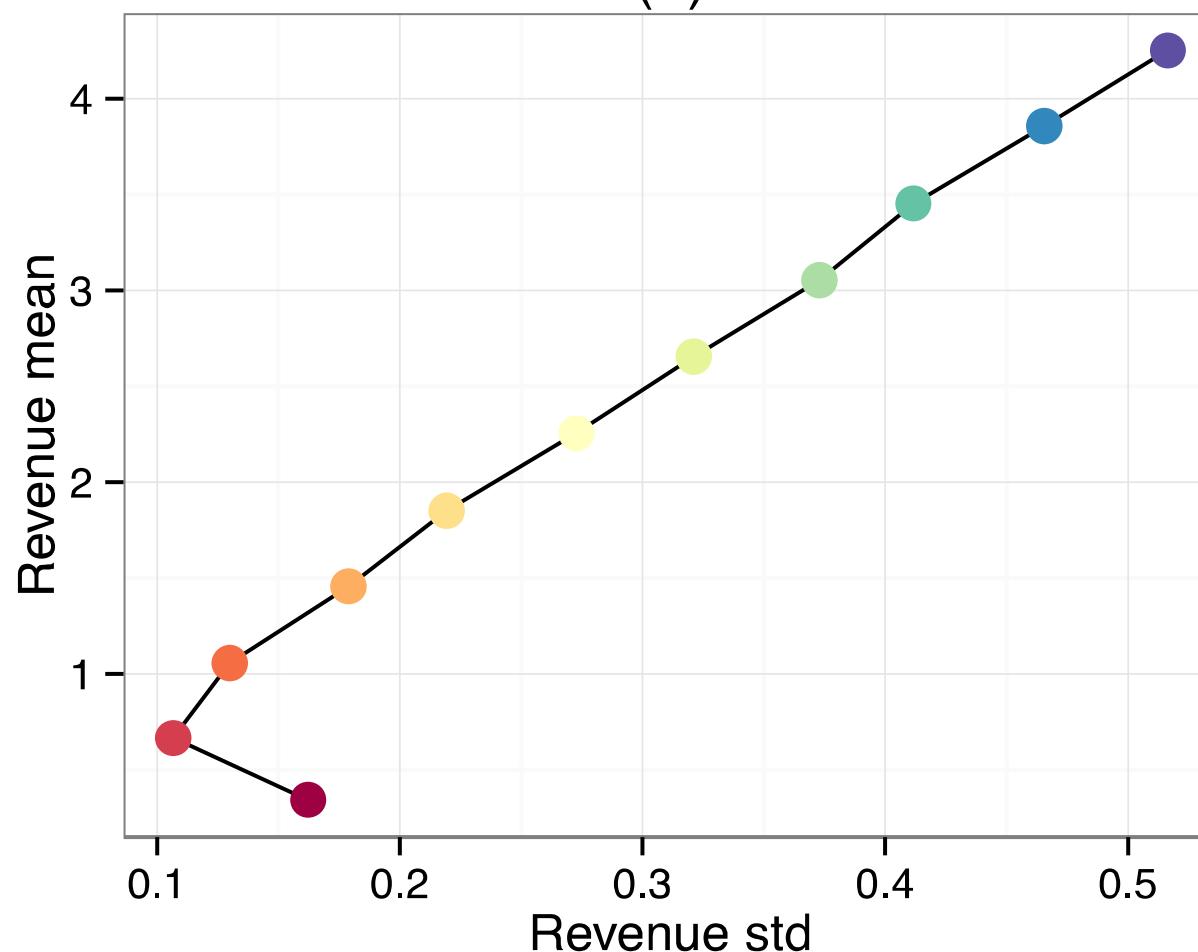
Exercising the option

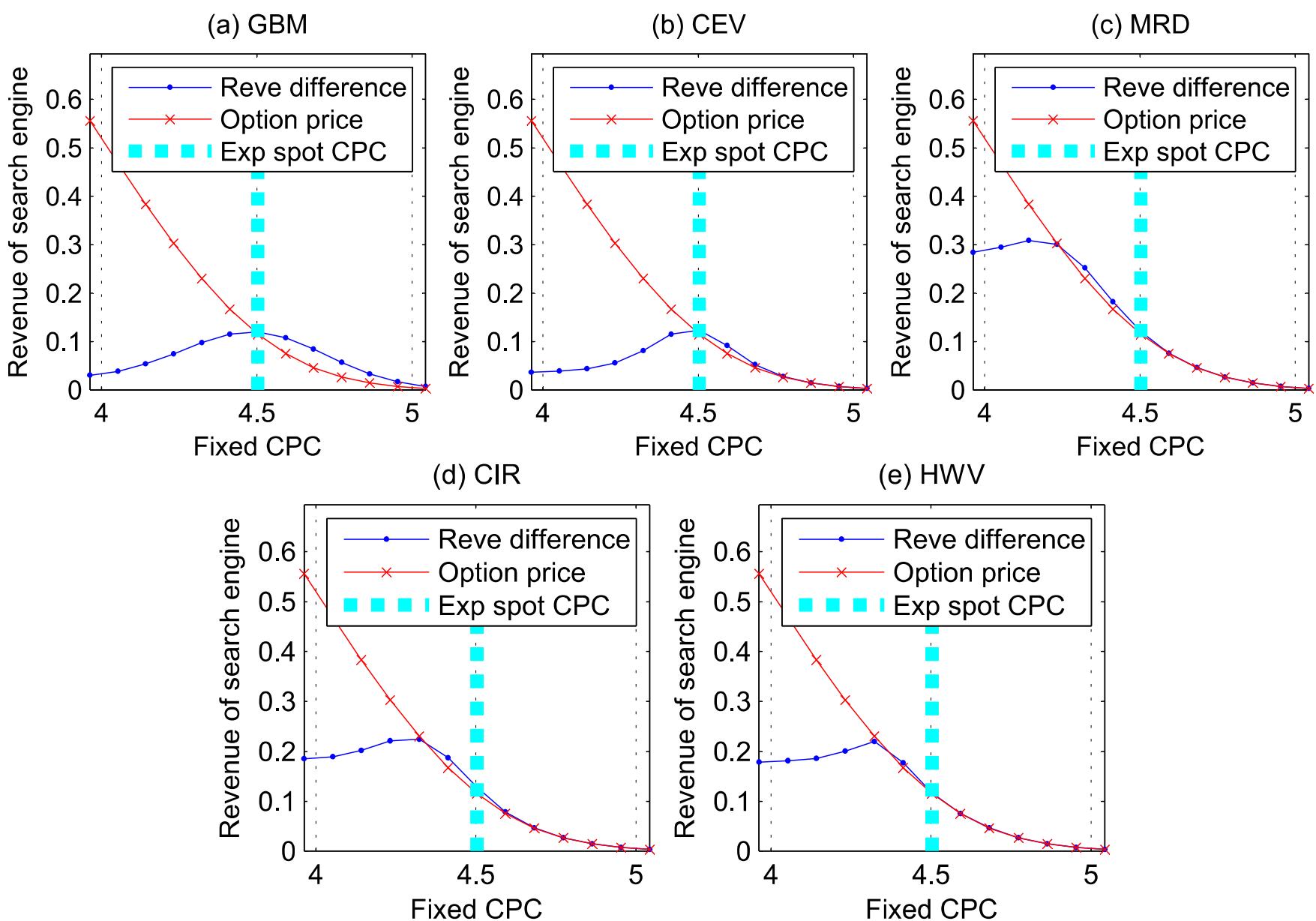


Not exercising the option



Risk Hedge when Ad Options and RTB spot are combined





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

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- Internet advertising and the generalized second price auction: selling billions of dollars worth of keywords, B Edelman, 2005
- Price cycles in online advertising auctions, X Zhang and J Feng, 2005
- Budget optimization in search-based advertising auctions, J Feldman et al., 2007
- The economics of the online advertising industry, DS Evans, 2008
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- Algorithmic methods for sponsored search advertising, J Feldman and S Muthukrishnan, 2008
- Internet ad auctions: Insights and directions, S Muthukrishnan, 2008
- The online advertising industry: economics, evolution, and privacy, , DS Evans, 2009
- Ad exchanges: Research issues, S Muthukrishnan, 2009
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- Computational advertising in social networks, A Bhavin, 2012
- Size, labels, and privacy in targeted display advertising, C Perlich, 2012
- Estimating conversion rate in display advertising from past performance 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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- 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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-----Break (20min)-----

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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