ECIR16 Tutorial

Real-Time Bidding based Display Advertising: Mechanisms and Algorithms

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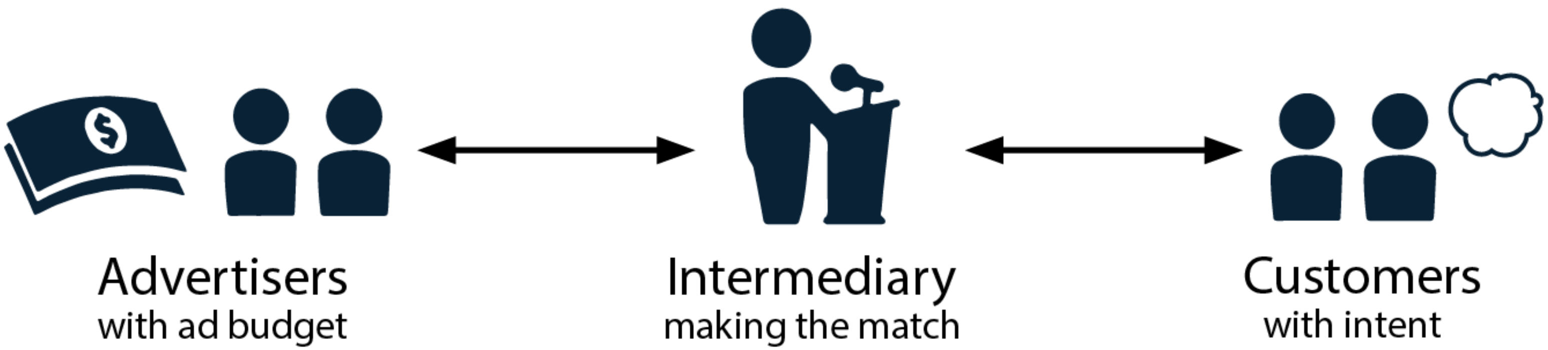
- Auction mechanisms
- User response estimation
- Conversion attribution
- Learning to bid
- Data Management Platform (DMP) techniques
- Floor price optimisation
- Fighting against fraud

Advertising



- Make the best match between advertisers and customers with economic constraints

"Half the money I spend on advertising is wasted; the trouble is I don't know which half."

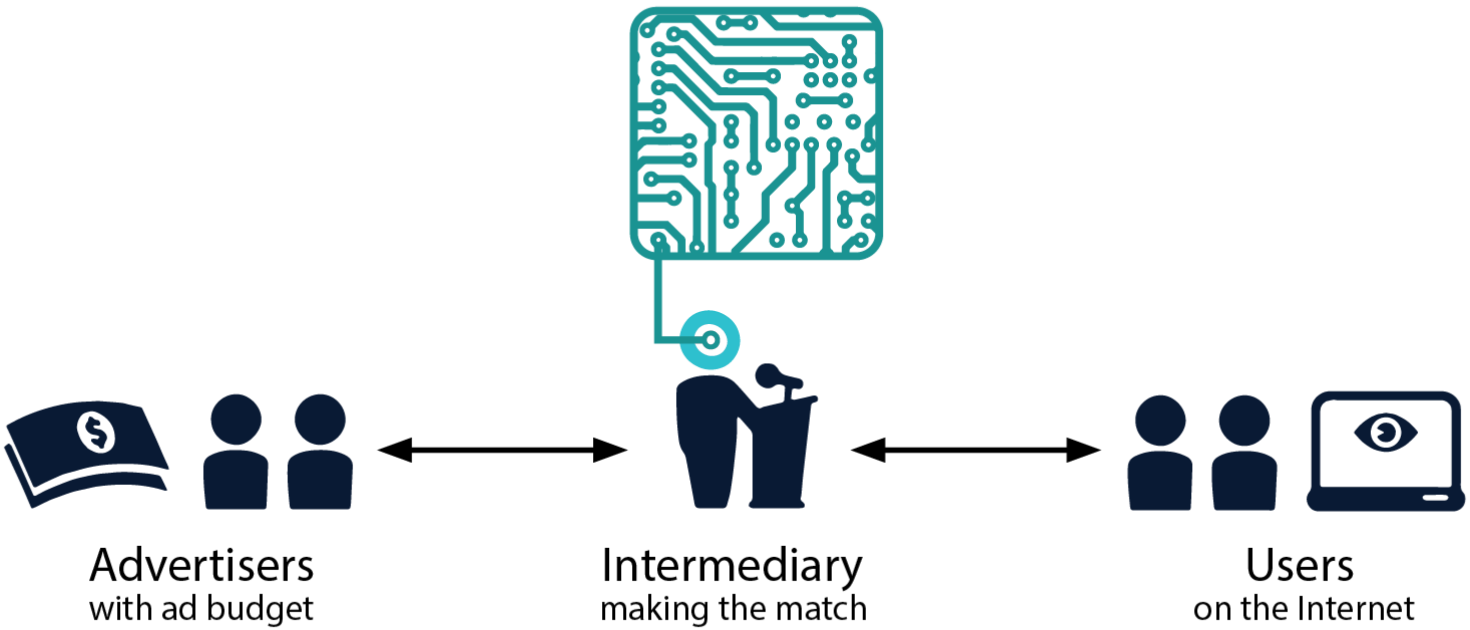
- *John Wanamaker*

(1838-1922)

Father of modern advertising and a pioneer in marketing

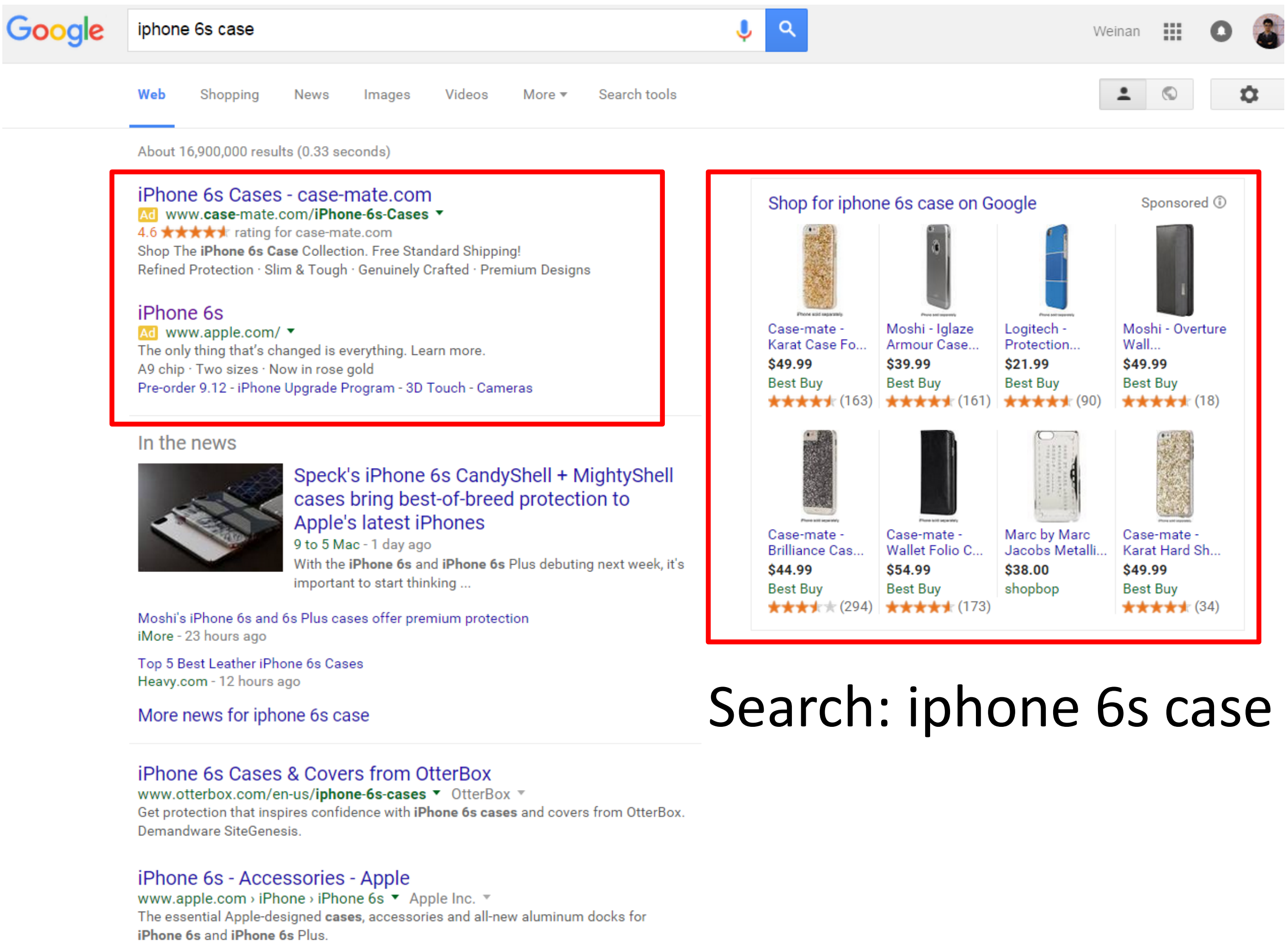
Wasteful Traditional Advertising

Computational Advertising



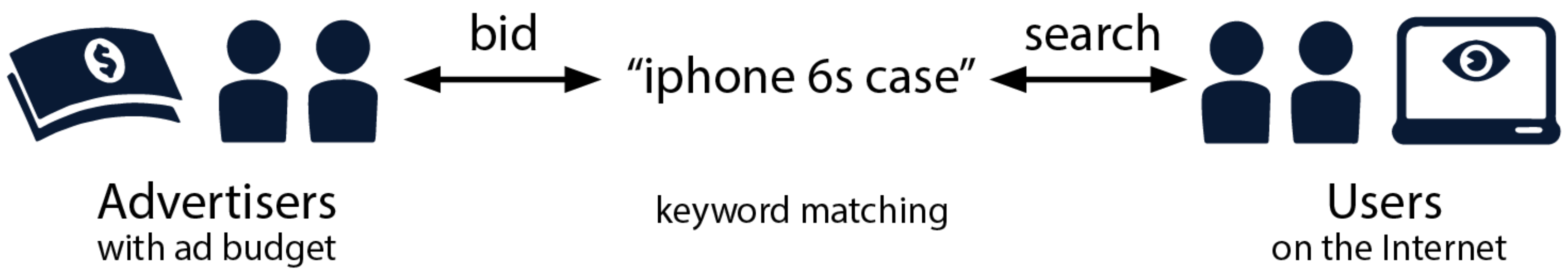
- Design **algorithms** to make the best match between the advertisers and Internet users with economic constraints

Sponsored Search



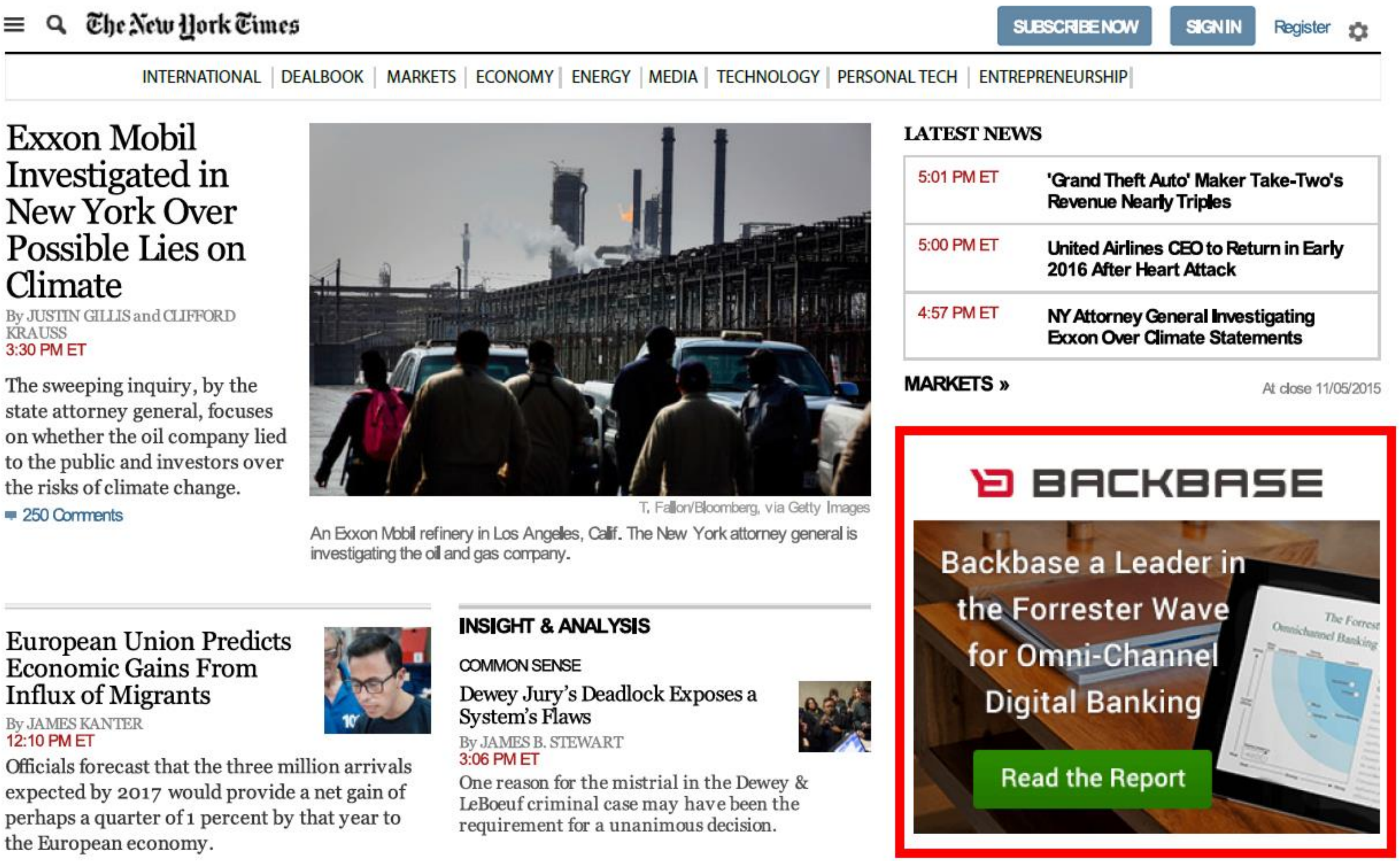
Search: iphone 6s case

Sponsored Search



- Advertiser sets a bid price for the keyword
- User searches the keyword
- Search engine hosts the auction to ranking the ads

Display Advertising



http://www.nytimes.com/

Internet Advertising Frontier:

Real-Time Bidding (RTB) based Display Advertising

What is Real-Time Bidding?

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

	DSP/Exchange	daily traffic
Advertising	iPinYou, China	18 billion impressions
	YOYI, China	5 billion impressions
	Fikisu, US	32 billon impressions
Finance	New York Stock Exchange	12 billion shares daily
	Shanghai Stock Exchange	14 billion shares daily

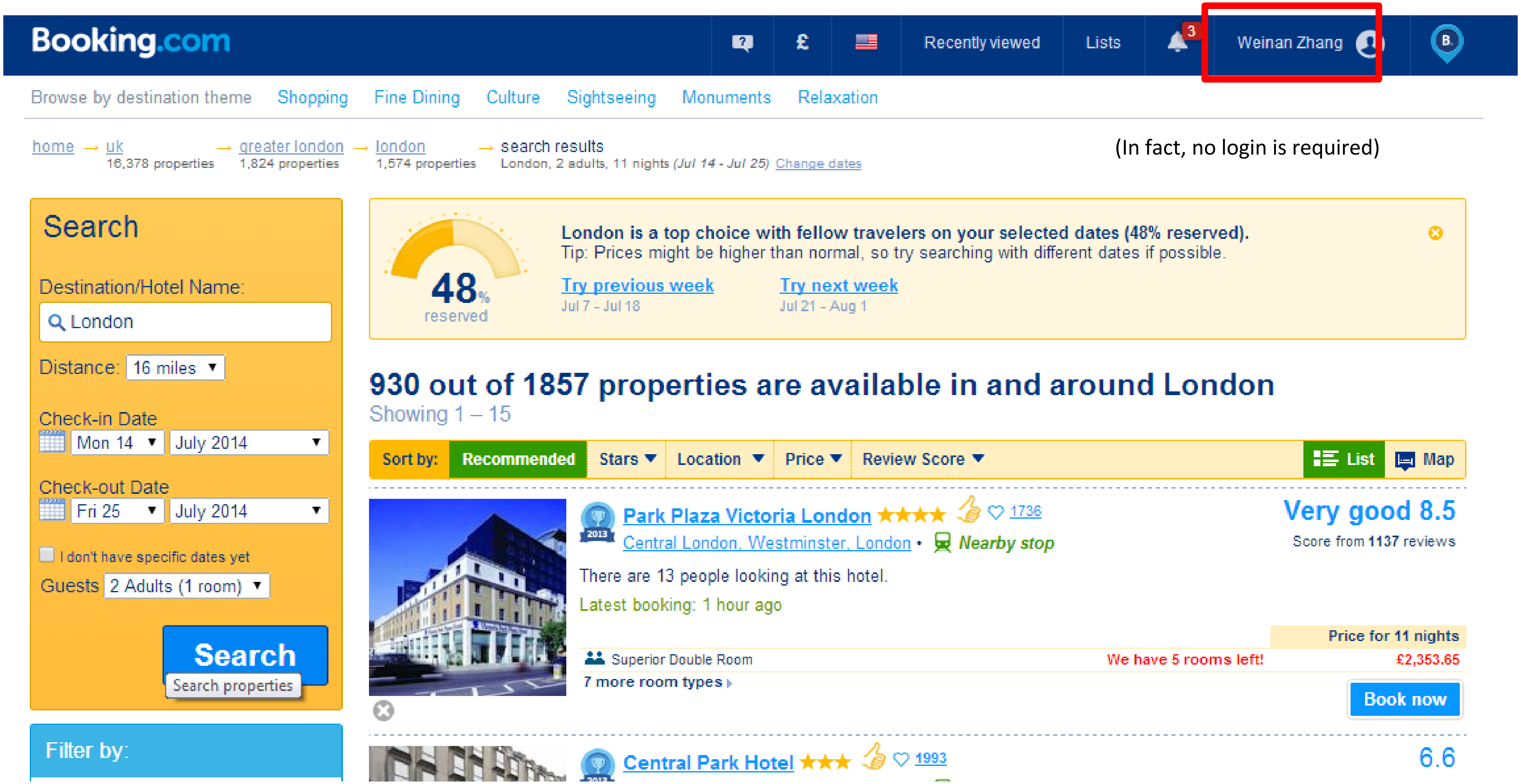
	Query per second
Turn DSP	1.6 million
Google	40,000 search

Shen, Jianqiang, et al. "From 0.5 Million to 2.5 Million: Efficiently Scaling up Real-Time Bidding." Data Mining (ICDM), 2015 IEEE International Conference on. IEEE, 2015.

Suppose a student regularly reads articles on emarketer.com

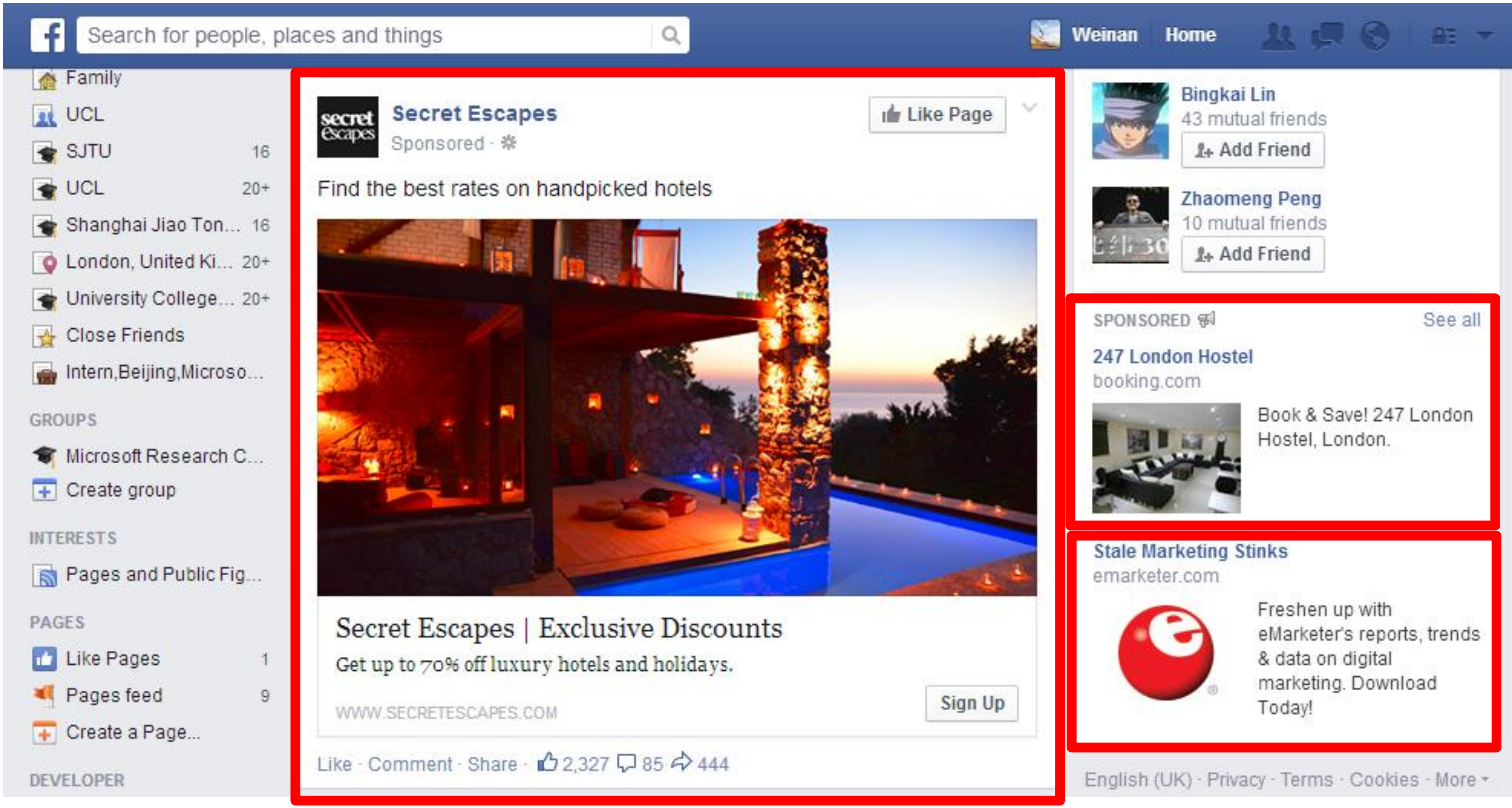
Content-related ads

He recently checked the London hotels

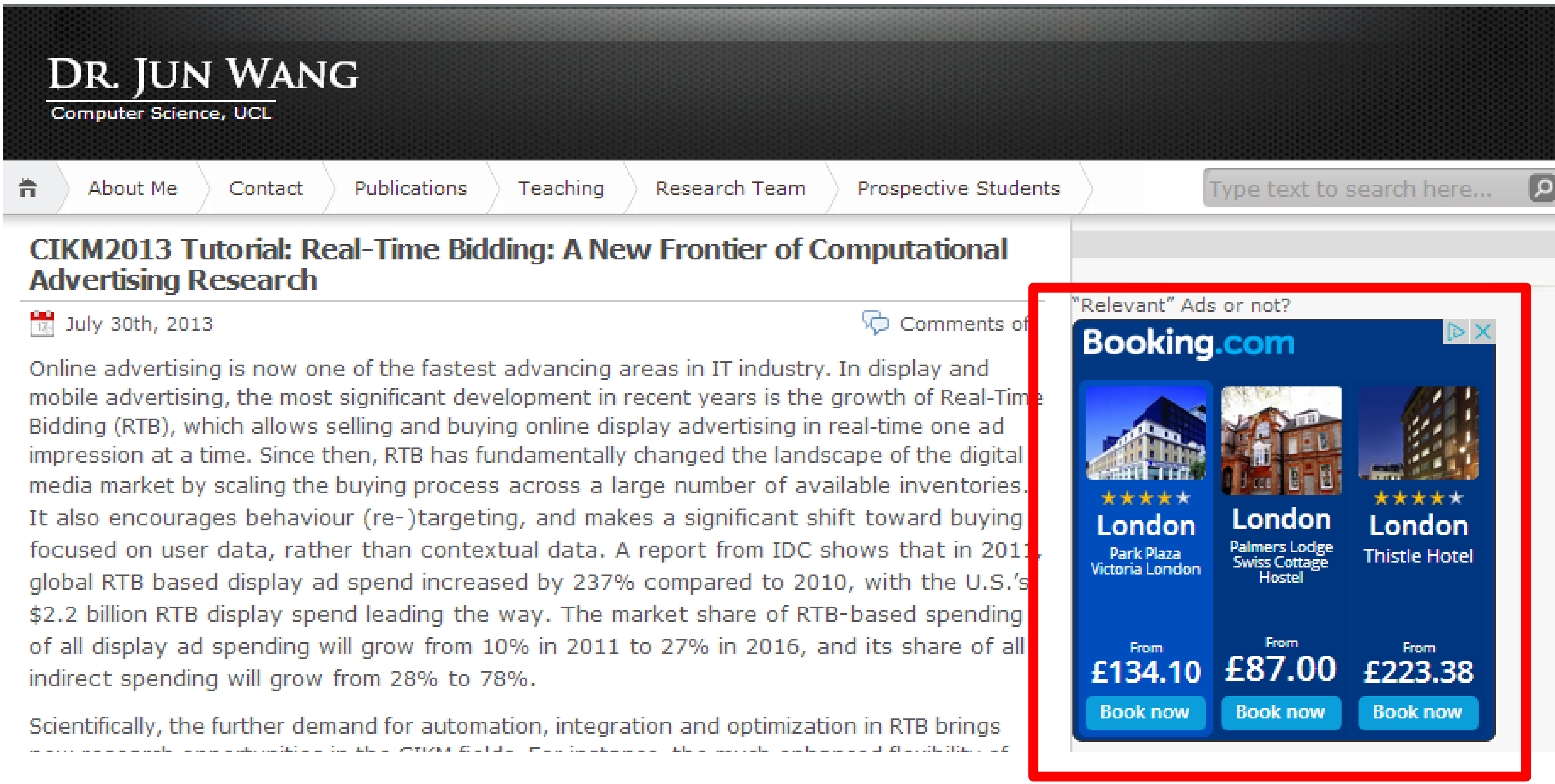


(In fact, no login is required)

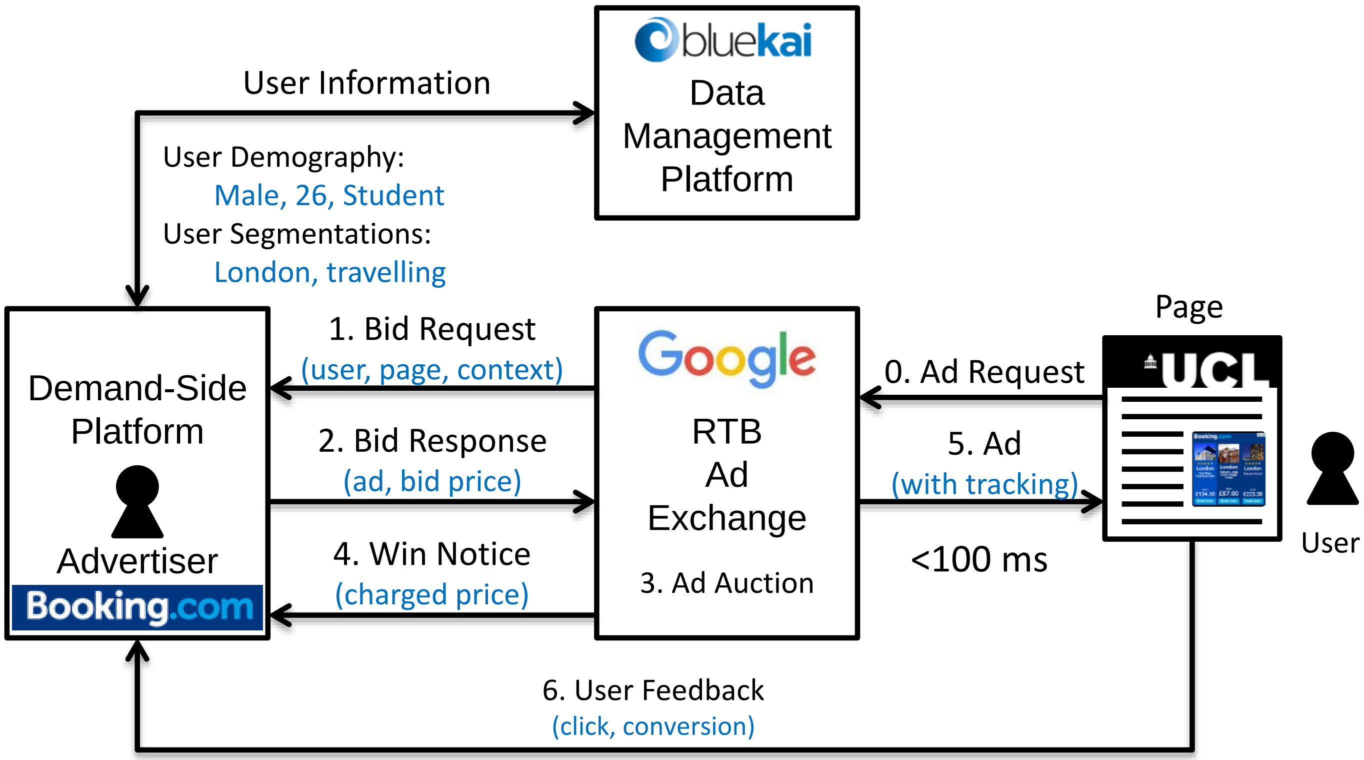
Relevant ads on facebook.com



Even on supervisor's homepage!
(User targeting dominates the context)



RTB Display Advertising Mechanism



- Buying ads via real-time bidding (RTB), 10B per day

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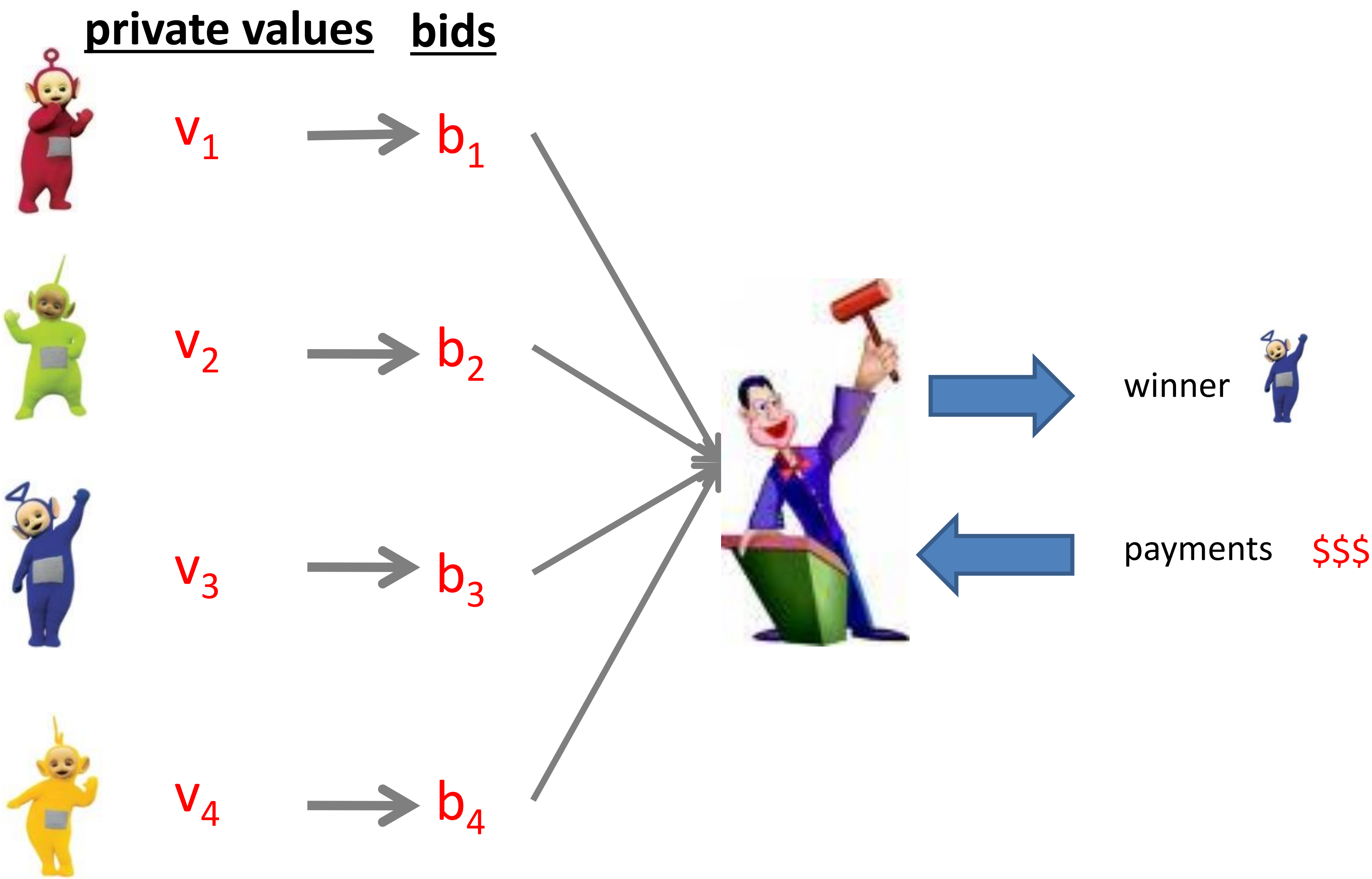
Auctions scheme



Modeling

- n bidders

- Each bidder has value v_i for the item
  - "willingness to pay"
  - Known only to him – "private value"

- If bidder i wins and pays p_i, his utility is $v_i - p_i$
  - In addition, the utility is 0 when the bidder loses.

- <u>Note:</u> bidders prefer losing than paying more than their value.

Strategy

- A strategy for each bidder
  - how to bid given your intrinsic, private value?
  - a strategy here is a *function*, a plan for the game. Not just a bid.
- Examples for strategies:
  - $b_i(v_i) = v_i$ (truthful)
  - $b_i(v_i) = v_i/2$
  - $b_i(v_i) = v_i/n$
  - *If* $v<50$, $b_i(v_i) = v_i$
    otherwise, $b_i(v_i) = v_i+17$

	B(v)=v	**B(v)=v /2**	**B(v)=v /n**	**....**
B(v)=v				
…				

- Can be modeled as normal form game, where these strategies are the pure strategies.
- Example for a *game with incomplete information*.

Strategies and equilibrium

- An equilibrium in the auction is a profile of strategies $B_1, B_2, \ldots, B_n$ such that:
  - Dominant strategy equilibrium: each strategy is optimal whatever the other strategies are.
  - Nash equilibrium: each strategy is a best response to the other strategies.

	B(v)=v	**B(v)=v/2**	**B(v)=v/n**	**….**
B(v)=v				
…				

Bayes-Nash equilibrium

- Recall a set of bidding strategies is a **Nash equilibrium** if each bidder's strategy maximizes his payoff given the optimal strategies of the others.
  - In auctions: bidders do not know their opponent's values, i.e., there is *incomplete information.*
  - Each bidder's strategy must maximize her *expected* payoff accounting for the uncertainty about opponent values.

1^{st} price auctions

- Truthful($b_i = v_i$)? NO!

$31

$30 ~~$100~~

Equilibrium in 2rd-price auctions

- bidder *1*'s payoff

$$\begin{cases} v_1 - b_i & if\ b_1 > b_i > \max\{b(v_2),\dots,b(v_{i-1}),b(v_{i+1}),\dots,b(v_n)\} \\ 0 & if\ b_1 \le \max\{b(v_2),\dots,b(v_n)\} \end{cases}$$

- The expected payoff of bidding b_1 is given by

$$\pi(v_1,b_1) = \int_0^{b_1} (v_1 - x)\, dF^{N-1}(x) = \int_0^{b_1} (N-1)(v_1 - x) f(x) F^{N-2}(x) dx$$

- Suppose $b_1 < v_1$, if b_1 is increased to v_1 the integral increases by the amount

$$\int_{b_1}^{v_1} (N-1)(v_1 - x) f(x) F^{N-2}(x) dx$$

- The reverse happens if $b_1 > v_1$

Menezes, Flavio M., and Paulo Klinger Monteiro. An introduction to auction theory. Oxford University Press, USA, 2005.

Reserve Prices and Entry Fees

- *Reserve Prices*: the seller is assumed to have committed to not selling below the reserve
  - Reserve prices are assumed to be known to all bidders
  - The reserve prices = the minimum bids
- *Entry Fees*: those bidders who enter have to pay the entry fee to the seller
- They reduce bidders' incentives to participate, but they might increase revenue as 1) the seller collects extra revenues 2) bidders might bid more aggressively

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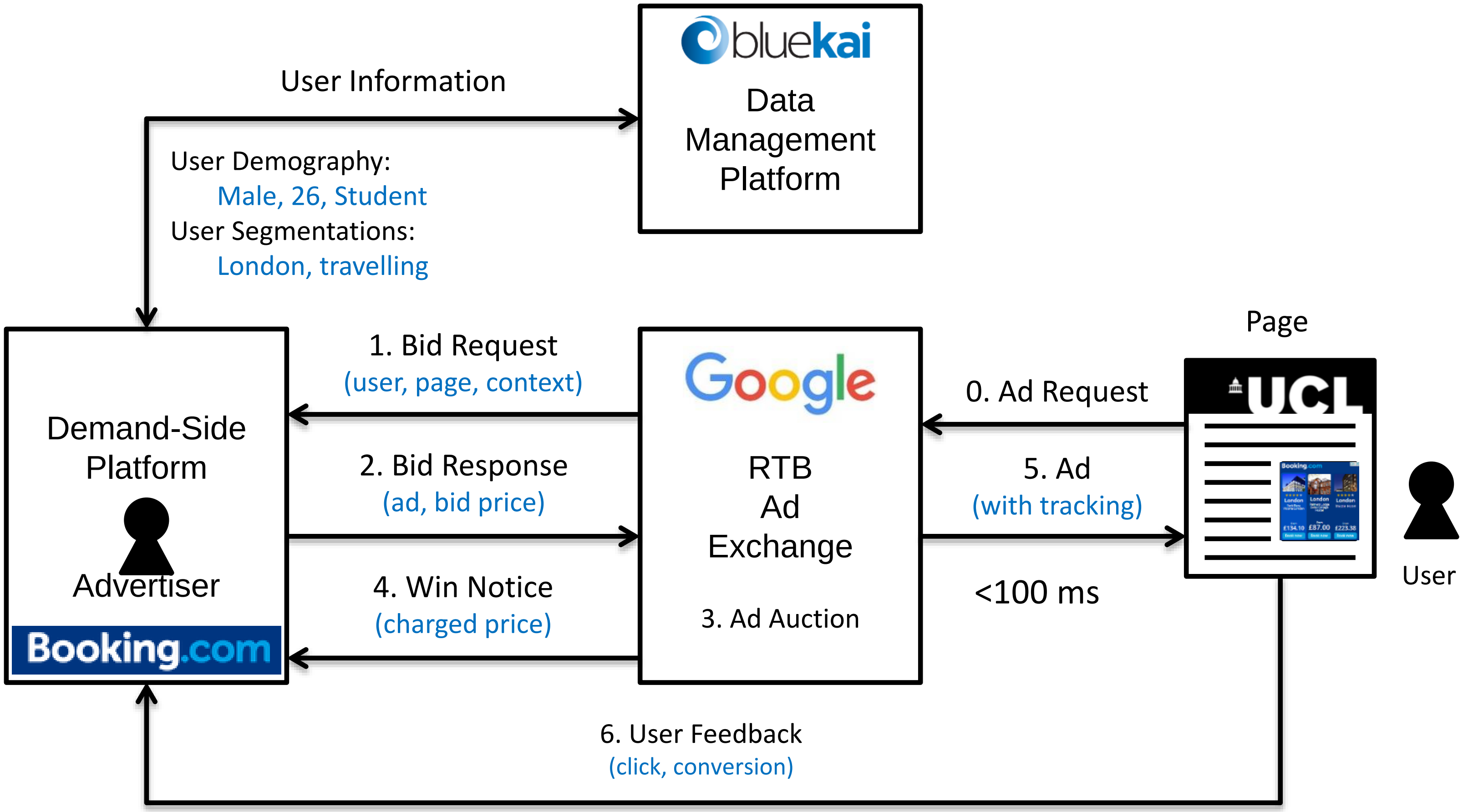
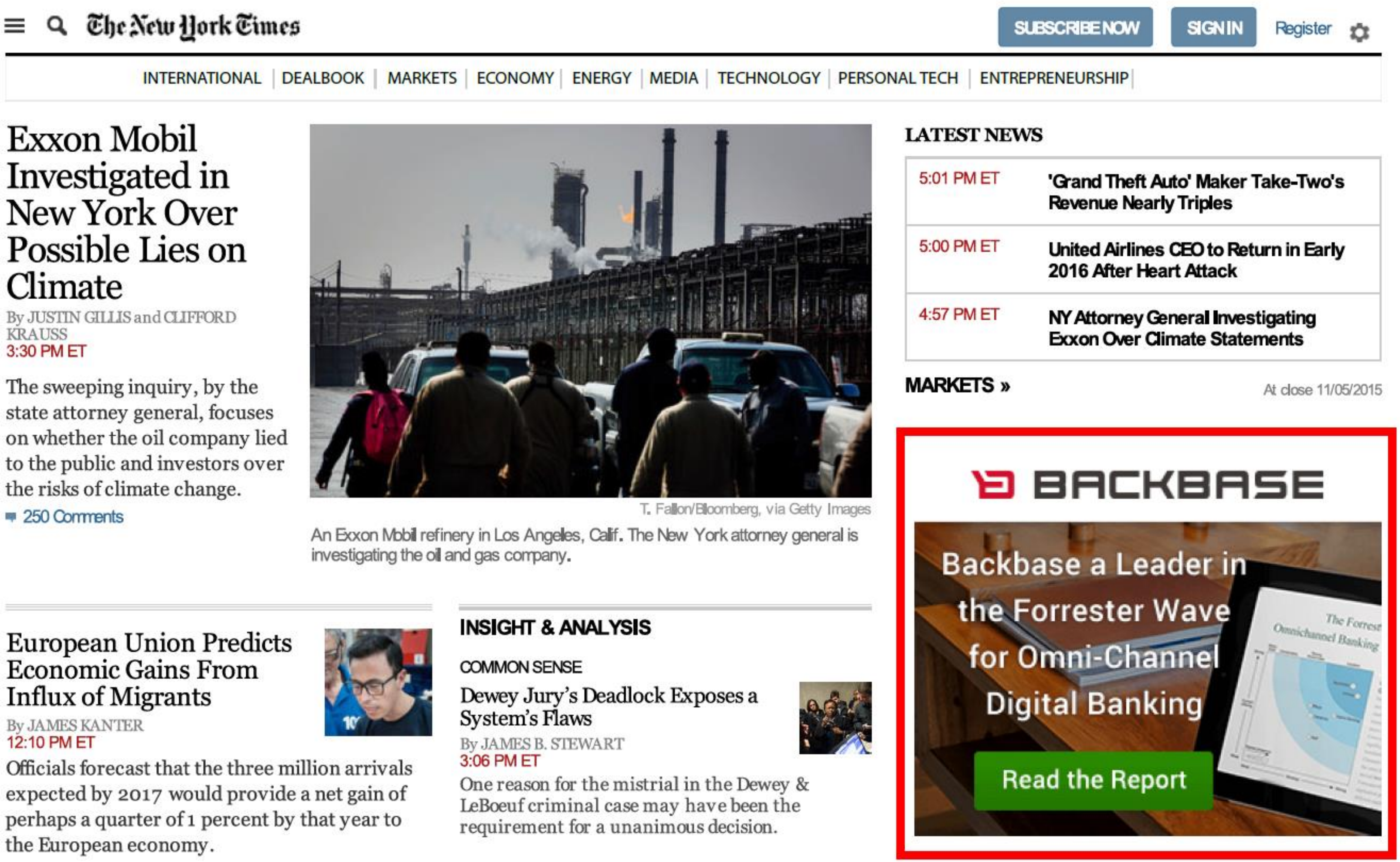
RTB Display Advertising Mechanism



- Buying ads via real-time bidding (RTB), 10B per day

Predict how likely the user is going to click the displayed ad.


The New York Times

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Exxon Mobil Investigated in New York Over Possible Lies on Climate

By JUSTIN GILLIS and CLIFFORD KRAUSS
3:30 PM ET

The sweeping inquiry, by the state attorney general, focuses on whether the oil company lied to the public and investors over the risks of climate change.

250 Comments

T. Fallon/Bloomberg, via Getty Images

An Exxon Mobil refinery in Los Angeles, Calif. The New York attorney general is investigating the oil and gas company.

LATEST NEWS

5:01 PM ET	'Grand Theft Auto' Maker Take-Two's Revenue Nearly Triples
5:00 PM ET	United Airlines CEO to Return in Early 2016 After Heart Attack
4:57 PM ET	NY Attorney General Investigating Exxon Over Climate Statements

MARKETS »

At close 11/05/2015

European Union Predicts Economic Gains From Influx of Migrants

By JAMES KANTER
12:10 PM ET

Officials forecast that the three million arrivals expected by 2017 would provide a net gain of perhaps a quarter of 1 percent by that year to the European economy.

INSIGHT & ANALYSIS

COMMON SENSE

Dewey Jury's Deadlock Exposes a System's Flaws

By JAMES B. STEWART
3:06 PM ET

One reason for the mistrial in the Dewey & LeBoeuf criminal case may have been the requirement for a unanimous decision.

User response estimation problem

- Click-through rate estimation as an example

- Date: 20160320
- Hour: 14
- Weekday: 7
- IP: 119.163.222.*
- Region: England
- City: London
- Country: UK
- Ad Exchange: Google
- Domain: yahoo.co.uk
- URL: http://www.yahoo.co.uk/abc/xyz.html
- OS: Windows
- Browser: Chrome
- Ad size: 300*250
- Ad ID: a1890
- User tags: Sports, Electronics

➡ Click (1) or not (0)?

Predicted CTR (0.15)

Feature Representation

- Binary one-hot encoding of categorical data

x=[Weekday=Wednesday, Gender=Male, City=London]

x=[0,0,1,0,0,0,0 0,1 0,0,1,0…0]

High dimensional sparse binary feature vector

Linear Models

- Logistic Regression
  - With SGD learning
  - Sparse solution
- Online Bayesian Profit Regression

ML Framework of CTR Estimation

- A binary regression problem

$$\min_{\boldsymbol{w}} \sum_{(y,\boldsymbol{x})\in D} \mathcal{L}(y, \hat{y}) + \lambda\Phi(\boldsymbol{w})$$

  – Large binary feature space (>10 millions)
    - Bloom filter to detect and add new features (e.g., > 5 instances)
  – Large data instance number (>10 millions daily)
  – A seriously unbalanced label
    - Normally, #click/#non-click = 0.3%
    - Negative down sampling
    - Calibration

Logistic Regression

- Prediction

$$\hat{y} = \frac{1}{1 + e^{-\boldsymbol{w}^T \boldsymbol{x}}}$$

- Cross Entropy Loss

$$\mathcal{L}(y, \hat{y}) = -y \log \hat{y} - (1 - y) \log(1 - \hat{y})$$

- Stochastic Gradient Descent Learning

$$\boldsymbol{w} \leftarrow (1 - \lambda)\boldsymbol{w} + \eta(y - \hat{y})\boldsymbol{x}$$

[Lee et al. Estimating Conversion Rate in Display Advertising from Past Performance Data. KDD 12]

Logistic Regression with SGD

$$\boldsymbol{w} \leftarrow (1 - \lambda)\boldsymbol{w} + \eta(y - \hat{y})\boldsymbol{x}$$

- Pros
  - Standardised, easily understood and implemented
  - Easy to be parallelised
- Cons
  - Learning rate η initialisation
  - Uniform learning rate against different binary features

Logistic Regression with FTRL

- In practice, we need a sparse solution as >10 million feature dimensions
- Follow-The-Regularised-Leader (FTRL) online Learning

$$\mathbf{w}_{t+1} = \arg\min_{\mathbf{w}} \left(\mathbf{g}_{1:t} \cdot \mathbf{w} + \frac{1}{2} \sum_{s=1}^{t} \sigma_s \|\mathbf{w} - \mathbf{w}_s\|_2^2 + \lambda_1 \|\mathbf{w}\|_1 \right)$$

adaptively selects regularization functions

s.t. $\mathbf{g}_{1:t} = \sum_{s=1}^{t} \mathbf{g}_s$

$$\sigma_s = \sqrt{s} - \sqrt{s-1}$$

t: current example index

g_s: gradient for example t

- Online closed-form update of FTRL

$$w_{t+1,i} = \begin{cases} 0 & \text{if } |z_{t,i}| \leq \lambda_1 \\ -\eta_t (z_{t,i} - \operatorname{sgn}(z_{t,i})\lambda_1) & \text{otherwise.} \end{cases}$$

$$\mathbf{z}_{t-1} = \mathbf{g}_{1:t-1} - \sum_{s=1}^{t-1} \sigma_s \mathbf{w}_s \qquad \eta_{t,i} = \frac{\alpha}{\beta + \sqrt{\sum_{s=1}^{t} g_{s,i}^2}}$$

[McMahan et al. Ad Click Prediction : a View from the Trenches. KDD 13]

[Xiao, Lin. "Dual averaging method for regularized stochastic learning and online optimization." Advances in Neural Information Processing Systems. 2009]

Online Bayesian Probit Regression

Given feature x, predicting click y

$$p(y|\boldsymbol{x},\boldsymbol{w}) := \Phi\left(\frac{y\cdot\boldsymbol{w}^T\boldsymbol{x}}{\beta}\right)$$

Where probit function $\Phi(t) \coloneqq \int_{-\infty}^{t} \mathcal{N}(s;0,1)\,ds$

And prior distribution $p(\boldsymbol{w}) = \prod_{i=1}^{N}\prod_{j=1}^{M_i} \mathcal{N}\left(w_{i,j};\mu_{i,j},\sigma_{i,j}^2\right)$

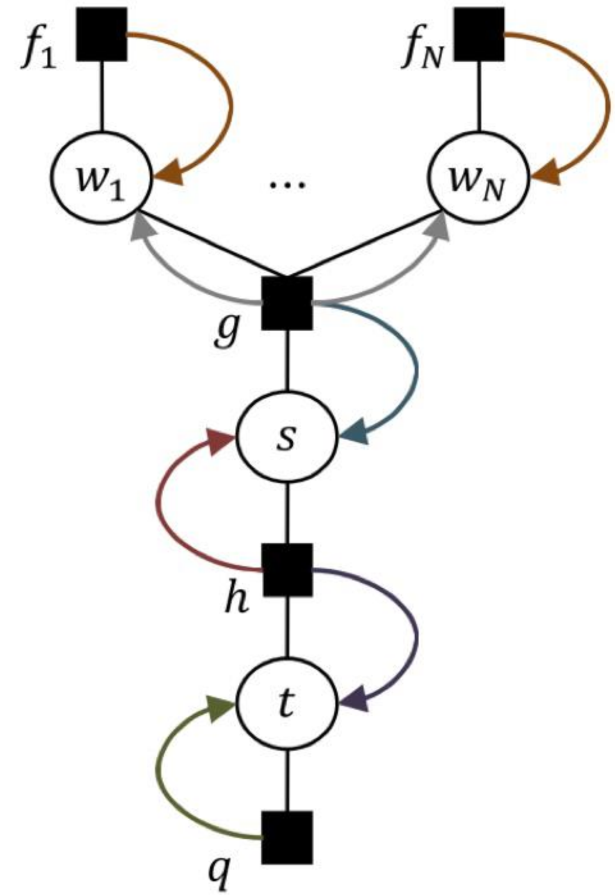
The factorised model

$$p(y \mid t)\cdot p(t \mid s)\cdot p(s \mid \boldsymbol{x},\boldsymbol{w})\cdot p(\boldsymbol{w})$$

Where $p(s|\boldsymbol{x},\boldsymbol{w}) := \delta(s = \boldsymbol{w}^T\boldsymbol{x})$.

$p(t|s) := \mathcal{N}(t; s, \beta^2)$

$p(y|t) := \delta(y = \mathrm{sign}(t))$.



Approximated inference via Expectation Propagation

[Graepel et al. Web-Scale Bayesian Click-Through Rate Prediction for Sponsored Search Advertising in Microsoft's Bing Search Engine. ICML 10]

Linear Prediction Models

$$\hat{y} = f(\boldsymbol{w}^T \boldsymbol{x})$$

- Pros
  - Highly efficient and scalable
  - Explore larger feature space and training data
- Cons
  - Modelling limit: feature independence assumption
  - Cannot capture feature interactions unless defining high order combination features
    - E.g., hour=10AM & city=London & browser=Chrome

Non-linear Models

- Gradient Boosting Decision Trees
- Factorisation Machines
- Combined Models
- Deep Neural Networks

Factorisation Machines

- Prediction based on feature embedding

$$\hat{y}(\boldsymbol{x}) = \sigma\left(w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} x_i x_j \boldsymbol{v}_i^T \boldsymbol{v}_j\right)$$

  – Explicitly model feature interactions
    - Second order, third order etc.
  – Empirically better than logistic regression
  – A new way for **user profiling**

[Rendle. Factorization machines. ICDM 2010.]

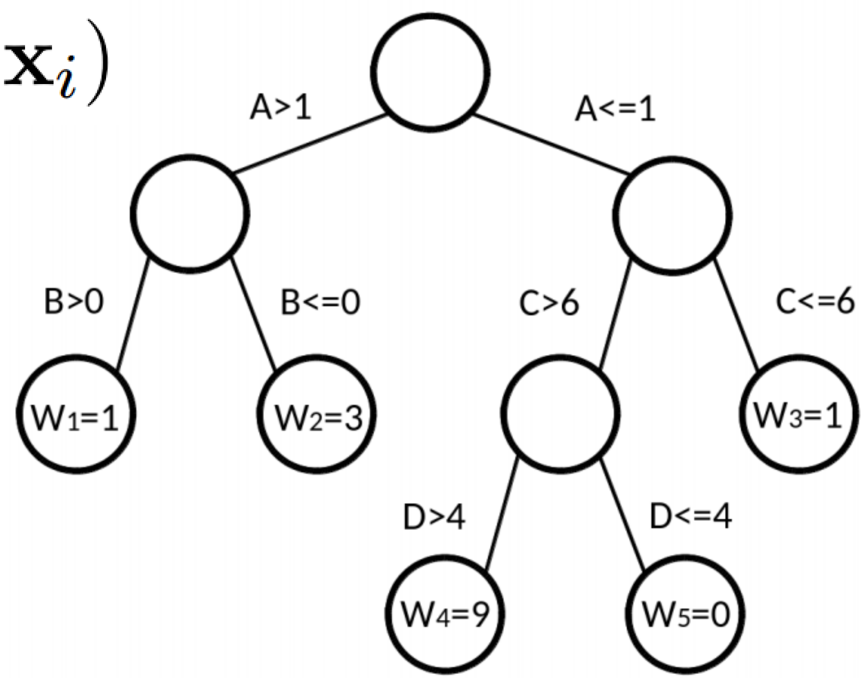
[Oentaryo et al. Predicting response in mobile advertising with hierarchical importance-aware factorization machine. WSDM 14]

Gradient Boosting Decision Trees

- Additive decision trees for prediction

$$\hat{y}_i = \phi(\mathbf{x}_i) = \sum_{k=1}^{K} f_k(\mathbf{x}_i), \quad f_k \in \mathcal{F}$$

- Each decision tree $f_k(\mathbf{x}_i)$



[Chen and He. Higgs Boson Discovery with Boosted Trees . HEPML 2014.]

Gradient Boosting Decision Trees

$$\hat{y}_i = \phi(\mathbf{x}_i) = \sum_{k=1}^{K} f_k(\mathbf{x}_i), \quad f_k \in \mathcal{F}$$

- Learning

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t)}) + \sum_{i=1}^{t} \Omega(f_i)$$

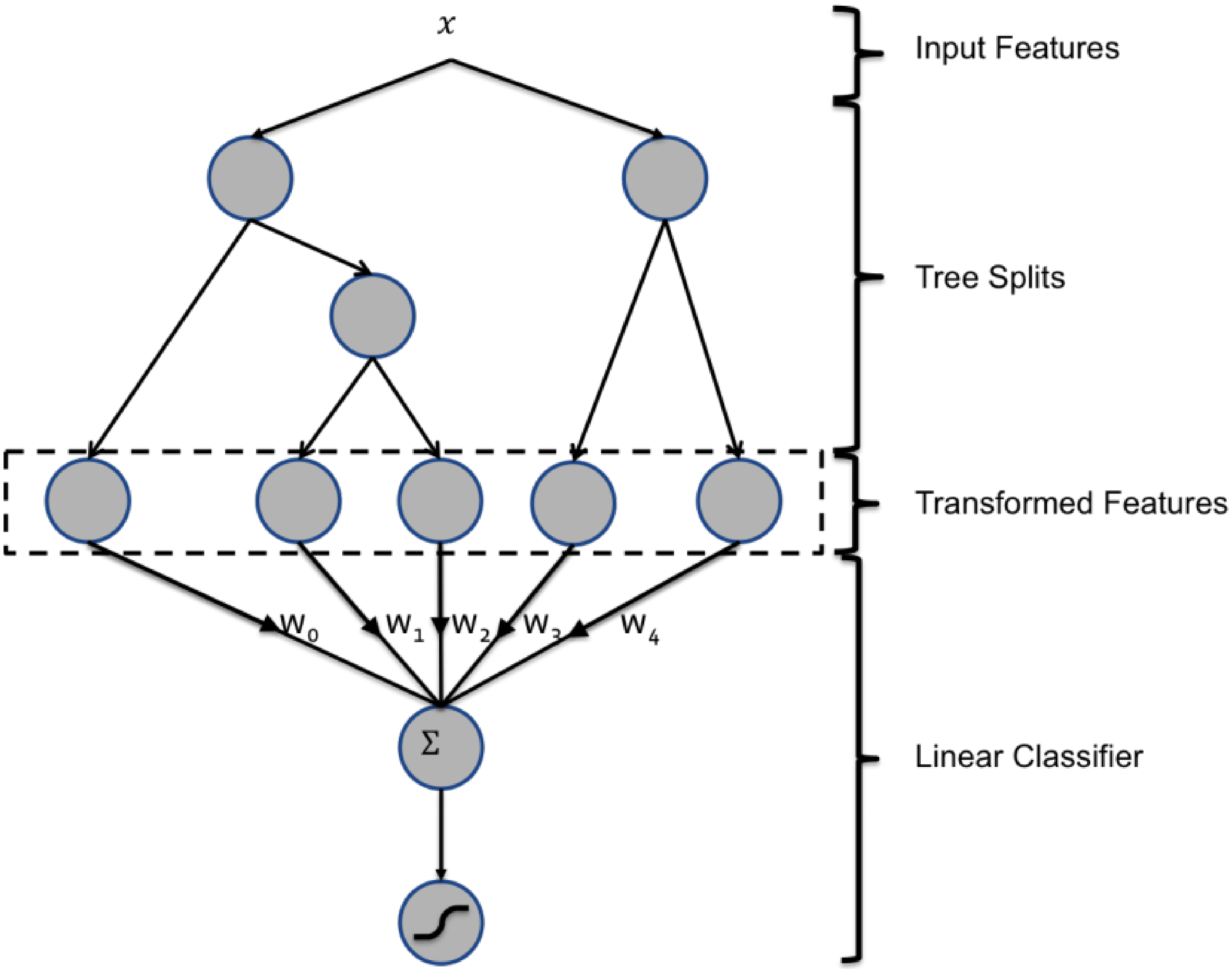
$$= \sum_{i=1}^{n} l(y_i, \hat{y_i}^{(t-1)} + f_t(\mathbf{x}_i)) + \sum_{i=1}^{t} \Omega(f_i)$$

$$\mathcal{L}^{(t)} \simeq \sum_{i=1}^{n} [l(y_i, \hat{y}^{(t-1)}) + g_i f_t(\mathbf{x}_i) + \frac{1}{2} h_i f_t^2(\mathbf{x}_i)] + \sum_{i=1}^{t} \Omega(f_i)$$

$$g_i = \partial_{\hat{y}^{(t-1)}} l(y_i, \hat{y}^{(t-1)}) \qquad h_i = \partial^2_{\hat{y}^{(t-1)}} l(y_i, \hat{y}^{(t-1)})$$

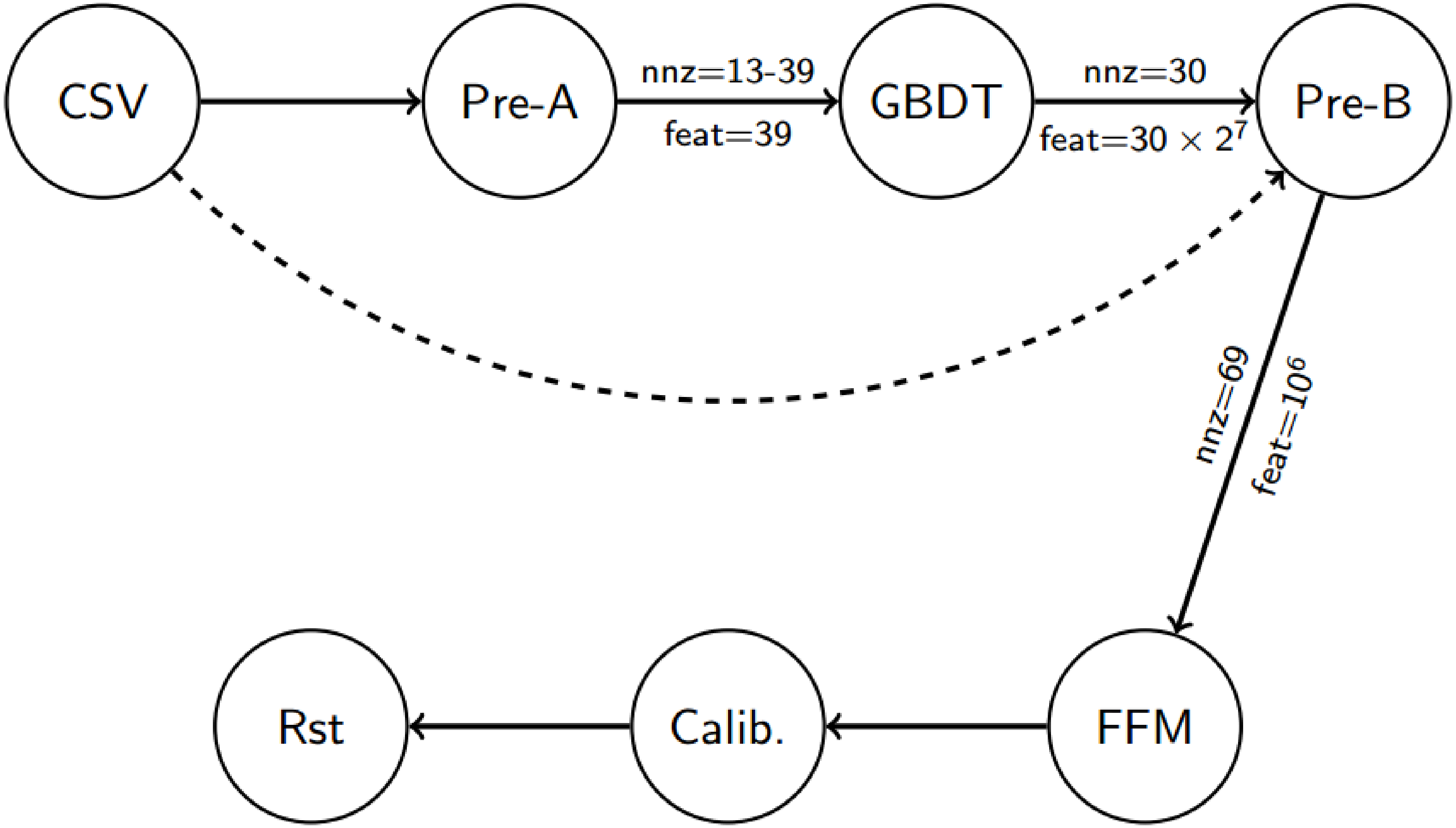
[Chen and He. Higgs Boson Discovery with Boosted Trees . HEPML 2014.]

Combined Models: GBDT + LR



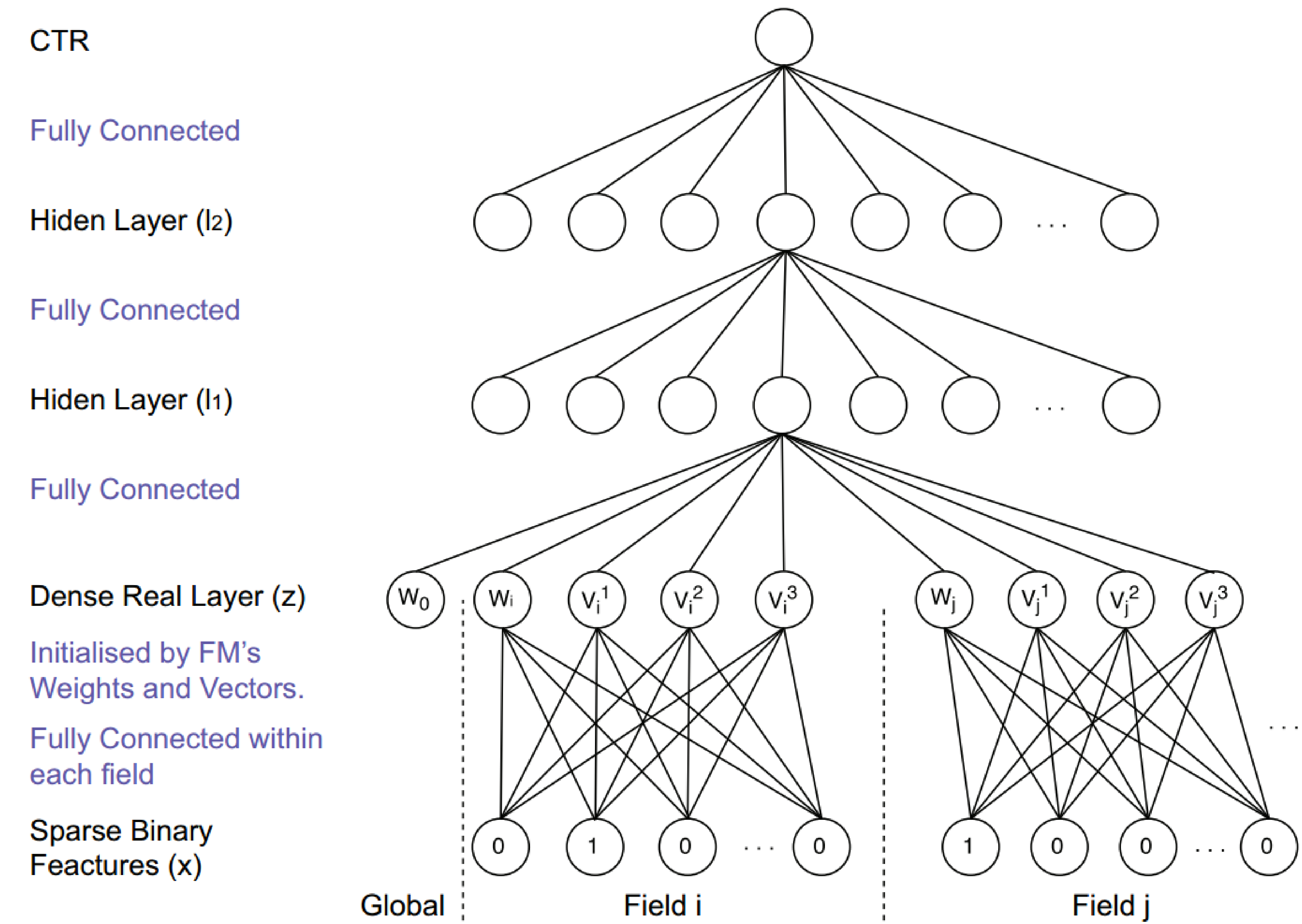
[He et al. Practical Lessons from Predicting Clicks on Ads at Facebook . ADKDD 2014.]

Combined Models: GBDT + FM



"nnz" means the number of non-zero elements of each impression; "feat" represents the size of feature space.

[http://www.csie.ntu.edu.tw/~r01922136/kaggle-2014-criteo.pdf]



[Zhang et al. Deep Learning over Multi-field Categorical Data – A Case Study on User Response Prediction. ECIR 16] in Monday Machine Learning Track

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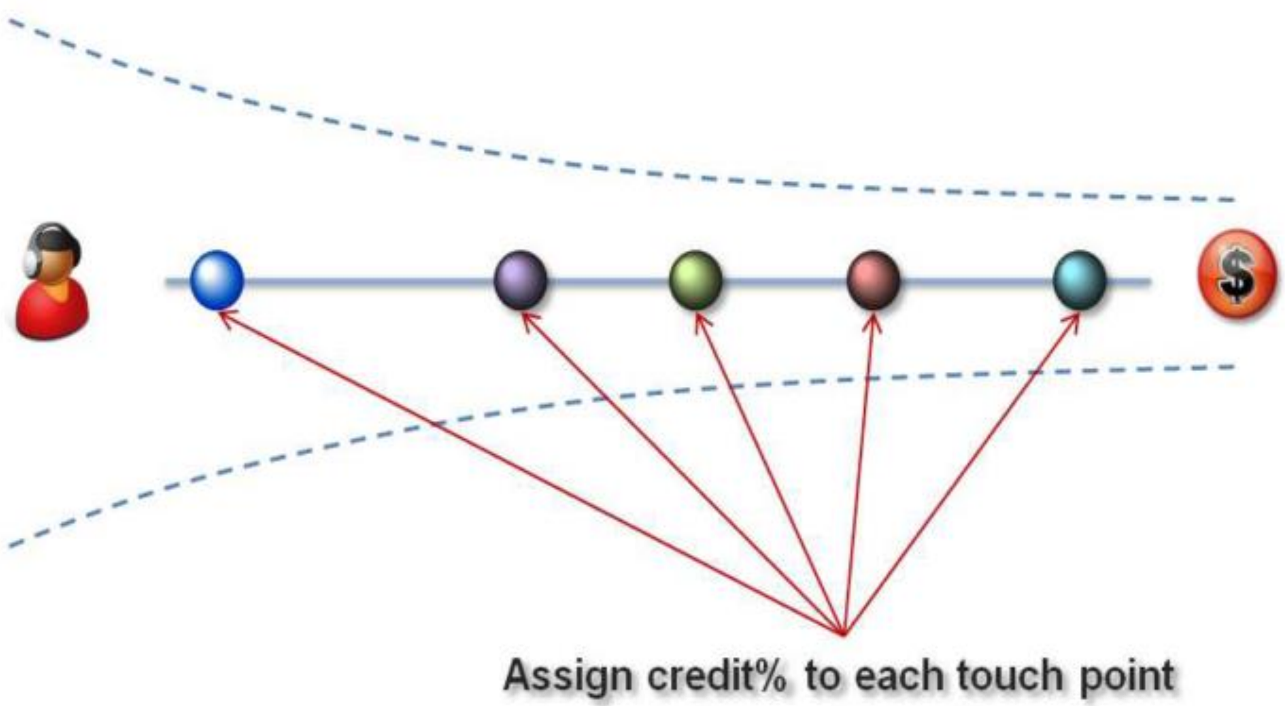
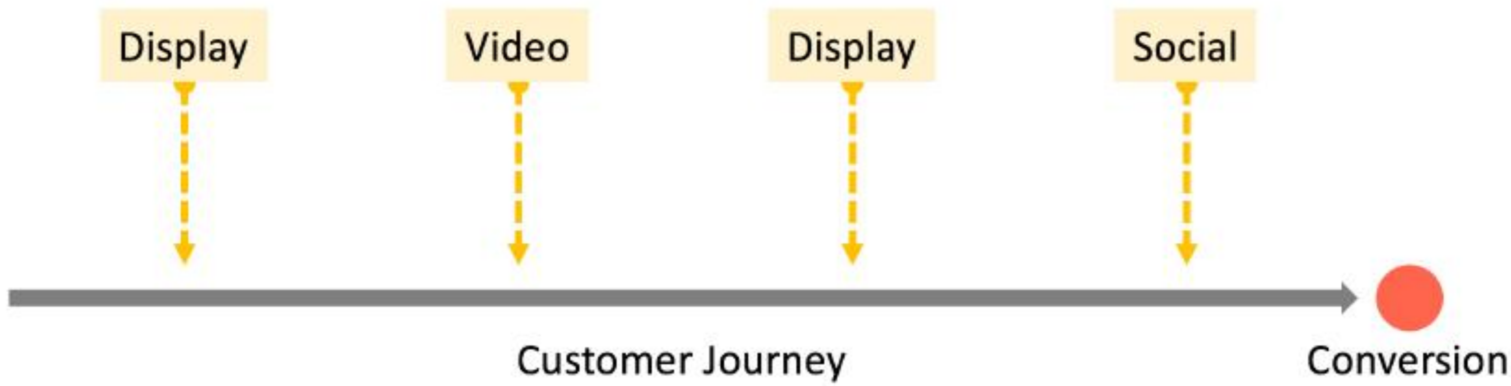
Conversion Attribution



- Assign credit% to each channel according to contribution
- Current industrial solution: last-touch attribution

[Shao et al. Data-driven multi-touch attribution models. KDD 11]

Heuristics-based Attribution



Model	Attribution			
Last Touch	0%	0%	0%	100%
First Touch	100%	0%	0%	0%
Linear	25%	25%	25%	25%
Time Decay	10%	20%	30%	40%
Position Based	40%	10%	10%	40%

[Kee. Attribution playbook – google analytics. Online access.]

A Good Attribution Model

- Fairness
  - Reward an individual channel in accordance with its ability to affect the likelihood of conversion
- Data driven
  - Using ad touch and conversion data for each campaign to build its model
- Interpretability
  - Generally accepted by all parties

[Dalessandro et al. Casually Motivated Attribution for Online Advertising. ADKDD 11]

Bagged Logistic Regression

Display	Search	Mobile	Email	Social	Convert?
1	1	0	0	1	1
1	0	1	1	1	0
0	1	0	1	0	1
0	0	1	1	1	0

- For M iterations
  - Sample 50% data instances and 50% features
  - Train a logistic regression and record the weights
- Average the feature weights

[Shao et al. Data-driven multi-touch attribution models. KDD 11]

Bagged Logistic Regression

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- For M iterations
  - Sample 50% data instances and 50% features
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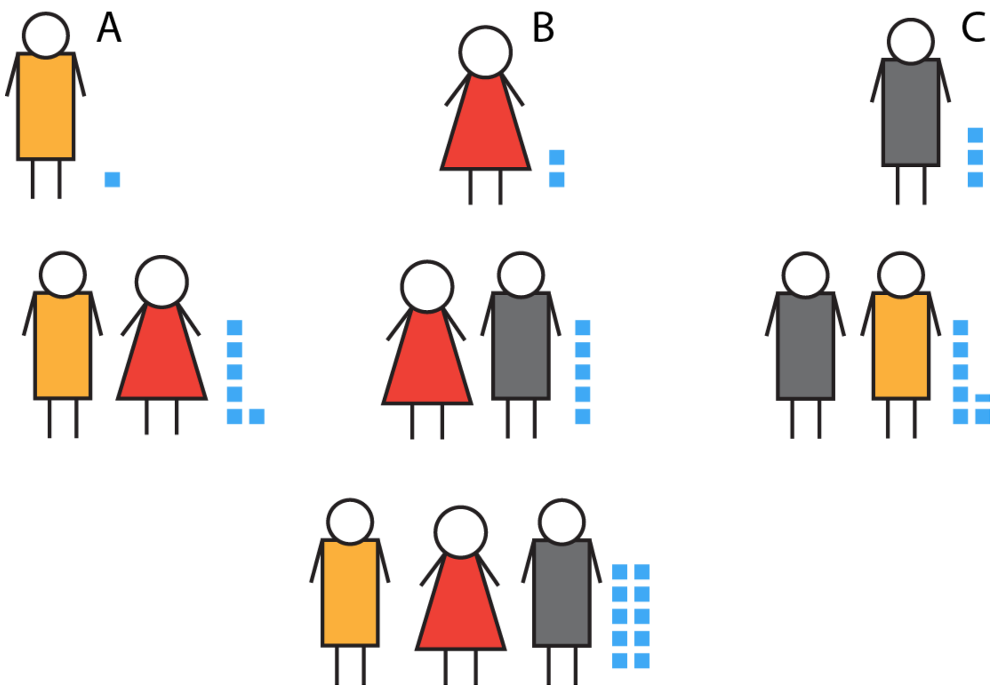
[Shao et al. Data-driven multi-touch attribution models. KDD 11]

Shapley Value based Attribution

- Coalition game
  - How much does a player contribute in the game



[Fig source: https://pjdelta.wordpress.com/2014/08/10/group-project-how-much-did-i-contribute/]

Shapley Value based Attribution

- Coalition game

$$V_k = \sum_{S \subseteq C/k} \omega_{S,k} \cdot [E[\gamma|S \cup C_k] - E[\gamma|S]]$$

$$\omega_{S,k} = \frac{|S|!(|C| - |S| - 1)!}{|C|!}$$

A Probabilistic Attribution Model

- Conditional probabilities

$$P(y|x_i) = \frac{N_{positive}(x_i)}{N_{positive}(x_i) + N_{negative}(x_i)}$$

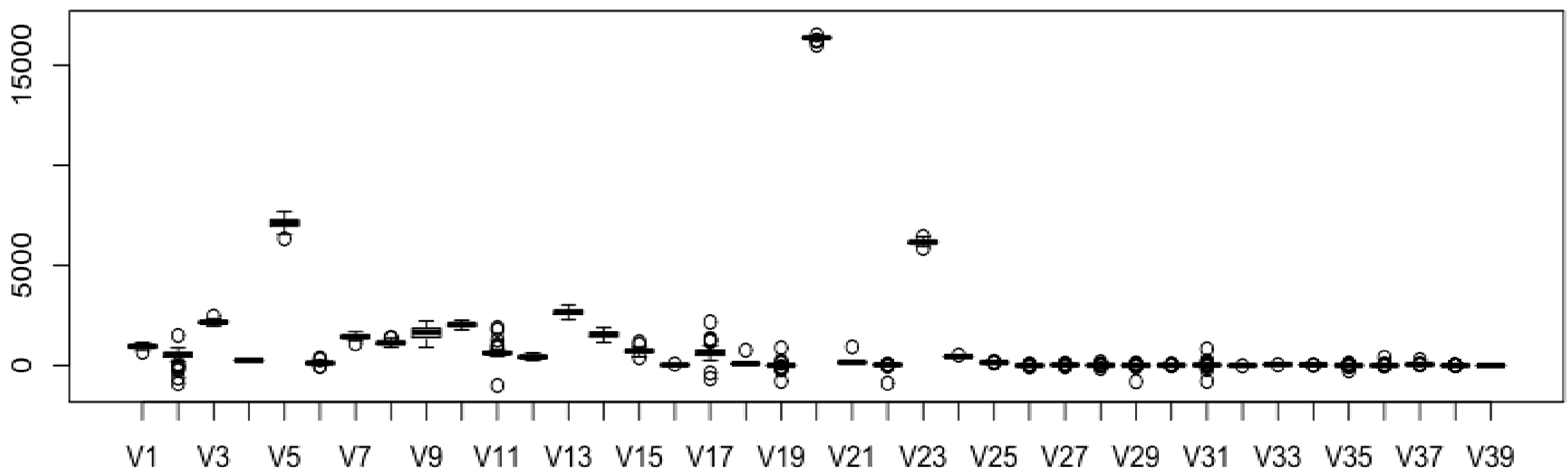
$$P(y|x_i, x_j) = \frac{N_{positive}(x_i, x_j)}{N_{positive}(x_i, x_j) + N_{negative}(x_i, x_j)}$$

- Attributed contribution

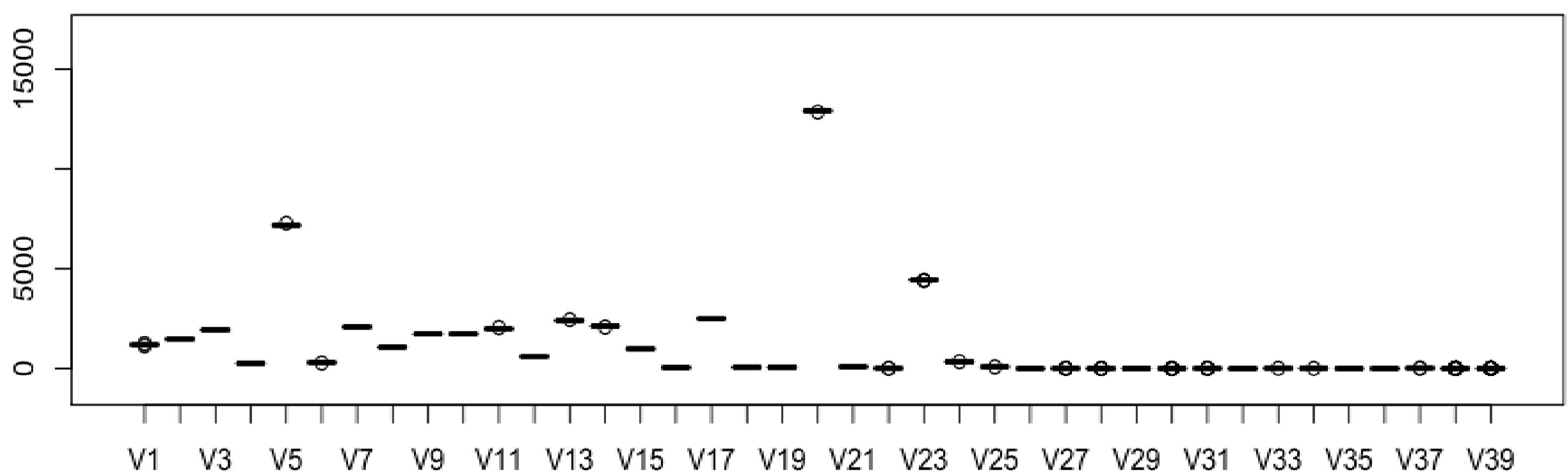
$$V(x_i) = \frac{1}{2}P(y|x_i) + \frac{1}{2N_{j \neq i}} \sum_{j \neq i} \Big(P(y|x_i, x_j) - P(y|x_j) \Big)$$

[Shao et al. Data-driven multi-touch attribution models. KDD 11]

bagged logistic regression model



simple probabilistic model



[Shao et al. Data-driven multi-touch attribution models. KDD 11]

Table 2: The MTA user-level attribution analysis.

Channel	MTA Total	LTA Total	Difference
Search Click	17,494	17,017	97%
Email Click	6,938	7,340	106%
Display Network A	5,567	8,148	146%
Display Network G	2,037	470	23%
Display Network B	1,818	1,272	70%
Display Trading Desk	1,565	1,367	87%
Display Network C	1,494	1,373	92%
Display Network D	1,491	1,233	83%
Email View	1,420	458	32%
Display Network E	1,187	1,138	96%
Brand Campaign	907	1,581	174%
Social	768	1,123	146%
Display Network H	746	284	38%
Display Network F	673	787	117%
Display Network I	489	136	28%
Retail Email Click	483	491	102%
Display Network J	222	92	41%
Retail Email	168	110	66%
Social Click	133	153	115%
Video	58	31	54%

Data-Driven Probabilistic Models

- The “relatively heuristic” data-driven model
  [Shao et al. Data-driven multi-touch attribution models. KDD 11]

$$V(x_i) = \frac{1}{2}P(y|x_i) + \frac{1}{2N_{j\neq i}} \sum_{j\neq i} \Big(P(y|x_i, x_j) - P(y|x_j) \Big)$$

- A more generalized and data-driven model
  [Dalessandro et al. Casually Motivated Attribution for Online Advertising. ADKDD 11]

$$V(x_i) = \sum_{S \subseteq I \setminus i} w_{S,i} (P(y|S, x_i) - P(y|S))$$

  – $w_{S,i}$: the probability that the sequence begin with (S, C_i)

Attribution Comparison

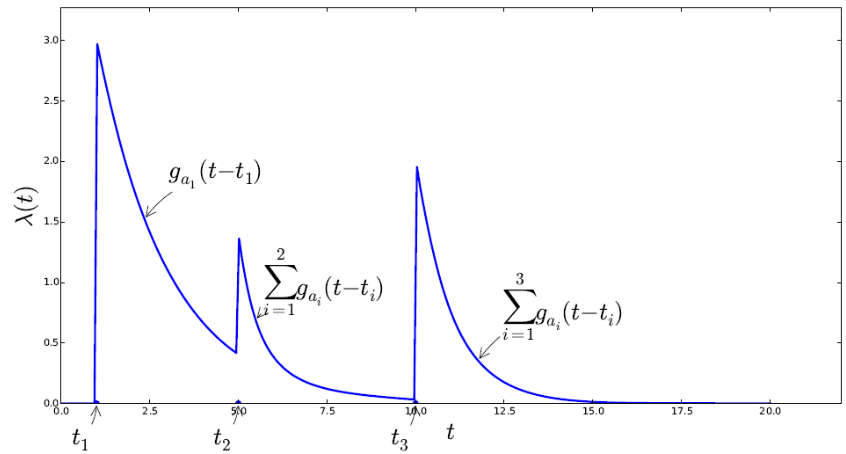
		Data Generating Parameters			Attribution Results			
Channel	Group	Ad Propensity Likelihood	Simulated Conversion Rate	Last Touch Propensity	Last Touch Conversions	Multi Touch Conversions	Delta N	Delta %
1	Gen Prospecting	5.0%	0.100%	0.2%	1,023	2,176	1,153	113%
2	Gen Prospecting	10.0%	0.080%	0.2%	1,932	3,284	1,352	70%
3	Gen Prospecting	10.0%	0.070%	0.2%	1,854	3,085	1,231	66%
4	Gen Prospecting	15.0%	0.050%	0.2%	2,491	3,434	943	38%
5	Gen Prospecting	15.0%	0.050%	1.8%	3,134	3,143	9	0%
6	Gen Prospecting	20.0%	0.010%	1.7%	2,998	736	-2,262	-75%
7	Gen Prospecting	20.0%	0.008%	6.7%	3,558	260	-3,298	-93%
8	Gen Prospecting	25.0%	0.008%	6.8%	4,406	409	-3,997	-91%
9	Retargeting	2.5%	0.500%	3.0%	3,921	5,673	1,752	45%
10	Retargeting	2.5%	0.400%	6.0%	3,375	4,489	1,114	33%
11	Retargeting	3.0%	0.300%	10.5%	3,468	4,068	600	17%
12	Retargeting	3.5%	0.250%	15.3%	3,728	3,997	269	7%
13	Search	0.5%	1.000%	23.7%	2,109	2,430	321	15%
14	Search	0.5%	2.000%	23.6%	5,329	5,045	-284	-5%

- Help find some “cookie bombing” channels

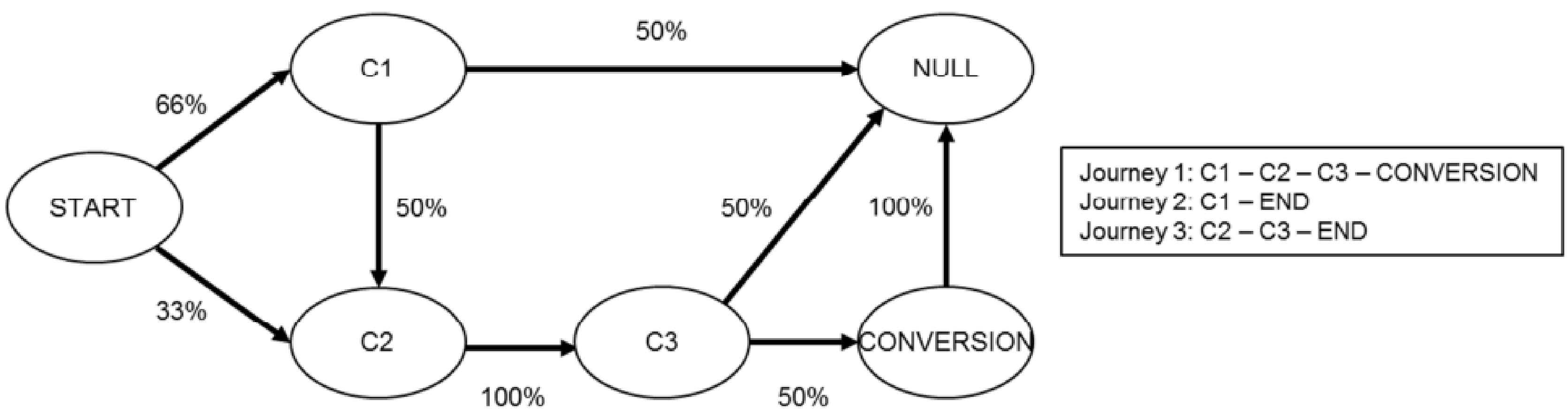
Other Attribution Models

- Survival models with time

[Zhang et al. Multi-Touch Attribution in Online Advertising with Survival Theory. ICDM 2014]



- Markov graph



[Anderl et al. Mapping the customer journey: A graph-based framework for online attribution modeling. SSRN 2014]

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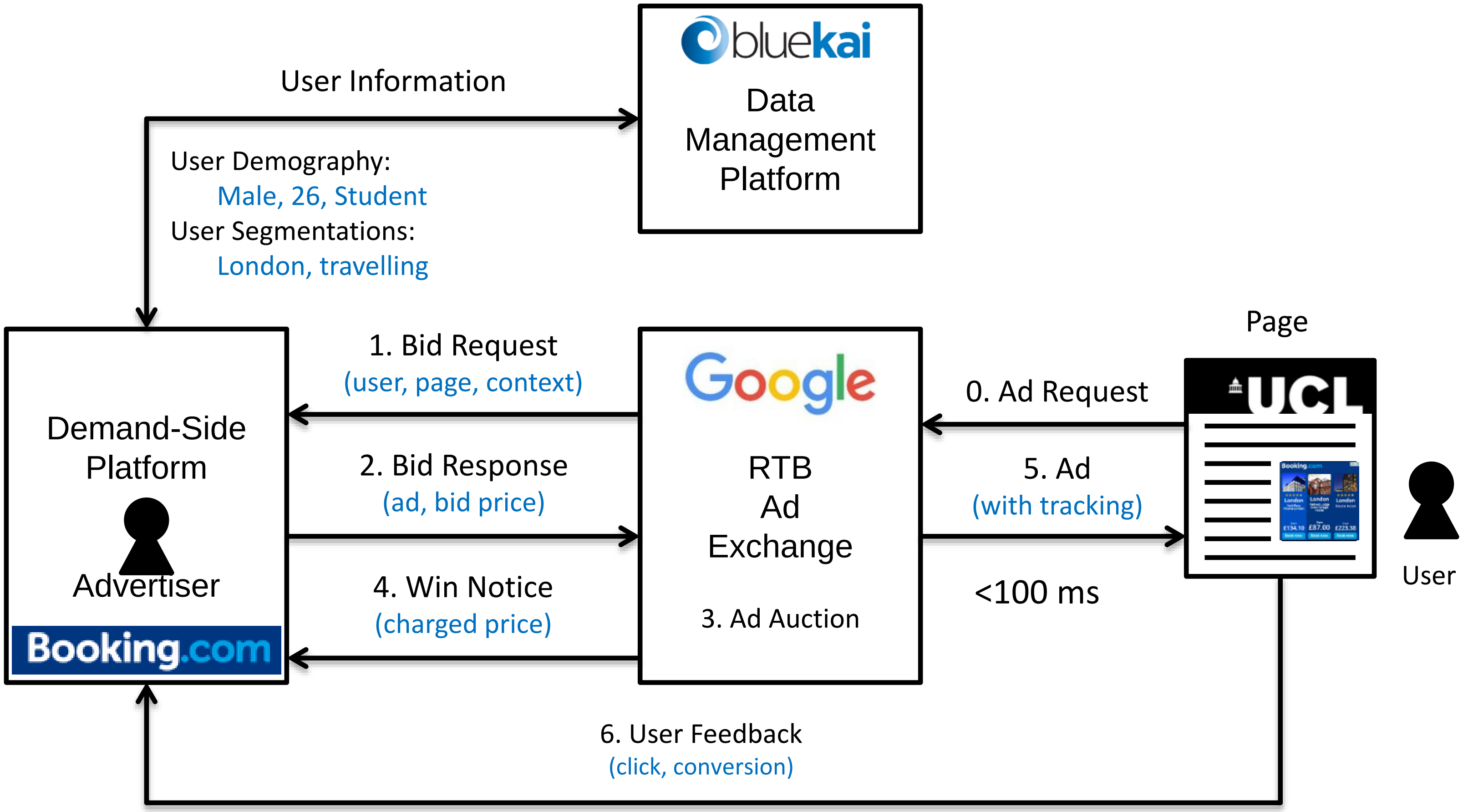
RTB Display Advertising Mechanism



- Buying ads via real-time bidding (RTB), 10B per day

Data of Learning to Bid

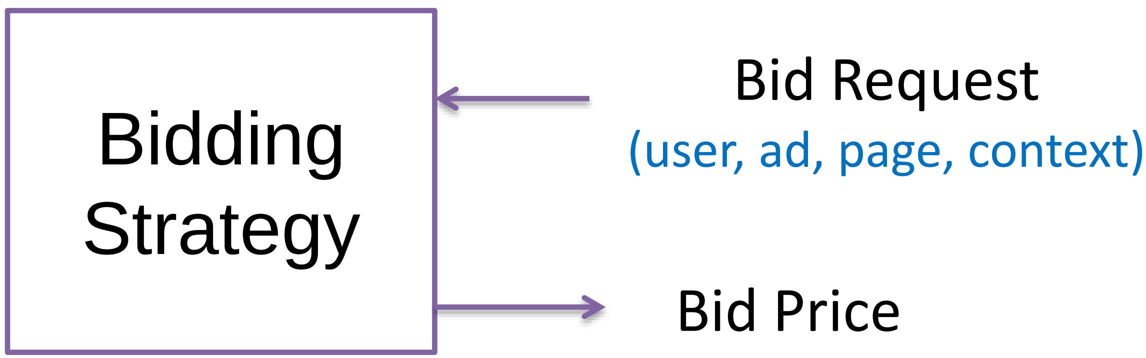
- Data

$(\mathbf{x}, t)$	b	w	c	y
(up,1500×20,Shanghai,0)	5	1	4	1
(down,1200×25,Paris,1)	4	1	3	0
(left,20×1000,Los Angeles,2)	3	0	×	×
(right,35×600,London,3)	0	0	×	×

  - Bid request features: High dimensional sparse binary vector
  - Bid: Non-negative real or integer value
  - Win: Boolean
  - Cost: Non-negative real or integer value
  - Feedback: Binary

Problem Definition of Learning to Bid

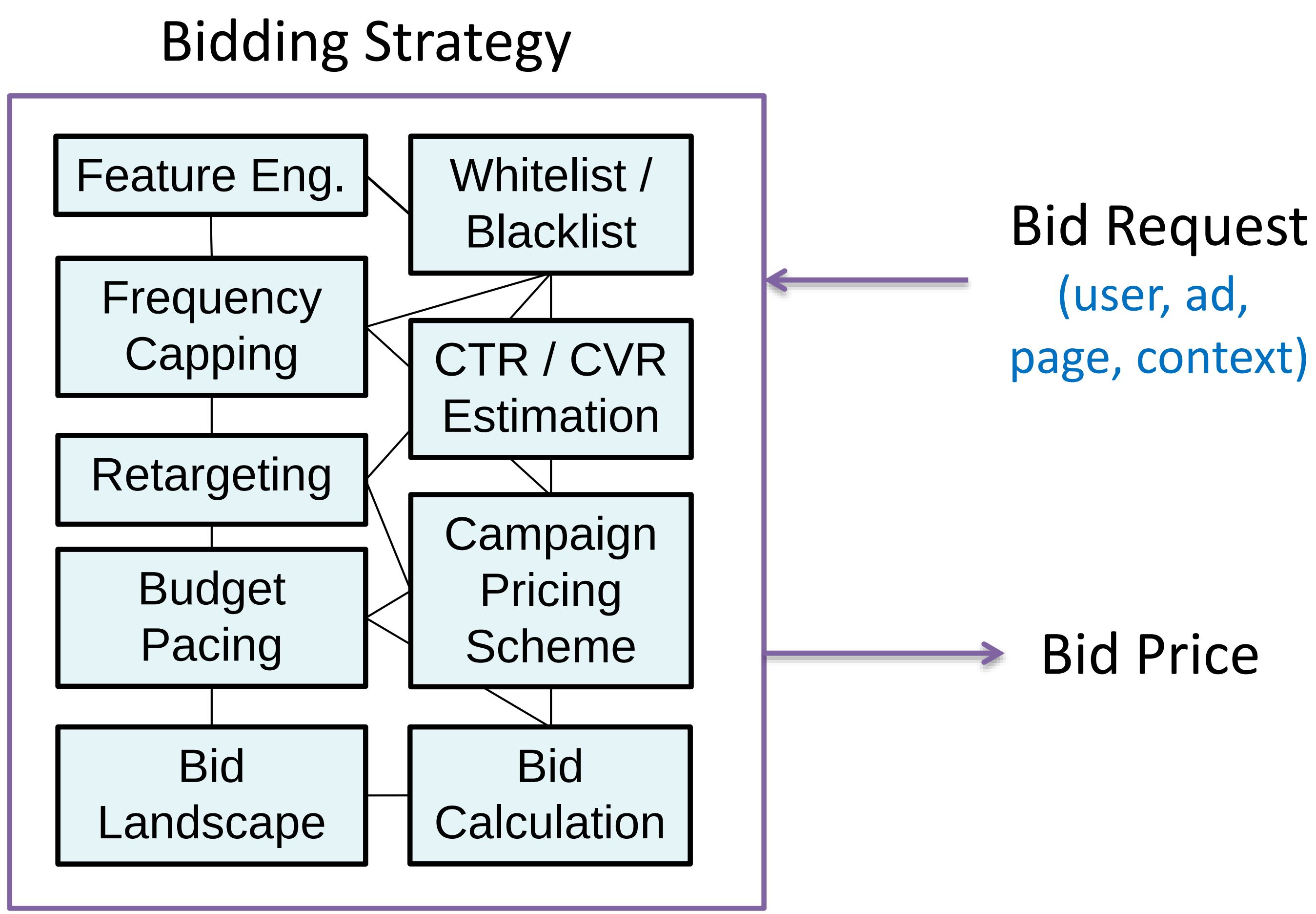
- How much to bid for each bid request?
  - Find an optimal bidding function b(x)



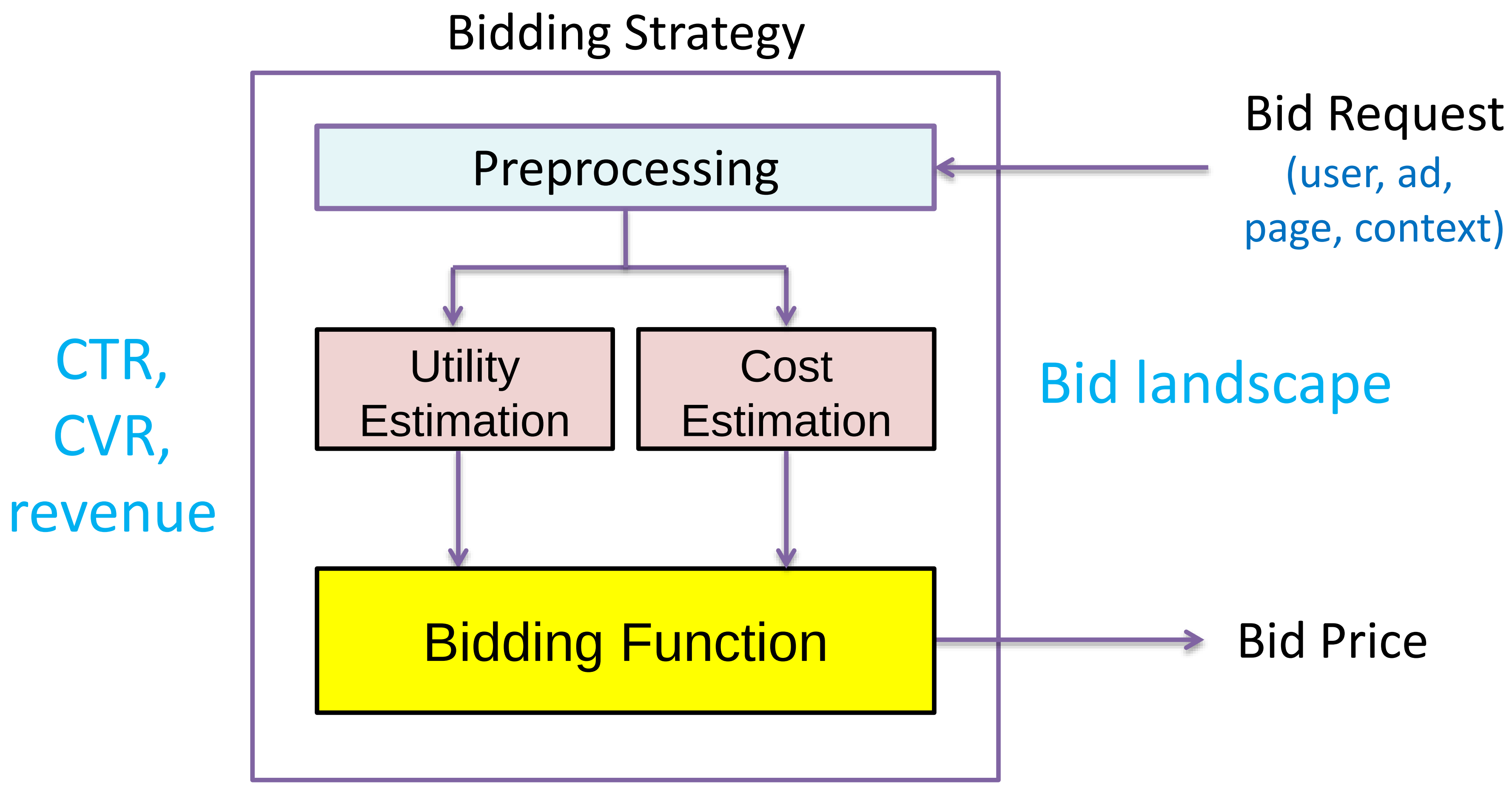
- Bid to optimise the KPI with budget constraint

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

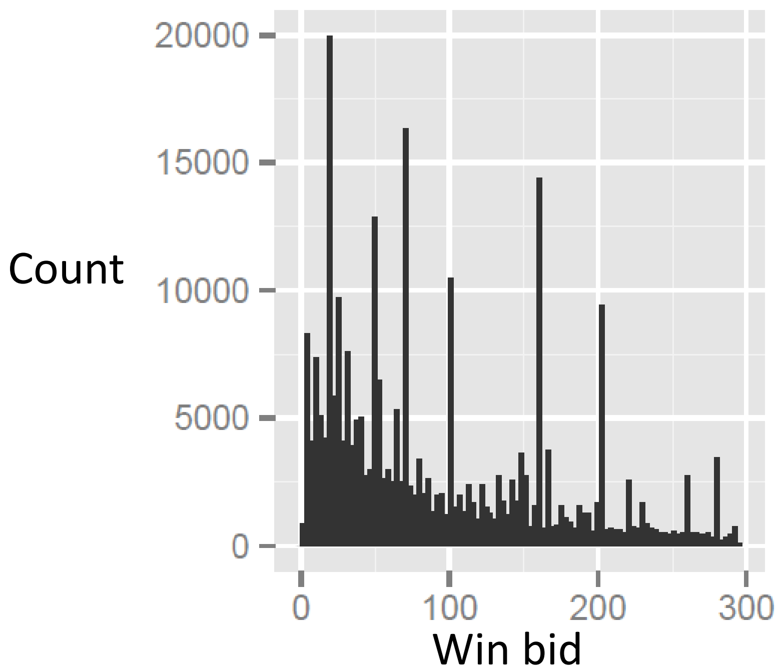
Bidding Strategy in Practice

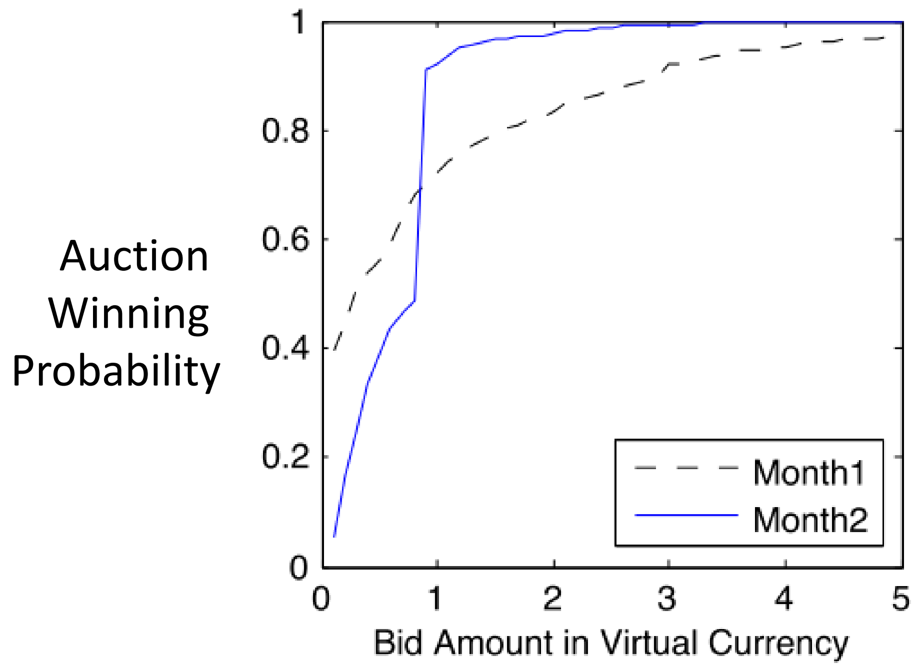


Bidding Strategy in Practice: A Quantitative Perspective



Bid Landscape Forecasting





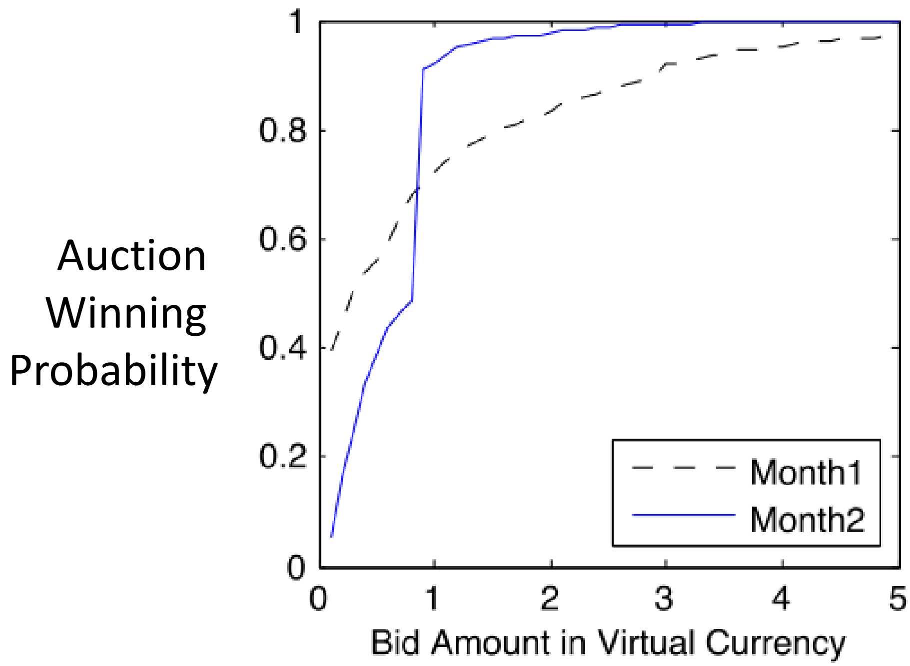
Win probability:

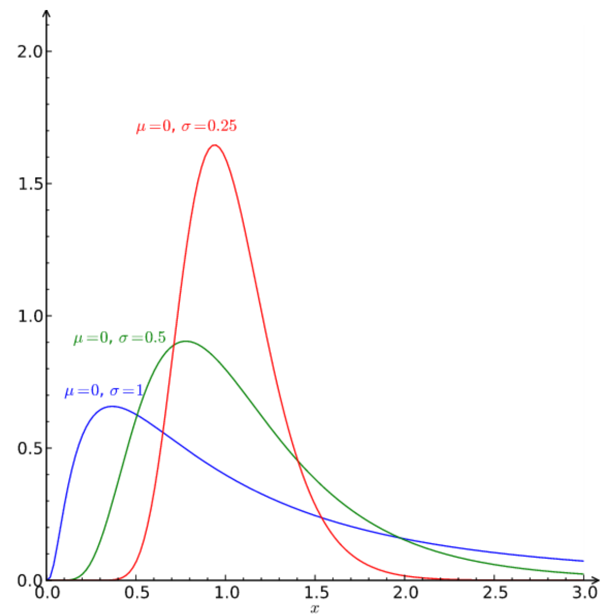
$$w(b) = \int_{z=0}^{b} p(z)dz$$

Expected cost:

$$c(b) = \frac{\int_{z=0}^{b} zp(z)dz}{\int_{z=0}^{b} p(z)dz}$$

Bid Landscape Forecasting





- Log-Normal Distribution

$$f_{\mathbf{s}}(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{\frac{-(ln x-\mu)^2}{2\sigma^2}}, x > 0$$

[Cui et al. Bid Landscape Forecasting in Online Ad Exchange Marketplace. KDD 11]

Bid Landscape Forecasting

- Price Prediction via Linear Regression

$$z = \boldsymbol{\beta}^T \boldsymbol{x} + \epsilon \qquad \max_{\boldsymbol{\beta}} \sum_{i \in W} \log \phi\Big(\frac{z_i - \boldsymbol{\beta}^T \boldsymbol{x}_i}{\sigma}\Big)$$

  - Modelling censored data in lost bid requests

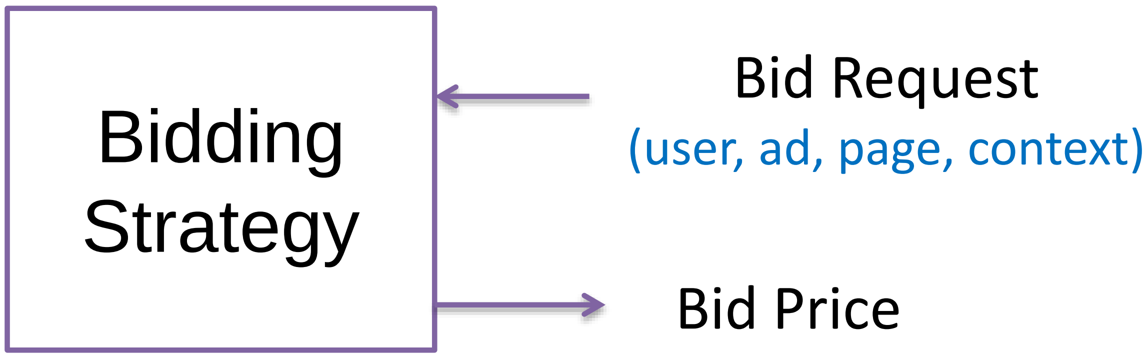
$$P(b_i < z_i) = \Phi\Big(\frac{\boldsymbol{\beta}^T \boldsymbol{x}_i - b_i}{\sigma}\Big)$$

$$\max_{\boldsymbol{\beta}} \sum_{i \in W} \log \phi\Big(\frac{z_i - \boldsymbol{\beta}^T \boldsymbol{x}_i}{\sigma}\Big) + \sum_{i \in L} \log \Phi\Big(\frac{\boldsymbol{\beta}^T \boldsymbol{x}_i - b_i}{\sigma}\Big)$$

[Wu et al. Predicting Winning Price in Real Time Bidding with Censored Data. KDD 15]

Bidding Strategies

- How much to bid for each bid request?



- Bid to optimise the KPI with budget constraint

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

Classic Second Price Auctions

- Single item, second price (i.e. pay market price)

Reward given a bid: $$R(b) = \int_0^b (r - z)p(z)dz$$

Optimal bid: $$b^* = \max_b R(b)$$

$$\frac{\partial R(b)}{\partial b} = (r - b)p(b)$$

$$\frac{\partial R(b)}{\partial b} = 0 \Rightarrow b^* = r$$ Bid true value

Truth-telling Bidding Strategies

- Truthful bidding in second-price auction
  - Bid the true value of the impression
  - Impression true value = $\begin{cases} \text{Value of click, if clicked} \\ \text{0, if not clicked} \end{cases}$
  - Averaged impression value = value of click * CTR
  - Truth-telling bidding:

$$\text{bid} = r_{\text{conv}} \times \text{CVR} \quad \text{or} \quad \text{bid} = r_{\text{click}} \times \text{CTR}$$

[Chen et al. Real-time bidding algorithms for performance-based display ad allocation. KDD 11]

Truth-telling Bidding Strategies

$$\text{bid} = r_{\text{conv}} \times \text{CVR} \quad \text{or} \quad \text{bid} = r_{\text{click}} \times \text{CTR}$$

- Pros
  - Theoretic soundness
  - Easy implementation (very widely used)
- Cons
  - Not considering the constraints of
    - Campaign lifetime auction volume
    - Campaign budget
  - Case 1: $1000 budget, 1 auction
  - Case 2: $1 budget, 1000 auctions

[Chen et al. Real-time bidding algorithms for performance-based display ad allocation. KDD 11]

Non-truthful Linear Bidding

- Non-truthful linear bidding

$$\text{bid} = \text{base\_bid} \times \frac{\text{predicted\_CTR}}{\text{base\_CTR}}$$

  - Tune base_bid parameter to maximise KPI
  - Bid landscape, campaign volume and budget indirectly considered

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

[Perlich et al. Bid Optimizing and Inventory Scoring in Targeted Online Advertising. KDD 12]

ORTB Bidding Strategies

- Direct functional optimisation

winning function CTR

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

bidding function

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

Est. volume cost upperbound

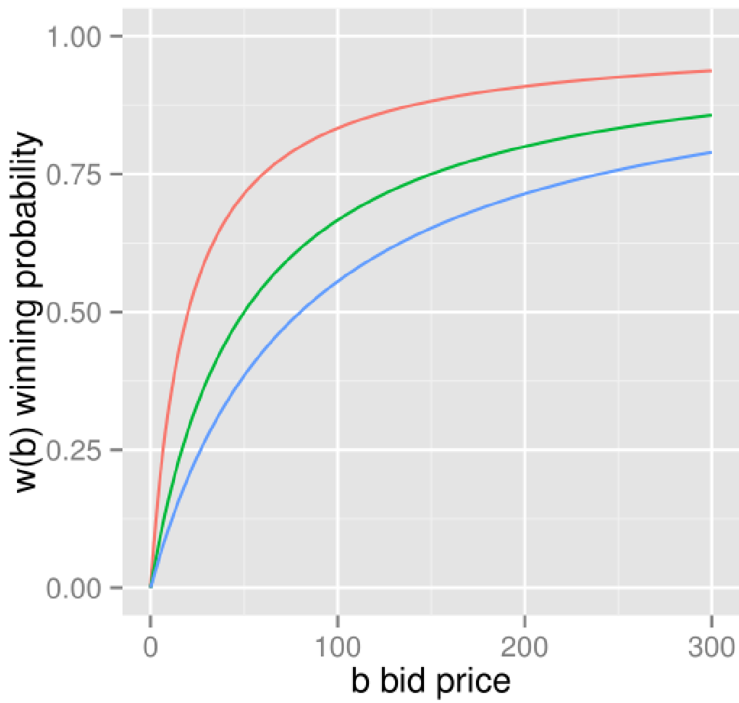
- Solution: Calculus of variations

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

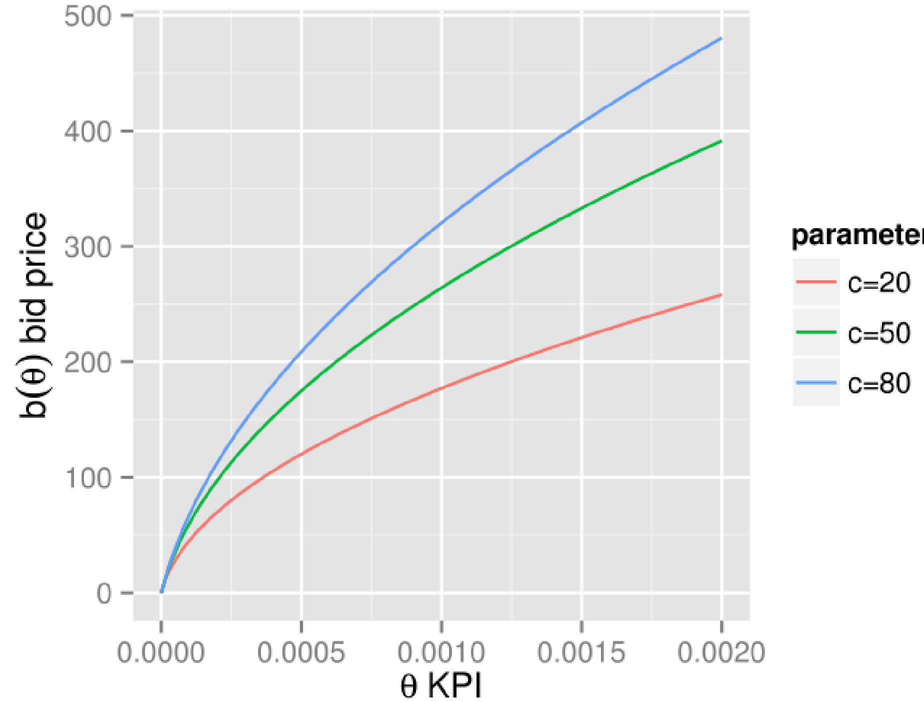
$$\frac{\partial \mathcal{L}(b(\theta), \lambda)}{\partial b(\theta)} = 0 \quad ➡ \quad \boxed{\lambda w(b(\theta)) = \Big[\theta - \lambda b(\theta)\Big] \frac{\partial w(b(\theta))}{\partial b(\theta)}}$$

[Zhang et al. Optimal real-time bidding for display advertising. KDD 14]

Optimal Bidding Strategy Solution



(a) Winning function 1.



(b) Bidding function 1.

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

[Zhang et al. Optimal real-time bidding for display advertising. KDD 14]

Bidding in Multi-Touch Attribution Mechanism

- Current bidding strategy
  - Driven by last-touch attribution b(CVR)

$$\text{bid} = r_{\text{conv}} \times \text{CVR}$$

- A new bidding strategy
  - Driven by multi-touch attribution

$$\text{bid} = r_{\text{conv}} \times \text{CVR} \times P(\text{attribution}|\text{conversion})$$

$$\Delta P = P(y|S, a) - P(y|S)$$

$$\text{bid} = \Delta P \times \text{base\_bid}$$

[Xu et al. Lift-Based Bidding in Ad Selection. AAAI 2016.]

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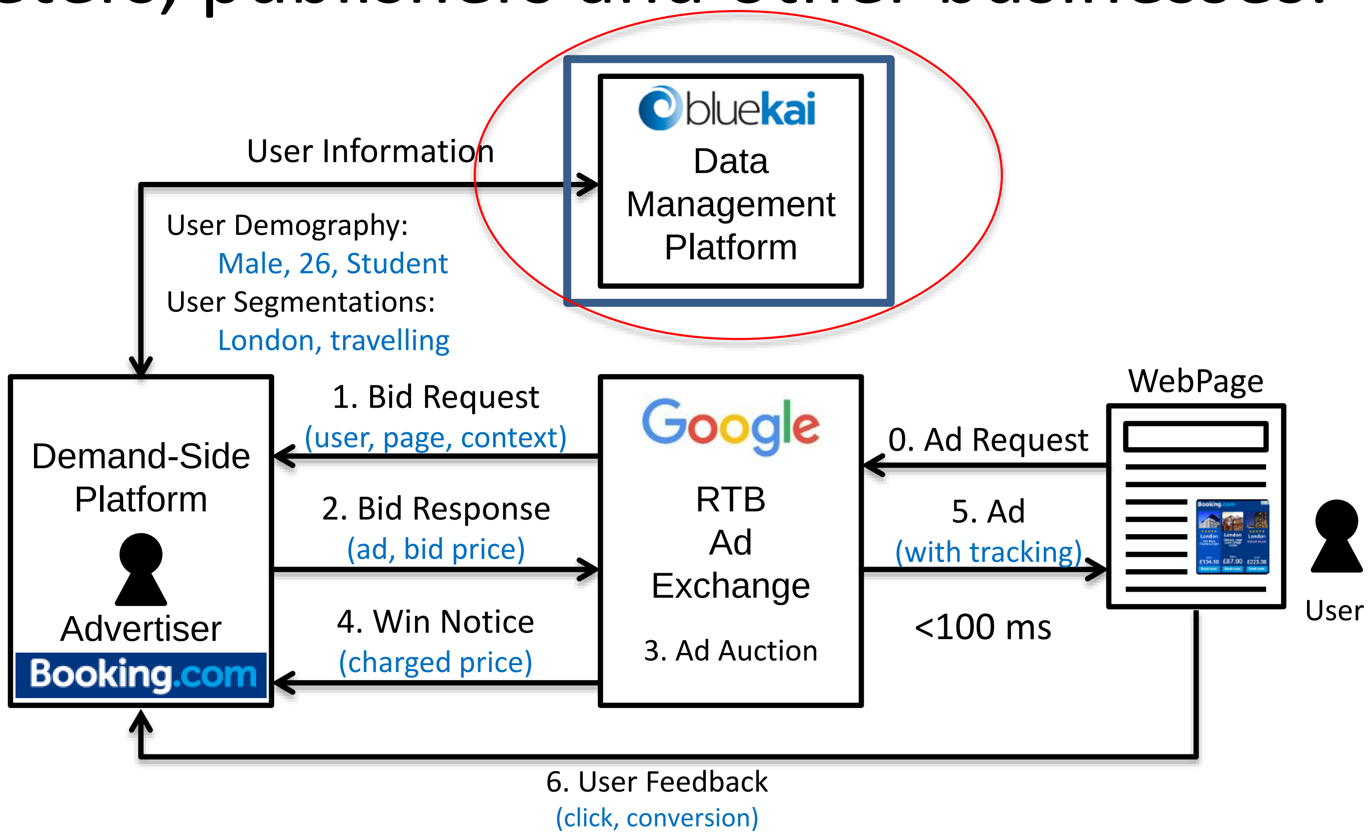
- RTB System
- Auction Mechanisms
- CTR Estimation
- Conversion Attribution
- Learning to Bid
- Data Management Platform (DMP) techniques
- Floor price optimisation
- Fighting against fraud

DMP Summary

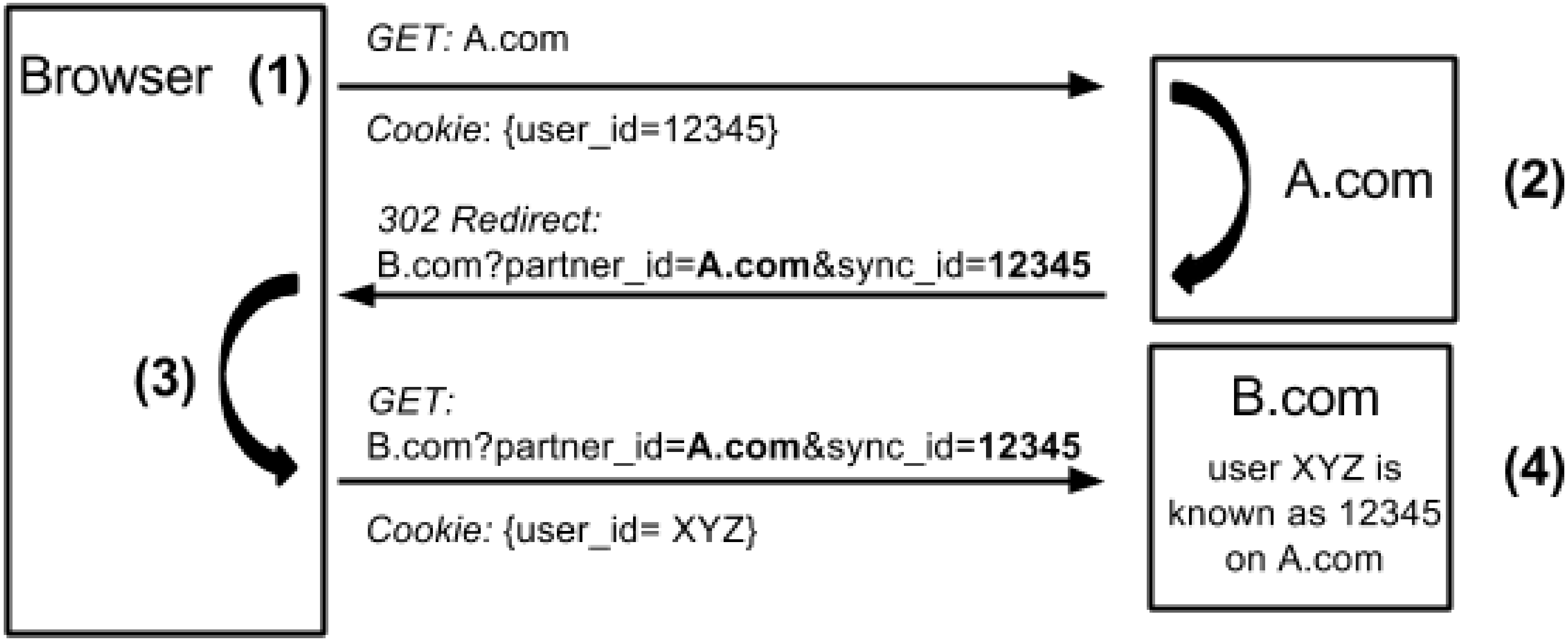
- What is data management platform
- Cook sync
- Browser fingerprinting
- CF and Lookalike model

What is DMP
(Data Management Platform)

- A data warehouse that stores, merges, and sorts, and labels it out in a way that's useful for marketers, publishers and other businesses.



Cookie sync: merging audience data



When a user visits a site (e.g. ABC.com) including A.com as a third-party tracker.

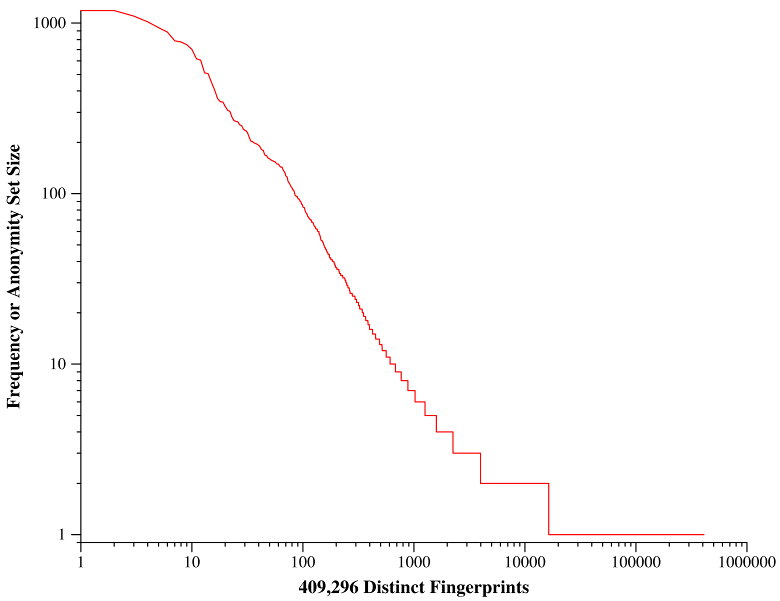
(1) The browser makes a request to A.com, and included in this request is the tracking cookie set by A.com.
(2) A.com retrieves its tracking ID from the cookie, and redirects the browser to B.com, encoding the tracking ID into the URL.
(3) The browser then makes a request to B.com, which includes the full URL A.com redirected to as well as B.com's tracking cookie.
(4) B.com can then link its ID for the user to A.com's ID for the user2

https://freedom-to-tinker.com/blog/englehardt/the-hidden-perils-of-cookie-syncing/

Browser fingerprinting

- A device fingerprint or browser fingerprint is information collected about the remote computing device for the purpose of identifying the user
- Fingerprints can be used to fully or partially identify individual users or devices even when cookies are turned off.

94.2% of browsers with Flash or Java were unique in a study

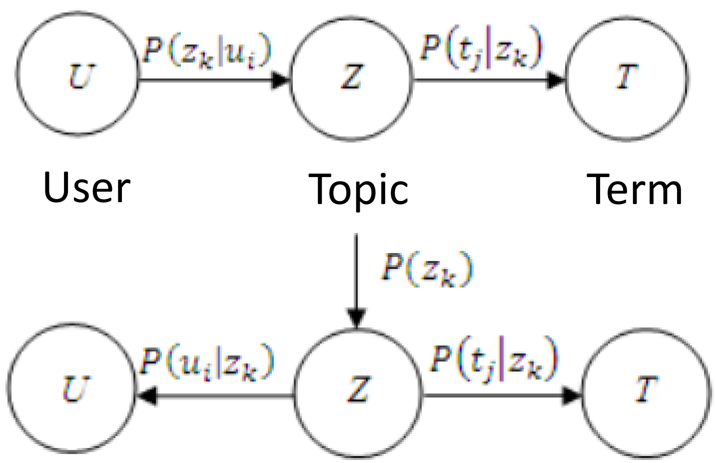


Eckersley, Peter. "How unique is your web browser?." Privacy Enhancing Technologies. Springer Berlin Heidelberg, 2010.

Acar, Gunes, et al. "The web never forgets: Persistent tracking mechanisms in the wild." Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security. ACM, 2014.

User segmentation and Behavioural Targeting

- Behavioural targeting helps online advertising
- From user – documents to user – topics
  - Latent Semantic Analysis / Latent Dirichlet Allocation



J Yan, et al., How much can behavioral targeting help online advertising? WWW 2009
X Wu, et al., Probabilistic latent semantic user segmentation for behavioral targeted advertising, Intelligence for Advertising 2009

Lookalike modelling

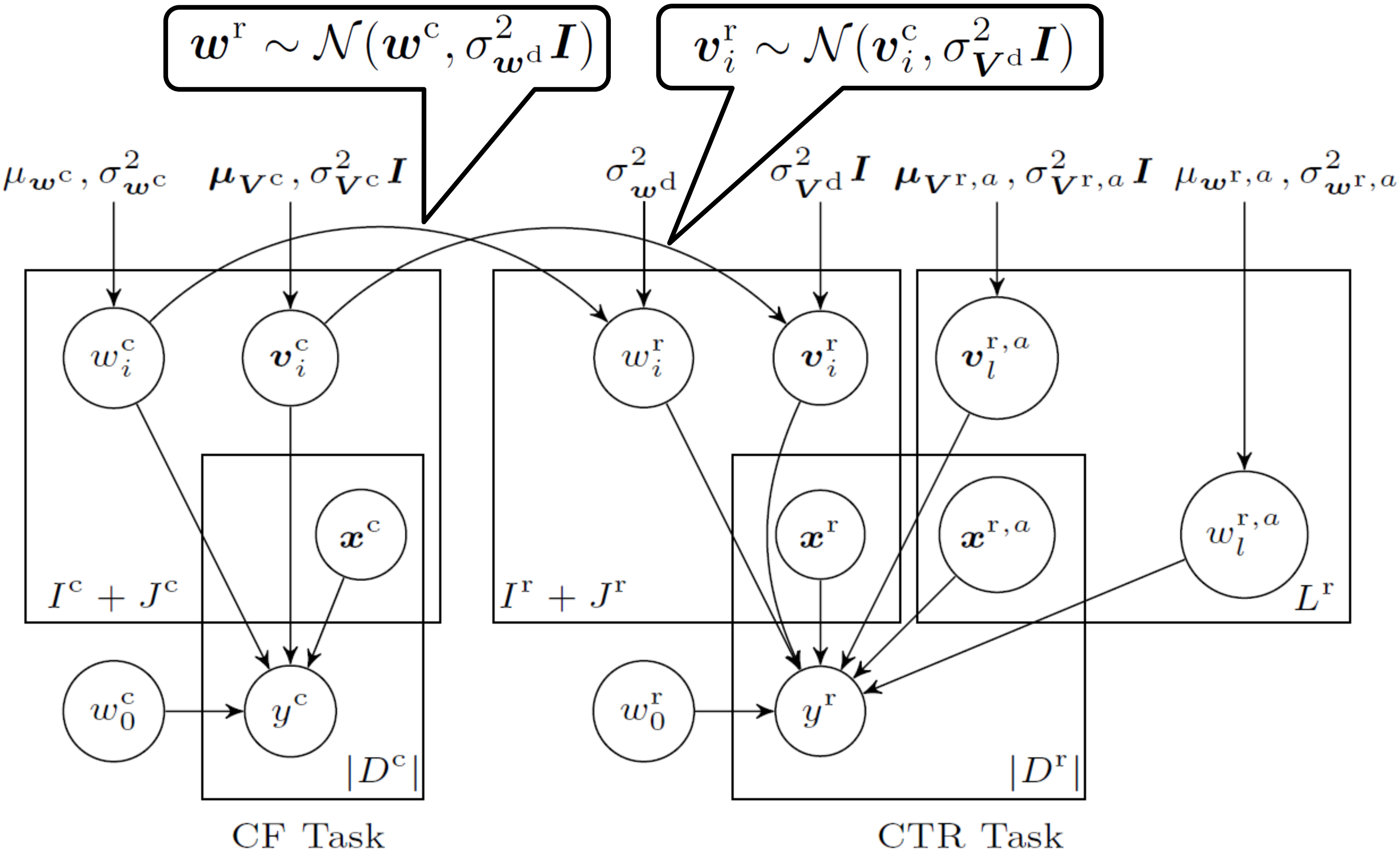
- Lookalike modeling: finding new people who behave like current customers (converted)

	 Die Hard	 Mission: Impossible	 GoldenEye	 Casino Royale	 Titanic	 Notting Hill	 Bridget Jones's Diary	 Love Actually
Boris	★★★☆☆	★★★★☆	★★★★★			★☆☆☆☆		?
Dave		★★★★★	★★★★★	★★★★★				★☆☆☆☆
Will		★★☆☆☆			★★★★★	★★★★★	★★★☆☆	★★★★☆
George	★★★★☆	★★★★★	★★★★☆	★★★★☆				★★☆☆☆

Zhang, Weinan, Lingxi Chen, and Jun Wang. "Implicit Look-alike Modelling in Display Ads: Transfer Collaborative Filtering to CTR Estimation." ECIR (2016).

Transferred lookalike

Using web browsing data, which is largely available, to infer the ad clicks



Zhang, Weinan, Lingxi Chen, and Jun Wang. "Implicit Look-alike Modelling in Display Ads: Transfer Collaborative Filtering to CTR Estimation." ECIR (2016). In Wednesday Information Filtering Track

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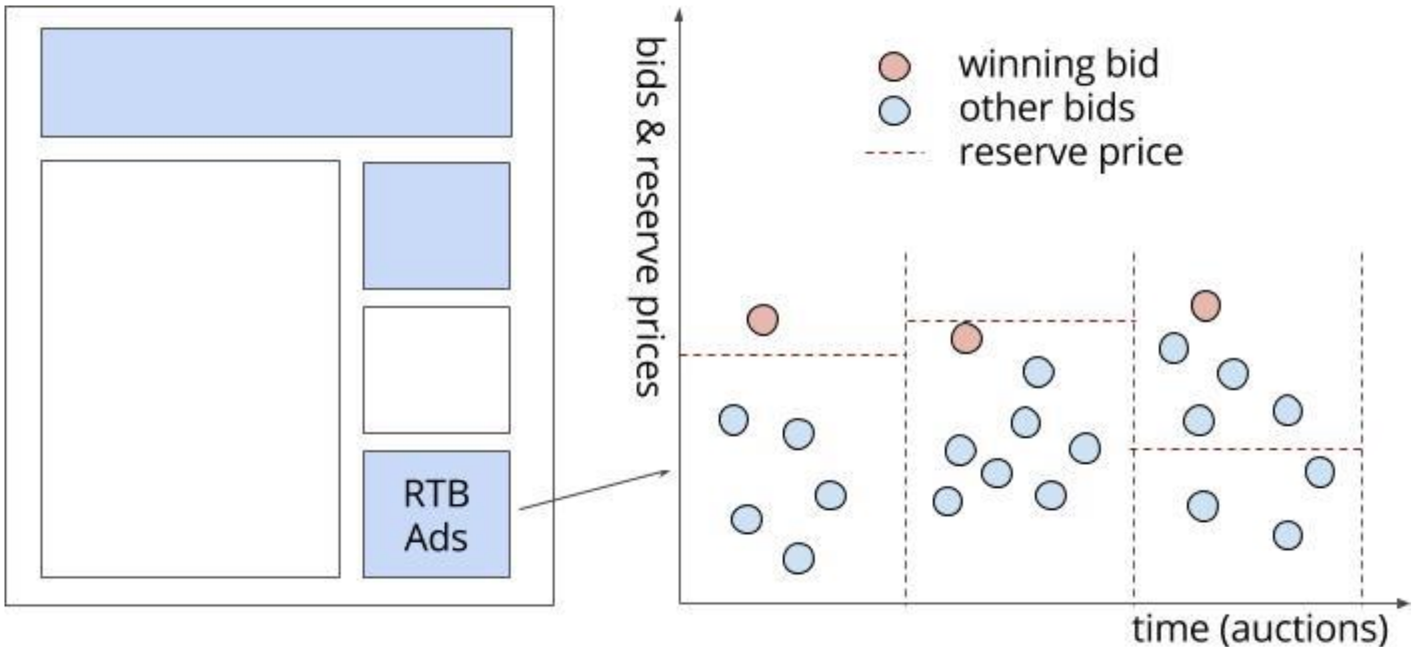
Reserve price optimisation



The task:

- To find the optimal reserve prices

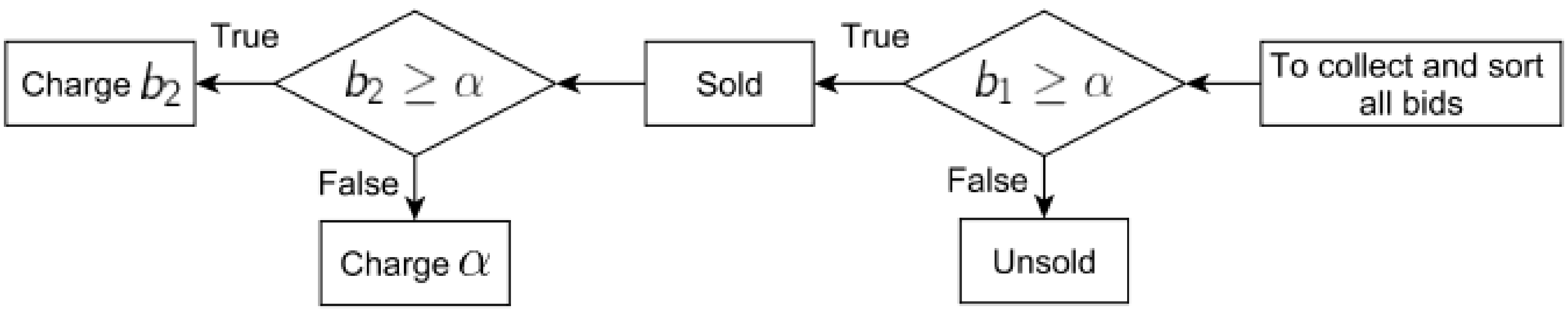
The challenge:

- 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 $[b_1, \dots, b_K]$ $F(\boldsymbol{b}) = F_1(b_1) \times \cdots \times F_K(b_K)$
- Private values -> Bids' distributions
  - Uniform
  - Log-normal
- The publisher also has a private value V_p
- The optimal reserve price is given by: $\alpha - \dfrac{1 - F(\boldsymbol{b})}{F'(\boldsymbol{b})} - V_p = 0$

Levin and Smith, Optimal Reservation Prices in Auctions, 1996

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 $\geq 20¢$)

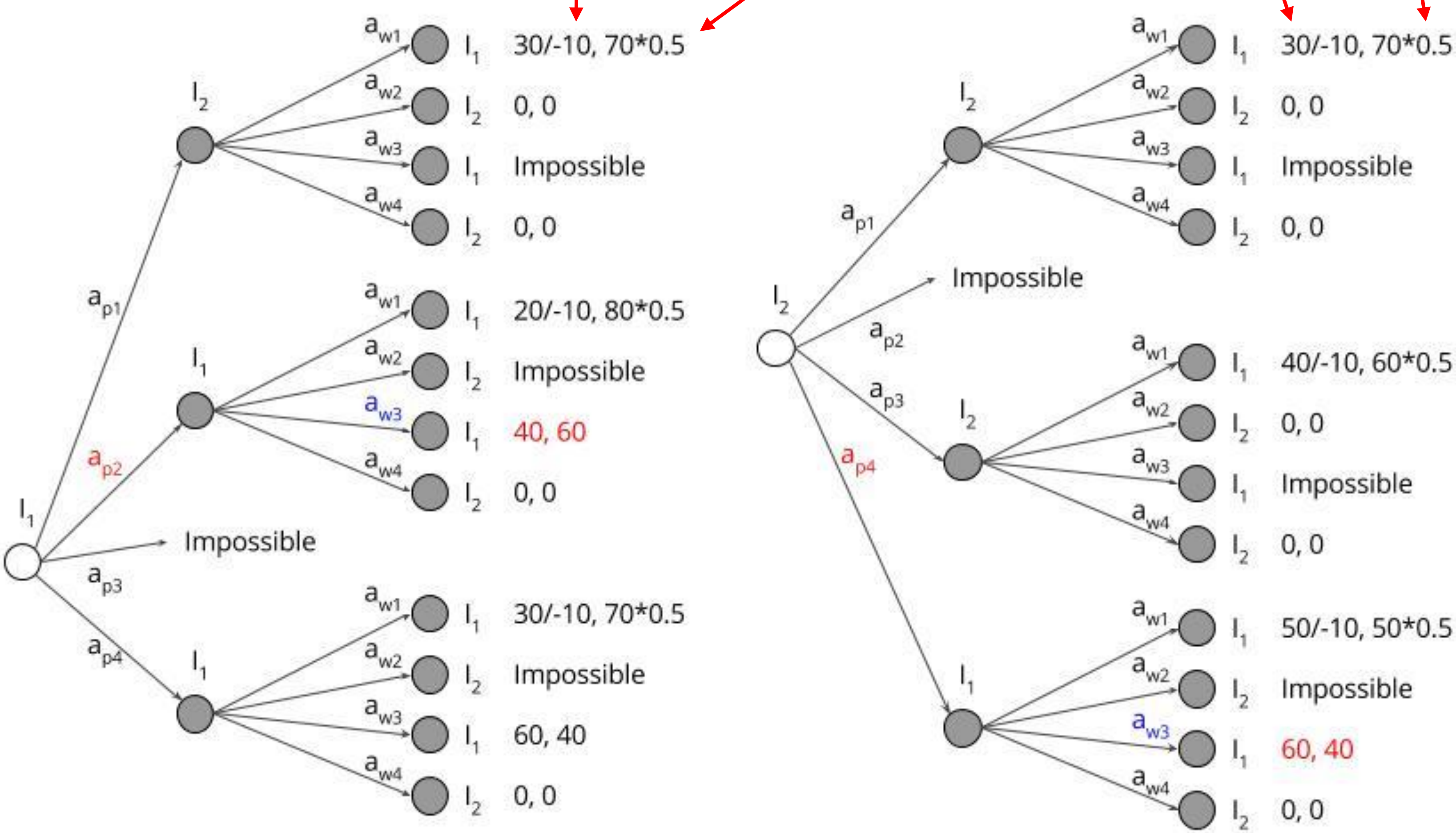
Variable	Value	t-statistic	p-value
Number of keywords (T – treatment group)	216,383		
Number of keywords (C – control group)	11,401		
(Mean change in depth in T)−(mean change in depth in C)	−0.9664	−55.09	< 0.0001
(Mean change in revenue in T)−(mean change in revenue in C)	14.59%	1.79	0.0736
Estimated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

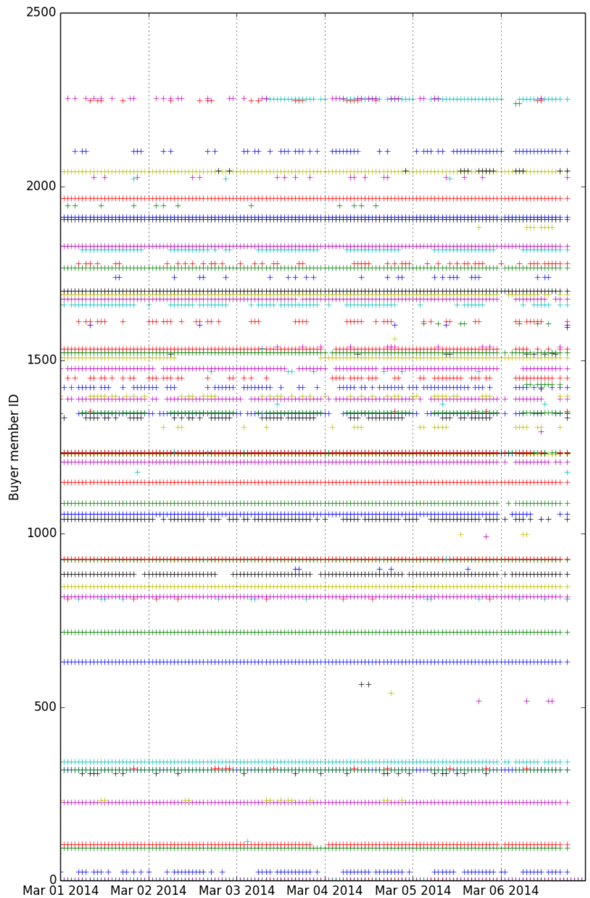
Ostrovsky and Schwarz , Reserve prices in internet advertising auctions: A field experiment, 2011

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 $b_1 \geq \alpha$)

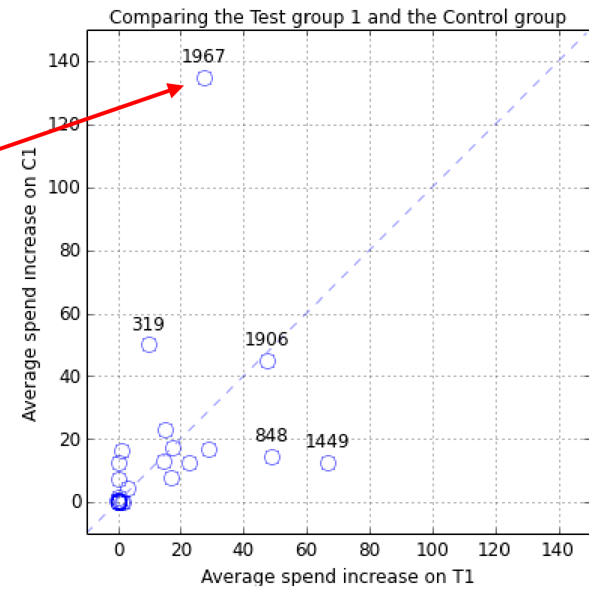
3) One won't do that,
so discounted publisher's payoff



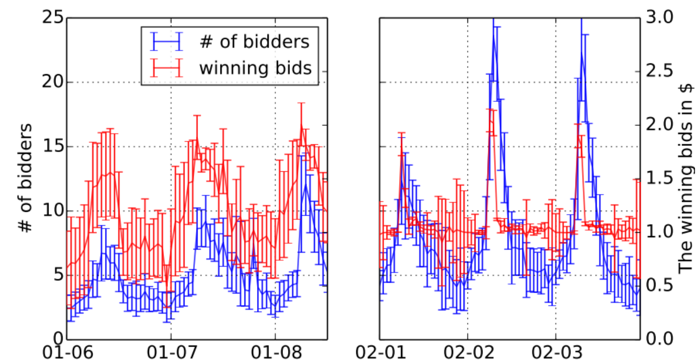


The continuous bidding activity

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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Fighting publisher fraud

- Non intentional traffic (NIT) / Non human traffic
  - Web scrapers / crawlers
  - Hacking tools
  - Botnet

  - Much of the spurious traffic is created by human but without users' knowledge

A Serious Problem

We realized this by testing out a buying platform in Atlas last year. During that test, we plugged into a number of the usual exchanges and bought across several formats. There were two major takeaways:

1. We were able to deliver ads to real people with unprecedented accuracy, but came up against many bad ads and fraud (like bots). While we were fortunately able to root out the bad actors and only buy quality ads, we were amazed by the volume of valueless inventory.
2. Only two ad formats delivered significant value: native & video.

Based on those findings, we began to dig into the ads that came through LiveRail. And when we saw the same thing, we immediately shut off the low quality ads. In fact, we removed over 75% of the volume coming from our exchange by turning off publishers circulating bad inventory into LiveRail. We knew that in good conscience, we couldn't sell what Atlas and our people-based measurement told us was valueless. Unfortunately, those ads were almost certainly dumped into another low-quality exchange where all of them were most likely purchased.

Dave Jakubowski, Head of Ad Tech, Facebook, March 2016

The Old Fashion Way

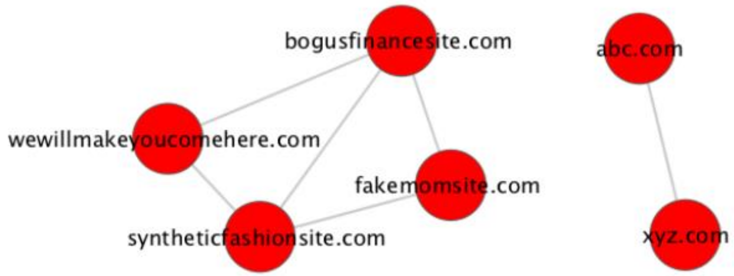
- Put the police on the street
  - Manually eyeball the webpage
  - Verify the address on the Google map
- Follow how the money flows
- This approach just can’t scale and is not sustainable

Possible Solutions

- Rules
- Anomaly detection
- Classification algorithm
  - Tricky to obtain negative samples
- Clustering algorithm
  - Bots could display dramatically different behavior
- Content Analysis
  - Fraudulent websites often scrape content from each other or legit websites

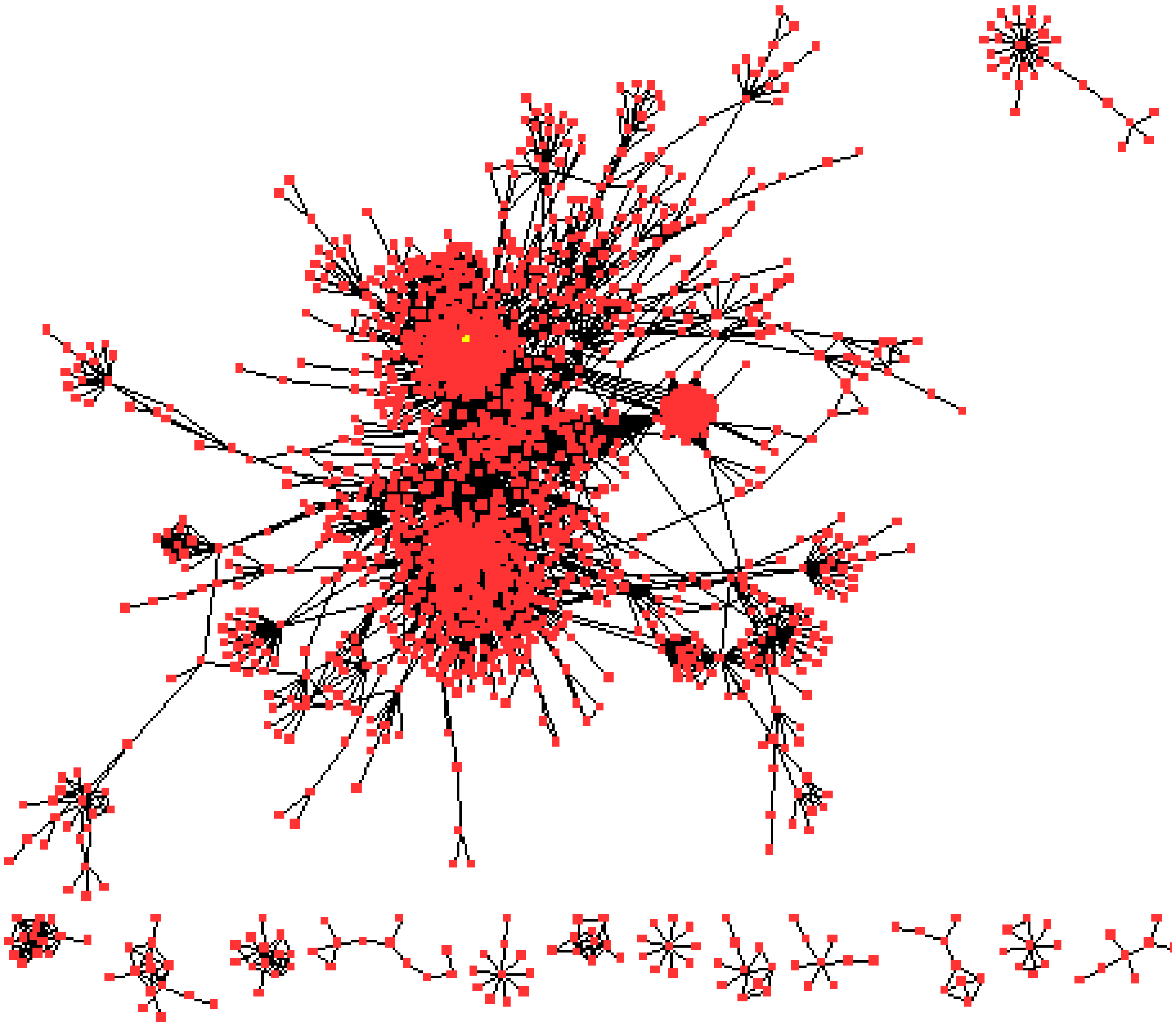
Co-Visitation Networks

- Key observation:
  - Even the major sites only share at most 20% cookieID within a few hours, let alone those long tail sites.
- Define a graph:
  - Node: site
  - Weighted edge: user overlap ratio of two sites



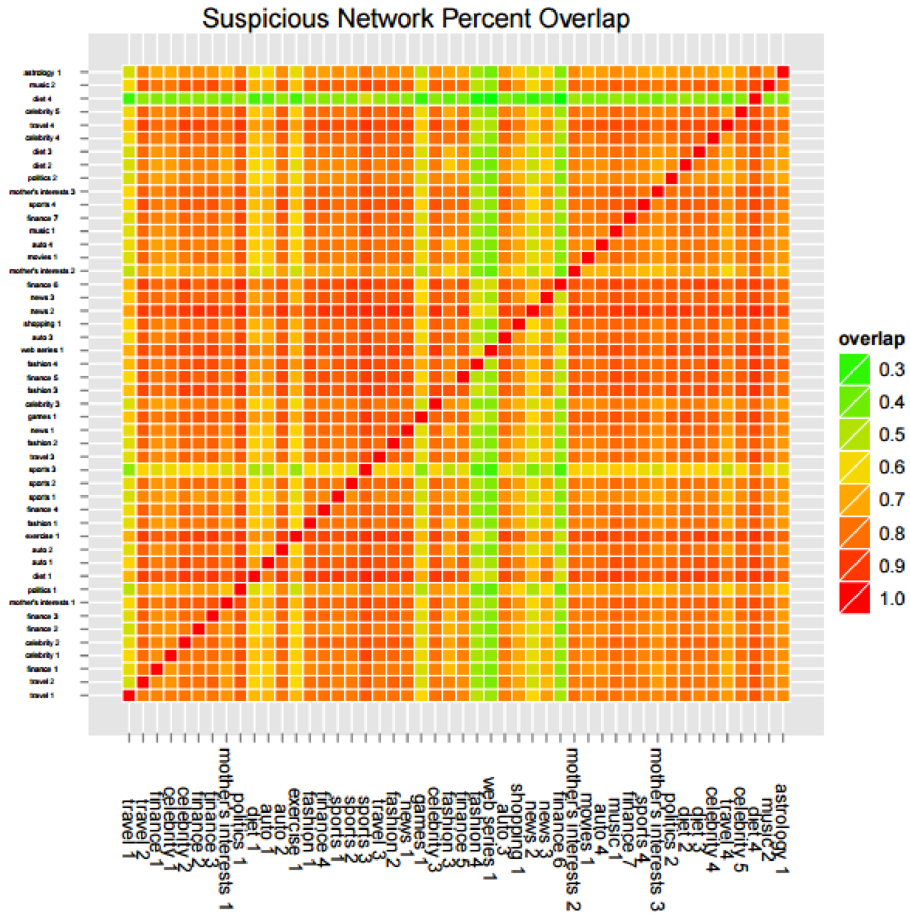
- Cluster this weighted undirected graph
- Fraud: big cluster with long tail sites

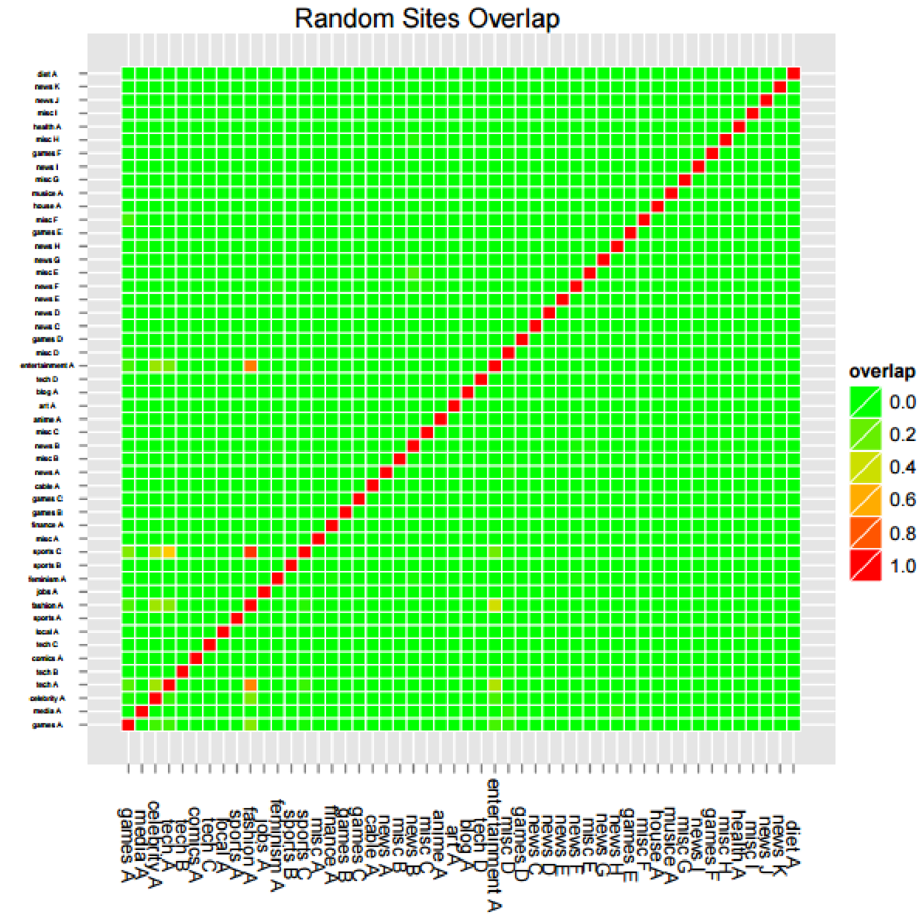
O Stitelman, et al., Using Co-Visitation Networks For Classifying Non-Intentional Traffic, KDD 2013



December 2011 Co-visitation Network where and edge indicates at least 50% overlap be- tween the browsers of both websites

O Stitelman, et al., Using Co-Visitation Networks For Classifying Non-Intentional Traffic, KDD 2013





O Stitelman, et al., Using Co-Visitation Networks For Classifying Non-Intentional Traffic, KDD 2013

Real-Time Bidding based Display Advertising: Mechanisms and Algorithms

Thank You

- RTB system
- Auction mechanisms
- User response estimation
- Conversion attribution
- Learning to bid
- Data Management Platform (DMP) techniques
- Floor price optimisation
- Fighting against fraud