Research Frontier of Real-Time Bidding based Display Advertising

Weinan Zhang
University College London
w.zhang@cs.ucl.ac.uk
http://www0.cs.ucl.ac.uk/staff/w.zhang

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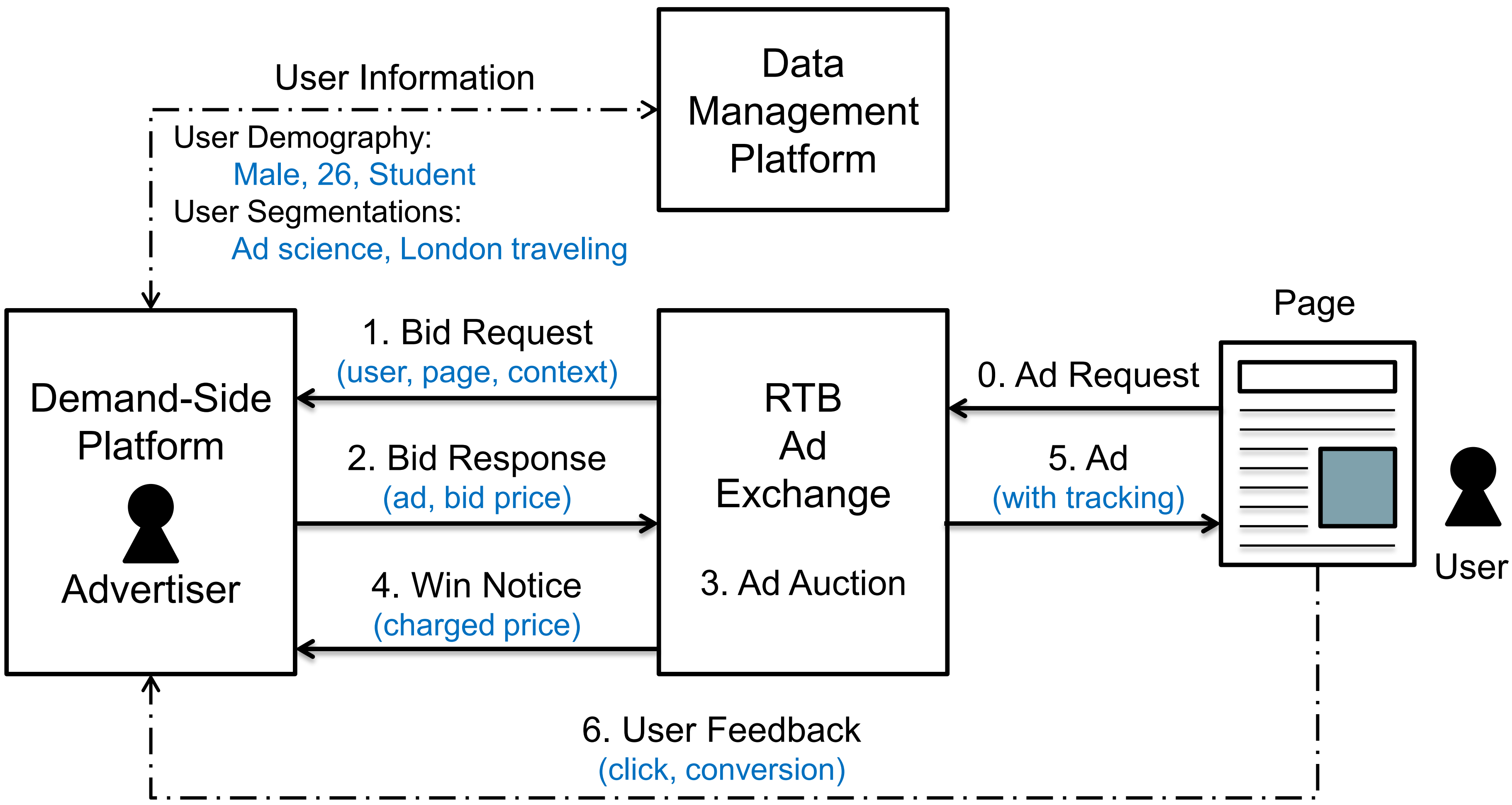
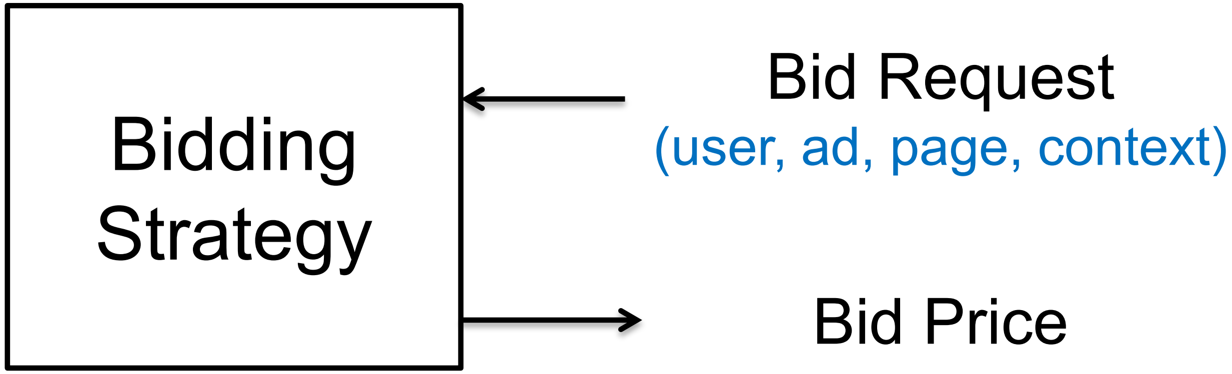
Basic RTB Process

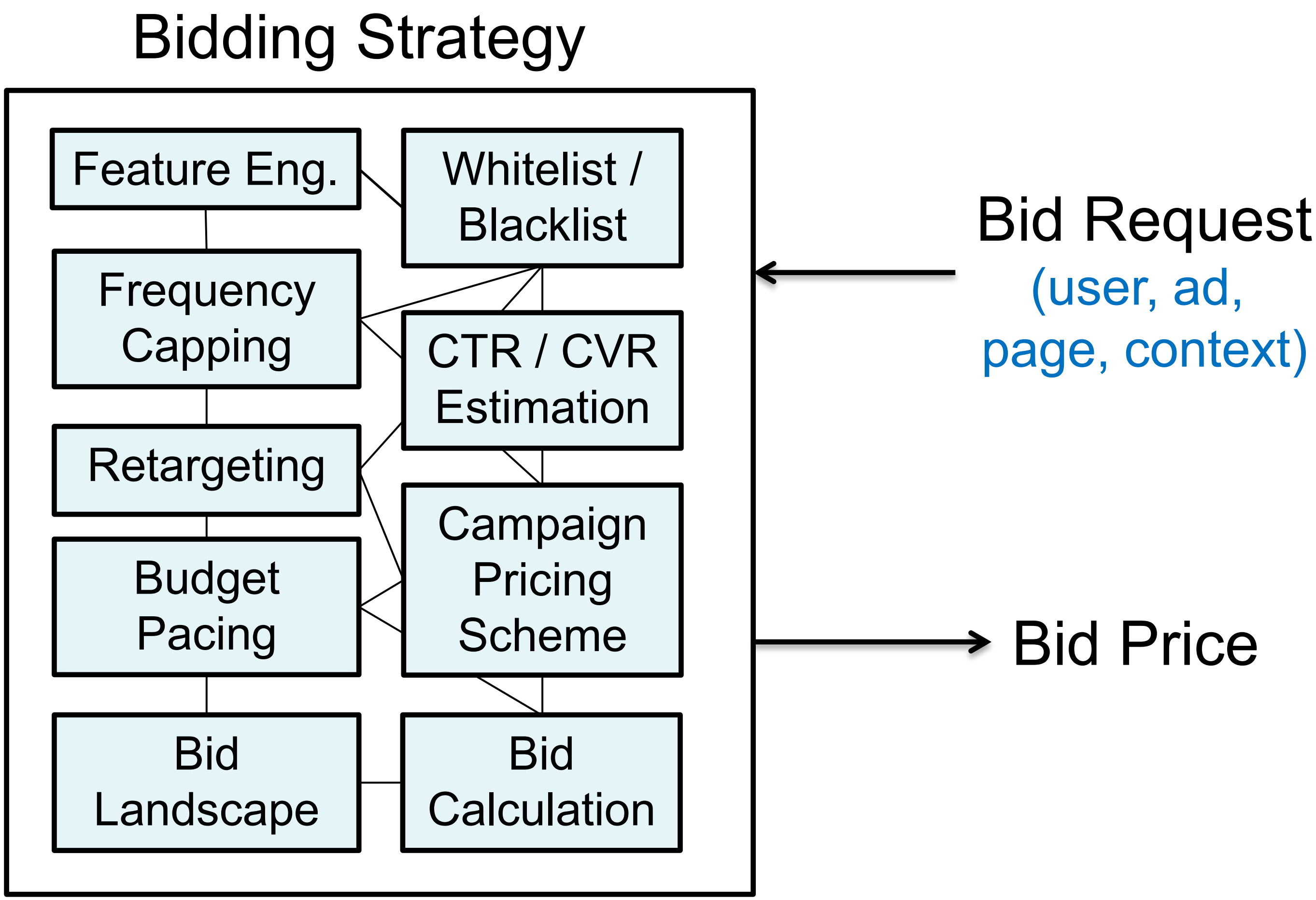


Model Bidding Strategy

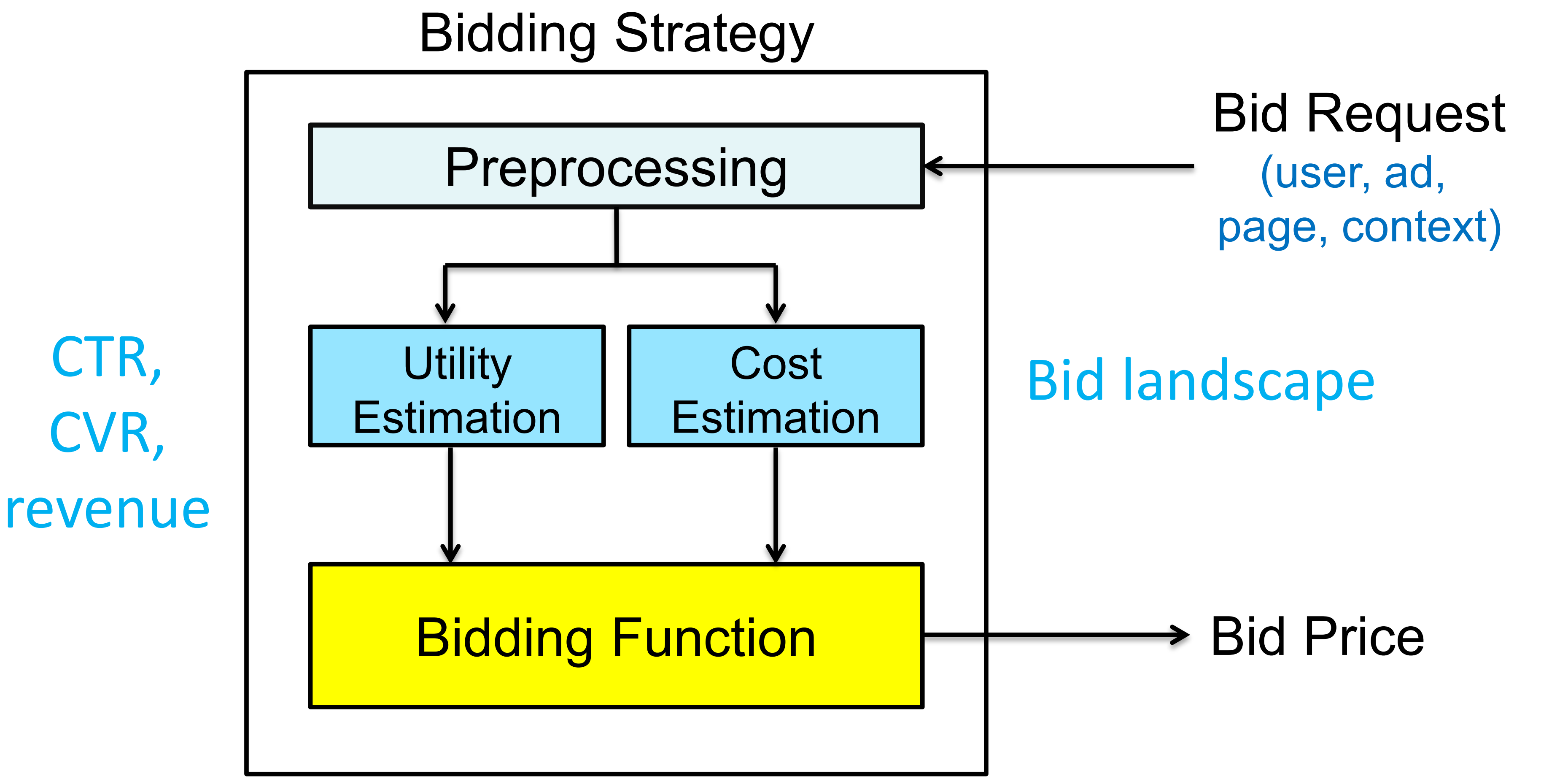


- A function mapping from bid request feature space to a bid price
- Design this function to optimise the advertising key performance indicators (KPIs)

Bidding Strategy in Practice



Bidding Strategy in Practice: New Perspective



Discussed Topics of This Talk

Fundamentals

- CTR/CVR Estimation
- Bid Landscape Forecasting
- Bidding Strategies

Advances

- Arbitrage
- Unbiased Training and Optimisation
- Conversion Attribution

CTR/CVR Estimation

- A seriously unbalanced-label binary regression problem

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

  – Negative down sampling, calibration

- Logistic Regression

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

$$\min_{\boldsymbol{w}} \sum_{(y,\boldsymbol{x})\in D} \log(1 + e^{-y\boldsymbol{w}^T\boldsymbol{x}}) + \frac{\lambda}{2}||\boldsymbol{w}||_2^2$$

CTR/CVR Estimation

- Follow-The-Regularised-Leader (FTRL) regression
  [McMahan et al. Ad Click Prediction : a View from the Trenches. KDD 13]

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

$$\mathbf{g}_{1:t} = \textstyle\sum_{s=1}^{t} \mathbf{g}_s \qquad \sigma_s = \sqrt{s} - \sqrt{s-1}$$

Closed-form solution

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

$$\mathbf{z}_{t-1} = \mathbf{g}_{1:t-1} - \textstyle\sum_{s=1}^{t-1} \sigma_s \mathbf{w}_s$$

CTR/CVR Estimation

- Factorisation Machines

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

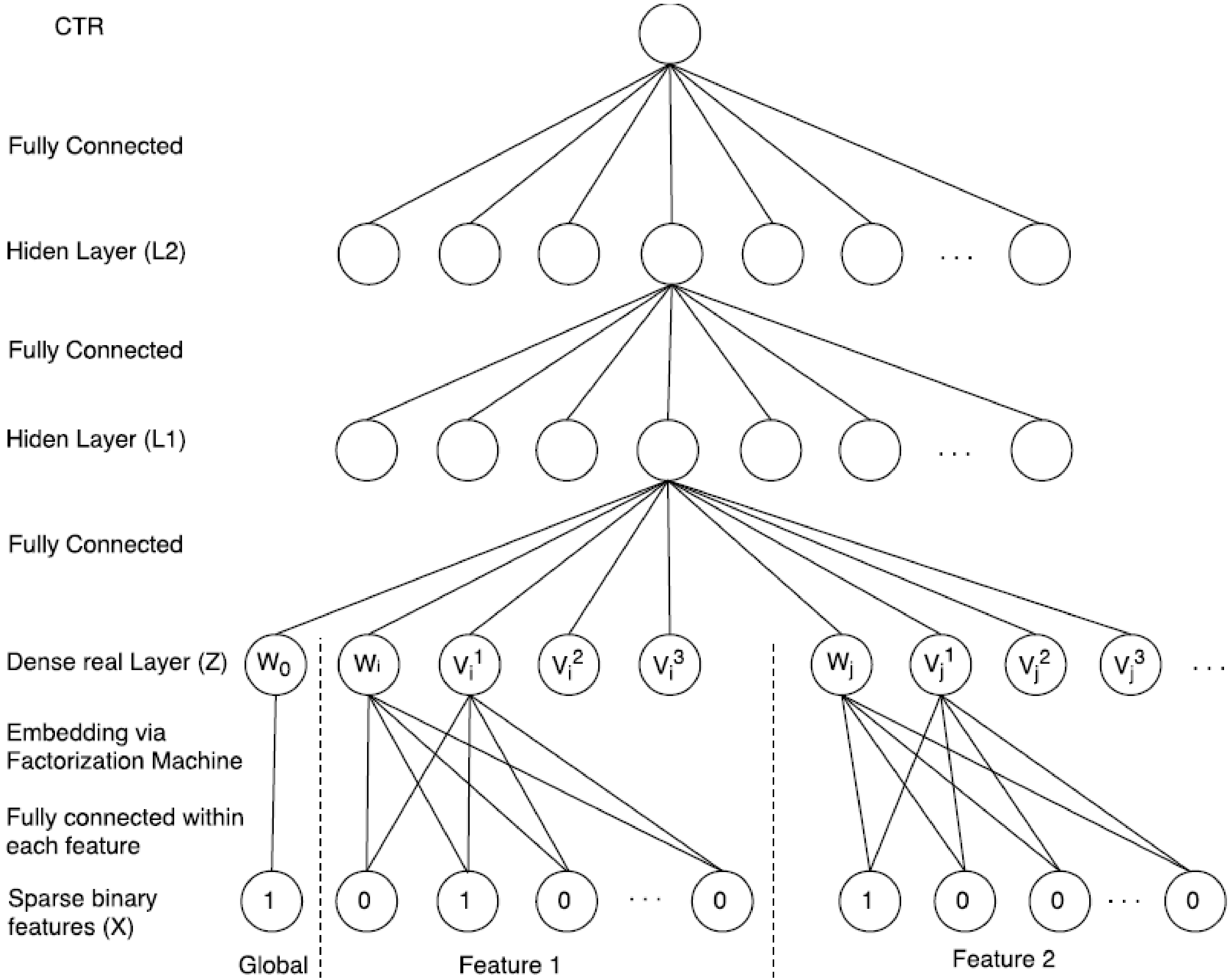
$$\hat{y}(\boldsymbol{x}) = \sigma\left(w_0 + \sum_{i=1}^{n} w_i x_i + \sum_{i=1}^{n} \sum_{j=i+1}^{n} x_i x_j \boldsymbol{v}_i^T \boldsymbol{v}_j\right)$$

  - Explicitly model feature interactions
  - Empirically better than logistic regression
  - A new way for **user profiling**

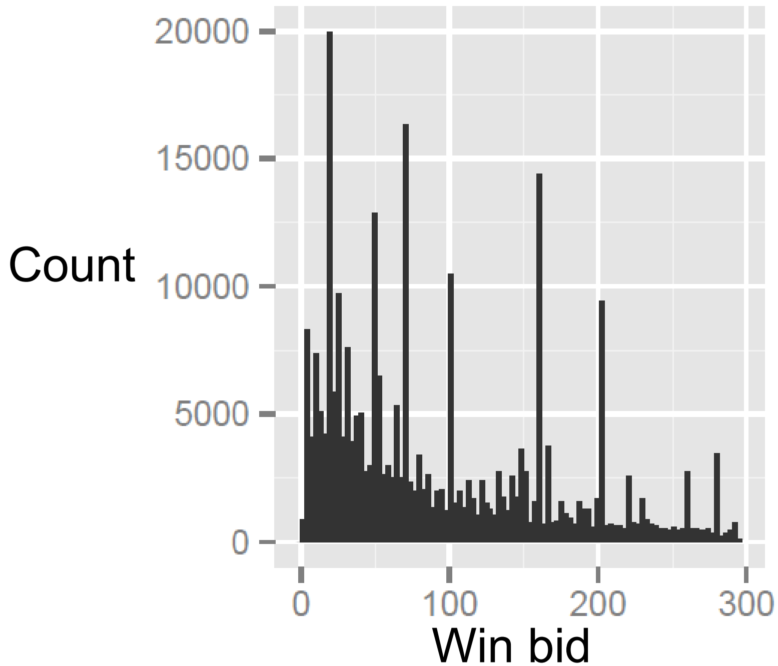
- GBDT+FM

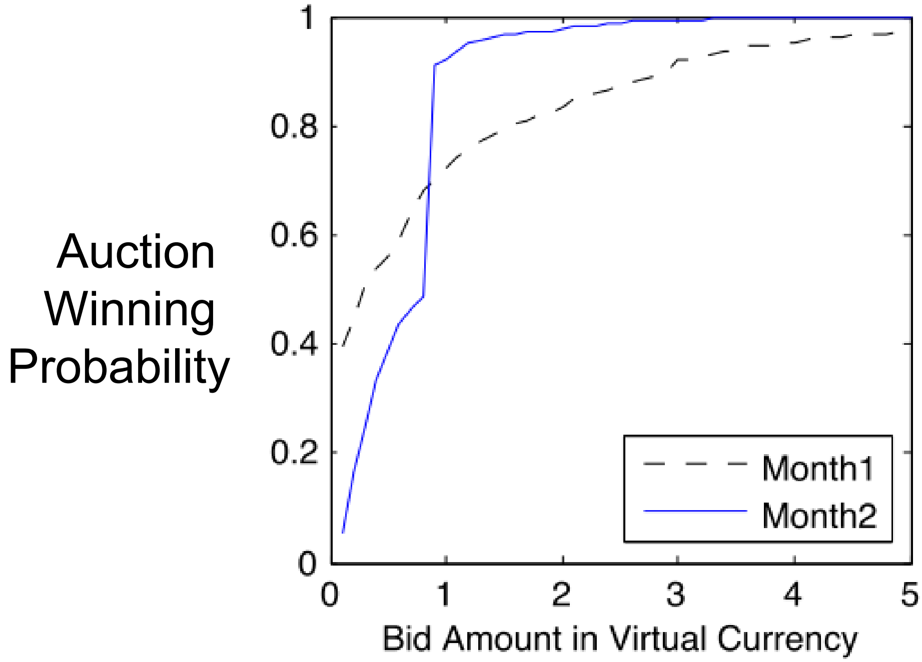
  [http://www.csie.ntu.edu.tw/~r01922136/kaggle-2014-criteo.pdf]

Deep Learning Models [our working project]



Bid Landscape Forecasting





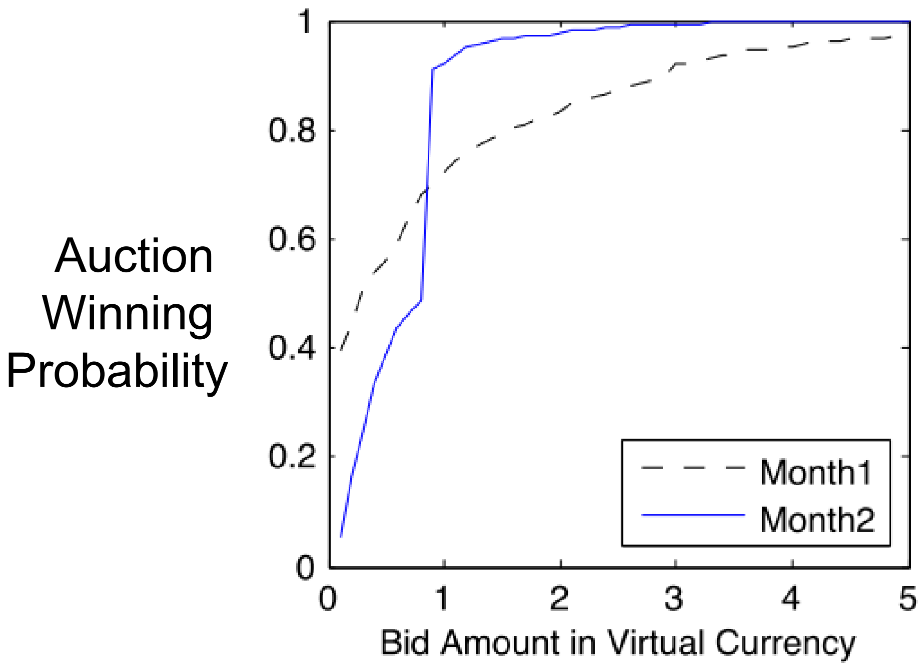
Win probability:

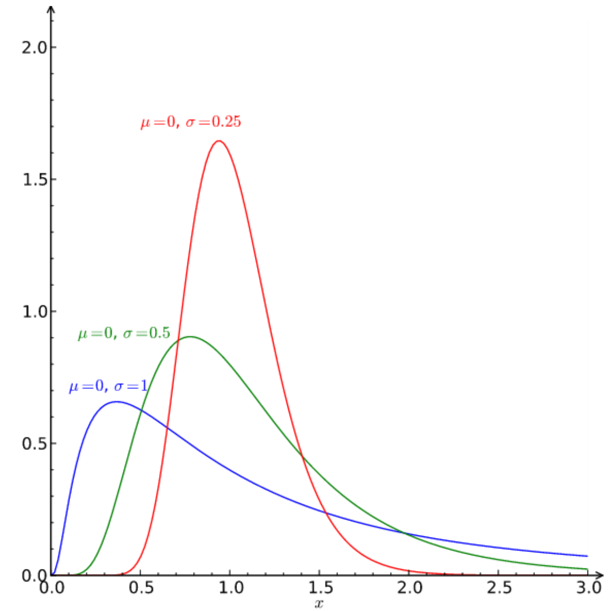
$$w(b) = \int_{z=0}^{b} p(z)dz$$

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

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

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

Bid Landscape Forecasting

- Price Prediction via Linear Regression

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

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

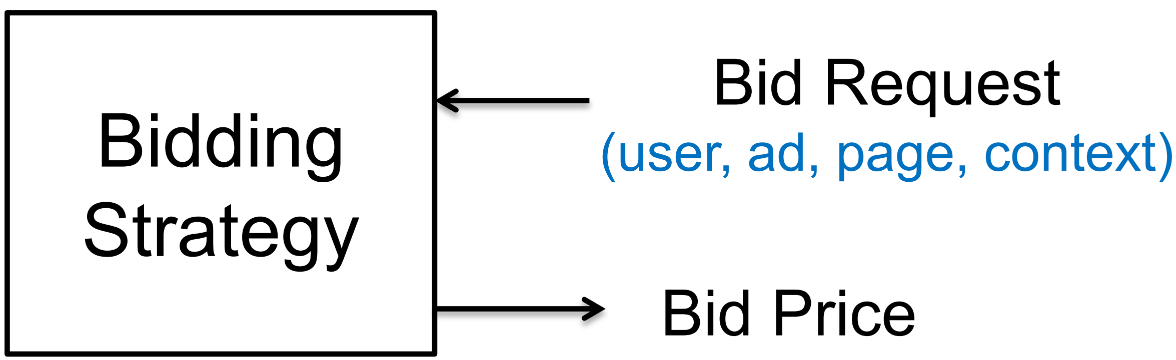
  - Modelling censored data in lost bid requests

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

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

Bidding Strategies

- How much to bid for each bid request?



- Bid to optimise the KPI with budget constraint

$$\max_{\text{bidding strategy}} \quad \text{KPI}$$

$$\text{subject to} \quad \text{cost} \leq \text{budget}$$

Bidding Strategies

- Truthful bidding in second-price auction
  [Chen et al. Real-time bidding algorithms for performance-based display ad allocation. KDD 11]
  - Bid the true value of the impression

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

- Non-truthful linear bidding
  [Perlich et al. Bid Optimizing and Inventory Scoring in Targeted Online Advertising. KDD 12]
  - With budget and volume consideration

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

Bidding Strategies

- Direct functional optimisation

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

winning function CTR

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

bidding function

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

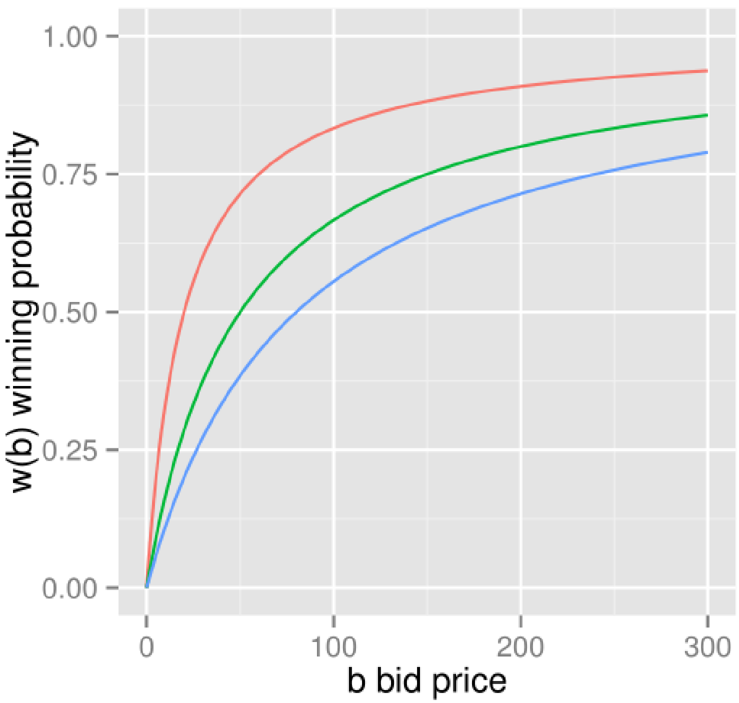
Est. volume

- Solution: Calculus of variations

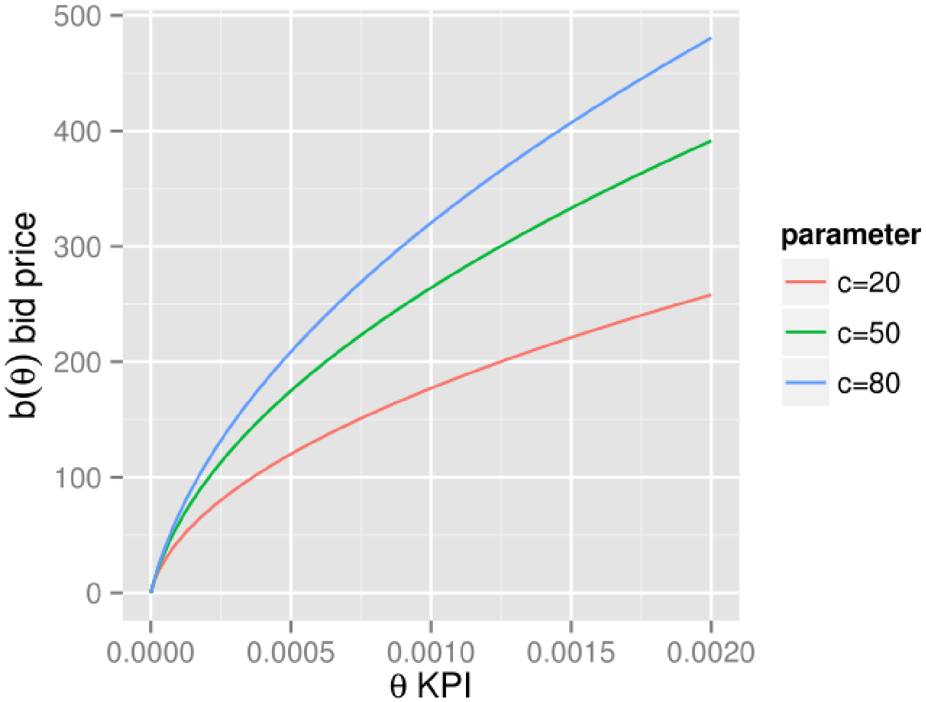
$$\mathcal{L}(b(\theta), \lambda) = \int_\theta \theta w(b(\theta)) p_\theta(\theta) d\theta \; - \lambda \int_\theta b(\theta) w(b(\theta)) p_\theta(\theta) d\theta + \frac{\lambda B}{N_T}$$

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

Optimal Bidding Strategy Solution



(a) Winning function 1.



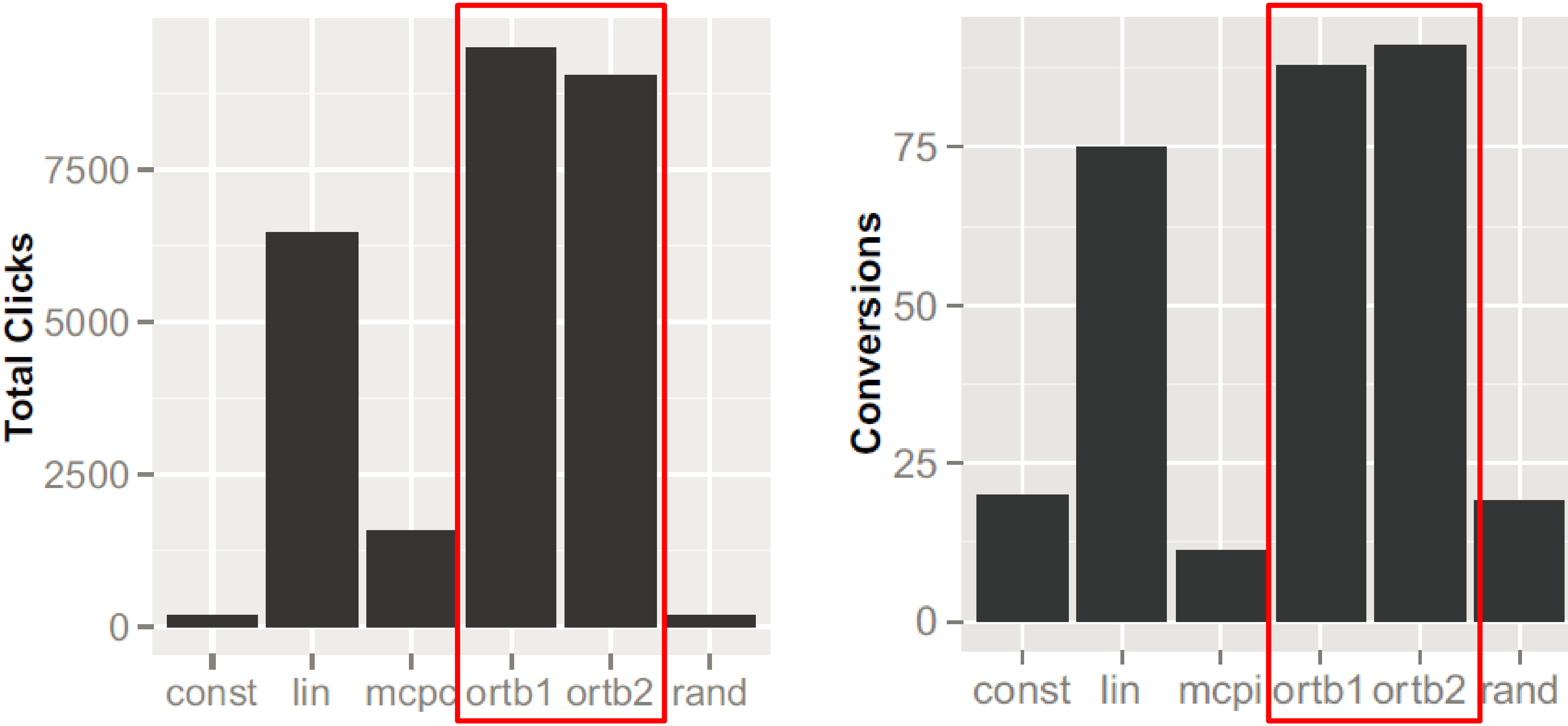
(b) Bidding function 1.

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

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

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

Overall Performance – Optimising Clicks or Conversions



iPinYou dataset

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

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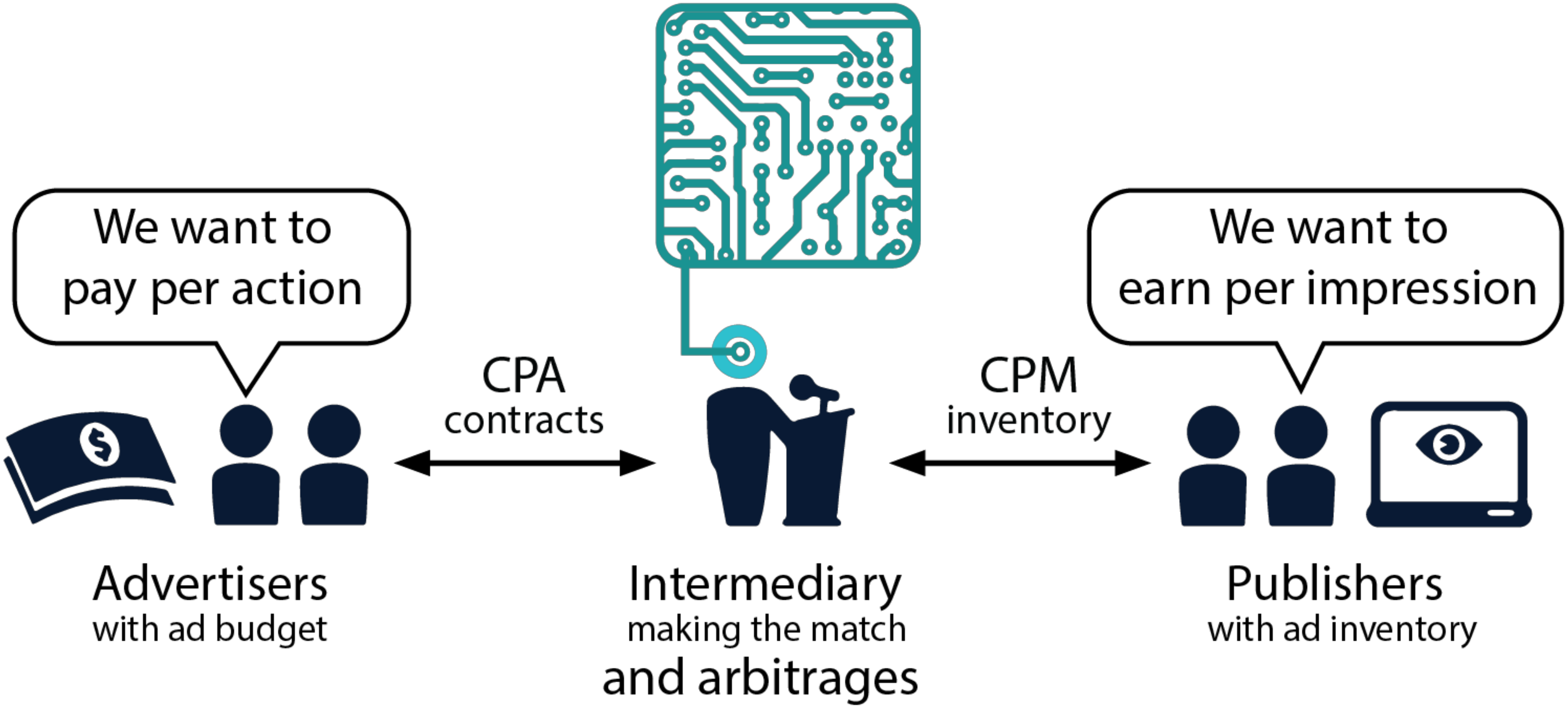
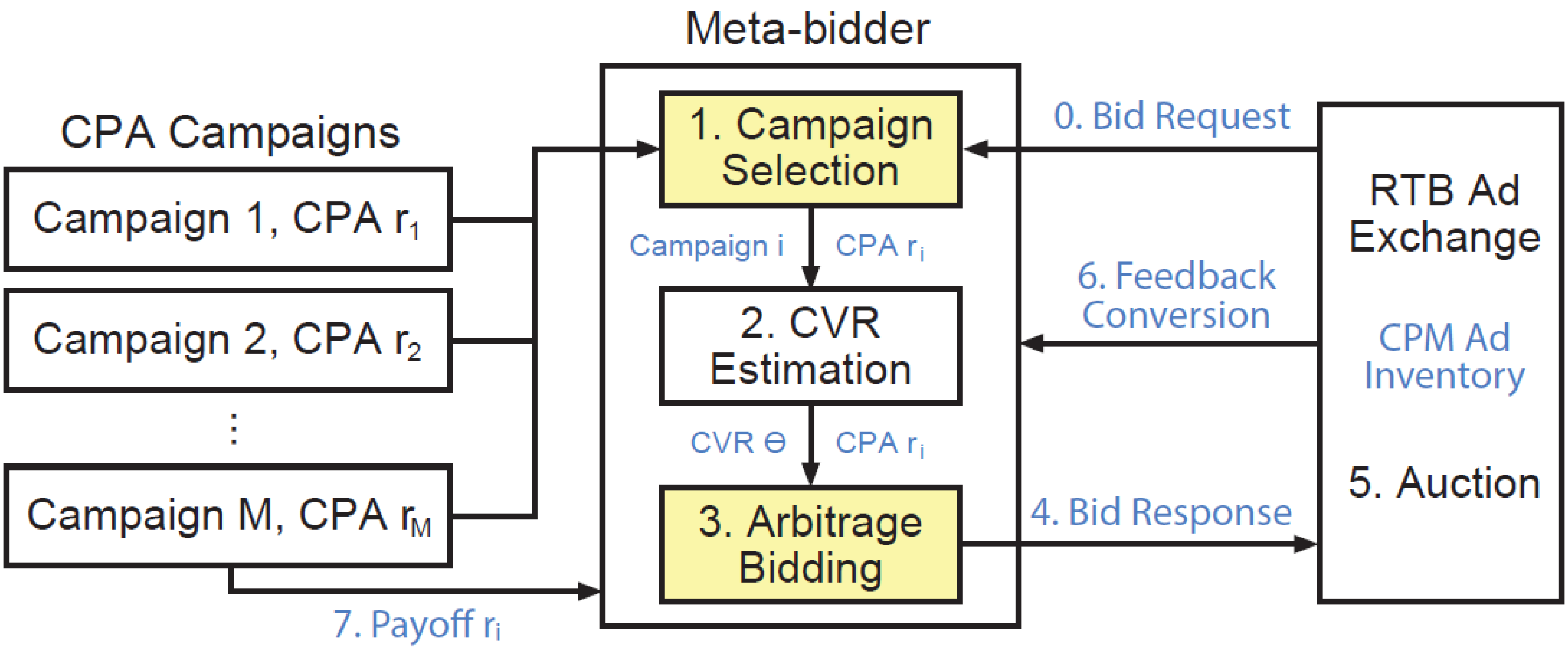
Display Advertising Intermediaries



This work: Intermediary arbitrage algorithms in RTB display advertising.

[Zhang et al. Statistical Arbitrage Mining for Display Advertising. KDD 15]

Intermediary's Statistical Arbitrage via RTB



- Statistical arbitrage opportunity occurs, e.g., when

(CPM) cost per conversion < (CPA) payoff per conversion

1000 impressions * 5 cent < 8000 cent for 1 conversion

Statistical Arbitrage Mining

- Expected utility (net profit) and cost on multiple campaigns

Bid request vol. Est. payoff winning function CVR estimation

$$\mathbb{E}[R(\boldsymbol{v}, b(\theta, r))] = T \sum_{i=1}^{M} v_i \int_{\theta} \Big(\theta r_i - b(\theta, r_i)\Big) w(b(\theta, r_i)) p_{\theta}^{i}(\theta) d\theta$$

bidding function

$$\mathbb{E}[C(\boldsymbol{v}, b(\theta, r))] = T \sum_{i=1}^{M} v_i \int_{\theta} b(\theta, r_i) w(b(\theta, r_i)) p_{\theta}^{i}(\theta) d\theta$$

Cost upper bound

Prob. of selecting Campaign i

Statistical Arbitrage Mining

- Optimising net profit by tuning bidding function and campaign volume allocation

$$
\begin{aligned}
b_{\mathrm{SAM}}(), \boldsymbol{v}^* = \operatorname*{argmax}_{b(), \boldsymbol{v}} \quad & \mathbb{E}[R] \\
\text{s.t.} \quad & \mathbb{E}[C] \le B \\
& \mathrm{Var}[R] \le h \\
& \mathbf{0} \le \boldsymbol{v} \le \mathbf{1} \\
& \boldsymbol{v}^T \mathbf{1} = 1
\end{aligned}
$$

Total arbitrage net profit

Total cost constraint

Risk control

M-Step

E-Step

- Solve it in an EM fashion

M-Step: Bidding function optimisation

- Fix ***v*** and tune ***b***()

$$\max_{b()} \; T \sum_{i=1}^{M} v_i \int_{\theta} \Big(\theta r_i - b(\theta, r_i)\Big) w(b(\theta, r_i)) p_\theta^i(\theta) d\theta$$

$$\text{s.t.} \;\; T \sum_{i=1}^{M} v_i \int_{\theta} b(\theta, r_i) w(b(\theta, r_i)) p_\theta^i(\theta) d\theta \leq B.$$

$$\frac{\mathcal{L}(b(), \boldsymbol{v})}{b()} = 0 \Rightarrow \Big(\frac{\theta r_i}{1+\lambda} - b(\theta, r_i)\Big) \frac{\partial w(b(\theta, r_i))}{\partial b(\theta, r_i)} = w(b(\theta, r_i))$$

$$\Downarrow$$

$$w(b(\theta, r)) = \frac{b(\theta, r)}{l} \Rightarrow b_{\text{sam1}}(\theta, r) = \frac{r\theta}{2(1+\lambda)}$$

$$w(b(\theta, r)) = \frac{b(\theta, r)}{b(\theta, r) + l} \Rightarrow b_{\text{sam2}}(\theta, r) = \sqrt{\frac{rl\theta}{1+\lambda} + l^2} - l$$

E-Step: Campaign volume allocation

- Multi-campaign portfolio optimisation

Portfolio margin mean

Portfolio margin variance

$$\max_{\boldsymbol{v}} \quad \boxed{\boldsymbol{v}^T \boldsymbol{\mu}(b)} - \alpha \boxed{\boldsymbol{v}^T \boldsymbol{\Sigma}(b) \boldsymbol{v}},$$

where $$\text{s.t.} \quad \boldsymbol{v}^T \mathbf{1} = 1, \quad \mathbf{0} \leq \boldsymbol{v} \leq \mathbf{1}$$

Net profit margin on each campaign

$$\boldsymbol{\mu}(b) = (\mu_1(b), \mu_2(b), \ldots, \mu_M(b))^T$$

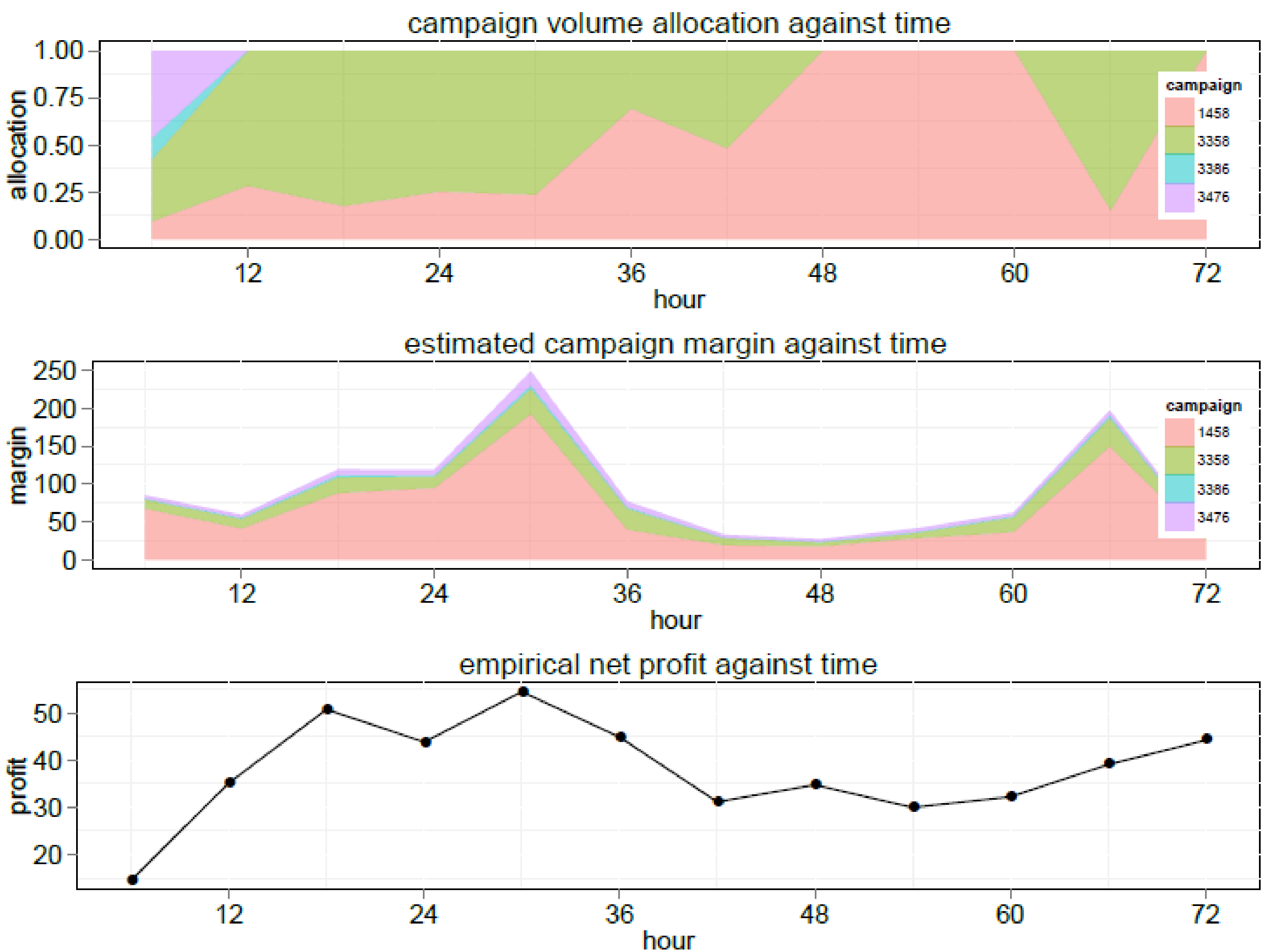
$$\boldsymbol{\Sigma}(b) = \{\sigma_{i,j}(b)\}_{i=1\ldots M, j=1\ldots M}$$

$$\mu_i(b) = \mathbb{E}[\gamma_i] = \mathbb{E}\left[\frac{R_i(\boldsymbol{v}_{i=1}, b)}{C_i(\boldsymbol{v}_{i=1}, b)}\right], \quad \sigma_i^2(b) = \mathbb{E}\left[\frac{R_i(\boldsymbol{v}_{i=1}, b)^2}{C_i(\boldsymbol{v}_{i=1}, b)^2}\right] - \mathbb{E}\left[\frac{R_i(\boldsymbol{v}_{i=1}, b)}{C_i(\boldsymbol{v}_{i=1}, b)}\right]^2$$

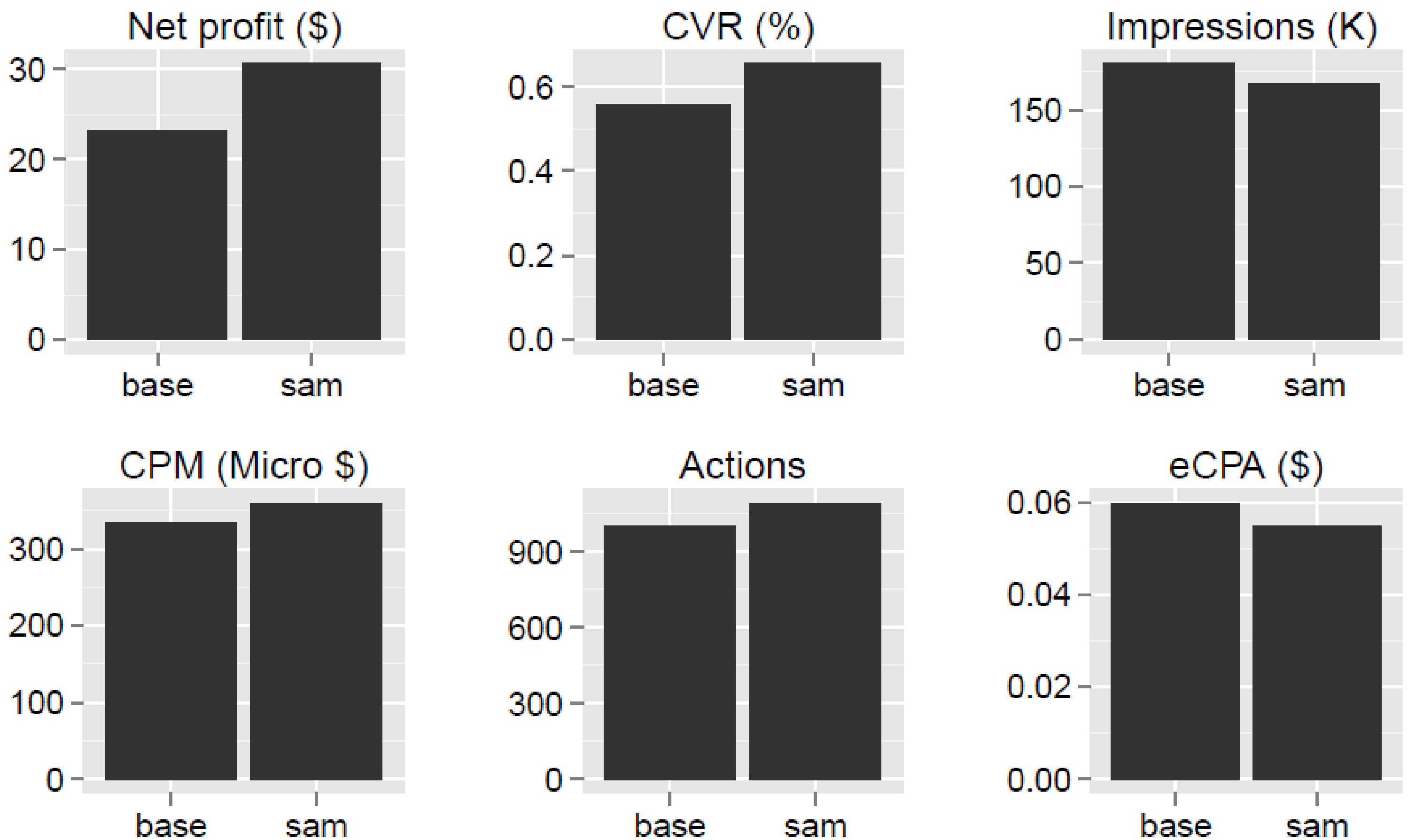
Campaign Portfolio Optimisation Results

strategies		easy payoff		hard payoff	
bid. algo.	cam. select.	profit (CNY)	margin	profit (CNY)	margin
lin	greedy	501.12	6.63	68.59	0.91
lin	portfolio	925.45	13.11	181.54	2.50
lin	uniform	747.00	9.53	127.14	1.62
ortb	greedy	517.02	6.65	70.96	0.91
ortb	portfolio	802.15	10.32	146.13	1.88
ortb	uniform	765.12	9.89	133.16	1.72
sam1	greedy	966.02	20.81	230.38	11.13
sam1	portfolio	**1,037.98**	15.84	240.63	7.96
sam1	uniform	768.38	9.78	172.43	7.57
sam2	greedy	961.68	28.73	235.31	24.00
sam2	portfolio	983.01	17.21	**248.65**	13.61
sam2	uniform	774.09	10.32	168.15	5.16
truth	greedy	787.10	14.69	227.86	29.05
truth	portfolio	787.10	14.69	242.07	18.34
truth	uniform	326.57	4.14	101.12	5.36

Dynamic Portfolio Optimisation



Online A/B Test on BigTree™ DSP



- 23 hours, 13-14 Feb. 2015, with $60 budget each

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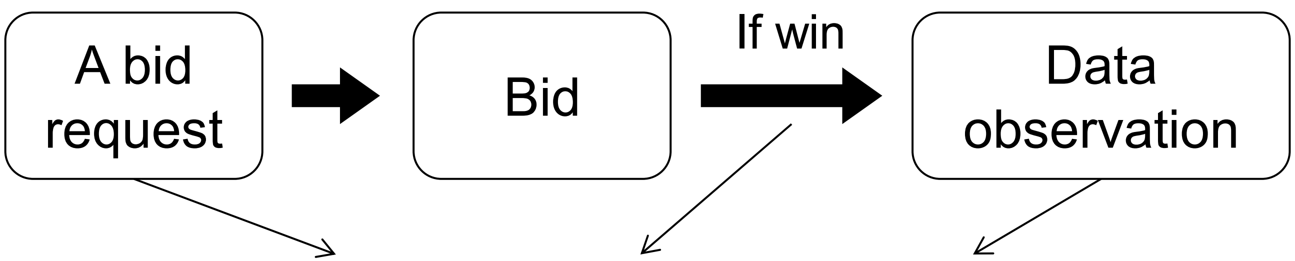
Advances

- Arbitrage
- **Unbiased Training and Optimisation**
- Conversion Attribution

Problem of Training Data Bias

- Data observation process



$$p_x(\boldsymbol{x})w(b_{\boldsymbol{x}}) = q_x(\boldsymbol{x})$$

- We want to train the model

$$\min_{\boldsymbol{\theta}} \quad \mathbb{E}_{\boldsymbol{x}\sim p_x(\boldsymbol{x})}[\mathcal{L}(y, f_{\boldsymbol{\theta}}(\boldsymbol{x}))] + \lambda\Phi(\boldsymbol{\theta})$$

- But we train on the biased data

$$\min_{\boldsymbol{\theta}} \quad \mathbb{E}_{\boldsymbol{x}\sim q_x(\boldsymbol{x})}[\mathcal{L}(y, f_{\boldsymbol{\theta}}(\boldsymbol{x}))] + \lambda\Phi(\boldsymbol{\theta})$$

[Zhang et al. Learning and Optimisation with Censored Auction Data in Display Advertising. AAAI 2016 Submission]

Unbiased Training

- Training target

$$\min_{\boldsymbol{\theta}} \ \mathbb{E}_{\boldsymbol{x} \sim p_x(\boldsymbol{x})}[\mathcal{L}(y, f_{\boldsymbol{\theta}}(\boldsymbol{x}))] + \lambda \Phi(\boldsymbol{\theta})$$

- Eliminate the data bias via importance sampling

$$\mathbb{E}_{\boldsymbol{x} \sim p_x(\boldsymbol{x})}[\mathcal{L}(y, f_{\boldsymbol{\theta}}(\boldsymbol{x}))] = \int_{\boldsymbol{x}} p_x(\boldsymbol{x}) \mathcal{L}(y, f_{\boldsymbol{\theta}}(\boldsymbol{x})) d\boldsymbol{x}$$

$$= \int_{\boldsymbol{x}} q_x(\boldsymbol{x}) \frac{\mathcal{L}(y, f_{\boldsymbol{\theta}}(\boldsymbol{x}))}{w(\boldsymbol{x}, b_{\boldsymbol{x}})} d\boldsymbol{x} = \mathbb{E}_{\boldsymbol{x} \sim q_x(\boldsymbol{x})} \left[\frac{\mathcal{L}(y, f_{\boldsymbol{\theta}}(\boldsymbol{x}))}{w(\boldsymbol{x}, b_{\boldsymbol{x}})} \right]$$

- Modelling winning probability via bid landscape

$$w(\boldsymbol{x}, b_{\boldsymbol{x}}) = \int_0^{b_{\boldsymbol{x}}} p_z^{\boldsymbol{x}}(z) dz$$

Unbiased Training

- Modelling winning probability via bid landscape

$$w(\boldsymbol{x}, b_{\boldsymbol{x}}) = \int_0^{b_{\boldsymbol{x}}} p_z^{\boldsymbol{x}}(z) dz$$

- Only use observed impression data [UOMP]

$$w_o(b_{\boldsymbol{x}}) = \frac{\sum_{(y,\boldsymbol{x}) \in D} \delta(z_{\boldsymbol{x}} < b_{\boldsymbol{x}})}{|D|}$$

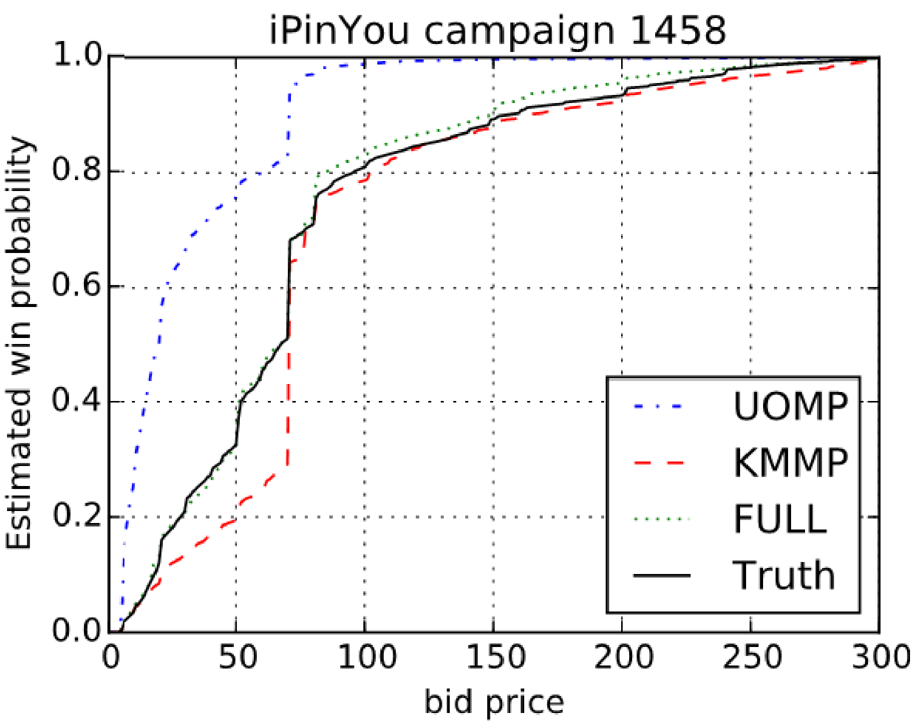
- Also use lost bid request data (censored data) [KMMP]

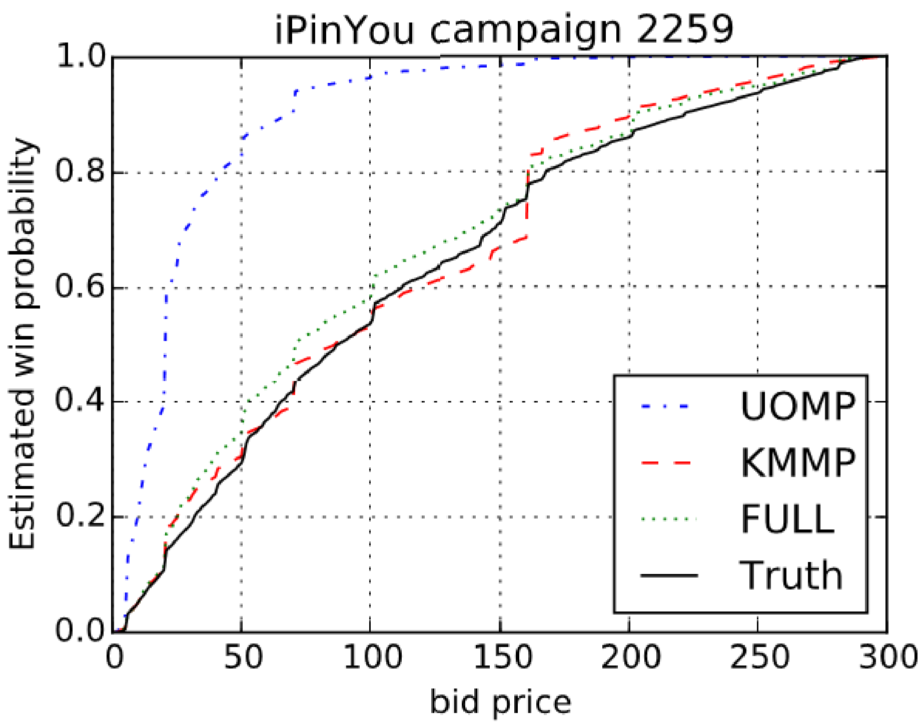
$$w(b_{\boldsymbol{x}}) = 1 - \prod_{b_j < b_{\boldsymbol{x}}} \frac{n_j - d_j}{n_j}$$

nj: # {winning prices > bj}   dj: # {winning prices = bj}

Experimental Results

- Winning probability estimation





Experimental Results

- CTR estimation: immediate performance improvement

Camp.	AUC (%)				Cross Entropy (‰)			
	BIAS	UOMP	KMMP	FULL	BIAS	UOMP	KMMP	FULL
1458	98.26	98.56	99.13	98.57	2.42	2.39	2.39	2.32
2259	60.27	60.94	62.00	67.37	4.04	4.03	4.02	4.00
2261	57.49	58.86	59.05	60.91	3.75	3.74	3.74	3.72
2821	59.25	59.69	60.28	62.36	7.07	7.06	7.04	6.92
2997	59.35	60.50	60.79	59.28	32.89	32.84	32.81	32.38
3358	96.59	96.78	97.01	97.32	4.48	4.47	4.38	4.36
3386	73.74	74.01	74.16	78.23	8.84	8.83	8.83	8.64
3427	96.04	96.42	96.78	97.02	3.37	3.37	3.33	3.31
3476	93.66	93.55	92.19	95.93	4.35	4.34	4.34	4.08
all	71.76	73.84	74.80	78.38	7.71	7.61	7.55	7.31

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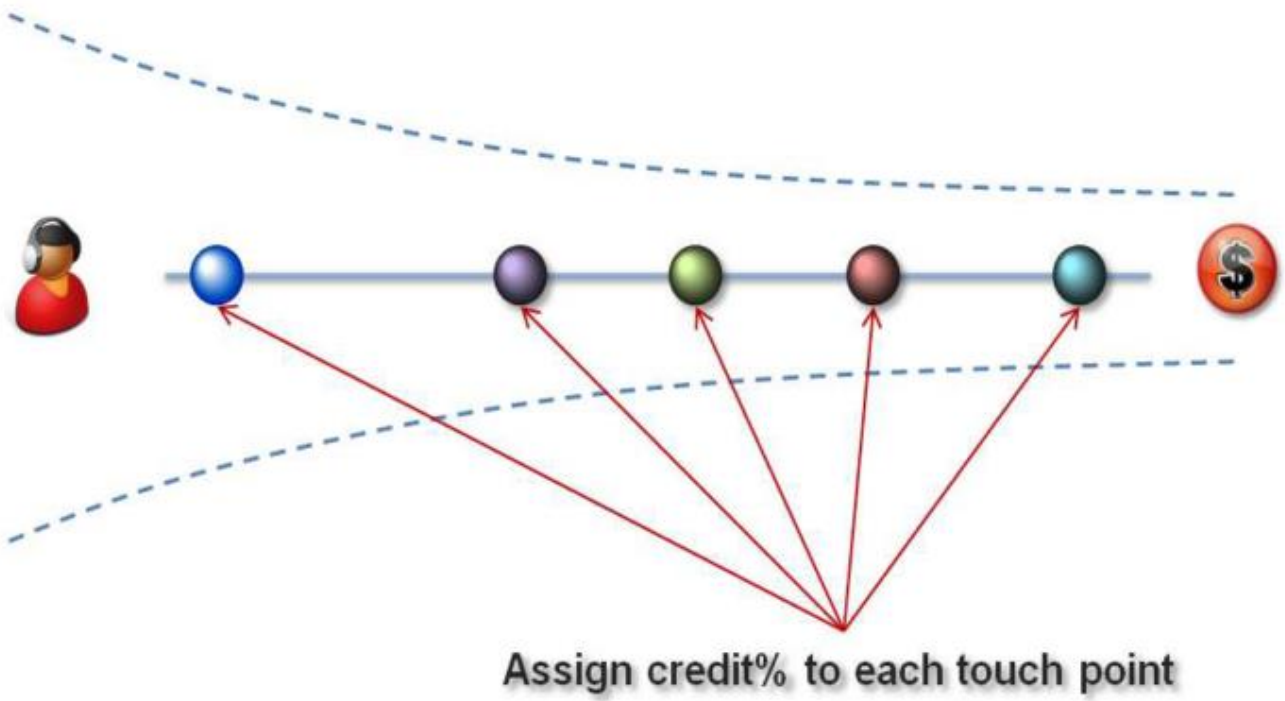
Conversion Attribution



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

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

Multi-Touch Attribution

- How to estimate the contribution of each channel?
  [Shao et al. Data-driven multi-touch attribution models. KDD 11]

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

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

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

- A more general formula
  [Dalessandro et al. Casually Motivated Attribution for Online Advertising. ADKDD 11]

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

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%

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

Bidding in Multi-Touch Attribution Mechanism

- Current bidding strategy
  - Driven by last-touch attribution

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

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

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

[Xu et al. Lift-Based Bidding in Ad Selection. ArXiv 1507.04811. 2015]

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

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

Value-based bidding v.s. Lift-based bidding

Adv	No bid		Value-based bidding		Incremental action	**Action lift**
	# imps	# actions	# imps	# actions		
1	0	642	53,396	714	72	**11.2%**
2	0	823	298,333	896	73	**8.9%**
3	0	1,438	11,048,583	1,477	39	**2.7%**
4	0	1892	3,915,792	2,016	124	**6.6%**
5	0	5,610	6,015,322	6,708	1,098	**19.6%**

Table 2. Blind A/B test on five pilot advertisers - Value-based bidding v.s. "No bid".

Adv	No bid		Lift-based bidding		Incremental action	**Action lift**
	# imps	# actions	# imps	# actions		
1	0	642	59,703	826	184	**28.7%**
2	0	823	431,637	980	157	**19.1%**
3	0	1,438	11,483,360	1509	71	**4.9%**
4	0	1892	4,368,441	2,471	579	**30.6%**
5	0	5,610	8,770,935	8,291	2,681	**47.8%**

Table 3. Blind A/B test on five pilot advertisers - Lift-based bidding v.s. "No bid".

Value-based bidding v.s. Lift-based bidding

Adv	Value-based bidding			Lift-based bidding			**Inventory-cost diff**	**Cost-per-imp diff**
	# imps	# attrs	Inventory cost	# imps	# attrs	Inventory cost		
1	53,396	50	$278.73	59,703	50	$300.31	**7.7%**	**-3.6%**
2	298,333	80	$1,065.05	431,637	80	$1,467.57	**37.8%**	**-4.8%**
3	11,048,583	240	$25,522.22	11,483,360	240	$25,837.56	**1.2%**	**-2.6%**
4	3,915,792	200	$10,846.74	4,368,441	200	$11,183.21	**3.1%**	**-7.6%**
5	6,015,322	500	$19,296.51	8,770,935	500	$23,501.90	**21.8%**	**-16.5%**

- Comparison
  - Lift-based bidding help brings more conversions to advertisers
  - but its eCPA is higher than value-based bidding because of last-touch attribution
- Lift-based bidding with multi-touch attribution could bring a better eco-system

Taking-home Messages

- **Statistical Arbitrage Mining:** The internal auction selects the ad with highest arbitrage margin instead of the highest bid price.

- **Unbiased Training**: Add the weight to each instance to eliminate the auction-selection bias.

- **Attribution and Bidding**: Bidding proportional to the CVR lift instead of CVR value.

Computational Advertising Research in Academia

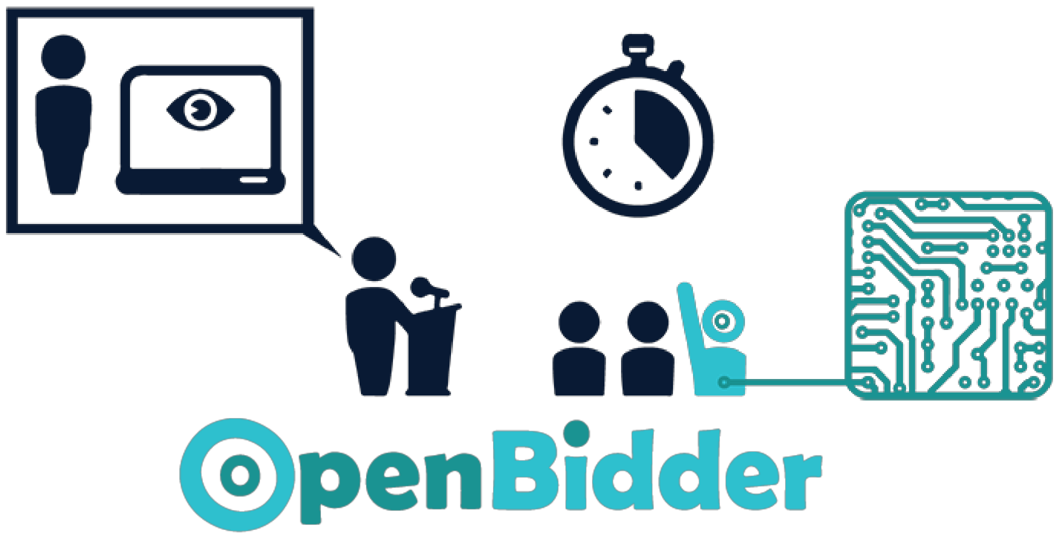
Disadvantages

- Lack of data and online test platform
- Lack of specific domain knowledge

Advantages

- Good at mathematic modelling
- Focus on knowledge collection and communication
- More research human resource

OpenBidder Project: www.openbidder.com



- Online open-source benchmarking project
  - Bid optimisation, CTR estimation, Bid landscape etc.
- Bridge academia and industry research on computational advertising

Collaborations

UK:

US:

CN:

- Collaborations are more than welcome!

Thank You!
Questions?

http://www.computational-advertising.org
http://www0.cs.ucl.ac.uk/staff/w.zhang

Ad Science
WeChat Group