Risk-aware dynamic reserve prices of programmatic guarantee in display advertising

Bowei Chen

University of Lincoln
United Kingdom

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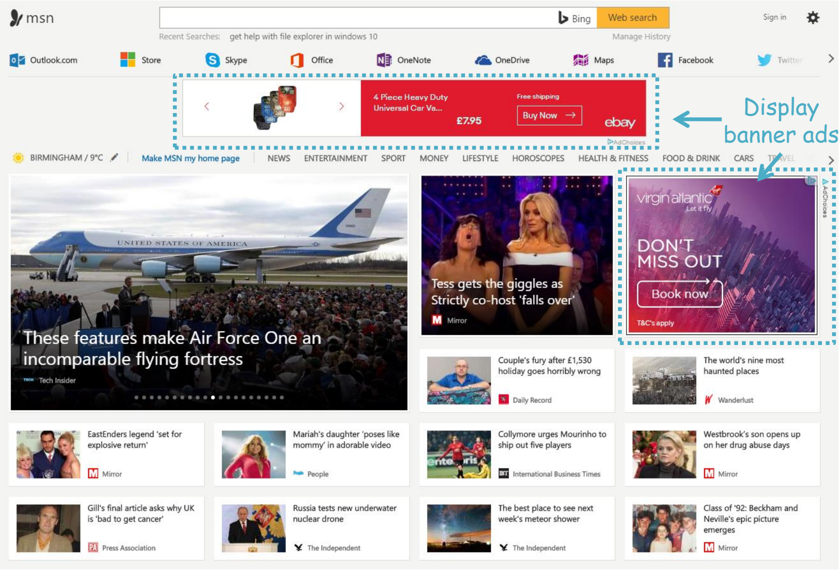
Background

What is display advertising?



Display banner ads

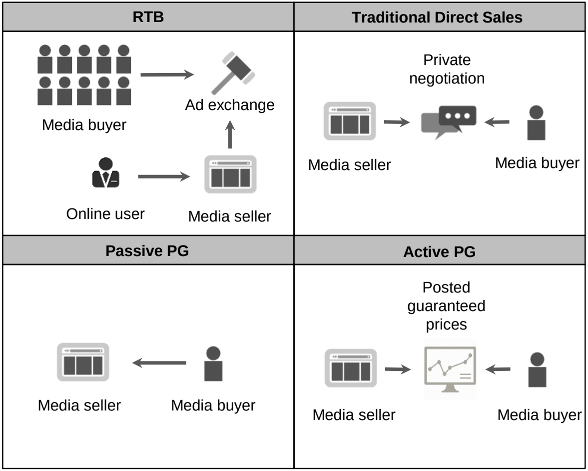
Background

Who are the participants?

- **Online user** expresses information need by web surfing or searching.
- **Media buyer**
  - **Advertiser** wants to deliver marking messages to online users.
  - **Demand-side platform (DSP)** helps advertisers to purchase ad services.
- **Media seller**
  - **Publisher** provides advertising services/inventories.
  - **Supply-side platform (SSP)** help publishers to sell their ad services.

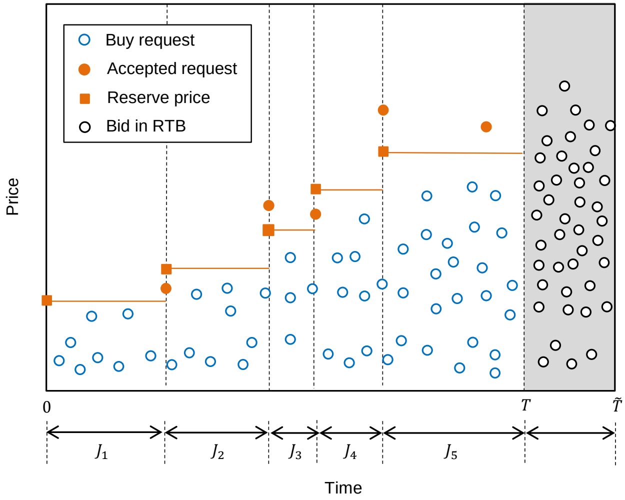
Background

How are display banner ads are sold?



Model

Schematic illustration



Model

Decision making at time t

At time t, if an advertiser submits a buy request and proposes the guaranteed price $G(t)$ for an impression, the publisher's decision making can be expressed as

$$\max_{x(t)\in\{0,1\}} \Big\{ R(t)x(t) + V\big(t + \delta t, s - x(t)\big) \Big\}.$$

- $x(t)$ is the decision variable
- $R(t)$ is the expected revenue if accepting the buy request
- $V(t,s)$ is the publisher's value function at time t, representing the expected total value of s remaining impressions which will be created in $[T, \widetilde{T}]$

Model

Lower bound of reserve price

Given time t and remaining impressions s, if there is a guaranteed price that makes the publisher's two decisions **indifferent**, this price is the **lower bound of reserve price** for the guaranteed impression, denoted by $r(t, s)$, then

$$r(t,s) = \frac{1}{1-\omega\gamma}\Big(V(t+\delta t, s) - V(t+\delta t, s-1)\Big).$$

Hence, the decision variable $x(t) = \mathbb{I}_{\{G(t) \geq r(t,s)\}}$.

- ω is the probability that the publisher fails to deliver a guaranteed impression
- γ is the size of penalty

By employing the Bellman's Principle of Optimality, we have

$$
\begin{aligned}
V(t,s) &= \mathbb{E}\left[\max_{x(t)\in\{0,1\}}\Big\{r(t,s)(1-\gamma\omega)x(t) + V(t+\delta t, s-x(t))\Big\}\right] \\
&= \mathbb{P}[G(t)\geq r(t,s)]\Big(r(t,s)(1-\gamma\omega) + V(t+\delta t, s-1)\Big) \\
&\quad + \Big(1-\mathbb{P}[G(t)\geq r(t,s)]\Big)V(t+\delta t, s).
\end{aligned}
$$

Time-independent properties

$$
\begin{aligned}
V(t,s) &= V(k,s), k\in[t,T], \\
r(t,s) &= r(k,s), k\in[t,T].
\end{aligned}
$$

For detailed simple derivation, see paper III A.

The publisher's value function at time T can be expressed as

$$V(T,s) = \begin{cases} s\big(\phi(\xi) + \lambda\psi(\xi)\big), & \text{if } \pi(\xi) \geq \phi(\xi) + \lambda\psi(\xi), \\ s\pi(\xi), & \text{if } \pi(\xi) < \phi(\xi) + \lambda\psi(\xi), \end{cases}$$

- ξ is the per-impression demand in RTB.
- $\phi(\cdot)$ computes the expected per-impression payment in RTB for the given ξ.
- $\psi(\cdot)$ computes the standard deviation of payments in RTB for the given ξ.
- $\pi(\cdot)$ computes the expected winning bid in RTB for the given ξ.
- λ is the level of risk aversion of the publisher.

Model

Static supply and demand, and estimation of ξ

The total supply of and demand for impressions that will be created in the period $[T, \widetilde{T}]$ are assumed to be static, denoted by S and Q, respectively. If there are s remaining impressions, then there are $Q - (S - s)$ remaining demand, therefore

$$\xi = (Q - S)/s + 1.$$

- Probabilistic method:

$$\phi(\xi) = \int_{x \in \Omega} x\xi(\xi - 1)g(x)\Big(1 - \mathbb{F}(x)\Big)\Big(\mathbb{F}(x)\Big)^{\xi-2} dx.$$

  - If $X \sim \mathbf{U}[0, v]$, $\phi(\xi) = v(\xi - 1)/(\xi + 1)$.
  - If $X \sim \mathbf{LN}(\mu, \sigma^2)$, $\phi(\xi)$ can be obtained via numerical integration.

- Empirical method: robust locally weighted regression (RLWR) method.

- x is an advertiser's bid in RTB
- $g(\cdot)$ is the density function
- $\mathbb{F}(\cdot)$ is the cumulative distribution function.

Model

Revenue analysis

- Expected total revenue of selling all S impressions in RTB:

$$\mathbf{R}_{\mathbf{RTB}} = S\phi(Q/S),$$

- Expected total revenue of selling some impressions in advance through PG and selling the remaining impressions in RTB:

$$\mathbf{R}_{\mathbf{PG+RTB}} = \sum_{t=0}^{T} R(t)x(t) + \Big(S - \sum_{t=0}^{T} x(t)\Big)\phi(\xi^*),$$

where $\xi^* = \frac{Q-\sum_{t=0}^{T} x(t)}{S-\sum_{t=0}^{T} x(t)}$.

Increased Revenue

$$\mathbf{R}_{\mathbf{PG+RTB}} \geq \mathbf{R}_{\mathbf{RTB}}.$$

For detailed derivation, see the paper III. C

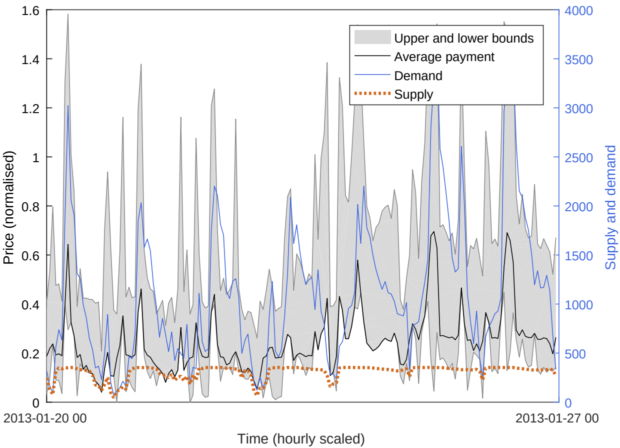
Experiments

Data

Dataset	SSP-01	SSP-02	DSP
Market	UK	UK	China
From	08 Jan 2013	01 Jan 2014	19 Oct 2013
To	14 Feb 2013	07 Jan 2014	27 Oct 2013
# of ad slots	31	14	53571
# of user tags	NA	16600	69
# of publishers	NA	5932	NA
# of advertisers	374	NA	4
# of impressions	6646643	7752546	3158171
# of bids	33043127	7752546	11457419
Bid quote	GBP/CPM	GBP/CPM	CNY/CPM
Bids of each campaign	$\surd$	NA	NA
Reserve price	NA	$\surd$	NA
Winning bid	$\surd$	$\surd$	$\surd$
Winning payment	$\surd$	$\surd$	$\surd$

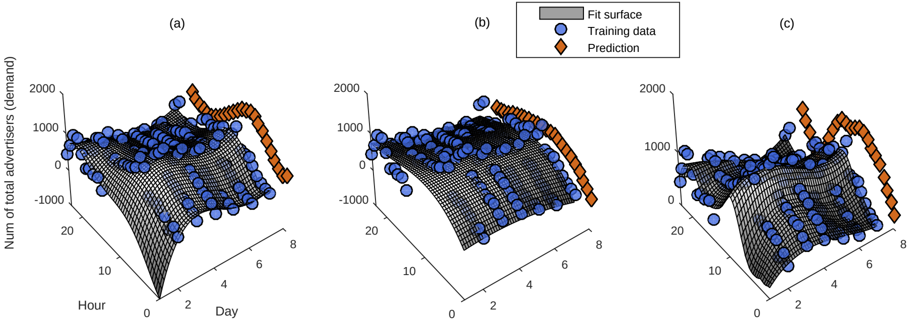
Experiments

Periodical patterns in hourly data



Experiments

Surface regressions for S and Q



Empirical example of demand regressions: (a) PNR(5,5); (b) PNR(2,3); (c) LQR

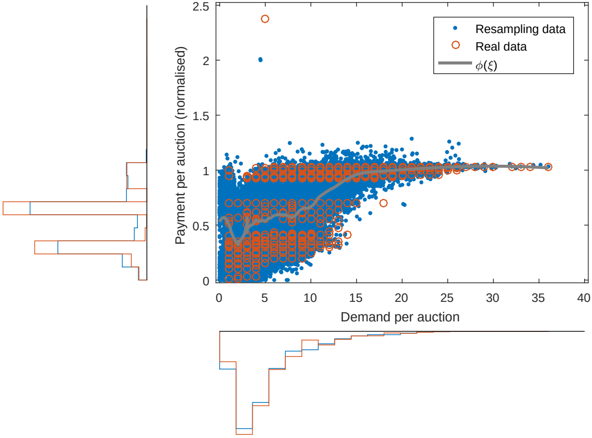
Experiments

Surface regressions for S and Q

Model	Demand		Supply	
	$\mathscr{L}^2$ norm avg.	$\mathscr{L}^2$ norm std.	$\mathscr{L}^2$ norm avg.	$\mathscr{L}^2$ norm std.
PNR(5,5)	0.2887	0.2544	0.2235	0.2375
PNR(4,5)	0.1123	0.0824	0.0938	0.0662
PNR(3,5)	0.0875	0.0507	0.0786	0.0503
PNR(2,5)	0.0623	0.0435	0.0482	0.0285
PNR(1,5)	0.0449	0.0309	0.0441	0.0276
PNR(5,4)	0.2979	0.2534	0.2207	0.2379
PNR(4,4)	0.0874	0.0661	0.0605	0.0434
PNR(3,4)	0.0856	0.0494	0.0737	0.0493
PNR(2,4)	0.0597	0.0415	0.0406	0.0234
PNR(1,4)	0.0496	0.0338	0.0431	0.0271
PNR(5,3)	0.3024	0.2538	0.2248	0.2374
PNR(4,3)	0.0877	0.0662	0.0607	0.0433
PNR(3,3)	0.0736	0.0455	0.0735	0.0517
PNR(2,3)	0.0579	0.0394	0.0447	0.0256
PNR(1,3)	0.0476	0.0332	0.0453	0.0280
PNR(5,2)	0.3061	0.2546	0.2346	0.2368
PNR(4,2)	0.0896	0.0674	0.0680	0.0456
PNR(3,2)	0.0789	0.0490	0.0767	0.0534
PNR(2,2)	0.0622	0.0417	0.0462	0.0267
PNR(1,2)	0.0529	0.0369	0.0471	0.0273
PNR(5,1)	0.2807	0.2562	0.2401	0.2340
PNR(4,1)	0.0880	0.0691	0.0651	0.0438
PNR(3,1)	0.0804	0.0483	0.0761	0.0538
PNR(2,1)	0.0672	0.0430	0.0478	0.0310
PNR(1,1)	0.0566	0.0377	0.0480	0.0307
LQR	0.0592	0.0354	0.0546	0.0363

Experiments

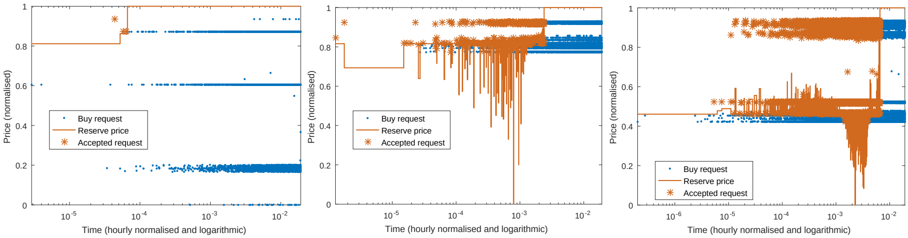
Estimating $\phi(\xi)$ using the RLWR method*



*Chen et al. A dynamic pricing model for unifying programmatic guarantee and real-time bidding in display advertising. In ADKDD, 2014. Algorithm 1.

Experiments

Risk-aware dynamic reserve prices



*The arrival of guaranteed buy requests follows a homogeneous Poisson process with the intensity rate QT where T is expressed in terms of year (i.e., $\#days/365$). The proposed guaranteed buy prices are randomly sampled from RTB.

Experiments

Revenue results

Dataset	Number of advertisers	Ratio of payment to winning bid	Ratio of reserve price to payment
SSP-01	374	51.44%	NA
SSP-02	NA	77.09%	0.01%
DSP	4	30.24%	NA

	Using data in the delivery period	Learning data in the training period
$\mathbf{R}_{\mathbf{PG+RTB}}^{\mathbf{Predict}} \geq \mathbf{R}_{\mathbf{RTB}}^{\mathbf{Predict}}$	100%	100%
$\mathbf{R}_{\mathbf{PG+RTB}}^{\mathbf{Predict}} \geq \mathbf{R}_{\mathbf{RTB}}^{\mathbf{Real}}$	80.77%	100%
$(\mathbf{R}_{\mathbf{RTB}}^{\mathbf{Predict}} - \mathbf{R}_{\mathbf{RTB}}^{\mathbf{Real}})/\mathbf{R}_{\mathbf{RTB}}^{\mathbf{Real}}$	-0.07	26.17

- This paper discusses a simple framework for passive PG, which
  - Considers risk into reserve prices
  - Has less limitations on buyer's purchase behaviour
  - Generates increased revenue compared to only RTB
- Future directions include:
  - Uncertain total supply and demand
  - Optimal passive PG
  - Comparison of active PG and passive PG

Thank you and welcome questions (?_?)

bchen@lincoln.ac.uk