Learning, Prediction and Optimisation in RTB Display Advertising

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http://www.optimalrtb.com/cikm16/
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Speakers

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  – Machine learning, data mining in computational advertising and recommender systems

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  – Principal Data Scientist at TouchPal, Mountain View
  – Previous Senior Data Scientist and Senior Research Engineer at Yahoo! US
  – Data mining, machine learning, and computational advertising
Tutorial Materials

• Web site:
  http://www.optimalrtb.com/cikm16

• Supporting documents:
  – RTB monograph
    https://arxiv.org/abs/1610.03013
  – RTB paper list:
    https://github.com/wnzhang/rtb-papers
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- RTB system
- Auction mechanisms
- User response estimation
- Learning to bid
- Conversion attribution
- Pacing control
- Targeting and audience expansion
- Reserve price optimization

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<tr>
<th>Speaker</th>
<th>Time</th>
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<tbody>
<tr>
<td>Weinan Zhang</td>
<td>90 min</td>
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<td>30 min break</td>
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<tr>
<td>Jian Xu</td>
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• RTB system
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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
Display Advertising

- Advertiser targets a segment of users
- Intermediary matches users and ads by user information

Advertisers with ad budget  →  target  “20-40, male” “travel”  ←  attributes  Users on the Internet

user information matching
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.

<table>
<thead>
<tr>
<th>DSP/Exchange</th>
<th>daily traffic</th>
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<tbody>
<tr>
<td>Advertising</td>
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<tr>
<td>iPinYou, China</td>
<td>18 billion impressions</td>
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<tr>
<td>YOYI, China</td>
<td>5 billion impressions</td>
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<tr>
<td>Fikisu, US</td>
<td>32 billion impressions</td>
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<td>Finance</td>
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<td>New York Stock Exchange</td>
<td>12 billion shares</td>
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<td>Shanghai Stock Exchange</td>
<td>14 billion shares</td>
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<tr>
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<th>Query per second</th>
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<tr>
<td>Turn DSP</td>
<td>1.6 million</td>
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<tr>
<td>Google</td>
<td>40,000 search</td>
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</tbody>
</table>

[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
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

User Information

User Demography:
Male, 26, Student
User Segmentations:
London, travelling

0. Ad Request
1. Bid Request
   (user, page, context)
2. Bid Response
   (ad, bid price)
3. Ad Auction
4. Win Notice
   (charged price)
5. Ad
   (with tracking)
6. User Feedback
   (click, conversion)
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Auctions scheme

private values  bids

\( v_1 \rightarrow b_1 \)
\( v_2 \rightarrow b_2 \)
\( v_3 \rightarrow b_3 \)
\( v_4 \rightarrow b_4 \)

winner
payments $$$
Modeling

- $n$ bidders

- Each bidder $i$ 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.

- **Note:** 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 \textit{a function}, a plan for the game. Not just a bid.

• Examples for strategies:
  – \( b_i(v_i) = v_i \) (truthful)
  – \( b_i(v_i) = v_i/2 \)
  – \( b_i(v_i) = v_i/n \)
  – \( \text{If } v < 50, b_i(v_i) = v_i \)
    \( \text{otherwise, } b_i(v_i) = v_i + 17 \)

• Can be modeled as \textit{normal form game}, where these strategies are the pure strategies.

• Example for a \textit{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.

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<th>$B(v)=v$</th>
<th>$B(v)=v/2$</th>
<th>$B(v)=v/n$</th>
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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.
1st price auctions

- Truthful($b_i = v_i$)? NO!
Equilibrium in 1\textsuperscript{st}-price auctions

- Suppose bidder \( i \)'s value is \( v_i \) in \([0,1]\), which is only known by bidder \( i \).
- Given this value, bidder \( i \) must submit a sealed bid \( b_i(v_i) \).
- We view bidder \( i \)'s strategy as a bidding function \( b_i : [0,1] \rightarrow \mathbb{R}_+ \). Some properties:
  - Bidders with higher values will place higher bids. So \( b_i \) is a strictly increasing function.
  - Bidders are also \textit{symmetric}. So bidders with the same value will submit the same bid: \( b_i = b \) (\textit{symmetric Nash equilibrium}).
  - \( \text{Win}(b_i) = F(v_i) \), where \( F \) is the C.D.F. of the true value distribution.
Equilibrium in 1st-price auctions

- Bidder 1’s payoff

\[
\begin{cases} 
v_1 \quad \text{if } b_1 > \max\{b(v_2),...,b(v_n)\} \\
0 \quad \text{if } b_1 \leq \max\{b(v_2),...,b(v_n)\} 
\end{cases}
\]

- The expected payoff of bidding \( b_1 \) is given by

\[
(b_1) = (v_1 \quad b_1)P(b_1 > \max\{b(v_2),...,b(v_n)\}) \\
= (v_1 \quad b_1)P(b_1 > b(v_2),...,b_1 > (v_n))
\]

- An optimal strategy \( b_i \) should maximize \((b_1)\)
Suppose that bidder $i$ cannot attend the auction and that she asks a friend to bid for her

- The friend knows the equilibrium bidding function $b^*$ but does not know $v_i$
- Bidder tells his friend the value as $x$ and wants him to submit the bid $b^*(x)$
- The expected payoff in this case is

$$ (b^*, x) = (v_1 - b^*(x)) P(b^*(x) > b^*(v_2), ..., b^*(x) > b^*(v_n)) $$

$$ = (v_1 - b^*(x)) P(x > v_2, ..., x > v_n) = (v_1 - b^*(x)) F_{N-1}^N(x) $$

- The expected payoff is maximized when reporting his true value $v_i$ to his friend ($x = v_i$)
Equilibrium in 1st-price auctions

• So if we differentiate the expected payoff with respect to $x$, the resulting derivative must be zero when $x = v_i$:

$$\frac{d}{dx} b^*(x) = \frac{d}{dx} (v_1 b^*(x)) F_N^1(x)$$

$$= (N - 1) F_N^2(x) f(x)(v_1 b^*(x)) F_N^1(x) b^*(x)$$

• The above equals zero when $x = v_i$; rearranging yields:

$$(N - 1) F_N^2(v_1) f(v_1) v_1$$

$$= F_N^1(v_1) b^*(v_1) + (N - 1) F_N^2(v_1) f(v_1) b^*(v_1)$$

$$= \frac{dF_N^1(v_1) b^*(v_1)}{dv}$$
Equilibrium in 1\textsuperscript{st}-price auctions

• Taking the integration on both side

\[ F^{N-1}(v_1)b^*(v_1) = (N - 1) \int_{0}^{v_i} xf(x)F^{N-2}(x) \, dx + \text{constant} \]

• If we assume a bidder with value zero must bid zero, the above constant is zero. Therefore, we have (replace $v_i$ with $v$)

\[ b^*(v) = \frac{(N - 1) \int_{0}^{v} xf(x)F^{N-2}(x) \, dx}{F^{N-1}(v)} = \frac{\int_{0}^{v} x \, dF^{N-1}(x)}{F^{N-1}(v)} \]

• It shows that in the equilibrium, each bidder bids the expectation of the second-highest bidder’s value conditional on winning the auction.
Untruthful bidding in 1st-price auctions

• Suppose that each bidder’s value is uniformly distributed on [0,1].
  – Replacing \( F(v) = v \) and \( f(v) = 1 \) gives

\[
b^*(v) = \frac{\int_0^v x \, dF^{N-1}(x)}{F^{N-1}(v_1)} = \frac{\int_0^v x \, dx^{N-1}}{v^{N-1}}
\]

\[
= \frac{\int_0^v x(N-1)x^{N-2} \, dx}{v^{N-1}} = \frac{(N-1)\int_0^v x^{N-1} \, dx}{v^{N-1}}
\]

\[
= \frac{(N-1)}{v^{N-1}} \frac{1}{N} v^N = v - \frac{v}{N}
\]
Equilibrium in 2\textsuperscript{nd}-price auctions

- bidder 1’s payoff
  \[
  \begin{cases}
    v_1 - b_i & \text{if } b_1 > b_i > \max\{b(v_2),\ldots,b(v_{i-1}),b(v_{i+1}),\ldots,b(v_n)\} \\
    0 & \text{if } b_1 \leq \max\{b(v_2),\ldots,b(v_n)\}
  \end{cases}
  \]
- 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 $b_1 > v_1$
Equilibrium in 2\textsuperscript{nd}-price auctions

- bidder 1’s payoff

\[
\begin{cases}
  v_1 - b_i & \text{if } b_1 > b_i > \max\{b(v_2),...,b(v_{i-1}),b(v_{i+1}),...,b(v_n)\} \\
  0 & \text{if } b_1 \leq \max\{b(v_2),...,b(v_n)\}
\end{cases}
\]

- The expected payoff of bidding $b_1$ is given by

\[
\pi(v_1, b_1) = \int_{0}^{b_1} (v_1 - x) dF^{N-1}(x) = \int_{0}^{b_1} (N-1)(v_1 - x)f(x)F^{N-2}(x)dx
\]

- Or taking derivative of $\pi(v_1, b_1)$ w.r.t. $b_1$ yields $b_1 = v_1$

So telling the truth $b_1 = v_1$ is a Bayesian Nash equilibrium bidding strategy!
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
RTB Auctions

• Second price auction with reserve price

• From a bidder’s perspective, the market price $z$ refers to the highest bid from competitors

• Payoff: $(v_{impression} - z) \times P(win)$

• Value of impression depends on user response
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• Auction mechanisms
• **User response estimation**
• Learning to bid
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• Pacing control
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• Reserve price optimization
• Buying ads via real-time bidding (RTB), 10B per day
Predict how likely the user is going to click the displayed ad.
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

Let \( x = [\text{Weekday=Wednesday}, \text{Gender=Male}, \text{City=London}] \)

\[
x = [0,0,1,0,0,0,0,\ 0,1 \ 0,0,1,0...0]
\]

High dimensional sparse binary feature vector
Linear Models

- Logistic Regression
  - With SGD learning
  - Sparse solution

- Online Bayesian Probit Regression
ML Framework of CTR Estimation

• A binary regression problem

\[
\min_w \sum_{(y, x) \in D} \mathcal{L}(y, \hat{y}) + \lambda \Phi(w)
\]

– 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
    – An isotonic mapping from prediction to calibrated prediction
Logistic Regression

• Prediction

\[ \hat{y} = \frac{1}{1 + e^{-\mathbf{w}^T \mathbf{x}}} \]

• Cross Entropy Loss

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

• Stochastic Gradient Descent Learning

\[ \mathbf{w} \leftarrow (1 - \lambda) \mathbf{w} + \eta(y - \hat{y}) \mathbf{x} \]

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

\[ \mathbf{w} \leftarrow (1 - \lambda) \mathbf{w} + \eta (y - \hat{y}) \mathbf{x} \]

• Pros
  – Standardised, easily understood and implemented
  – Easy to be parallelised

• Cons
  – Learning rate $\eta$ 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**

\[
\begin{align*}
\mathbf{w}_{t+1} &= \arg \min_{\mathbf{w}} \left( \mathbf{g}_{1:t} \cdot \mathbf{w} + \frac{1}{2} \sum_{s=1}^{t} \sigma_s \left\| \mathbf{w} - \mathbf{w}_s \right\|_2^2 + \lambda_1 \left\| \mathbf{w} \right\|_1 \right) \\
\text{s.t.} \quad \mathbf{g}_{1:t} &= \sum_{s=1}^{t} \mathbf{g}_s \\
\sigma_s &= \sqrt{s} - \sqrt{s - 1}
\end{align*}
\]

- **Online closed-form update of FTRL**

\[
\begin{align*}
\mathbf{w}_{t+1,i} &= \begin{cases} 
0 & \text{if } |z_{t,i}| \leq \lambda_1 \\
-\eta_t (z_{t,i} - \text{sgn}(z_{t,i}) \lambda_1) & \text{otherwise}.
\end{cases} \\
\mathbf{z}_{t-1} &= \mathbf{g}_{1:t-1} - \sum_{s=1}^{t-1} \sigma_s \mathbf{w}_s \\
\eta_{t,i} &= \frac{\alpha}{\beta + \sqrt{\sum_{s=1}^{t} g_{s,i}^2}}
\end{align*}
\]

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

Given feature \( x \), predicting click \( y \)

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

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

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

The factorised model

\[
p(y \mid t) \cdot p(t \mid s) \cdot p(s \mid x, w) \cdot p(w)
\]

Where \( p(s \mid x, w) := \delta(s = w^T x) \).

\[
p(t \mid s) := \mathcal{N}(t; s, \beta^2)
\]

\[
p(y \mid t) := \delta(y = \text{sign}(t)).
\]

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

\[ \hat{y} = f(w^T x) \]

• 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

• Factorisation Machines

• Gradient Boosting Decision Trees

• Combined Models

• Deep Neural Networks
Factorisation Machines

• Prediction based on feature embedding

\[ y_{FM}(x) := \text{sigmoid} \left( w_0 + \sum_{i=1}^{N} w_i x_i + \sum_{i=1}^{N} \sum_{j=i+1}^{N} \langle \mathbf{v}_i, \mathbf{v}_j \rangle x_i x_j \right) \]

- 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]
Factorisation Machines

- Prediction based on feature embedding

\[
y_{FM}(x) := \text{sigmoid}\left( w_0 + \sum_{i=1}^{N} w_i x_i + \sum_{i=1}^{N} \sum_{j=i+1}^{N} \langle \mathbf{v}_i, \mathbf{v}_j \rangle x_i x_j \right)
\]

Logistic Regression  
Feature Interactions

For \(x=[\text{Weekday}=\text{Friday}, \text{Gender}=\text{Male}, \text{City}=\text{Shanghai}]\)

\[
y_{FM}(x) = \text{sigmoid}\left( w_0 + w_{\text{Friday}} + w_{\text{Male}} + w_{\text{Shanghai}} + \langle \mathbf{v}_{\text{Friday}}, \mathbf{v}_{\text{Male}} \rangle + \langle \mathbf{v}_{\text{Friday}}, \mathbf{v}_{\text{Shanghai}} \rangle + \langle \mathbf{v}_{\text{Male}}, \mathbf{v}_{\text{Shanghai}} \rangle \right)
\]

[Rendle. Factorization machines. ICDM 2010.]

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

- Feature embedding for another field

\[ y_{FFM}(x) = \text{sigmoid} \left( w_0 + \sum_{i=1}^{N} w_i + \sum_{i=1}^{N} \sum_{j=i+1}^{N} \langle v_{i,\text{field}(j)}, v_{j,\text{field}(i)} \rangle x_i x_j \right) \]

Field-aware field embedding

For \( x = \{ \text{Weekday=Friday, Gender=Male, City=Shanghai} \} \)

\[ y_{FFM}(x) = \text{sigmoid} \left( w_0 + w_{\text{Friday}} + w_{\text{Male}} + w_{\text{Shanghai}} \right. \\
 \left. + \langle v_{\text{Friday},\text{Gender}}, v_{\text{Male},\text{Weekday}} \rangle + \langle v_{\text{Friday},\text{City}}, v_{\text{Shanghai},\text{Weekday}} \rangle \\
 \left. + \langle v_{\text{Male},\text{City}}, v_{\text{Shanghai},\text{Gender}} \rangle \right) \]

[Juan et al. Field-aware Factorization Machines for CTR Prediction. RecSys 2016.]
Gradient Boosting Decision Trees

- Additive decision trees for prediction

\[ \hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F} \]

- Each decision tree \( f_k(x_i) \)

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

\[ \hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F} \]

- Learning

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

\[
= \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \sum_{i=1}^{t} \Omega(f_i)
\]

\[
L^{(t)} \approx \sum_{i=1}^{n} [l(y_i, \hat{y}^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)] + \sum_{i=1}^{t} \Omega(f_i)
\]

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

[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

CSV → Pre-A → GBDT → Pre-B

feat=39 \rightarrow \text{nnz}=13-39 \rightarrow \text{nnz}=30 \rightarrow \text{feat}=30 \times 2^7

Rst → Calib. → FFM

\text{nnz}=69 \rightarrow \text{feat}=106

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

Neural Network Models

• Difficulty:
  Impossible to directly deploy neural network models on such data

E.g., input features 1M, first layer 500, then 500M parameters for first layer
**Review Factorisation Machines**

- Prediction based on feature embedding

\[
y_{FM}(x) := \text{sigmoid} \left( w_0 + \sum_{i=1}^{N} w_i x_i + \sum_{i=1}^{N} \sum_{j=i+1}^{N} \langle \mathbf{v}_i, \mathbf{v}_j \rangle x_i x_j \right)
\]

- Embed features into a k-dimensional latent space
- Explore the feature interaction patterns using vector inner-product

[Rendle. Factorization machines. ICDM 2010.]

[Oentaryo et al. Predicting response in mobile advertising with hierarchical importance-aware factorization machine. WSDM 14]
Factorisation Machine is a Neural Network

\[ y_{FM}(x) := \text{sigmoid}\left( w_0 + \sum_{i=1}^{N} w_i x_i + \sum_{i=1}^{N} \sum_{j=i+1}^{N} \langle v_i, v_j \rangle x_i x_j \right) \]
Factorisation-machine supported Neural Networks (FNN)

\[ \hat{y} = \text{sigmoid}(W_3l_2 + b_3) \]

\[ l_2 = \tanh(W_2l_1 + b_2) \]

\[ l_1 = \tanh(W_1z + b_1) \]

\[ z_i = (w_i, v_{i1}^1, v_{i1}^2, \ldots, v_{i1}^K) = W_0^i \cdot x[\text{start}_i: \text{end}_i] \]

[Factorisation Machine Initialised]

[Zhang et al. Deep Learning over Multi-field Categorical Data – A Case Study on User Response Prediction. ECIR 16]
Factorisation-machine supported Neural Networks (FNN)

Chain rule to update factorisation machine parameters:

\[
\frac{\partial L(y, \hat{y})}{\partial W^i_0} = \frac{\partial L(y, \hat{y})}{\partial z_i} \frac{\partial z_i}{\partial W^i_0} = \frac{\partial L(y, \hat{y})}{\partial z_i} x[\text{start}_i : \text{end}_i]
\]

\[
W^i_0 \leftarrow W^i_0 - \eta \cdot \frac{\partial L(y, \hat{y})}{\partial z_i} x[\text{start}_i : \text{end}_i].
\]

[Zhang et al. Deep Learning over Multi-field Categorical Data – A Case Study on User Response Prediction. ECIR 16]
But factorisation machine is still different from common additive neural networks.

$$y_{FM}(x) := \text{sigmoid} \left( w_0 + \sum_{i=1}^{N} w_i x_i + \sum_{i=1}^{N} \sum_{j=i+1}^{N} \langle v_i, v_j \rangle x_i x_j \right)$$
Product Operations as Feature Interactions

City: Shanghai  Occupation: Student

Inner Product Operation

City: Shanghai  Occupation: Student

Outer Product Operation

[Yanru Qu et al. Product-based Neural Networks for User Response Prediction. ICDM 2016]
Product-based Neural Networks (PNN)

[Yanru Qu et al. Product-based Neural Networks for User Response Prediction. ICDM 2016]
Convolutional Click Prediction Model (CCPM)

- CNN to (partially) select good feature combinations

[Qiang Liu et al. A convolutional click prediction model. CIKM 2015]
### Overall Performance

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
<th></th>
<th>Log Loss</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Criteo</td>
<td>iPinYou</td>
<td>Criteo</td>
</tr>
<tr>
<td>LR</td>
<td>71.48%</td>
<td>73.43%</td>
<td>0.1334</td>
<td>5.581e-3</td>
</tr>
<tr>
<td>FM</td>
<td>72.20%</td>
<td>75.52%</td>
<td>0.1324</td>
<td>5.504e-3</td>
</tr>
<tr>
<td>FNN</td>
<td>75.66%</td>
<td>76.19%</td>
<td>0.1283</td>
<td>5.443e-3</td>
</tr>
<tr>
<td>CCPM</td>
<td>76.71%</td>
<td>76.38%</td>
<td>0.1269</td>
<td>5.522e-3</td>
</tr>
<tr>
<td>PNN-I</td>
<td><strong>77.79%</strong></td>
<td>79.14%</td>
<td><strong>0.1252</strong></td>
<td>5.195e-3</td>
</tr>
<tr>
<td>PNN-II</td>
<td>77.54%</td>
<td><strong>81.74%</strong></td>
<td>0.1257</td>
<td>5.211e-3</td>
</tr>
<tr>
<td>PNN-III</td>
<td>77.00%</td>
<td>76.61%</td>
<td>0.1270</td>
<td><strong>4.975e-3</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>RMSE</th>
<th></th>
<th>RIG</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Criteo</td>
<td>iPinYou</td>
<td>Criteo</td>
</tr>
<tr>
<td>CCPM</td>
<td>8.938e-4</td>
<td>5.343e-07</td>
<td>1.124e-1</td>
<td>8.335e-2</td>
</tr>
<tr>
<td>PNN-I</td>
<td><strong>8.803e-4</strong></td>
<td>4.851e-07</td>
<td><strong>1.243e-1</strong></td>
<td>1.376e-1</td>
</tr>
<tr>
<td>PNN-II</td>
<td>8.846e-4</td>
<td>5.293e-07</td>
<td>1.211e-1</td>
<td>1.349e-1</td>
</tr>
<tr>
<td>PNN-III</td>
<td>8.988e-4</td>
<td><strong>4.819e-07</strong></td>
<td>1.118e-1</td>
<td><strong>1.740e-1</strong></td>
</tr>
</tbody>
</table>
Training with Instance Bias

\[ p_x(x) \cdot P(\text{win}|x, b_x) = q_x(x) \]

\[ w(b_x) \equiv P(\text{win}|x, b_x) = \int_0^{b_x} p_z(z)dz \]

[Zhang et al. Bid-aware Gradient Descent for Unbiased Learning with Censored Data in Display Advertising. KDD 2016.]
Unbiased Learning

• General machine learning problem

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

• But the training data distribution is \( q(x) \)
  – A straightforward solution: importance sampling

\[
\mathbb{E}_{x \sim p_x(x)} [\mathcal{L}(y, f_\theta(x))] = \int_{x} p_x(x) \mathcal{L}(y, f_\theta(x)) dx
\]
\[
= \int_{x} q_x(x) \frac{\mathcal{L}(y, f_\theta(x))}{w(b_x)} dx = \mathbb{E}_{x \sim q_x(x)} \left[ \frac{\mathcal{L}(y, f_\theta(x))}{w(b_x)} \right]
\]

[Zhang et al. Bid-aware Gradient Descent for Unbiased Learning with Censored Data in Display Advertising. KDD 2016.]
Unbiased CTR Estimator Learning

Table: Online A/B testing of CTR estimation (Yahoo!).

<table>
<thead>
<tr>
<th>Camp.</th>
<th>BIAS AUC</th>
<th>KMMP AUC</th>
<th>AUC Lift</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>63.78%</td>
<td>64.12%</td>
<td>0.34%</td>
</tr>
<tr>
<td>C2</td>
<td>87.45%</td>
<td>88.58%</td>
<td>1.13%</td>
</tr>
<tr>
<td>C3</td>
<td>69.73%</td>
<td>75.52%</td>
<td>5.79%</td>
</tr>
<tr>
<td>C4</td>
<td>88.82%</td>
<td>89.55%</td>
<td>0.73%</td>
</tr>
<tr>
<td>C5</td>
<td>69.71%</td>
<td>72.29%</td>
<td>2.58%</td>
</tr>
<tr>
<td>C6</td>
<td>89.33%</td>
<td>90.70%</td>
<td>1.37%</td>
</tr>
<tr>
<td>C7</td>
<td>77.76%</td>
<td>78.92%</td>
<td>1.16%</td>
</tr>
<tr>
<td>C8</td>
<td>74.57%</td>
<td>76.98%</td>
<td>2.41%</td>
</tr>
<tr>
<td>C9</td>
<td>71.04%</td>
<td>73.12%</td>
<td>2.08%</td>
</tr>
<tr>
<td>all</td>
<td>73.48%</td>
<td>76.45%</td>
<td>2.97%</td>
</tr>
</tbody>
</table>

[Zhang et al. Bid-aware Gradient Descent for Unbiased Learning with Censored Data in Display Advertising. KDD 2016.]
Table of contents

- RTB system
- Auction mechanisms
- User response estimation
- **Learning to bid**
- Conversion attribution
- Pacing control
- Targeting and audience expansion
- Reserve price optimization
RTB Display Advertising Mechanism

- Buying ads via real-time bidding (RTB), 10B per day
Data of Learning to Bid

- **Data**

<table>
<thead>
<tr>
<th>((x,t))</th>
<th>(b)</th>
<th>(w)</th>
<th>(c)</th>
<th>(y)</th>
</tr>
</thead>
<tbody>
<tr>
<td>((\text{up},1500\times20,\text{Shanghai},0))</td>
<td>5</td>
<td>1</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>((\text{down},1200\times25,\text{Paris},1))</td>
<td>4</td>
<td>1</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>((\text{left},20\times1000,\text{Los Angeles},2))</td>
<td>3</td>
<td>0</td>
<td>(\times)</td>
<td>(\times)</td>
</tr>
<tr>
<td>((\text{right},35\times600,\text{London},3))</td>
<td>0</td>
<td>0</td>
<td>(\times)</td>
<td>(\times)</td>
</tr>
</tbody>
</table>

- 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 $b(x)$

$$\text{Bid Strategy} \rightarrow \text{Bid Request} \quad \text{(user, ad, page, context)} \rightarrow \text{Bid Price}$$

• Bid to optimise the KPI with budget constraint

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

subject to $\text{cost} \leq \text{budget}$
Bidding Strategy in Practice

Bidding Strategy

- Feature Eng.
- Frequency Capping
- Retargeting
- Budget Pacing
- Bid Landscape
- Whitelist / Blacklist
- CTR / CVR Estimation
- Campaign Pricing Scheme
- Bid Calculation

Bid Request
(user, ad, page, context)

Bid Price
Bidding Strategy in Practice: A Quantitative Perspective

Bidding Strategy

Preprocessing

Utility Estimation

Cost Estimation

Bidding Function

Bid Request (user, ad, page, context)

CTR, CVR, revenue

Bid landscape

Bid Price
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

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

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

- Price Prediction via Linear Regression

\[ z = \beta^T x + \epsilon \quad \max_{\beta} \sum_{i \in W} \log \phi \left( \frac{z_i - \beta^T x_i}{\sigma} \right) \]

- Modelling censored data in lost bid requests

\[ P(b_i < z_i) = \Phi \left( \frac{\beta^T x_i - b_i}{\sigma} \right) \]

\[ \max_{\beta} \sum_{i \in W} \log \phi \left( \frac{z_i - \beta^T x_i}{\sigma} \right) + \sum_{i \in L} \log \Phi \left( \frac{\beta^T x_i - b_i}{\sigma} \right) \]

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

Node split
Based on
Clustering
categories

Yuchen Wang et al. Functional Bid Landscape Forecasting for Display Advertising. ECMLPKDD 2016
Bidding Strategies

• How much to bid for each bid request?

Bid Request
(user, ad, page, context)

Bid Price

• Bid to optimise the KPI with budget constraint

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

subject to $\text{cost} \leq \text{budget}$
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 = \[
    \begin{cases} 
    \text{Value of click, if clicked} \\
    0, \text{ if not clicked} 
    \end{cases}
  \]
  – Averaged impression value = value of click \times 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

\[
\max_{\text{bidding strategy}} \quad \text{KPI}
\]
subject to \(\text{cost} \leq \text{budget}\)

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

- Direct functional optimisation

\[ b(\text{ORTB}) = \arg \max_{b()} \quad N_T \int_{\theta} \theta w(b(\theta)) p_\theta(\theta) d\theta \]

subject to \( N_T \int_{\theta} b(\theta) w(b(\theta)) p_\theta(\theta) d\theta \leq B \) \( \leftarrow \) budget

- Solution: Calculus of variations

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

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

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

(a) Winning function 1.

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

(b) Bidding function 1.

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

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

• Bid optimization on ‘true’ distribution

\[
\arg \max_{b()} \quad T \int_x f(x) w(b(f(x))) p_x(x) dx
\]

subject to \( T \int_x b(f(x)) w(b(f(x))) p_x(x) dx = B \)

• Unbiased bid optimization on biased distribution

\[
\arg \max_{b()} \quad T \int_x f(x) w(b(f(x))) \frac{q_x(x)}{w(b_x)} dx
\]

subject to \( T \int_x b(f(x)) w(b(f(x))) \frac{q_x(x)}{w(b_x)} dx = B \)

[Zhang et al. Bid-aware Gradient Descent for Unbiased Learning with Censored Data in Display Advertising. KDD 2016.]
Unbiased Bid Optimisation

A/B Testing on Yahoo! DSP.

[Zhang et al. Bid-aware Gradient Descent for Unbiased Learning with Censored Data in Display Advertising. KDD 2016.]
That’s the first half of the tutorial! Questions?
Part 2

Speaker: Jian Xu, TouchPal Inc.
(jian.xu AT cootek.cn)

Google Play Best Apps of 2015

usjobs@cootek.cn
Table of contents

• RTB system
• Auction mechanisms
• User response estimation
• Learning to bid
• Conversion attribution
• Pacing control
• Targeting and audience expansion
• Reserve price optimization
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• RTB system
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• Pacing control
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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]
Rule-based Attribution

<table>
<thead>
<tr>
<th>Model</th>
<th>Attribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Last Touch</td>
<td>0% 0% 0% 100%</td>
</tr>
<tr>
<td>First Touch</td>
<td>100% 0% 0% 0%</td>
</tr>
<tr>
<td>Linear</td>
<td>25% 25% 25% 25%</td>
</tr>
<tr>
<td>Time Decay</td>
<td>10% 20% 30% 40%</td>
</tr>
<tr>
<td>Position Based</td>
<td>40% 10% 10% 40%</td>
</tr>
</tbody>
</table>

[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
  – It should be built based on ad touch and conversion data of a campaign

• Interpretability
  – Generally accepted by all the parties

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

<table>
<thead>
<tr>
<th>Display</th>
<th>Search</th>
<th>Mobile</th>
<th>Email</th>
<th>Social</th>
<th>Convert?</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

• For M iterations
  – Sample 50% data instances and 50% features
  – Train a logistic regression model and record the feature weights

• Average the weights of a feature

[Shao et al. Data-driven multi-touch attribution models. KDD 11]
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 (not-normalized)

\[
C(x_i) = p(y|x_i) + \frac{1}{2N_{j\neq i}} \sum_{j\neq i} \left\{ p(y|x_i, x_j) - p(y|x_i) - p(y|x_j) \right\}
\]

[Shao et al. Data-driven multi-touch attribution models. KDD 11]
[Shao et al. Data-driven multi-touch attribution models. KDD 11]
Table 2: The MTA user-level attribution analysis.

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

• The “relatively heuristic” data-driven model
  [Shao et al. Data-driven multi-touch attribution models. KDD 11]
  \[ V(x_i) = \frac{1}{2} P(y|x_i) + \frac{1}{2N_{j \neq i}} \sum_{j \neq i} \left( P(y|x_i, x_j) - P(y|x_j) \right) \]

• A more generalized and data-driven model
  [Dalessandro et al. Causally Motivated Attribution for Online Advertising. ADKDD 11]
  \[ V(x_i) = \sum_{S \subseteq I \setminus i} w_{S,i} (P(y|S, x_i) - P(y|S)) \]

  \[ w_{S,i} \] is the probability that the ad touch sequence begins with \( S, x_i \)
## Attribution Comparison: LTA vs MTA

<table>
<thead>
<tr>
<th>Channel</th>
<th>Group</th>
<th>Data Generating Parameters</th>
<th>Attribution Results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Ad Propensity Likelihood</td>
<td>Simulated Conversion Rate</td>
</tr>
<tr>
<td>1</td>
<td>Gen Prospecting</td>
<td>5.0%</td>
<td>0.100%</td>
</tr>
<tr>
<td>2</td>
<td>Gen Prospecting</td>
<td>10.0%</td>
<td>0.080%</td>
</tr>
<tr>
<td>3</td>
<td>Gen Prospecting</td>
<td>10.0%</td>
<td>0.070%</td>
</tr>
<tr>
<td>4</td>
<td>Gen Prospecting</td>
<td>15.0%</td>
<td>0.050%</td>
</tr>
<tr>
<td>5</td>
<td>Gen Prospecting</td>
<td>15.0%</td>
<td>0.050%</td>
</tr>
<tr>
<td>6</td>
<td>Gen Prospecting</td>
<td>20.0%</td>
<td>0.010%</td>
</tr>
<tr>
<td>7</td>
<td>Gen Prospecting</td>
<td>20.0%</td>
<td>0.008%</td>
</tr>
<tr>
<td>8</td>
<td>Gen Prospecting</td>
<td>25.0%</td>
<td>0.008%</td>
</tr>
<tr>
<td>9</td>
<td>Retargeting</td>
<td>2.5%</td>
<td>0.500%</td>
</tr>
<tr>
<td>10</td>
<td>Retargeting</td>
<td>2.5%</td>
<td>0.400%</td>
</tr>
<tr>
<td>11</td>
<td>Retargeting</td>
<td>3.0%</td>
<td>0.300%</td>
</tr>
<tr>
<td>12</td>
<td>Retargeting</td>
<td>3.5%</td>
<td>0.250%</td>
</tr>
<tr>
<td>13</td>
<td>Search</td>
<td>0.5%</td>
<td>1.000%</td>
</tr>
<tr>
<td>14</td>
<td>Search</td>
<td>0.5%</td>
<td>2.000%</td>
</tr>
</tbody>
</table>

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

• Coalitional 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

• Coalitional game
  – $\nu$ is the conversion rate of different subset of publishers
  – The Shapley value of publisher $i$ is

$$\phi_i(\nu) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! (n - |S| - 1)!}{n!} \left( \nu(S \cup \{i\}) - \nu(S) \right)$$

CVR of those touched by all the publishers in $S \cup \{i\}$

[Berman, Ron. Beyond the last touch: Attribution in online advertising.” Available at SSRN 2384211 (2013)]
Survival theory-based model

- Use **addictive** hazard functions to explicitly model:
  - the strength of influence, and
  - the time-decay of the influence

\[ \lambda(t) = \sum_{i=1}^{3} g_{a_i}(t-t_i) \]

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

- Establish a graph from observed user journeys

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

- Attribute based on probability change of reaching conversion state

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

- Typical advertiser hierarchy

- Typical budget allocation scheme

[Gevik et al. Multi-Touch Attribution Based Budget Allocation in Online Advertising. ADKDD 14]
MTA-based budget allocation

• Estimate sub-campaign spending capability
  – New sub-campaign: assign a learning budget
  – Existing sub-campaign: assign an x% more budget

• Calculate ROI of each sub-campaign

\[
\text{ROI}_{l_i} = \frac{\sum_{a_j} p(l_i|a_j) v(a_j)}{\text{Money spent by } l_i} \]

1 if \( l_i \) is the last touch point else 0 (LTA)

\[
\frac{V(l_i)}{\sum_{l_k \in S_{a_j}} V(l_k)} \quad \text{(MTA)}
\]

• Allocate budget in a cascade fashion

[Geyik et al. Multi-Touch Attribution Based Budget Allocation in Online Advertising. ADKDD 14]
MTA-based budget allocation

• Results on a real ad campaign

[Geik et al. Multi-Touch Attribution Based Budget Allocation in Online Advertising. ADKDD 14]
Attribution and Bidding

• For CPA campaigns, *conventional* bidding strategy is to bid prop. to estimated action rate (a.k.a. conversion rate). Is that always correct?

---

A tiny example

Two users: $a$ and $b$

$AR_a$: 0.04 if exposed to the ad, 0.03 if not;

$AR_b$: 0.02 if exposed to the ad, 0.001 if not.

💡 If only one of them can be exposed to the ad, who will you select?
Attribution and Bidding

A not-so-tiny example

Two users: $a$ and $b$, campaign CPA: $100$
$AR_a$: 0.04 if exposed to the ad, 0.03 if not (lift: 0.01);
$AR_b$: 0.02 if exposed to the ad, 0.001 if not (lift: 0.019).
Bidder$_1$ bids prop. to AR assuming exposed: $4$ for $a$, $2$ for $b$;
Bidder$_2$ bids prop. to AR lift: $2$ for $a$, $3.8$ for $b$.
Incremental value from Bidder$_1$: 0.01 conversions;
Incremental value from Bidder$_2$: 0.19 conversions.
Expected attribution to Bidder$_1$: 0.04 conversions;
Expected attribution to Bidder$_2$: 0.02 conversions.

💡 Prevalent bidding strategy does not optimize campaign performance;
💡 Bidders are not rewarded fairly.
Rational DSPs for CPA advertisers

- DSP’s perspective:
  - *Cost*: second price in the auction
  - *Reward*: CPA if (1) there is action, and (2) the action is attributed to it
  - A *rational DSP* will always bid
    \[
    \text{bid} = AR \times CPA \times p(\text{attribution}|\text{action})
    \]

In LTA, \( p(\text{attribution}|\text{action}) \) is always 1 for the last toucher. *Therefore DSPs are bidding to maximize their chance to be attributed instead of maximizing conversions.*
Bidding in Multi-Touch Attribution

• Current bidding strategy (driven by LTA)
  \[ \text{bid} = \text{AR} \times \text{CPA} \]

• A new bidding strategy (driven by MTA)
  – If attribution is based on the AR lift

  \[ \Delta p = p(action|s_+(a)) - p(action|s) \]

  \[ \text{bid} = \Delta p \times \text{base\_bid} \]

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

\[ \text{bid} = \Delta p \times \text{base\_bid} \]

- Estimating action rate lift
  - Learn a \textit{generic} action prediction model \( \hat{P} \) on top of features extracted from \textit{user\_states} \( F(s) \)
  - Then action rate lift can be estimated by
    \[ \hat{\Delta}p = \hat{P}(\text{action}|F(s_+(a))) - \hat{P}(\text{action}|F(s)) \]

- Deriving the base\_bid
  \[ \beta = \frac{\bar{p}}{\Delta p} \times \text{CPA} \]

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

Value-based bidding vs. lift-based bidding - Advertiser's perspective

<table>
<thead>
<tr>
<th>Adv</th>
<th>Value-based bidding</th>
<th>Lift-based bidding</th>
<th>Action lift</th>
<th>Lift-over-lift</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># imps</td>
<td># actions</td>
<td>Action lift (vs &quot;No bid&quot;)</td>
<td># imps</td>
</tr>
<tr>
<td>1</td>
<td>53,396</td>
<td>714</td>
<td>11.2%</td>
<td>59,703</td>
</tr>
<tr>
<td>2</td>
<td>298,333</td>
<td>896</td>
<td>8.9%</td>
<td>431,637</td>
</tr>
<tr>
<td>3</td>
<td>11,048,583</td>
<td>1,477</td>
<td>2.7%</td>
<td>11,483,360</td>
</tr>
<tr>
<td>4</td>
<td>3,915,792</td>
<td>2,016</td>
<td>6.6%</td>
<td>4,368,441</td>
</tr>
<tr>
<td>5</td>
<td>6,015,322</td>
<td>6,708</td>
<td>19.6%</td>
<td>8,770,935</td>
</tr>
</tbody>
</table>

Value-based bidding vs. lift-based bidding - DSP's perspective

<table>
<thead>
<tr>
<th>Adv</th>
<th>Value-based bidding</th>
<th>Lift-based bidding</th>
<th>Inventory-cost diff</th>
<th>Cost-per-imp diff</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td># imps</td>
<td># attrs</td>
<td>Inventory cost</td>
<td># imps</td>
</tr>
<tr>
<td>1</td>
<td>53,396</td>
<td>50</td>
<td>$278.73</td>
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</tr>
<tr>
<td>2</td>
<td>298,333</td>
<td>80</td>
<td>$1,065.05</td>
<td>431,637</td>
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<td>11,048,583</td>
<td>240</td>
<td>$25,522.22</td>
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<tr>
<td>4</td>
<td>3,915,792</td>
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<td>$10,846.74</td>
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<tr>
<td>5</td>
<td>6,015,322</td>
<td>500</td>
<td>$19,296.51</td>
<td>8,770,935</td>
</tr>
</tbody>
</table>
Table of contents

• RTB system
• Auction mechanisms
• User response estimation
• Learning to bid
• Conversion attribution
• Pacing control
• Targeting and audience expansion
• Reserve price optimization
Pacing Control

- *Budget pacing control* helps advertisers to define and execute how their budget is spent over the time.

- **Why?**
  - Avoid premature campaign stop, overspending and spending fluctuations.
  - Reach a wider range of audience
  - Build synergy with other marketing campaigns
  - Optimize campaign performance
Examples

(a) Premature Stop

(b) Fluctuating Budget

(c) Uniform Pacing

(d) Traffic Based Pacing

(e) Performance Based Pacing

[Lee et al. Real Time Bid Optimization with Smooth Budget Delivery in Online Advertising. ADKDD 13]
Two streams of approaches

Bid modification

Probabilistic throttling

[Xu et al. Smart Pacing for Effective Online Ad Campaign Optimization. KDD 2015.]
Bid modification with PID controller

- Add a monitor, a controller and an actuator module into the bidding system
- Achieve reference KPI (e.g. eCPC) by bid modification

[Zhang et al. Feedback Control of Real-Time Display Advertising. WSDM 2016.]
Bid modification with PID controller

• Current control signal is calculated by PID controller:

\[ e(t_k) = x_r - x(t_k), \]

\[ \phi(t_{k+1}) \leftarrow \lambda_P e(t_k) + \lambda_I \sum_{j=1} e(t_j) \Delta t_j + \lambda_D \frac{\Delta e(t_k)}{\Delta t_k} \]

• Bid price is adjusted by taking into account current control signal:

\[ b_a(t) = b(t) \exp\{\phi(t)\} \]

• A baseline controller: Water-level controller:

\[ \phi(t_{k+1}) \leftarrow \phi(t_k) + \gamma (x_r - x(t_k)) \]

[Zhang et al. Feedback Control of Real-Time Display Advertising. WSDM 2016.]
Bid modification with PID controller

- Online eCPC control performance of a mobile game campaign

[Zhang et al. Feedback Control of Real-Time Display Advertising. WSDM 2016.]
Probabilistic throttling with conventional feedback controller

- $P(t)$: pacing-rate at time slot $t$

- Leverage a *conventional feedback controller*:
  - $P(t) = P(t-1)(1-R)$ if budget spent $> allocation$
  - $P(t) = P(t-1)(1+R)$ if budget spent $< allocation$

[Agarwal et al. Budget Pacing for Targeted Online Advertisements at LinkedIn. KDD 2014.]
Probabilistic throttling with adaptive controller

• Leverage an adaptive controller

\[
pacing\_rate(t+1) = \frac{b_{t+1}}{s(t)} \cdot \frac{\text{reqs}(t) \cdot \text{win\_rate}(t)}{\text{reqs}(t+1) \cdot \text{win\_rate}(t+1)}
\]

Desired spending in the next time-slot

Forecasted request volume and bid win rate in the next time-slot

\(b_{t+1}\) is the desired spend (allocated) at time slot \(t+1\). Different desired spending patterns can incur different calculation.

[Lee et al. Real Time Bid Optimization with Smooth Budget Delivery in Online Advertising. ADKDD 13]
Pacing control for campaign optimization

• Campaign optimization objectives:
  – Reach delivery and performance goals
    • *Branding campaigns*: Spend out budget > Campaign performance (e.g., in terms of eCPC or eCPA)
    • *Performance campaigns*: Meet performance goal > Spend as much budget as possible.
  – Execute the budget pacing plan
  – Reduce creative serving cost

Can we achieve all these objectives by pacing control?

[Xu et al. Smart Pacing for Effective Online Ad Campaign Optimization. KDD 2015.]
Smart pacing

[Xu et al. Smart Pacing for Effective Online Ad Campaign Optimization. KDD 2015.]
Smart pacing performance

The graph compares spending and eCPC for different pacing strategies over time slots. The x-axis represents time slots, and the y-axes show spending ($\text{Spending}$) and eCPC ($\text{eCPC}$). The strategies compared are:

- Spending Baseline
- Spending SmartPacing
- eCPC Baseline
- eCPC SmartPacing

The graph illustrates how each strategy performs over the time slots, with the SmartPacing strategies generally showing more variability and fluctuation compared to the Baseline strategies.
Smart pacing vs conventional feedback controller
Smart pacing vs conventional feedback controller

![Chart showing cumulative spending and time slot]
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Does targeting help online advertising?

- Segment user based on ...
  - LP: Long-term Page-view, SP: Short-term Page-view
  - LQ: Long-term Query, SQ: Short-term Query

Compare the best CTR segment with baseline (random users)

[J Yan, et al. How much can behavioral targeting help online advertising? WWW 2009]
User segmentation

- Different user segmentation algorithms may have different results

[J Yan, et al. How much can behavioral targeting help online advertising? WWW 2009]
User segmentation

- From user – documents to user – topics
  - Topic modeling using PLSA, LDA, etc.

[X Wu et al. Probabilistic latent semantic user segmentation for behavioral targeted advertising. Intelligence for Advertising 2009]
Targeting landscape

- Targeting: reach the *precise* users who are receptive to the marketing messages.

**Geo-targeting**
- Demo-targeting
- Web-site targeting
- Behavioral Targeting
- Social Targeting
- Search Re-targeting
- Mail Re-targeting
- Proximity Targeting

**Desired users**
Targeting landscape

- A bit too complicated ...
Audience expansion

- AEX Simplifies targeting by discovering similar (prospective) customers

Given a segment $S$, find a larger audience that is
- Similar to the audience inside $S$
- Able to bring good ROI

[J Shen, et al., Effective Audience Extension in Online Advertising, KDD 2015]
Rule mining-based approach

• Identify feature-pair-based associative classification rules
  – Affinity that a feature-pair towards conversion:
    \[ F-LLR = P(f) \times \log \left( \frac{P(f | \text{conversion})}{P(f | \text{non-conversion})} \right) \]

  Probability to observe feature-pair \( f \) in data

  – Top \( k \) feature (pairs) are kept as scoring rules

  Especially good for those tail campaigns (e.g. CVR < 0.01%)

Rule mining-based approach

- Campaign C1: a *tail* campaign
- Campaign C2: a *head* campaign

<table>
<thead>
<tr>
<th>Table 1: Results for Campaign $C_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline</strong></td>
</tr>
<tr>
<td>Random Targeting</td>
</tr>
<tr>
<td>Linear SVM</td>
</tr>
<tr>
<td>GBDT</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2: Results for Campaign $C_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline</strong></td>
</tr>
<tr>
<td>Random Targeting</td>
</tr>
<tr>
<td>Linear SVM</td>
</tr>
<tr>
<td>GBDT</td>
</tr>
</tbody>
</table>

Weighted criteria-based approach

- **Similarity Criterion:**

  \[
  \text{sim}(c_{new}, S) = p(c_{new} \mid S) = \frac{|\text{aud}(c_{new}) \cap \text{aud}(S)|}{|\text{aud}(S)|}
  \]

- **Novelty Criterion:**

  \[
  \text{nov}(c_{new}, S) = p(!S \mid c_{new}) = 1 - p(S \mid c_{new})
  \]

<table>
<thead>
<tr>
<th></th>
<th>Similarity $P(\text{New} \mid \text{Original})$</th>
<th>Novelty $P(\text{Original} \mid \text{New})$</th>
<th>Value Good/OK/Bad?</th>
</tr>
</thead>
<tbody>
<tr>
<td>New / Original</td>
<td>1</td>
<td>0</td>
<td>Bad</td>
</tr>
<tr>
<td>New</td>
<td>1</td>
<td>$\approx 0.5$</td>
<td>Good</td>
</tr>
<tr>
<td>New</td>
<td>$\approx 0.5$</td>
<td>0</td>
<td>Bad</td>
</tr>
<tr>
<td>New</td>
<td>$\approx 0.2$</td>
<td>$\approx 0.8$</td>
<td>OK</td>
</tr>
<tr>
<td>New</td>
<td>$\approx 0.8$</td>
<td>$\approx 0.2$</td>
<td>OK</td>
</tr>
</tbody>
</table>

[J Shen, et al., Effective Audience Extension in Online Advertising, KDD 2015]
Weighted criteria-based approach

- Quality Criterion:

\[ q(c_{new}) = \frac{\sum_{u \in aud(c_{new})} \text{click}(u, adv)}{\sum_{u \in aud(c_{new})} \text{imp}(u, adv)} \]

- Final score

\[ \log \text{Score}(c_{new} \mid S) = \theta_1 \log(p(c_{new} \mid S)) + \theta_2 \log(1 - p(S \mid c_{new})) + \theta_3 \log(q(c_{new})) \]

[J Shen, et al., Effective Audience Extension in Online Advertising, KDD 2015]
Weighted criteria-based approach

(a) Sizes of audiences for the original segment and different recommended extensions.

(b) Amount of original audience covered by different recommended extensions.

(b) CTR values for the original segment and different recommended extensions.
Audience Expansion for OSN Advertising

- Campaign-agnostic: enrich member profile attributes
- Campaign-aware: identify similar members

[H Liu et al. Audience expansion for online social network advertising. KDD 2016]
Audience Expansion for OSN Advertising

• Member similarity evaluation
  
  – Density of a segment:

  \[ D = \frac{2|C|}{|M||M| - 1} \]

  – Expansion ratio vs Density ratio

[H Liu et al. Audience expansion for online social network advertising. KDD 2016]
Transferred lookalike

- Web browsing prediction (CF task)

\[
\hat{y}_{u,p}^c = \sigma\left( w_0^c + \sum_i w_i^c x_i^u + \sum_j w_j^c x_j^p + \sum_i \sum_j \langle v_i^c, v_j^c \rangle x_i^u x_j^p \right)
\]

- Ad response prediction (CTR task)

\[
\hat{y}_{u,p,a} = \sigma\left( w_0^r + \sum_i w_i^r x_i^u + \sum_j w_j^r x_j^p + \sum_l w_l^r x_l^a + \sum_i \sum_j \langle v_i^r, v_j^r \rangle x_i^u x_j^p + \sum_i \sum_l \langle v_i^r, v_l^r \rangle x_i^u x_l^a + \sum_j \sum_l \langle v_j^r, v_l^r \rangle x_j^p x_l^a \right)
\]

[Zhang et al. 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

\[ w^r \sim \mathcal{N}(w^c, \sigma^2_{wd} I) \]

\[ v^r_i \sim \mathcal{N}(v^c_i, \sigma^2_{vd} I) \]

\[ \mu_{wd}, \sigma^2_{wd} \quad \mu_{vd}, \sigma^2_{vd} \quad \mu_{vd,a}, \sigma^2_{vd,a} \quad \mu_{wr,a}, \sigma^2_{wr,a} \]

[Zhang et al. Implicit Look-alike Modelling in Display Ads: Transfer Collaborative Filtering to CTR Estimation. ECIR 2016]
Joint Learning in Transferred lookalike

\[
\hat{\Theta} = \max_{\Theta} P(\Theta) \left[ \prod_{(x^c, y^c) \in D^c} P(y^c | x^c; \Theta) \right]^{\frac{\alpha}{|D^c|}} \cdot \left[ \prod_{(x^r, y^r) \in D^r} P(y^r | x^r; \Theta) \right]^{\frac{1-\alpha}{|D^r|}} \\

P(\Theta) = P(w^c)P(V^c)P(w^r | w^c)P(V^r | V^c)P(w_r^r)P(V_r^r)
\]

[Zhang et al. Implicit Look-alike Modelling in Display Ads: Transfer Collaborative Filtering to CTR Estimation. ECIR 2016]
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The task:
• To find the optimal reserve prices to maximize publisher revenue

The challenge:
• Practical constraints v.s theoretical assumptions

Why

• Suppose it is second price auction and $b_1, b_2$ are first and second prices
  – Preferable case: $b_1 \geq \alpha > b_2$ (increases revenue)
  – Undesirable case: $\alpha > b_1$ (lose revenue)
An example

- Suppose: two bidders, whose private values $b_1, b_2$ are both drawn from Uniform[0, 1]
- Without a reserve price, the expected payoff $r$ is:
  
  $$r = E[\min(b_1, b_2)] = 0.33$$

- With $\alpha = 0.2$:
  
  $$r = E[\min(b_1, b_2) | b_1 > 0.2, b_2 > 0.2] + (0.8 \times 0.2) \times 2 \times 0.2 = 0.36$$

- With $\alpha = 0.5$:
  
  $$r = E[\min(b_1, b_2) | b_1 > 0.5, b_2 > 0.5] + (0.5 \times 0.5) \times 2 \times 0.5 = 0.42$$

- With $\alpha = 0.6$:
  
  $$r = E[\min(b_1, b_2) | b_1 > 0.6, b_2 > 0.6] + (0.6 \times 0.4) \times 2 \times 0.6 = 0.405$$

[Ostrovsky et al, Reserve prices in internet advertising auctions: A field experiment. EC 2011]
Theoretically optimal reserve price

• In the second price auctions, an advertiser bid its private value $b$

• Suppose bidders are risk-neutral and symmetric (i.e. having same distributions) with bid C.D.F $F(b)$

• The publisher also has a private value $V_p$

• The optimal reserve price is given by:

$$\alpha = \frac{1 - F(\alpha)}{F'(\alpha)} + V_p$$

[Levin and Smith, Optimal Reservation Prices in Auctions, 1996]
Results from a field experiment

• Using the theoretically optimal reserve price on Yahoo! Sponsored search

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>t-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of keywords (T – treatment group)</td>
<td>222,249</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of keywords (C – control group)</td>
<td>11,615</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Mean change in depth in T) – (mean change in depth in C)</td>
<td>-0.8612</td>
<td>-60.29</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>(Mean change in revenue in T) – (mean change in revenue in C)</td>
<td>-11.88%</td>
<td>-2.45</td>
<td>0.0144</td>
</tr>
<tr>
<td>Estimated impact of reserve prices on revenues</td>
<td>-9.19%</td>
<td>-11.1</td>
<td>&lt; 0.0001</td>
</tr>
</tbody>
</table>

Mixed results

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

<table>
<thead>
<tr>
<th>Variable</th>
<th>Value</th>
<th>t-statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of keywords (T – treatment group)</td>
<td>216,383</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of keywords (C – control group)</td>
<td>11,401</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Mean change in depth in T) – (mean change in depth in C)</td>
<td>-0.9664</td>
<td>-55.09</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td>(Mean change in revenue in T) – (mean change in revenue in C)</td>
<td>14.59%</td>
<td>1.79</td>
<td>0.0736</td>
</tr>
<tr>
<td>Estimated impact of reserve prices on revenues</td>
<td>3.80%</td>
<td>5.41</td>
<td>&lt; 0.0001</td>
</tr>
</tbody>
</table>

[Ostrovsky et al, Reserve prices in internet advertising auctions: A field experiment. EC 2011]
Bidding strategy is a mystery

- Advertisers have their own bidding strategies (No access to publishers)
- They change their strategies frequently

Many advertisers bid at fixed values with bursts and randomness.

And they come and go

Uniform/Log-normal distributions do NOT fit well

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

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

A simplified dynamic game

- Players: auction winner $w$, publisher $p$
- Initial status: $I_1: b \geq \alpha$; $I_2$ otherwise

- The action set of the winner $A_w$:
  $a_{w1}$, to increase $b$ to higher than $\alpha$;
  $a_{w2}$, to increase $b$ to lower than $\alpha$;
  $a_{w3}$, to decrease or hold $b$ to higher than $\alpha$;
  $a_{w4}$, to decrease or hold $b$ to lower than $\alpha$.

- The action set of the publisher $A_p$:
  $a_{p1}$, to increase or hold $\alpha$ to higher than $b$;
  $a_{p2}$, to increase or hold $\alpha$ to lower than $b$;
  $a_{p3}$, to decrease $\alpha$ to higher than $b$;
  $a_{p4}$, to decrease $\alpha$ to lower than $b$.

$$s_p^*(I) = \begin{cases} a_{p2}, & \text{if } I = I_1 \\ a_{p4}, & \text{if } I = I_2 \end{cases}$$

$$s_w^*(I) = \begin{cases} a_{w3}, & \text{if } I = I_1 \\ a_{w1}, & \text{if } I = I_2 \end{cases}$$

OneShot: the algorithm based on dominant strategy

• The algorithm essentially uses a conventional feedback controller

\[
\begin{align*}
\alpha(t + 1) &= (1 - \epsilon^t \lambda_h) \alpha(t) \quad \text{if } \alpha(t) > b_1(t) \\
\alpha(t + 1) &= (1 + \epsilon^t \lambda_e) \alpha(t) \quad \text{if } b_1(t) \geq \alpha(t) \geq b_2(t) \\
\alpha(t + 1) &= (1 + \epsilon^t \lambda_l) \alpha(t) \quad \text{if } b_2(t) > \alpha(t)
\end{align*}
\]

• A practical example setting of the parameters:

\[
\epsilon = 1.0, \quad \lambda_h = 0.3, \quad \lambda_e = 0.01, \quad \text{and} \quad \lambda_l = 0.02
\]

OneShot performance

Advertiser attrition concern
Optimal reserve price in upstream auctions

- A different problem setting
  - Upstream charges a revenue-share (e.g. 25%) from each winning bid.
  - What is the optimal reserve price for such a marketplace?

[Alcobendas et al., Optimal reserve price in upstream auctions: Empirical application on online video advertising. KDD 2016]
Optimal reserve price in upstream auctions

- Assume bidder’s valuation of the inventory is an i.i.d. realization of the random variable $V$, and bidders are risk neutral, the optimal reserve price for upstream marketplace satisfies

$$
\left[ \rho_c^{*} f_V(\rho_c^{*}) - 1 + F_V(\rho_c^{*}) \right] F_V(\rho_c^{*})^{N-1} P_D(\rho_c^{*}) = \frac{\partial P_D(\bar{w}_T(\rho_c^{*}))}{\partial \rho_c^{*}} \int_{\rho_c^{*}}^{\bar{v}} [u f_V(u) - 1 + F(u)] F_V(u)^{N-1} du
$$

- Probability of winning downstream auction
- Support interval of $V$
- Expected price if having at least one bidder above reserve price
- Probability that a bidder wins the upstream auction with bid $u$

If without downstream auction, optimal condition is

$$
\left[ \rho_u^{*} f_V(\rho_u^{*}) - 1 + F_V(\rho_u^{*}) \right] = 0
$$
Optimal reserve price in upstream auctions

<table>
<thead>
<tr>
<th>Type of Placement</th>
<th>Nb Placements</th>
<th>Placements with Positive Revenue Lift (%)</th>
<th>Expected Revenue Lift (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Downstream Auction ($\rho_u^*$)</td>
<td>71</td>
<td>77%</td>
<td>39%</td>
</tr>
<tr>
<td>Downstream Auction: No Correction ($\rho_u^*$)</td>
<td>30</td>
<td>67%</td>
<td>25%</td>
</tr>
<tr>
<td>Downstream Auction: Correction ($\rho_c^*$)</td>
<td>30</td>
<td>77%</td>
<td>29%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Type of Placement</th>
<th>Nb Placements</th>
<th>Placements with Positive Revenue Lift (%)</th>
<th>Expected Revenue Lift (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Downstream Auction ($\rho_u^*$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Above Current Floor</td>
<td>24</td>
<td>88%</td>
<td>38%</td>
</tr>
<tr>
<td>- Below Current Floor</td>
<td>47</td>
<td>72%</td>
<td>40%</td>
</tr>
<tr>
<td>Downstream Auction: No Correction ($\rho_u^*$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Above Current Floor</td>
<td>9</td>
<td>100%</td>
<td>92%</td>
</tr>
<tr>
<td>- Below Current Floor</td>
<td>21</td>
<td>52%</td>
<td>11%</td>
</tr>
<tr>
<td>Downstream Auction: Correction ($\rho_c^*$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>- Above Current Floor</td>
<td>13</td>
<td>100%</td>
<td>88%</td>
</tr>
<tr>
<td>- Below Current Floor</td>
<td>17</td>
<td>71%</td>
<td>22%</td>
</tr>
</tbody>
</table>

[Alcobendas et al., Optimal reserve price in upstream auctions: Empirical application on online video advertising. KDD 2016]
Learning, Prediction and Optimisation in RTB Display Advertising

Thank You

- RTB system
- Auction mechanisms
- User response estimation
- Learning to bid
- Conversion attribution
- Pacing control
- Targeting and audience expansion
- Reserve price optimization

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