Attribution Modeling Increases Efficiency of Bidding in Display Advertising

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Outline

• The problem: bidding in display advertising

• Model:
  • Attribution model
  • Attribution aware bidder

• Impact on offline evaluation metrics

• Experience & results
Real-time bidding for display advertising
Performance Display Advertising

1. User visits a publisher webpage
2. Criteo receives real-time auction
3. Displays ad on behalf of advertiser
4. User converts on advertiser website (click / sale / lead)
Baseline Bidding Policy

- Under 2nd price auction hypothesis, dominant strategy is to bid expected value

\[ bid^* = CPA \times pSale \]

« Value of a conversion »

« Probability of post-click attributed conversion »
« Post-click attributed conversions »?

- **Last-click** is the de facto attribution model…
  … but advertisers are moving towards “better” attribution models:
  - Rule-based, uniform, linear, etc..
  - Data driven: regression, shapley value, etc..

- But what is the impact from a bidder’s perspective?
  - What is the optimal bidding strategy right after a click?
Attribution-aware bidder
Attribution Probability Through Time Matters

Attribution probability given conversion
Attribution Model

• How can we model probability of getting the attribution given there will be a conversion?

\[ Pr(A = 1|S = 1, X = x, \Delta = \delta) = e^{-\lambda(x)\delta}, \]
\[ \lambda(x) \geq 0 \]

• \( S \): Post click conversion
• \( A \): Attributed conversion
• \( X \): Contextual features
• \( \Delta \): Delay click/conversion
Conversion Modeling

\[ \text{bid}^* = CPA \times pSale \]

« Probability of post-click attributed conversion »

- Baseline solution:
  - 0/1 prediction problem \( \Rightarrow \) Logistic Regression
  - Large scale / latency constraint \( \Rightarrow \) Hashing trick

But what are positives / negatives?
From Attribution Model to an Attribution Aware Bidder

Cast the problem as an internal attribution problem

<table>
<thead>
<tr>
<th></th>
<th>Cast the problem as an internal attribution problem</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A_{LC}$</td>
<td>0</td>
</tr>
<tr>
<td>$A_{UN}$</td>
<td>$1/3$</td>
</tr>
<tr>
<td>$A_{FC}$</td>
<td>1</td>
</tr>
<tr>
<td>$A_{ALL}$</td>
<td>1</td>
</tr>
<tr>
<td>$A_{AM}$</td>
<td>0.6</td>
</tr>
</tbody>
</table>
Attribution Aware Bidder: An Intuitive View

AB: previous click gives us the attribution, only bid « marginal value »

LCB: user is engaged, go for last-click

New display opportunity
Attribution Aware Bidder

• Baseline Last-click Bidder (LCB)

\[ bid = CPA \times Pr(A_{LC} = 1 \mid X = x) \]

• Attribution-aware Bidder (AB):

\[ bid = CPA \times Pr(A_{ALL} = 1 \mid X = x) \left(1 - e^{-\lambda(x)\delta_c}\right), \]

\[ \delta_c : time elapsed since lastc click \]

*Bid proportionally to the marginal contribution of the display*
Impact on the offline evaluation metrics
Offline Evaluation of Bidders

- **Utility** metric on logged feedbacks:

\[ U(p') = \sum_{i \in D} (a_i v_i - c_i) \cdot I(p'_i v_i > c_i) \]

- **Expected Utility**: add uncertainty on the cost distribution:

\[ c \sim \Gamma(\alpha = \beta c_i + 1, \beta) \]
Attribution Aware Expected Utility*

• Inject attribution function in the Utility:

\[ AU(p', a) = \sum_{i \in D} (a(x_i)v_i - c_i) \mathbb{I}(p'_i v_i > c_i) \]

Internal attribution function:
• can be last-click, first click, etc..
• can be the proposed attribution model

* Evaluation of the proposed metric would require a proper offline / online correlation analysis
Experiments & Results
Attribution Rates vs Time

Decay of attribution rate after a click

> 40% of conversions have more than one click in the preceding 30d
Offline Evaluation - Dataset

Log sampled from 30 days of Criteo traffic

- Anonymized
- Each line is an impression with:
  - Timestamp
  - Price paid
  - Contextual features (user, advertiser, publisher)
  - Click*, click position*, click number*
  - Conversion*, conversion value*
  - Attribution label (conversion was attributed to Criteo)
- 16M displays, 5M clicks, 800k conversions

Will be available at http://research.criteo.com/ soon
Offline Evaluation – Impact on Bid Profiles

Post-click bid profiles for 3 bidders:
• Last-Click Bidder (LCB)
• First-Click Bidder (FCB)
• Attribution Bidder (AB)

All models are learn using regularized logistic regression + hashing trick
Offline Evaluation – Bidders Comparison

Results for 3 bidders on the Attribution Aware Expected Utility

<table>
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<th></th>
<th>LCB</th>
<th>FCB</th>
<th>AB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Win Rate</td>
<td>0.94</td>
<td>0.90</td>
<td>0.89</td>
</tr>
<tr>
<td>$U_A^*, \beta = 1000$</td>
<td>2852 ± 43</td>
<td>2888 ± 43</td>
<td>3396 ± 53</td>
</tr>
</tbody>
</table>

- We limit user over exposure after a click
- We get closer to lift-based bidding
- We can reinvest budget on more profitable campaigns / more incremental ads
Online result

We tested online a *simple* modification of baseline through A/B testing:

\[ bid_{test} = bid_{ref} \times A (1 - Be^{-\lambda \delta c}) \]

<table>
<thead>
<tr>
<th>$\Delta OEC$ (long term)</th>
<th>Revenue (short term)</th>
<th>Advertiser ROI</th>
<th>User ad exposure</th>
</tr>
</thead>
<tbody>
<tr>
<td>+5.5% worldwide</td>
<td>negative</td>
<td>positive</td>
<td>lower</td>
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Future Research Directions
Work in progress & Next steps

- Better attribution modeling
  - Exponential decay is naive: build a better model (e.g. travel partners have different attribution schemes)
- Model both conversion lift and attribution lift
  - Delayed feedback in both cases
- Derive a robust (counterfactual) offline metric
Questions?