

A Practical Framework of Conversion Rate Prediction for Online Display Advertising

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CPA vs CPC Trend



Percentage of campaigns with each goal type



Number of publications at each year

Rarity



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Challenges of Conversion Predictions Due to Conversion Rarity

- Worse performance
- Low delivery
- Costly exploration



CVR Safe Prediction Framework

Evolution stage

Each region's predicted CVR is converted to its own empirical mean. So, some regions' outputs automatically fade out.

Initial stage

Exploration regions are derived from the trained GBDT models. Each region may have different CVR priors.

Growing stage

New exploration regions are added based on the cross region conversions to provide continuously explorations.



Performance Comparison

Campaign	Machine-Learning Tree			Machine-Learning + Data-Driven Tree			CVD lift	eCPA drop	impe lift
	CVR	eCPA	imps	CVR	eCPA	imps		eern urop	mps m
Campaign1	6.96E-06	63.5419	1,174,131	7.06E-06	61.9564	1,293,526	1.52%	-2.50%	10.17%
Campaign2	5.38E-06	130.2857	1,300,893	9.66E-06	83.8571	1,448,639	79.60%	-35.64%	11.36%
Campaign3	1.49E-03	0.8359	576,431	2.13E-03	0.5987	678,384	42.78%	-28.37%	17.69%

Table 1: Online test results from 3 campaigns. It shows performance and delivery improvements after adding data-driven trees on top of machine-learning trees.

Conversion Adjustment for Delayed Feedbacks

- Trade-off of including new data with compensating empirical estimation.
- Formulate and solve as the following linear programming problem.



P4

P3

Bid Price Adjustment for Last-Win-All Attribution

- For post-view-conversion campaign, impression value decreases when user has been shown the same impression before.
- The discounted value positively correlates to the elapsed time between the last shown impression at the same user
- The key is to conduct noise reduction and do fast approximation of the integration value online

Algorithm 1 Value Adjustment Factor Estimation

- Input: time related parameters:
 t₀: time the previous impression was shown;
 t: the current time to bid for a new impression;
 T: length of attribution window (in hours);
 W: length of conversion window (in hours).
 Input: n hours of historical data.
 1: For i, j ∈ {1, 2, 3..., n}, find counts C_{i,j}, the number of conversions from hour j that are attributed to impressions shown at hour i.
 - 2: Calculate the probability mass of $\kappa(x)$ at hour $h \le W$:

$$\hat{\kappa}(h) = \frac{\sum_{i=T+1}^{n} \sum_{i=1}^{j} C_{i,j}}{\sum_{j=T+1}^{n} \sum_{i=1}^{j} C_{i,j}} \Big/ \Big| \Big\{ h' \le W : \operatorname{hod}(h') = \operatorname{hod}(h) \Big\} \Big|,$$

and we set $\hat{\kappa}(h) = 0$ for h > W. Note that we excluded the first *T* hours of conversions since their attributed impressions may be incomplete.

3: Calculate the probability mass of $q(x - t_0)$ at hour *h*:

$$\hat{q}(h-t_0) = \frac{\sum_{j=T+1}^{n} C_{j-(h-t_0),j}}{\sum_{j=T+1}^{n} \sum_{i=1}^{j} C_{i,j}}.$$

4: Calculate attribution probabilities:

$$\hat{f}_{t_0}(t) = \sum_{h=t}^{t_0+T} \hat{q}(h-t_0) \cdot \hat{\kappa}(h), \text{ and } \hat{f}_t(t) = \sum_{h=t}^{t+T} \hat{q}(h-t_0) \cdot \hat{\kappa}(h).$$

Output: estimated value adjustment factor

$$1 - \frac{\hat{f}_{t_0}(t)}{\hat{f}_t(t)} = 1 - \frac{\sum_{h=t}^{t_0+T} \hat{q}(h-t_0) \cdot \hat{\kappa}(h)}{\sum_{h=t}^{t+T} \hat{q}(h-t_0) \cdot \hat{\kappa}(h)}.$$

Over-prediction Gap Brought by RTB

- Gaps between observations and predictions could be partially introduced by real-time bidding.
- For CPA remarketing impressions, this phenomenon is more obvious due to sharing common information



Problems are not stop signs, they are guidelines

Robert H. Schuller