Demystifying Advertising Campaign for CPA Goal Optimization

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ABSTRACT

In cost-per-click (CPC) or cost-per-impression (CPM) advertising campaigns, advertisers always run the risk of spending the budget without getting enough conversions. Moreover, the bidding on advertising inventory has few connections with propensity that can reach to cost-per-acquisition (CPA) goals. To address this problem, this paper presents a bid optimization scenario to achieve the desired CPA goals for advertisers. In particular, we build the optimization engine to make a decision by solving the constrained optimization problem. The proposed model can naturally recommend the bid that meets the advertisers' expectations by making inference over history auction behaviors. The bid optimization model outperforms the baseline methods on real-world campaigns, and can be applied into a wide range of scenarios for performance improvement and revenue uplift.

CCS CONCEPTS

• Information systems → Computational advertising;

KEYWORDS

Advertising; Optimization; Bidding

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1 INTRODUCTION

Online advertising uses the internet to deliver the promotional marketing messages provided by advertisers to consumers on the publisher platform by integrating the advertisements into its online content. Bid optimization is a technique to optimize the bidding process, which allows the advertiser to bid for winning the impressions and clicks. The effective and efficient bidding strategies have been proposed to bring more benefits for advertisers, consumers and third-party platforms. For example, for the same key word "buy jeans", there is 20 conversions with 2 CPC bid for advertiser 1 but only 5 conversions with the same price for advertiser 2. To effectively learn the useful "signals" available for bid adjustment for advertisers, we build effective models to capture what the cost and win rate will look like if the advertisers change the bidding price.

In this paper, we focus on cost per acquisition (CPA) goal, which helps the advertisers programmatically choose the best "smart" bid,

and then derive the most possible scale for the targets, which in turn, acquires more traffic for e-commerce business. We present an effective way to automatically set bids for auctions to get as many conversions as possible within the target CPA goals. Then we can recommend bid to advertisers for adjustment based on how likely a click is to lead to a conversion. It therefore can help advertisers to plan CPA goals and revenue targeting. We believe all the algorithm advancement can bring in more predictive signals and better target accuracy compared to inflection point [4], portfolio optimization [3] and etc. Compared to CPA, cost per mille impressions (CPM)¹ poses high risk on the conversions, cost per sale (CPS) ignores the value of click which potentially provides worse traffic liquidating, and cost per click (CPC) controls the cost of clicks after running page views without giving enough attention to the true conversions that may actually bring in revenue increases for advertisers.

2 METHODOLOGY

An illustrative example. Let's say the advertiser is measuring sales for several online electronic stores by optimizing the bids based on the value of a shopping cart in total. The goal is 50 per conversation (that leads to sales) based on every dollar one spends on ads. If one is setting a target CPA goal as \$50 - for every \$50 you spend on ads, you'd like to get 1 conversion (and get the corresponding revenue based on conversion value). More concretely,

Store 1: \$100 in spend ÷ 2 conversions = \$50 CPA goal

Store 2: \$150 in spend ÷ 4 conversions = \$37.5 CPA goal

Store 3: \$500 in spend ÷ 5 conversions = \$100 CPA goal

Based on these data one would decide to spend more budget at store 1 and store 2, as one is hitting the goal on these websites. At store 3, the advertiser pays the double of the goal per conversion, so the campaign will stop bidding there.

Optimization Goal A question that naturally follows is: *how to set the bid price in order to achieve these CPA goals?* More formally, given the CPA goal with value C , we aim to provide the bid recommendation that can maximize the clicks while considering CPA goal for the advertiser i , i.e.,

$$\max_{bid} Click(bid); \quad s.t \quad CPA(bid) = C; \quad (1)$$

where $click(bid)$ denotes the number of clicks the advertiser can obtain given the bidding price at bid , $CPA(bid)$ tells the CPA goal one can achieve with bidding price bid ².

Algorithm Workflow

(i) Get all supply impressions

In performance buying scenarios, number of impression one can get from the inventory is determined by a combination of the content of the site and a specific campaign's creative and targeting,

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¹As the social media ads, Facebook actually used optimized cost per mille (oCPM) criterion to allow advertisers to bid for click and actually pay per impression

²For notation simplicity purpose, advertising campaign i is ignored in the paper next, and all the modeling is applied for the particular campaign i .

Figure 1: CPA vs. bid, Click vs. bid, Spend vs. bid curves for an advertising campaign. CVR of this ad campaign is 0.0270.

which is proportional to the available number of impressions on the particular publisher, goe location and targeting attribution settings.

(ii) Click and Conversion prediction

Translating Goals of CPA into click and conversion number prediction is necessary for advertisers, because advertisers typically pay for a particular user response via a cost-per-click (CPC) or CPM. More formally,

$$Click(bid) = Impression \times Winrate(bid) \times pCTR, \quad (2)$$

$$Conversion(bid) = Click(bid) \times pCVR, \quad (3)$$

where $Click(bid)$ tells the number of click the advertiser can obtain at bid price, $Impression$ is the available impressions based on the combination of publisher and targeting information. $Winrate(bid)$ is the winning ratio from all available impressions, $Conversion(bid)$ is the number of conversions obtained at price bid , $pCTR$, $pCVR$ are the predicted click-through-rate (CTR) [2] and predicted conversion-rate (CVR) for the particular advertiser based on history campaigns.

(iii) CPA optimization for bid

The CPA goal is transformed into CPC bids based on a variety of factors, including historical win rates for a particular type of impression, and actual cost at that bid price. For example, if the historical rates indicate that the win rate is low, then a lower bid will be submitted. On the other hand, if the response rate is high, then a higher bid will be submitted. More formally,

$$\begin{aligned} CPA(bid) &= \frac{Spend(bid)}{Conversion(bid)} = \frac{Click(bid) \times CPC_cost(bid)}{Click(bid) \times pCVR} \\ &= \frac{CPC_cost(bid)}{pCVR} = \frac{eCPM_cost(bid)}{1000 \times pCTR \times pCVR}, \end{aligned} \quad (4)$$

where $Spend(bid)$ is the money spent, CPC_cost is the cost-per-click, and $eCPM_cost$ is the cost-per-mille at price bid , respectively.

3 EXPERIMENT

Given the fact that we only know the ground-truth for the current bid, *i.e.*, the true number of conversions and the true spend for current campaign at current bid price, we therefore design experiments to compare the differences between the true CPA (denoted as CPA) and the forecasted CPA (denoted as $\hat{CPA}$) at current bid. More formally, we use the mean absolute percentage error (MAPE) and root mean square percentage error (RMSPE) as the measurement, *i.e.*, $MAPE = \sum_{i=1}^n \frac{|y_i - \hat{y}_i|}{y_i}$, $RMSPE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\frac{\hat{y}_i - y_i}{y_i})^2}$, where y_i is the CPA for ads campaign i with current bid b_i , and $\hat{y}_i$ is the forecasted CPA for campaign i at current bid b_i . The smaller values of MAPE, RMSPE indicate better performance. We also compare the baselines: (a) **Nearest Neighbor Search (NNS)**. If the observed

Table 1: Performance comparisons of MAPE, RMSPE between CPA and predicted $\hat{CPA}$ using (1) proposed method; (2) baseline 1: nearest neighbor search (NNS); (3) baseline 2: linear interpolation (LI)

Method	MAPE	RMSPE
Our method	10.28%	15.68%
Nearest Neighbor Search (NNS)	23.86%	50.23%
Linear Interpolation (LI)	18.65%	32.65%

bid price exists in history, then we retrieve the corresponding CPA computed using spend and conversion in history. Otherwise, we use the nearest neighbor method to predict the CPA. For the observed bid b , if b'_i is the nearest neighbor of bid b_i in history, then we retrieve the corresponding CPA for bid b'_i as the predicted CPA; (b) **Linear interpolation (LI)** The idea is to use linear interpolation in historical bid price to predict CPA correspondingly³. Table. 1 shows the performance evaluation on observed 190,876 ad campaigns. Given that it is a challenging task to predict CPA for diversified, fluctuated ad campaigns, the result obtained using proposed model is competitive and reasonable, because it leverages all history information completely by smartly setting the bid price. Fig.1 shows the example of ad campaigns with forecasted CPA, total money of spend and number of clicks at different bid prices.

4 CONCLUSION

This paper presents a novel way for bid forecasting to achieve the desired CPA goals, which we believe is an important piece that powers the bid landscape for bid recommendation and forecasting. The approach is interesting in providing the optimal bid solution based on targeting CPA goals using history performance data. We also provide effective optimization strategy with demonstrated performance improvement.

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³Note that a regression model (*e.g.*, Gradient Boost Decision Tree method (GBDT)) for CPA prediction can be built using the features including the bid price, advertiser ID and other advertiser features (such as supply group, advertiser category, etc) [1]. The detailed comparisons will be added in full paper.