An Inflection Point Approach for Advertising Bid Optimization

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ABSTRACT

In online advertising, a common objective for advertisers is to get the maximum returns on investment given the budget. On one hand, if the bid is too high, the advertiser pays more money than he should pay for the same number of clicks. On the other hand, if the bid is too low, the advertiser cannot win in auctions and therefore it loses the opportunity. A challenging problem is how to recommend the bid to achieve the maximum values for advertisers. In this paper, we present an inflection point approach for bid recommendation from discovering the bid price of click(bid)¹ function at which the function changes from significant increase (i.e. concave downward) to slow increase (convex upward). We derive the optimal solution using history sparse and noisy observations given the budget limit. In real word advertising campaign evaluations, the proposed bid recommendation scenario brings in 15.37% bid increase and 30.24% click increase over the baselines.

CCS CONCEPTS

• Information systems → Computational advertising;

KEYWORDS

Advertising; Optimization; Bidding

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1 INTRODUCTION

Online advertising brings in a lot of revenues to major internet companies based on generalized second-price (GSP) [1] using algorithmic/dynamic pricing [5] with particular optimization optimization goals, such as CPA goal [4], portfolio optimization [3], etc. In online advertising, one major complaint of advertisers is: “*Half the money I spend on advertising is wasted; the trouble is I don’t know which half.*” As an advertiser, one always needs to consider the spending question, such as “am I spending enough on advertising?” and “am I spending too much on advertising”? One key observation in ad market is: advertisers’ return on investment has non-linearity

¹This is a function with bid price as the argument and the number of clicks as the function value.

²The original words are from John Wanamaker, who is a proponent of advertising and a pioneer in marketing.

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characteristics due to diminishing returns after the advertiser’s bid reaches to a certain point which in fact leads to saturation effect. For example, if the advertiser bids at \$3.60, it may get around 450k clicks; however, if the advertiser increases the bid to \$6.00, the true clicks are only 600k which is far less than two thirds more than the clicks at \$3.60. The diminishing return is known as “saturation effect” due to the reach of the limit of click where even higher bidder can have very minor incremental effect.

In this paper, we design an inflection point based strategy to achieve the maximum return increase using history ad campaign observations in marketplace, which we formalize as an optimization problem with the budget limit constraint. Our model is originated from the concept of inflection point, which aims to discover the significant change (a.k.a a turning point) in a function curve at which the sign of the curvature changes. The bid recommendation using inflection point demonstrates good performance and has graduated into production.

2 METHODOLOGY

For an advertiser, in order to maximize the returns for the amount of spend, the bid recommendation method aims to recommend the bid price to meet this criterion. There are many ways to define the returns over the amount of spend, such as the revenue increase over spend increase, click increase over cost increase, etc. In the context of this paper, we aim to find the best bid price which provides the maximum click increase $dClick$ over the cost increase $dCost$ for an advertiser, which is formulated below:

$$\max_{bid} \frac{dClick(bid)}{d eCPM_Cost(bid)} \quad s.t. \quad Spend(bid) \leq budget, \quad (1)$$

where $Click(bid)$ is the estimated clicks at bid price (cost-per-click), $eCPM_Cost(bid)$ is the effective-cost-per-mille (eCPM cost) at bid price, $Spend(bid)$ is the estimated money spent at bid price (cost-per-click), $budget$ is the available number of money for the campaign, $d(\cdot)$ is the first-order difference that reflects the changes in quantities, i.e.,

$$d h(bid) := \Delta h(bid) = h(bid + \Delta bid) - h(bid) \quad (2)$$

and function h could be the number of click, the amount of cost, and the amount of spend, etc. Given the advertiser history performance, we will have the estimated number of clicks, the amount of cost and the amount of spend, i.e.,

$$\begin{aligned} \textcircled{a} \quad Click(bid) &= Impression \times Winrate(bid) \times CTR; \\ \textcircled{b} \quad Spend(bid) &= Click(bid) \times \frac{eCPM_cost(bid)}{1000 \times CTR}; \end{aligned} \quad (3)$$

where impression is the total number of impressions the advertiser can win from the supply side (offered by publishers based on advertiser profile), CTR is the average click-through-rate, $Click(bid)$ is the number of winning clicks at price bid , and $winrate(bid)$ is the winning rate at price bid .

Optimization Notice that number of Click and eCPM_Cost are both functions of bid price, and therefore, Click can be modeled as a function of eCPM_Cost, *i.e.*,

$$\text{Click} := h(\text{eCPM_Cost}), \quad (4)$$

where h is a function that maps the eCPM_Cost to the number of Click. Then we have,

$$\begin{aligned} \frac{\Delta_{\text{Click}}}{\Delta_{\text{eCPM_Cost}}} &= \frac{dh}{de\text{CPM_Cost}} \\ &:= h'(\text{eCPM_Cost}), \end{aligned} \quad (5)$$

where h' is the first-order derivative of function $h(\cdot)$. Therefore Eq.(1) is transformed to solving the following problem,

$$\begin{aligned} \max_{\text{eCPM_cost}} & h'(\text{eCPM_Cost}), \\ \text{s.t.} & \text{Spend}(\text{eCPM_cost}) \leq \text{budget}. \end{aligned} \quad (6)$$

In practice, we need to fit the observations using $h(\cdot)$ function with parameter learning and derive the corresponding optimal solutions. Then the optimal eCPM_cost is given by:

$$\text{eCPM_cost}^* = \text{argmax}_x h'(x). \quad (7)$$

We can obtain the optimal solution by setting the second order of derive to zero, *i.e.*, $\frac{d^2h}{dx^2} = 0$. This is not done. We need to further check whether the spend exceeds the budget or not. In particular, if

$$\text{Spend}(\text{eCPM_cost}^*) \leq \text{budget}, \quad (8)$$

then $\text{eCPM_cost}^* = x^*$ is the optimal solution. Otherwise, if the spend already exceeds the budget, we need to decrease eCPM_cost^* until spend is within the budget because $h(\cdot)$ is a non-decreasing function. In particular, we use a binary search algorithm to search for the highest eCPM_cost* with the amount of spend at most equal to the budget, *i.e.*,

$$\text{eCPM_cost}^* = \text{binary_search}(0, x^*, \text{budget}). \quad (9)$$

Given the best eCPM_cost, one can easily obtain CPC bid price via transformation using click-through-rate (CTR), *i.e.*,

$$\text{CPC_cost}(\text{bid}) = \frac{\text{eCPM_cost}(\text{bid})}{1000 \times \text{CTR}}.$$

3 EXPERIMENT

We apply the proposed algorithm for real-world advertising campaigns. All experiments are performed on 120,796 ad campaign profiles. Fig.1 plots an example of number of Click vs. eCPM_cost curves using CTR prediction [2] and the corresponding derivatives ($\frac{d\text{Click}}{de\text{CPM_cost}}$). In left panel, we fit the observations. In the right panel, the maximum derivate (*i.e.*, the inflection point) is computed and denoted in red circle in the curve of derivative (in dashed blue). "Max 90%" is the point that achieves the 90% of maximum derivative but goes beyond the inflection point, where the bid price bid_{1P90}^* that achieves 90% of $\frac{d\text{Click}}{de\text{CPM_cost}}$ but goes beyond the inflection point.

In experiments, we can easily find the inflection point using our method. Our method gives the optimal solution that achieves the maximum derivative no matter whether there exist noisy or missing values in observations. Essentially, the outliers and missing values are smoothed out, making the result more robust and reliable. In order to see how the performance improves for real-world ad campaigns, we apply A/B test to the ad traffic using two scenarios

Figure 1: Number of Click vs. eCPM_cost curves and the corresponding derivatives ($\frac{d\text{Click}}{de\text{CPM_cost}}$) on ad campaigns. Left panel: curves to fit the observations. Right panel: the maximum derivate (*i.e.*, the inflection point) is obtained in red circle in derivative curve (in dashed blue). "Max 90%" is the point that achieves 90% of maximum derivatives but goes beyond the inflective point.

(1) without any bid optimization;

(2) adoption of the infection point as the recommended bid.

We have +15.37% in bid increase and +30.24% click increase compared to bidding without any optimization.

4 CONCLUSION

This paper presents a novel way for bid recommendation using inflection point in providing the optimal bid solution based on maximizing the click increase over the cost increase. Rigorous algorithm analysis and extensive experiments on real-world advertising campaigns demonstrate the effectiveness of our method over baselines.

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