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Real-Time Bidding by Proportional Control in Display Advertising

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Abstract. In real-time bidding (RTB), advertisers need to give a price for each ad request, but in the face of millions of ad requests per day, it is particularly important for advertisers to design an automatic bidding strategy. Linear bidding is the most popular bidding strategy in the industry. The model considers the value of every impression, but a static bidding model cannot adapt to a complex and changeable auction environment. Most previous works focused on dynamic bidding strategies with continuous feedback, but fine-grained optimization of each bid made the model more difficult to calculate, and there were certain errors in the model of advertising click-through rate prediction. This paper combines the advantages of the two models and proposes a dynamic bidding strategy based on the overall proportional control, which controls the advertiser's return on investment by controlling the number of low click-through rates and high-click-rate ads to a certain proportion. In addition, this model can realize the dynamic adjustment of the proportion through the increase or decrease of price. Finally, the effectiveness of the strategy is experimentally confirmed in real data sets.

Keywords: Real-Time Bidding; Bid Optimization; Dynamic Bidding Strategy.

1. Introduction

Building a green and stable Internet advertising ecosystem is beneficial to advertisers, users and publishers. Advertisers, users, and publishers are three important components of the RTB. Advertisers can accurately target their ads to potential users, which can reduce their inefficiency and increasing their profits. While browsing the web, users can receive advertisements that are recommended to their own interests. On the one hand, the user's experience on the publisher's website is improved, on the other hand, there is a way to meet their own needs; For publishers, improving the user experience not only means more secure traffic on these sites, but also attracts more traffic to the site. Most importantly, RTB provides a channel for publishers to monetize a large amount of surplus traffic that cannot be sold by contract, and improves the ability of publishers to monetize to maximize their profits. The emergence and development of RTB not only changed the trading model of advertising, but also accelerated the development of data processing and trading markets. Data exchange and data management platform (DMP) are two key products of data processing and trading. They start from the third-party data and the first party data respectively and provide valuable data sources or data processing services for the market. The process of real-time bidding is described as follows:

(1) When an Internet user browses a website of a publisher (media), the supply-side-platform (SSP) will send an advertisement request message to the advertisement transaction platform, advertising information request contains user label and the publisher of the corresponding labels and the reserve price of this auction.

(2) The ad exchange platform (ADX) will send the information of the auction (including the user and publisher's label and the reserve price) to each demand-side-platform (DSP) participating in the auction, sending out the inquiry request signal and waits for a reply from the DSP within an agreed fixed time (normally 100ms).

(3) After a series of data processing steps, the DSP will input the user tag, publisher tag and advertiser tag sent by ADX into the trained offline click-through prediction model and bidding engine to obtain a bid, and then return the bid to ADX.

(4) ADX sorts the bids received from multiple DSP from highest to lowest and compares the highest bid with the SSP reserve price. If the highest bid is greater than the reserve price of the auction, the highest DSP will be notified to win the auction. If the highest bid is less than the reserve price of the auction, the auction will fail.

(5) DSP planted advertisers advertising creative to the publishers in the sale of advertising, and advertising creative to the publisher of the user, at the same time to collect the corresponding user feedback information for subsequent optimization click-through-rate model and bidding engine system, DSP also have to pay the publishers the market price of the auction.

2. Related Work

In real-word, the linear bidding function [1] is widely used. The authors in [2] empirically showed that there existed non-linear bidding functions better than the linear ones under variant budget constraints, but it cannot depict well the real data distribute. When the data changes, the hypothetical bidding functions [3] cannot depict well the real data distribution. [4,5] influences the bid success rate by modifying the bid, the drawback is that it is difficult to control the budget carefully.

3. DSP Bid Optimization

3.1 Problem Definition

DSP is the agent of advertisers; whose main task is to achieve the advertising target of advertisers and maintain their interests. Therefore, the corresponding click-through rate prediction and bidding algorithm in RTB is implemented by DSP. For advertisers, the purpose is to generate more returns with a lower investment, which is the focus of the DSP design bidding strategy. Return on Investment (ROI) is used to measure the performance of a bidding strategy in the calculation of advertising. ROI is the ratio between the total output and the total investment of an advertising campaign, the formula is as follows:

$$ROI = \frac{return}{investment}$$

The total investment is the sum of all the expenses of the advertiser in an advertising campaign, and the total output can be represented by a variety of indicators. The main metrics in calculating ads are impressions (Imps), total clicks (Clicks), and total conversions (Convs).Imps is the number of times an ad is exposed; Clicks is the total number of user clicks resulting from an ad exposure across the campaign, or it can be replaced with the overall click-through rate; Convs refers to the total number of users converted to advertisers in the entire campaign, which can be replaced by CVR; Another indicator is a combination of multiple indicators. For example, in the bidding algorithm competition organized by iPinYou, the bidding algorithm's indicator is a linear combination represented by Clicks and Convs, which is expressed as follows:

$$\begin{aligned} &\max \quad click + N \times conversion \\ &subjectto \quad \cos t \le budget \end{aligned}$$

From the data set provided by iPinYou, it can be found that the click rate of most advertisers is about 1/1000, while on the basis of click, the conversion rate varies greatly for each advertiser, some as high as 50%, while some have no conversion at all. In this paper, the total number of clicks is used as the indicator of the total output, and the indicator of the total investment is the money invested by the advertisers.

Set $cost_i$ be the cost of the advertisers, $click_i$ is the return of the advertiser, p_i is the market price of advertising auction. The cost and return of advertisers can be expressed as:

$$\cos t_i = \begin{cases} b_i & ,b_i > p_i \\ 0 & ,b_i < p_i \end{cases} \qquad return_i = \begin{cases} 1 & ,click_i = 1 \\ 0 & ,click_i = 0 \end{cases}$$

In addition, advertisers will be subject to their own budget constraints in RTB.

The essence of a bidding strategy is to maximize the advertiser's ROI under budget constraints. The bidding strategy can be transformed into the following optimization problems:

$$\max \quad ROI$$
$$subjectto \quad \sum \cos t_i \le budget$$

Since the key performance indicator (KPI) used in this article is the total number of clicks, maximizing ROI is equivalent to minimizing cost per click (CPC)

As can be seen from the above formula, a good bidding strategy has the following characteristics:

(1) whether Imprs or Clicks is used as KPI, a good bidding strategy needs a high probability to win the auction. The greater number of times an ad is exposed, the ad is likely to be clicked. If the bid is too low, the chances of winning the auction will be small.

(2) With budget constraints, the cost of winning each auction must be considered. If the bid is too high, the probability of winning the auction increases, but the number of times the ad is exposed is reduced and the ROI may go down.

(3) A static bidding strategy cannot adapt to a competitive and changeable auction environment composed of many parties in RTB.

In summary, a good bidding strategy is best to take into account the value of the ad request and avoid bidding too low or too high; the bidding strategy should also be dynamic and able to change the bidding method according to the change of the environment.

3.2 Compared Bidding Strategies

Current industry common bid strategy has fixed bid, random range bid, linear bid. There are two scenarios for a fixed bid. One is to bid at a lower price each time. Its advantages are obvious, the cost of each cost is less if the auction is successful; The disadvantage is that the probability of winning the auction will be reduced. The other is to bid at a higher price each time, but the advertiser's budget will be consumed quickly, and it may not be able to get a better KPI. Random range bidding is to select a price at a time for bidding in a given price range. the disadvantage is that the bidding strategy is highly unstable. Linear bid is the mainstream bid strategy, its bid is a linear function of click-through rate. The model is expressed as:

$$b(c_i) = B \times \frac{{}_{p}CTR}{{}_{avg}CTR} \tag{1}$$

The parameter B is a fixed value, the parameter ${}_{p}CTR$ is the predicted click rate, and the parameter ${}_{avg}CTR$ is the average click-through rate of the entire advertising campaign. The advantage of a linear bidding strategy is that the model is simple and its bid takes into account the value of each ad request, but a static strategy is unable to adapt to a complex and volatile Internet environment. The nonlinear model is fine-grained for each bid optimization, although it is closer to reality, but the model is too complicated and the calculation difficulty is increased. Moreover, the model of advertising click-through rate prediction also has some errors

3.3 Proportional Control Dynamic Bidding Strategy

For an advertisement request with a low click rate, in addition to the error of the click rate model itself, it largely indicates that the quality of the advertisement request is not good. Even if the auction is won, and users are likely to remain non-clickable, a good solution would be to reduce the number of low-click ad requests. Conversely, for a high click-through rate ad request, it can be said that the user clicks on the advertisement with a high probability, which should increase the number of high-click rate advertisement requests.

This paper proposes a dynamic bidding strategy based on proportional control (PCDBS), which aims to optimize ROI by controlling the amount of advertisements with low click rate and high click

rate to a certain ratio. In addition, the model can adjust the actual ratio dynamically by adding or subtracting the price. R_l and R_h respectively represent low click-through ads and high click-through ads. Threshold parameters c_l and c_h represent the proportion of low click-through ads and high-click-through ads.c_l and c_h represent the overall proportion of low-click-rate ads and high-click-through ads.c_i is the ad click rate prediction for the current user. When predicting an ad as a low click-through rate, the model will compare the overall percentage of ads with low click-through rates. If the ratio is too high, the model will reduce the probability of winning the auction by reducing the bid to reduce the number of low-click ads. When predicting an ad as a high click-through rate, the model compares the percentage of ads with high click-through rates. If the ratio is too low, the model will increase the probability of winning the auction by increasing the bid, thereby increasing the number of high-click ads.

In addition to the above two situations, the bid engine will bid on the basic model. Because the linear bidding model takes into account the value of the ad request. so, in this article we will use a linear bidding model as the basis for the model.

H(t) is the Heaviside function and its representation are as follows:

$$H(t)=\begin{cases}1 & ,t\geq 1\\ 0 & ,t<0\end{cases}$$

$l(c_i)$ and $h(c_i)$ are used to detect whether the current bid model needs to be adjusted, if $l(c_i)+h(c_i)=1$, the model needs to be adjusted. $l(c_i)$ and $h(c_i)$ are expressed as follows:

$$l(c_i)=H(c_l-c_i)\times H(r_l-R_l) \tag{2}$$

$$h(c_i)=H(c_i-c_h)\times H(R_h-r_h) \tag{3}$$

The bid modifier function is $f(c_i)$, and its representation is as follows:

$$f(c_i)=\begin{cases}e^{a(R_h-r_h)} & ,c_i\geq c_h\\ e^{a(r_l-R_l)} & ,c_i\leq c_l\end{cases} \tag{4}$$

Combined with (1)(2)(3)(4), the final expression of the proportionally controlled dynamic bidding model is as follows:

$$b_i=b(c_i)+(l(c_i)+h(c_i))\times f(c_i) \tag{5}$$

4. Algorithm Design

The PCDBS algorithm process is as follows:

1)The DSP receives an inquiry request from the ad exchange.

2)The bidding engine will calculate $l(c_i)+h(c_i)$ according to c_i to detect whether to modify the bid.

3) The bidding engine will give the bid according to PCDBS.

4) If $b_i>p_i$, then update parameters budget.

5) Repeat steps (1) - (3) until budget<0.

The pseudo code for the algorithm is as follows:

Initialization: R_l, R_h, c_l, c_h, l, h, t, budget

Input: b_i

```
 while   budget>0   do
   if   l(ci)+h(ci)==1
          bi=b(ci)+(l(ci)+h(ci))*f(ci)
```

```
else
      bi=b(ci)
end if
if     bi>pi and l(ci)==1
        l=l+1,t=t+1,budget=budget-bi
elseif   bi>pi and l(ci)==1
      h=h+1,t=t+1,budget=budget-bi
else
      t=t+1,budget=budget-bi
end if
```

4.1 Experimental Results

The experimental data of bidding algorithm was based on the data set provided in the second season of 2013 iPinYou interactive DSP real-time bidding algorithm contest. Compare different bidding strategies under budgetary constraints. The experimental results are shown in Table 1.

Table 1. Comparison of different bid strategies Budget (1/32)

Adv	Const	Rand	Lin	PCDBS
1458	28	29	491	503
2259	12	11	15	20
2261	9	9	42	59
2812	37	44	78	78

Budget (1/2)

Adv	Const	Rand	Lin	PCDBS
1458	322	315	524	534
2259	73	79	87	84
2261	66	67	67	76
2812	240	236	253	246

From the experimental results in Table 1, it can be seen that the performance of fixed and random bids has a greater impact in the case of limited budget; Linear models and PCDBS still perform well with limited budgets. PCDBS's bidding performance takes precedence over the other three bidding strategies, but in the number 2812 advertiser, PCDBS is similar to linear model performance.

5. Summary

Based on the linear model, this paper proposes a dynamic bidding strategy based on proportional control, which compensates to some extent that the linear model can not adapt to the dynamic and variable RTB environment. Experiments show that PCDBS bidding strategy can effectively reduce the loss of clicks and increase the revenue of advertisers with clicks as KPI under low budget constraints.

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