MCMF: Multi-Constraints With Merging Features Bid Optimization in Online Display Advertising

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ABSTRACT

In the Real-Time Bidding (RTB), advertisers are increasingly relying on bid optimization to gain more conversions (i.e trade or arrival). Currently, the efficiency of bid optimization is still challenged by the (1) sparse feedback, (2) the budget management separated from the optimization, and (3) absence of bidding environment modeling. The conversion feedback is delayed and sparse, yet most methods rely on dense input (impression or click). Furthermore, most approaches are implemented in two stages: optimum formulation and budget management, but the separation always degrades performance. Meanwhile, absence of bidding environment modeling, model-free controllers are commonly utilized, which perform poorly on sparse feedback and lead to control instability.

We address these challenges and provide the Multi-Constraints with Merging Features (MCMF) framework. It collects various bidding statuses as merging features to promise performance on the sparse and delayed feedback. A cost function is formulated as dynamic optimum solution with budget management, the optimization and budget management are not separated. According to the cost function, the approximated gradients based on the Hebbian Learning Rule are capable of updating the MCMF, even without modeling of the bidding environment. Our technique performs the best in the open dataset and provides stable budget management even in extreme sparsity. The MCMF is applied in our real RTB production and we get 2.69% more conversions with 2.46% fewer expenditures.

1 INTRODUCTION AND RELATED WORKS

The Real-Time Bidding (RTB), as shown in Figure 1, can manage each ad impression through real-time auctions. Publishers offer advertising impressions to advertisers by organizing a fair and transparent real-time auction. When a user visits(1) a website or mobile app page, the Supply-Side Platform (SSP) sends and broadcasts a request(2) of an ad display opportunity to the Demand-Side Platforms (DSPs) via the ad exchange (ADX). An auction is held on the ADX in a very short time frame, and each DSP decides on a final bid(3) price for this request. The highest bidder wins(4) the impression opportunity, and the actual payment (cost) could be sent to the win DSP from SSP[1]. Following the impression(5), the user’s response(6) will be sent to the DSP as feedback. The auction occurs in the split second to load a Web page. The users’ responses include the impression, click, order, or pay. From the impression to pay, the delay and sparsity are increased sharply.

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The absence of bidding environment modeling is the third challenge of bid optimization. The very dynamic and variable bidding environment can hardly be represented or modeled exactly. Researches are proposed with very complicated models and plenty of parameters to represent the bidding environment[11, 12]. Even though, the model is not so exact to every bidding environment. Furthermore, lacking of the exact model, the advanced optimal controllers can hardly be utilized in bid optimization. The model free controllers such as the PID (Proportion Integration Differentiation) are commonly used[13]. The PID controller is not an ideal optimum controller, it is sensitive to its hyper-parameters and is frequently unstable due to latency. Although the optimal solution is right, the PID controller may provide unexpected consequences.

In this paper, we propose a unified framework named Multi-Constraints with Merging Features (MCMF) for bid optimization under sparse feedback even without an exact model of a dynamic bidding environment. Our MCMF is a gradient-based two-layers Multi Layer Perception (MLP), which updates weights by following the Hebbian Learning Rule[14].  

1. It collects various bidding statuses as merging features to forward propagation and decide a bid price. This can promise the bidding performance on the condition of sparse and delay feedback.  
2. (The weights of MCMF are updated in backward propagation by minimizing the cost function. The designed cost function can maximize the bidder’s utility dynamically with stabilized budget spending. Due to the design, the utility maximization and budget management are uniformed into one cost function instead of optimization in separate stages.  
3. We propose approximated gradients for the backward propagation by following the Hebbian Learning Rule. This can ensure that the gradient updating still works in each time period even in absence of exact bidding environment model. Our MCMF performs the best in a popular open dataset and provides a stable budget management even the feedback is extremely sparse. We also applied our method in our RTB production and get a well performance in conversion.

2 PROBLEM FORMULATION

The feedback from the bidding environment involves various statuses from the ADX, advertisers’ KPIs, and value estimation during the main loop in Figure 2(a). MCMF is a two-layer multi-layer perception (MLP). As shown in Figure 2(b), the input features are merged by various bidding statuses The status includes the KPIs with the corresponding feedback and extra features. The merged features can promise the performance of MCMF under the condition of sparse and delayed feedback. We designed a cost function to balance the bidder’s utility maximization and budget management dynamically as Figure 2(c). In every time period, the MLP’s weights are updated by minimizing the cost function. The updating is an approximated backward propagation by following the Hebbian Learning Rule. Even with no exact modelling of bidding environment, the updating is still working. We formulate the MCMF in Section 2.1, define the cost function in Section 2.2, and propose the approximated backward propagation in Section 2.3.

2.1 Bid adjustment

In the main loop, we defined a bid adjustment value $u^{(t)}$ in current time period $t$. The adjusted $eCPM$ (estimated cost-per-milles) can be denoted by the product of the original bid price and the adjustment value $u^{(t)}$ in Eq.1. The original bid price is a production of predicted click-through rate $pCTR$, predicted conversion rate $pCVR$ and the expected pay-per-conversion (PPC) which is denoted by $PPC_e$.

$$eCPM = 1000 \cdot pCTR \cdot pCVR \cdot PPC_e \cdot u^{(t)}$$

original bid price

The adjustment value $u^{(t)}$ can be calculated by a two-layers MLP forward propagation in Eq.2. The $W_e$ and $W_d$ are denoted the weights of Encoding Layer and Decision layer. We marked the encoded vector $h$ for explaining backward propagation in section 2.3. The input vector $x = [z_1, x_1, ..., z_i, x_i, v]$ can be concatenated by the set KPI $z_i$ with the corresponding feedback $x_i$ and other accumulated feedback merged feature $v$.

$$h = W_e \cdot x, \quad U = \sigma(W_d \cdot h)$$

2.2 Cost function

We define a cost function that is capable of optimizing dynamically and it uniforms utility maximization and budget management. The cost function is quadratic with a KPIs error term and a control term. A KPI error vector $E$ and an error-parameter matrix $Q$ are used to calculate the KPI error term, which can balance each KPI’s following error. The adjustment error vector $\Delta U$ and control-parameter matrix $R$ are used to calculate the control term, which represents the control cost and stability of the previous two periods. In Eq. 4, the error vector $E$ is the difference between KPIs (e.g., expected PPC or budget) $z_i$ and the corresponding accumulated feedback $\sum_{t} x_t$. In Eq. 5, the adjustment error vector $\Delta U$ is the difference of two adjacent time period adjustment values. For a more smooth

Figure 2: The MCMF framework (a)main loop,(b)forward propagation,(c)cost function and backward propagation.
control, we recommend using the last $t$ time period accumulation loss for backward propagation.

$$J = \int_1^{t+t} \frac{E^T Q E + \Delta U^T R A U}{\text{error term}} dt$$

(3)

$$E = [\sum_{i} x_1^{(t)} - z_1, \sum_{i} x_2^{(t)} - z_2, \ldots, \sum_{i} x_i^{(t)} - z_i]^T$$

(4)

$$\Delta U^{(t)} = U^{(t)} - U^{(t-1)} = [u_1^{(t)} - u_1^{(t-1)}, \ldots, u_j^{(t)} - u_j^{(t-1)}]^T$$

(5)

The error-parameter matrix is $Q = diag(q_1, \ldots, q_i), q_i > 0$, and the control-parameter matrix is $R = diag(r_1, \ldots, r_j), r_j > 0$. When $||Q|| >> ||R||$, the next time period adjustment value can be determined to bring the most recent feedback closer to the target KPIs. On the contrary, when $||R|| >> ||Q||$, the determined adjustment value is changed smoothly from the last time period.

### 2.3 Approximated gradients update

According to the chain rule, the gradients for backward propagation should be calculated by minimizing the cost function $J$. The gradients from the ADX cannot be computed since no model can represent the ADX. We propose an approximated gradients for the backward propagation by referring to the Hebbian Learning Rule[14] in Eq.6 and Eq.7.

$$\frac{dJ}{dW_e} = \left(\frac{\partial J_1}{\partial x} \frac{dx}{du} + \frac{\partial J_2}{\partial u} \frac{du}{dh} \frac{dh}{dW_e}\right)$$

(6)

$$\frac{dJ}{dW_d} = \left(\frac{\partial J_1}{\partial x} \frac{dx}{du} + \frac{\partial J_2}{\partial u} \frac{du}{dh} \frac{dh}{dW_d}\right)$$

(7)

The partial gradients $\frac{\partial J_1}{\partial x}$ and $\frac{\partial J_2}{\partial u}$ are denoted by Eq.8 and Eq.9. In Eq.9, the $(t-1)$-st adjustment value $u^{(t-1)}$ should be treated as a constant value in the latest time period.

$$\frac{\partial J_1}{\partial x} = 2q(x^{(t)} - z)$$

(8)

$$\frac{\partial J_2}{\partial u} = 2r(u^{(t)} - u^{(t-1)})$$

(9)

With no exact ADX model, we employ a sign function to approximate the gradients of $\frac{dx}{du}$ in Eq.10, which can obtain similar trends to the actual gradients of the ADX function. We use $x = f_{ADX}(u)$ to represent the input and output of the ADX for each time period.

$$\frac{dx}{du} = \frac{df_{ADX}}{du} \approx \text{sign}((x^{(t)} - x^{(t-1)}) \cdot (u^{(t)} - u^{(t-1)}))$$

(10)

The output $u^{(t)}$ is yielded from the Sigmoid function. The derivative of the Sigmoid function is included in gradients of $h$ and $W_d$, which are denoted as Eq.11.

$$\frac{du}{dh} = \frac{e^{-W_d^T h}}{(1 + e^{-W_d^T h})^2} \cdot W_d^T$$

$$\frac{du}{dW_d} = \frac{e^{-W_d^T h}}{(1 + e^{-W_d^T h})^2} \cdot h^T$$

(11)

Because the input of Encoding Layer includes target KPI, which is always a constant. The gradients related to the input KPI become irrelevant. Thus we define another approximation referred to the Hebbian Learning Rule to calculate the gradients of $\frac{dh}{dW_e}$ in Eq.12.

$$\frac{dh}{dW_e} = [z, x, v] \cdot \sum_k \text{sign}((h_k^{(t)} - h_k^{(t-1)}) \cdot (u^{(t)} - u^{(t-1)}))$$

(12)

The equation connects nodes of input, output, and hidden as well as the last time period of these nodes.

To avoid outlier disturbing, we use normalized last $t$-period average gradients for the backward propagation. In practice, the last $t$ period gradients are logged in $G_e = \{ \frac{df}{dW_e} \}$ and $G_d = \{ \frac{df}{dW_d} \}$. The normalized average gradients are calculated in Eq.13 and Eq.14.

A learning rate $\eta$ is applied to update weights in Eq.15. In practice, we recommend the learning rate is 0.01. Too small may lead to latency, and too large may lead to unstable adjustment values.

$$\nabla W_e = \frac{1}{t} \sum_{t} G_e, \quad \nabla W_d = \frac{1}{t} \sum_{t} G_d$$

(13)

$$\nabla W_e' = \frac{\nabla W_e}{\text{norm}(\nabla W_e)}, \quad \nabla W_d' = \frac{\nabla W_d}{\text{norm}(\nabla W_d)}$$

(14)

$$\nabla W_e = W_e - \eta \nabla W_e', \quad \nabla W_d = W_d - \eta \nabla W_d'$$

(15)

### 3 EXPERIMENTS

In this section, we conduct experiments on the famous open dataset iPinyou [15] and on our production RTB system. The iPinyou Dataset records three seasons’ 24 days’ logs and includes 78M bid records with 24M impressions, 20K clicks, and 1K conversions in total. As other algorithms[6], we select the 2nd season data which have enough conversions for our experiments. (1) Our MCMF has a well performance to gain conversion in Section 3.1. (2) The ablation experiments show the effectiveness of the merged feature in Section 3.2. (3) Even under the extreme sparsity feedback, the MCMF can get the best performance in Section 3.3. (4) The MCMF is applied on our RTB production and get a well performance in conversion in Section 3.4.

### 3.1 Base Experiment

According to Eq.1, we choose the data of IPinyou first six days for training models to get the pCTR and pCVR, and use these day’s average PPC as the expected PPC (PPC_e). Comparing methods are Non-linear(NL)[6], PID [7], and RL [10]. The MCMF extra input features are the accumulated CTR, CVR, pCTR, and pCVR, while the base input only includes the target KPIs and the corresponding feedback. For the fairness of experiments, conversion is chosen as the bidder’s utility for comparison (the more the better), and PPC should not exceed the expected PPC.

The base experiments mainly test all methods’ efficiency under different budget and constraint conditions. We set two budget conditions, Adequate and Tight, and cross them with two types of common constraints, Single and Multi, for a total of four base experiment conditions. The two kinds of budget is determined according to the average of last 6 days cost. Actually, the original budget (average cost of last 6 days) is surplus. Thus, we define an Adequate budget as 1/256 of the original budget, and a Tight budget as 1/1024 of the original budget. We set PPC as the Single constraint and set both PPC and budget as Multi-constraints. Once the cost exceeds the budget, the bid is terminated. The results of the experiments are displayed in Table 1. The variance in cumulative Conversion and Cost is displayed in Figure 3.
Table 1: Adequate: $\text{budget} = 182344$, $\text{PPC}_e = 1800$; Tight: $\text{budget} = 22793$, $\text{PPC}_e = 1800$. CONV: the more the better; PPC: not exceeding expected PPC.

Table 2: NG: Extra features not given. PO: Use posterior features. FT2: Use prior features. FULL: Use all of extra features.

3.2 Ablation Experiments

We set an ablation experiment to show the contribution of merged features. The extra input features are divided into posterior features (CTR and CVR) and prior features (pCTR and pCVR). Four kinds of input features are tested, including extra features not given (NG), posterior features (PO), prior features (PI) and all of the extra features (FULL). The results in Table 2 show that a trade-off between Conversion and PPC when all features are enabled (FULL).

3.3 Sparsity Experiments

The experiments are designed to demonstrate the performance of all methods under various sparsity circumstances. We drop out 10% to 90% of bids randomly, and all methods attend to the same bid

Figure 3: 1st Row: Conversion; 2nd Row: Cost. 1st Col.: Adequate; 2nd Col.: Tight. Solid line: Single; Dot line: Multi.

According to the results, for all conditions, our MCMF performs the best in Conversion, and the PPCs are all satisfied with the expected PPC. Comparing to the RL, our MCMF get an equal Conversions with a lower cost under the Adequate budget. Under the Tight budget, the RL’s performance of Conversion is far behind ours. For the PID, the method’s Conversion and PPC get average performances. According to Figure 3, its Conversion and Cost have a noticeable delay in the beginning. Compared to the Single and Multi-constraint conditions, all methods have a reduction of PPC under the same budget limitation. However, our MCMF has the capability to reduce the PPC without additional budget pacing or management.

3.4 Online A/B Test

We set an A/B test in our online RTB production. A is the current online approach, and B is our MCMF. Our advertising includes more than 7K goods, 22K advertisers, and 4M bids with daily ten billion requests. All of the bidders choose the Conversion as the utility, and use our MCMF to participate in the auction. The daily performance is illustrated in Figure 5. For 15 days, the total conversion of our MCMF is 2.96% more and ROI is 5.55% greater with 2.46% fewer expenditures.

Figure 5: LEFT: Conversion(The more the better); MIDDLE: ROI (The more the better.); RIGHT: Cost

4 CONCLUSION

We suggested a bid optimization approach for the Real-Time Bidding called Multi-Constraints with Merging Features (MCMF). It is
a two-layer MLP, with our developed cost function updating the weights using approximated gradients. Its input incorporates numerous bidding statuses as merging features, which can guarantee the performance under sparse and delayed feedback conditions. The cost function is proposed to make utility maximization and budget management more consistent. The approximated gradients are proposed by following the Hebbian Learning Rule, so that the updating can still work in backward propagation even in the absence of bidding environment modeling. Experiments on a popular open dataset and our RTB production showed that our MCMF achieves more conversions and fewer costs with stable budget management.

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