Budget Planning for Coupled Campaigns in Search Auctions

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Abstract: Budget-related decisions in search auctions are recognized as a structured decision problem, rather than a simple constraint. Budget planning over several coupled campaigns remains a challenging but utterly important task in search advertisements. In this paper, we propose a multi-campaign budget planning approach using optimal control techniques, with consideration of the substitute relationship between advertising campaigns. A measure of coupled relationships between campaigns is presented, e.g., the overlapping degree (O) in terms of campaign contents, promotional periods and target regions. We also discuss some desirable properties of our model and possible solutions. Furthermore, computational experiments are conducted to evaluate our model and identified properties, with real-world data collected from logs and reports of practical campaigns. Experimental results show that, (a) coupled campaigns with higher overlapping degrees can reduce the optimal budget level and the optimal revenue, and also arrive the budgeting cap earlier; (b) The advertising effort could be seriously weakened when ignoring the overlapping degree between campaigns.

1 Introduction

Search auctions have become the most successful business model accounting for 47.7% revenues of online advertisements in 2011 (IAB, 2011). On the one hand, more and more advertisers choose search auctions to promote their products or services. On the other hand, search advertisements form the dominating revenue resource for major search engine companies. One of the most difficult tasks for advertisers is how to effectively determine and allocate the optimum level of advertising budgets in search auctions.

Budget is an endogenous factor in search auctions, that heavily influences other advertising strategies. Moreover, budget-related decisions in search auctions are recognized as a structured decision problem, rather than a simple constraint (Yang et al., 2011). Specifically, throughout the entire lifecycle of search advertising campaigns, there exist three interweaving budget decisions and being affected by various factors (Yang et al., 2012): allocation across search markets, temporal distribution over a series of slots (e.g. day) and adjustment of the remaining budget (e.g., the daily budget). This work considers the following scenario: an advertiser usually has several campaigns simultaneously executed in a search market (e.g., Google Adwords); then given the advertising budget in a search market is determined, how to make budgeting plans for these campaigns simultaneously over time, in order to maximize the global advertising performance?

There have been some efforts along the line of budget-related decisions in search auctions. Most of them either take the budget as the constraint for other advertising strategies, or allocate the budget over keywords. However these efforts are not operationally suitable to practical paradigms provided by major search engines, because of ignoring the search advertising structure. Budget planning over several campaigns remains a challenging but utterly important task for advertisers in search auctions. First, the search marketing environments are essentially dynamic and uncertain, advertisers usually have no sufficient knowledge and time to track and adjust various advertising decisions. Secondly, an advertiser’s campaigns rarely independent. Similar to the case among products (Doyle and Saunder, 1990), there are certain relationships (e.g., complementarity and substitution) between advertising campaigns, which leads to cross elasticities. For example, for a retailing advertiser, one campaign featuring smart phones might have some substitution effects on another featuring cheap cellphones, and vice versa. Thirdly, the complex structure of search advertising
markets and campaigns consists of a lot of parameters, which made multi-campaign budgeting decisions not straightforward.

The objective of this research is to explore the dynamic budget planning problem for several coupled campaigns in terms of substitution relationships in search auctions. In this paper we formulate the multi-campaign budget planning problem as an optimal control process under a finite time horizon. First, we present a measure of coupled relationships between advertising campaigns by considering the overlapping degree ($O$) in terms of campaign contents, promotional periods and target regions. The overlapping degree refers to the degree to which target markets (or audiences) of these two campaigns overlap each other. Intuitively, it is defined as the probability that search users (e.g., potential customers) issuing with keywords in campaign $j$ can also be reached by campaign $j'$ in search auctions. Secondly, we propose a random walk-based approach for the ad overlapping degree ($\gamma$) in the context of a directed keyword graph relevant to a given advertiser. The higher the ad overlapping degree between two campaigns, the more advertising effort is weakened. Thirdly, we provide a feasible solution to our model and study some desirable properties. Furthermore, we also conduct computational experiments to validate and evaluate our budget planning approach, with real-world data collected from logs and reports of practical campaigns. Experimental results show that (a) the overlapping degree ($O$) between campaigns has serious effects on optimal budgets and the advertising effort, and the advertising effort can be seriously weakened if an advertiser ignore the overlapping degree between campaigns while making advertising decisions; (b) the case with the higher ad overlapping degree ($\gamma$) leads to lower optimal budget level and reaches the budgeting cap earlier; (c) the higher the overlapping degree is, the less optimal revenues can be obtained. The rest of this paper is organized as follows. In Section 2, we propose a measure of 3-dimensional relationship between campaigns, and present a budget planning strategy over several campaigns in search auctions. Section 3 studies some desirable properties and provides possible solutions for our model. Section 4 reports some experimental results to validate some normative findings from our model. Finally we conclude this work and discuss future research directions in Section 5.

2 Multi-campaign Budget Planning

2.1 The 3-dimensional Relationship between Campaigns

It is observed that, the overlapping degree between two campaigns $j$ and $j'$ is zero if there is no overlaps from any single one of those aspects (e.g., campaign contents, promotional intervals and target regions). Thus, the overlapping degree $O(j,j')$ is the product of overlaps from three aspects $O(j,j') = I_t(j,j') \times I_s(j,j') \times \gamma(j,j')$, where $I_t$ and $I_s$ represent the temporal indicator function (e.g., promotional intervals) and the spatial indicator function (e.g., target regions), respectively, and $\gamma(j,j')$ is the overlapping degree in terms of campaign contents.

Denote the indicator function $I_A(x)$ as follows: $I_A(x) = 1$ if $x \in A$, otherwise it is 0.

We will give the definition of the temporal indicator and the spatial indicator.

The Temporal Indicator Function: Let $T_j$ and $T_{j'}$ denote promotion intervals of campaign $j$ and campaign $j'$, respectively. The temporal indicator function is given as $I_t(j,j') = I_{T_j}(t)I_{T_{j'}}(t)$.

The Spatial Indicator Function: The overlaps with respect to target regions can be given in a similar way. Let $S_j$, $S_{j'}$ be target regions of campaign $j$ and campaign $j'$, respectively. The spatial indicator function is given as $I_s(j,j') = I_{S_j}(s)I_{S_{j'}}(s)$.

Next, we will discuss the ad overlapping degree (e.g., in terms of campaign contents) in search auctions.

2.2 The Ad Overlapping Degree

We construct a directed graph of keywords ($K$) relevant to a given advertiser (or her products/services) with the appearance probability as the edge weight. Let $K_j$ and $K_{j'}$ be keyword sets of campaigns $j$ and $j'$, respectively. For each pair of $k$ and $k'$, we can apply a random walk approach (Doyle and Snell, 1984) to compute the appearance probability $\omega_{k,k'}$, given as $\omega_{k,k'} = P(l_k = k') = \sum_{r:e(k,r)\in E} \beta_{k,r} \mu_{k,r} P(l_r = k')$. 


where \( l_k = k' \) represents starting at keyword \( k \) to hit keyword \( k' \), \( \mu_{k,r} = \omega_{k,r} \) if \( \beta_{k,r} = 1 \). Then, \( \zeta(j, j') = \frac{1}{|K_j|} \sum_{k \in K_j} \frac{1}{|K_{j'}|} \sum_{k' \in K_{j'}} \omega_{k,k'} \) represents the probability that search users (e.g., potential customers) issuing keywords in campaign \( j \) can also be reached by campaign \( j' \), and \( \zeta(j, j') \in [0, 1] \). Define \( \gamma(j, j') = [d_j \zeta(j, j') + d_{j'} \zeta(j', j)]/(d_j + d_{j'}) \), where \( d_j \) and \( d_{j'} \) represent the potential query demands of the \( j \)th and \( j' \)th campaign, respectively. Then \( \gamma \) represents the ad overlap degree between two campaigns (e.g., in terms of campaign contents).

2.3 The Model

In this section, we establish a budget planning model for coupled campaigns in search auctions. First, suppose the advertiser aims to maximize the total revenue from advertising activities. Let \( d_{t,s} \) denote the number of query demand (relevant to an advertiser’s promotions in a search market) in region \( s \) at time \( t \), \( \theta_{j,t,s} \) campaign \( j \)’s market share in region \( s \) at time \( t \). Then the number of potential query demands that might be obtained by the advertiser in region \( s \) at time \( t \) is \( d_{t,s} \theta_{j,t,s} \). Let \( c_{j,t,s} \) denote the (average) click-through-rate of campaign \( j \) in region \( s \) at time \( t \), \( v_{j,t} \) the (average) value-per-click of campaign \( j \) at time \( t \), and \( b_{j,t,s} \) the budget segment for campaign \( j \) in region \( s \) at time \( t \), then the total revenue for the advertiser can be represented as \( \sum_{j=1}^{m} \int S_j \sum_{s \in S_j} I_{T_j} e^{-rt}(d_{t,s} \theta_{j,t,s} c_{j,t,s} v_{j,t} - b_{j,t,s})dt \), where \( e^{-rt} \) is the discount factor.

Secondly, due to marketing dynamics in search auctions, an advertiser’s market share changes with time. Following (Yang et al., 2011), the response function in search markets can be given as \( d \theta_{j,t,s}/dt = \rho q u(t, s) / \sqrt{1 - \theta_{j,t,s}} \), where \( \rho \) is the response constant, \( \delta \) the decay constant, and \( q \) is the quality score. The advertising effort \( u \) represents the effective part of advertising budget \( b \).

Thirdly, let \( B_{market} \) denote the overall advertising budget allocated to a given search market, then the present value of total advertising budgets (or expenditures) under a finite time horizon should not exceed it. That is, \( \sum_{j=1}^{m} \int S_j \sum_{s \in S_j} I_{T_j} e^{-rt} b_{j,t,s} dt \leq B_{market} \).

Thus, we can the multi-campaign budget planning problem as follows,

\[
\begin{align*}
\max & \sum_{j=1}^{m} \sum_{s \in S_j} \int T_j e^{-rt}(d_{t,s} \theta_{j,t,s} c_{j,t,s} v_{j,t} - b_{j,t,s})dt \\
\text{s.t.} & \sum_{j=1}^{m} \sum_{s \in S_j} \int T_j e^{-rt} b_{j,t,s} dt \leq B_{market} \\
& d \theta_{j,t,s}/dt = \rho q u(t, s) \sqrt{1 - \theta_{j,t,s}} \\
& b_{j,t,s} \geq 0,
\end{align*}
\]

where \( b_{j,t,s} \) is the control variable, and \( \theta_{j,t,s} \) is the state variable.

3 The Solution & Properties

In this section, we study some desirable properties of our budget planning model, and provide possible solutions. Note that we focus on the case with two campaigns in this work.

Let us consider that there are two campaigns for an advertiser in a market. First, the objective function of model (1) can be written as \( \sum_{j=1}^{2} \sum_{s \in S_j} \int_0^T e^{-rt} I_{T_j}(t) I_{S_j}(s) (d_{t,s} \theta_{j,t,s} c_{j,t,s} v_{j,t} - b_{j,t,s})dt \). Secondly, the budget constraint becomes \( \sum_{j=1}^{2} \sum_{s \in S_j} \int_0^T e^{-rt} I_{T_j}(t) I_{S_j}(s) b_{j,t,s} dt \leq B_{market} \). Thirdly, if the two campaigns are mutually independent, the advertising effort can be given as \( u(t, s) = \sum_j (b_{j,t,s})^{\alpha_{j,t,s}} \), where \( b_{j,t,s} \) represents the budget of campaign \( j \) at time \( t \) in region \( s \), \( \alpha_{j,t,s} \) denotes the advertising elasticity of campaign \( j \) at time \( t \) in region \( s \). If there are overlaps in terms of campaign contents between \( j \) and \( j' \), then the advertising effort is weakened, given as \( u(t, s) = \sum_j (b_{j,t,s})^{\alpha_{j,t,s}} - \sum_j (O(j, j') b_{j,t,s})^{\alpha_{j,t,s}} \), where \( O(j, j') \) is the proportion of the allocated budget (for these two campaigns) where the advertising effort is weakened.

The optimal solution is \( b_{j,t,s}^* \). It represents the optimal budget allocated to campaign \( j \) in region \( s \) at time \( t \). With the optimal control trajectory of budget, we can also obtain the optimal budget allocated to campaign \( j \) in a finite time horizon (e.g., \( T \)) is \( \sum_s \int_0^T e^{-rt} b_{j,t,s}^* dt \).
Next, we study some properties and possible solutions of the model. By introducing a Lagrange multiplier $\lambda$, we employ the principle of dynamic programming and obtain the optimal feedback advertising decisions $b_1^*$ and $b_2^*$ satisfy the following conditions: 

$$
\alpha_i(I_T(t)I_S(s) - O^{\alpha_i})(b_1^* - b_2^*) = \frac{e^{-rt}(1+\lambda)}{\rho y 1 - \rho y b_{\lambda_1} b_{\lambda_2}}.
$$

Then we have, 

$$
\lambda \left( B_{market} - \sum_{s \in S} \int_0^T e^{-rt}(I_T(t)I_S(s)b_{\lambda_1}^*(t, \theta) + I_T(t)I_S(s)b_{\lambda_2}^*(t, \theta))dt \right) = 0.
$$

With infinite budget, we have $\lambda = 0$ and 

$$
\sum_{s \in S} \int_0^T e^{-rt}(I_T(t)I_S(s)b_{\lambda_1}^*(t, \theta) + I_T(t)I_S(s)b_{\lambda_2}^*(t, \theta))dt < B_{market}.
$$

Considering the case that the budget is limited, we choose the minimal $\lambda > 0$ so that 

$$
\sum_{s \in S} \int_0^T e^{-rt}(I_T(t)I_S(s)b_{\lambda_1}^*(t, \theta) + I_T(t)I_S(s)b_{\lambda_2}^*(t, \theta))dt = B_{market}, \lambda \geq 0.
$$

From the above analysis, we can come to the following theorems.

**Theorem 1.** If the total budget $B_{market}$ is less than 

$$
\frac{\sum_{s \in S} \int_0^T e^{-rt}(I_T(t)I_S(s)b_{\lambda_1}^*(t, \theta) + I_T(t)I_S(s)b_{\lambda_2}^*(t, \theta))dt}{B_{market}}
$$

the optimal budget allocation strategy is:

$$
B_1, B_2 = \arg\min_{b_{\lambda_1}, b_{\lambda_2}} \lambda
$$

s.t. 

$$
\sum_{s \in S} \int_0^T e^{-rt}(I_T(t)I_S(s)b_{\lambda_1}^*(t, \theta) + I_T(t)I_S(s)b_{\lambda_2}^*(t, \theta))dt = B_{market}, \lambda \geq 0.
$$

**Theorem 2.** If $B > \sum_{s \in S} \int_0^T e^{-rt}(I_T(t)I_S(s)b_{\lambda_1}^*(t, \theta) + I_T(t)I_S(s)b_{\lambda_2}^*(t, \theta))dt$, the optimal way is to invest 

$$
\sum_{s \in S} \int_0^T e^{-rt}(I_T(t)I_S(s)b_{\lambda_1}^*(t, \theta) + I_T(t)I_S(s)b_{\lambda_2}^*(t, \theta))dt
$$

in the search advertising market.

In reality, if we ignore the ad overlapping degrees ($\gamma$) between two campaigns, then the optimal revenue will be diminished because the corresponding advertising effort are weakened. This can be guaranteed by the following corollary.

**Corollary 3.** Let $U^*$ denote the optimal revenue of the model, and $\bar{U}$ the revenue corresponding to strategies $\bar{b}_1$ and $\bar{b}_2$, where $\bar{b}_1$ and $\bar{b}_2$ are optimal solutions ignoring the overlapping degree in terms of campaign contents between two campaigns, respectively. Then $U^* > \bar{U}$.

## 4 Experimental Validation

In this section, we design computational experiments to validate the proposed model and properties. We generate experimental datasets from historical advertising logs including operations and effects collected from real-world advertising campaigns of search auctions. In the following experiments we take a search advertising scenario where two campaigns are assigned same target regions, and different promotional intervals: one from Sep. 1st to 20th, 2009, another from Sep. 10th to 30th, 2009. Then we can get the ad overlapping degree (e.g., $\gamma = 0.11$) with the algorithm provided in Section 2.

### 4.1 The Ad Overlapping Degree ($\gamma$)

In the first experiment, we aim to prove the influence of the ad overlapping degree ($\gamma$) on the optimal budget and corresponding revenue. For this purpose, we set $B = 3000$, and compute the optimal budget and corresponding revenue with different settings of ad overlapping degrees. That is, the spatial and temporal overlapping degrees are kept unchanged (as described above), and the ad overlapping degrees are assigned different values (e.g., Case 1: $\gamma = 0.0$, Case 2: $\gamma = 0.1$, Case 3: $\gamma = 0.2$). The change of the optimal budget and corresponding revenue over time are illustrated in Figure 1(a) and Figure 1(b), respectively.

From Figure 1(a) and Figure 1(b), we can notice that,

1. As for the case with the higher ad overlapping degree ($\gamma$), the optimal budget is lower during the period when the overlapping degree $O > 0$, and is higher when the overlapping degree $O = 0$ (e.g., there is no overlapping degree), and vice versa. This phenomenon can be explained by the fact that, in the case with higher $\gamma$ the more advertising effort is weakened, thus the optimal budget and corresponding revenue are less (e.g., it is easier to reach the optimal level).
Concerning the accumulated revenue, the case with larger $\gamma$ is slightly bigger at the initial period, then the increasing speed becomes lower when the overlapping degree $O > 0$, and vice versa. The reason might be that, the case with larger $\gamma$ allocates more budgets when $O = 0$, thus it gets a bit more revenue at the initial stage; when $O > 0$ both its optimal budget and revenue are lower, thus the increasing speed of accumulated revenue become slower; then during the period from 21th to 30th, again it allocates more budgets but the accumulated revenue is kept lower due to previous performance.

4.2 The Optimal Revenue at Different Budgeting Levels

The second experiment intends to illustrate the relationship between the optimal budget and corresponding revenue of these two campaigns with different settings of the ad overlapping degree ($\gamma$) same as in the second experiment. We set $B \in [0, 6000]$. The experimental result is illustrated in Figure 1(c).

From Figure 1(c), we can see that,

1. The optimal revenue grows steadily until reaching the cap where the marginal revenue (e.g., the change in additional revenue) is 0, when the total budget increases. In other words, there exists a budgeting cap in the case with unlimited budgets. And the case with larger $\gamma$ arrives the budgeting cap earlier, and vice versa.

2. The optimal revenue in the case with larger $\gamma$ is always less (than that of other cases), and vice versa.

4.3 The Overlapping Degree ($O$)

The third experiment concerns if and how superior it is to consider the overlapping degree ($O$) when doing the budget planning for multiple campaigns in a search market. We implement our multi-campaign budget planning approach (MCBP) as provided in Section 3 into two strategies: with (MCBP-O) and without (MCBP-I) consideration of the overlapping degree. We choose the AVERAGE strategy as a baseline strategy, which allocates the budget averagely between each campaign and over time. The optimal budget and revenue are illustrated in Figure 2(a) and Figure 2(b), respectively.

From Figure 2(a) and Figure 2(b), we can see that,

1. The optimal (total) budget allocated to these two campaigns is 1847.17, 2459.08 and 3000.00 by the these three strategies (e.g., MCBP-O, MCBP-I and AVERAGE), respectively. And correspondingly the optimal payoff is 2363.70, 2340.06 and 2270.74, respectively.
The MCBP-O strategy and the MCBP-I strategy can obtain 1.280 and 0.952 payoff per unit budget, respectively. In other words, the payoff per unit budget is increased 34.45% by considering the overlapping degree \((O)\) between campaigns. This can be explained by the fact that the advertising effort is weakened when the overlapping degree between campaigns exists (e.g., \(O > 0\)). The situation might become even worse if the advertiser ignores the overlapping degree between campaigns while making budget planning decisions in sponsored search auctions.

The AVERAGE strategy can obtain 0.757 payoff per unit budget, and both MCBP-O and MCBP-I outperform the AVERAGE strategy from the view of payoff per unit budget (69.09% and 25.76%), which illustrates that our multi-campaign budget planning approach can help advertisers to increase the overall payoff in a certain degree.

4.4 Management Insights

Our work provides critical managerial insights for advertisers to make budgeting decisions over campaigns in search auctions. First, advertisers usually pay less attentions to relationships and cross-effects between their own campaigns in a search market, probably due to the fact that it is not easy to measure and manipulate the overlapping degree. This research indicates that the overlapping degree \((O)\) between campaigns have serious effects on optimal budget strategies at the campaign level. Secondly, for an advertiser, the larger the overlapping degree between campaigns, the more advertising effort is weakened, and thus the optimal revenue is less. Thus it’s important for an advertiser to reduce the overlapping degree among campaigns as much as possible, then correspondingly adjust the optimal budgets over campaigns in order to maximize the expected revenue. Thirdly, our normative findings of multi-campaign budget planning can also provide some valuable insights to other similar decision scenarios of advertising budget allocation, such as across several markets, across different medias (or channels).

5 Conclusions and Future Work

In this paper, we present a multi-campaign budget planning approach using optimal control techniques, under a finite time horizon. Our model takes into account the overlapping degree (e.g., the substitute relationship) between campaigns in search auctions, with respect to three dimensions: target regions, promotional periods, and campaign contents. We discuss some desirable properties of our model and possible solutions. Computational experimental studies are made to evaluate our model and identified properties. Experimental results show that the overlapping degree between campaigns has serious effects on budgeting decisions and advertising performance, and higher overlapping degrees weaken the advertising effort and thus diminish optimal budgets and revenues. We are in the process of extending our model in the following directions: (a) spatial heterogeneity and relationships to capture spatial effects on advertising decisions and performance; (b) stochastic budget planning strategies in uncertain marketing environments of search auctions; (c) the complementary relationship between campaigns and its effects on budgeting decisions.

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