Budget Planning for Coupled Campaigns in Sponsored Search Auctions

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ABSTRACT: Budget-related decisions in sponsored search auctions are recognized as a structured decision problem rather than a simple constraint. Budget planning over several coupled campaigns (e.g., substitution and complementarity) remains a challenging but important task for advertisers. In this paper, we propose a dynamic multicampaign budget planning approach using optimal control techniques, with consideration of the substitution relationship between advertising campaigns. A three-dimensional measure of substitution relationships between campaigns is presented, namely, the overlapping degree in terms of campaign contents, promotional periods, and target regions. We also study some desirable properties and possible solutions to our budget model. Computational simulations and experiments are conducted to evaluate our model using real-world data from practical campaigns in sponsored search auctions. Experimental results show that (1) our approach outperforms the baseline strategy that is commonly used in practice; (2) coupled campaigns with a higher overlapping degree in between reduce the optimal total budget level, then reduce the optimal payoff, and reach the budgeting cap earlier than those with a less overlapping degree; and (3) the advertising effort can be seriously weakened by ignoring the degree of overlapping between campaigns.

KEY WORDS AND PHRASES: Advertising campaigns, budget planning decision analysis, online advertising, operations research in marketing, optimal control, sponsored search, sponsored search auctions.

Sponsored search auctions have become the most successful online marketing model (www.iab.net/media/file/IABInternetAdvertisingRevenueReportFY2012POSTED.pdf), accounting for 46.3 percent of revenues of online advertisements in 2012 (http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1544580/). More and more advertisers are choosing sponsored search auctions to promote their products or services [14]. Sponsored search auctions form the dominating revenue resource for major search engine companies (e.g., Google gained 92.7 percent of its revenues from search advertisements in the first quarter of 2013). One of the most difficult tasks for advertisers is effectively determining and allocating the optimal level of advertising budget in search advertisements.

Budget is an endogenous factor in search advertisements, heavily constraining other advertising strategies [24]. Moreover, budget-related decisions in sponsored search auctions are recognized as a structured decision problem,

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rather than a simple constraint [29]. Specifically, throughout the entire life cycle of search advertising campaigns, there exist three intertwined budget decisions: allocation across search markets [27], temporal distribution over a series of slots (e.g., day) [28], and adjustment of the remaining budget (e.g., the daily budget) [30]. This work considers the following decision scenario: An advertiser has several campaigns in a search market (e.g., Google Adwords). Given that the advertising budget in a search market is determined (by a brand manager), how does the advertiser make budgeting plans for these campaigns simultaneously over time in order to maximize global advertising performance?

There have been some research efforts investigating budget-related decisions in search auctions. Most of these have either taken the budget as the constraint for other advertising strategies [2, 17] or allocated the budget over a set of keywords [21]. However, these works have not been directly operationally suitable to practical paradigms because they ignore the search advertising structure, game rules, and functionality provided by major search engines. As observed by Tull et al. [23] and Fischer et al. [9], profit improvement from better allocation strategies is much higher than from improving the overall budget.

Budget planning over several campaigns remains a challenging but utterly important task for advertisers in search auctions, for several reasons. First, search marketing environments are essentially dynamic, and advertisers usually have insufficient knowledge and time to track and adjust various advertising decisions. Second, an advertiser's campaigns are rarely independent of one another. As with the case among products [5], there are relationships (e.g., complementarity and substitution) between advertising campaigns, which leads to cross-elasticities. For example, for a retailing advertiser, a campaign featuring smart phones might have some substitution effects on another featuring cheap cell phones, and vice versa. Third, the complex structure of search advertising markets and campaigns is composed of many factors. For example, Jansen et al. [15] noted that the return on advertising dollars varies by average ranking position of the advertisement. The complex advertising structure clouds multicampaign budgeting decisions.

The objective of this research is to explore the dynamic budget planning problem for several campaigns coupled with substitution relationships in sponsored search auctions. In this paper, we formulate the multicampaign budget planning problem as an optimal control process under a finite time horizon. First, we present a measure of substitution relationship between advertising campaigns by considering the overlapping degree (O) from three dimensions: campaign contents, promotional periods, and target regions. By "overlapping degree," we refer to the degree to which target markets (or audiences) of two campaigns overlap each other in search advertisements. Intuitively, it is defined as the probability that search users (e.g., potential customers) issuing queries with keywords in campaign j can also be reached by campaign j'. Second, we propose a random-walk-based approach for the ad overlapping degree (γ) with respect to campaign contents in the context of a directed keyword graph: The higher the ad overlapping degree between two campaigns, the more advertising effort is weakened. Third, we provide a feasible solution to our budget planning model and study some of the model's desirable properties. Furthermore, we also conduct computational simulations and experiments to validate and evaluate our budget planning approach, using real-world data collected from logs and reports of practical campaigns.

Experimental results show that (1) our approach outperforms the baseline strategy that is commonly used in practice; (2) the overlapping degree (O) between campaigns has serious effects on optimal budget strategy; (3) the advertising effort can be seriously weakened if an advertiser ignores the overlapping degree between campaigns while making advertising decisions; (4) the case with higher ad overlapping degree (γ) leads to lower optimal budget level and earlier reaching of the budgeting cap; and (5) the higher the overlapping degree, the less optimal is the payoff that can be obtained.

The contributions of this work can be summarized as follows: (1) We propose a dynamic multicampaign budget planning model for coupled campaigns with substitution relationships in sponsored search auctions and study some desirable properties and possible solutions. (2) We define the concept of campaign overlapping degree (O) to measure the substitution relationship between advertising campaigns from three dimensions: campaign contents, promotional periods, and target regions. (3) We conduct computational simulations and experiments to validate the proposed budget planning model and its identified properties with real-world data from sponsored search campaigns.

The remainder of this paper is organized as follows: The next section provides a literature review. In the following section, we propose a measure of three-dimensional relationship between campaigns, and then, based on it, provide a budget planning strategy for several campaigns in sponsored search auctions. Next, we discuss some desirable properties and provide a feasible solution for our model. We also report experimental results to validate normative findings from our model and discuss managerial insights from our work as well as its shortcomings. Finally, we discuss future research directions.

Literature Review

Search renders advertising less important, perhaps even irrelevant, and allows a company to take temporary possession of a competitor's brand at a lower cost [3]. In sponsored search campaigns, advertisers bid on key phrases that relate to products or services that they provide and that they believe searchers will submit to the search engine. These key phrases provide the link between the results provided from the advertiser and the queries submitted by potential customers, who are the searchers on the Web search engines. Searchers submit queries to the search engines that match a key phrase, and the corresponding set of results is displayed on the search engine results page. Although published research is sparse, reports indicate that about 15 percent of search engine clicks occur on these keyword advertisements [16].

The keyword cost for the advertiser is determined via online auctions. The specific cost can be in continual flux, as the amount that an advertiser must bid to get an ad to display depends on the overall demand for that key phrase at a given time. The amount that an advertiser is willing to bid depends on the perceived possible value of the customer's converting (i.e., taking some desired action, such as purchasing a product). Several advertisers typically bid on the same key phrases simultaneously, so the online auction and bid price can be quite dynamic. The search advertising platforms provide advertisers an assortment of tools to effectively manage their bids, control risk, and maximize opportunity.

The sponsored results on the search engine results page are usually shown above the organic results listing (i.e., the north position), to the right of the organic results listing (i.e., the east position), and below the organic results listing (i.e., the south position). The specific display method depends on the search engine, as some engines may not use all three positions. The sponsored-results-ranking listing depends on the bid price, the other bids in the auction, and a quality score (which is determined by several factors, including bid amount, click-through history, and landing page relevance to the ad, although this formula varies somewhat by search engine). Given these factors, the sponsored search process is a complex integration of business processes, information technology, and information processing, making it an exciting area for multidisciplinary study.

The sponsored search results are normally textual in nature and consist of a short headline, two diminutive lines of text describing the product or service, and a hyperlink that points to the advertiser's landing page (i.e., an advertiser-designated Web page). The predominant keyword advertising model is pay per click (PPC), in which an advertiser pays the search engine only if a searcher actually clicks on the displayed ad hyperlink. So, the impression of an ad does not monetarily cost the advertiser. The advertising budget is determined by several important factors, such as the click-through rate (CTR) and the cost per click (CPC).

The sponsored search process can be extremely complex, and this brief overview cannot do it justice. The interested reader is referred to review articles of the search process (e.g., [17, 19]).

Search advertisers, especially those from small and medium enterprises, have budget constraints, of course. Thus, how to effectively allocate the limited advertising budget is a critical issue in search auctions. Under the umbrella term *budget optimization*, many research efforts have investigated how to place bids over a set of keywords to maximize the number of clicks expected for advertisers for a given budget [10, 20]. Feldman et al. [10] studied how to spread a given budget over keywords to gain maximal revenues and proposed a two-bid uniform bidding strategy. Muthukrishnan et al. [20] explored the problem using stochastic models.

Due to the dynamic nature of search auction markets, various optimal programming algorithms have been used to find optimal solutions for budget allocation. The search process for optimal budget allocation strategies can be modeled as an optimal programming problem, and optimal control theory has been used to study the optimal budget allocation problem, either over keywords [21] or among Web portals [11]. Results from Liu et al. [19] show that price elasticities of the CTR and response functions are key factors for budget decisions, and investing in more keywords under a certain threshold can help improve advertisers' profits. Xu et al. [26] investigated the interplay between organic and sponsored listings, finding that the presence of organic listings can alter a business's bidding incentives. Fruchter and Dou [11] utilized dynamic programming techniques to derive an analytical solution to the optimal budget allocation problem, and their conclusions indicate that budget allocation strategies rely nonlinearly on the targeted audiences, average CTRs, and adverting effectiveness of Web sites. Thus, advertisers are advised to allocate more of their budget to specialized Web portals in order to maximize click volumes in the long term.

In promotional activities, the optimal level of advertising budget for a single product depends on its margin and the advertising elasticity of demand. However, a retailing advertiser has to decide which product to promote and the optimal budget to spend over a broad product range [7], where cross-elasticities exist among products due to relationships of complementarity and substitution [4, 5]. Xu et al. [25] reported that it may not always be optimal for a business to bid for the highest position. Doyle and Saunders [5] explored the problem of budget optimization across a broad product range and derived a closed-form allocation solution and rules based on the semilog response model. Hosanagar and Abhishek presented an analytical model to compute the optimal bids for keywords in a sponsored search campaign (http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1544580/). Fischer et al. [9] proposed a budget allocation method for breaking down a global marketing budget into individual budgets at the country–product–marketing–activity level. They derived a simple but valuable heuristic rule for budget allocation, accounting for dynamics in marketing effects and product growth. Athey and Ellison [1] formulated a bidding model that incorporates the consumer as a searcher. Jansen and Schuster [13] showed that consumers follow a buying funnel approach to e-commerce searching.

These prior works on multiproduct budget decisions provide valuable clues; however, they cannot directly fit multicampaign budget planning problems, for three reasons. First, the first-class objects of budget decisions are different. These prior works focus on products, whereas our work concerns campaigns in sponsored search auctions. The decision factors are quite distinct from each other. Second, a one-to-one relationship does not necessarily exist between products and advertising campaigns. Third, the marketing environment of search auctions is dynamic and complex. So, it is necessary to fit search advertising scenarios by introducing inherent factors of sponsored search auctions (e.g., the dynamical advertising effort and quality score), because more search engines have adopted quality-based ranking and pricing mechanisms. To the best of our knowledge, this is the first research effort in this direction.

The Substitution Relationship Between Advertising Campaigns

In this section, we first provide a measure of substitution relationship between advertising campaigns in sponsored search auctions, taking into account three factors: campaign contents, promotional intervals, and target regions.

Table 1. List of Notations.

Notation	
B_{market}	The overall advertising budget allocated to a search market
T_j	The promotional period of campaign j, $T_j = [T_{j,start}, T_{j,end}]$
$d_{t,s}$	The number of query demands (relevant to the advertiser) in region s at time t
$\theta_{j,t,s}$	The campaign j's market share in region s at time t
$b_{j,t,s}$	The budget segment for campaign j in region s at time t; $j = 1, 2, \ldots, m$; $s = 1, 2, \ldots, n$
$c_{j,t,s}$	The (average) click through rate (CTR) of campaign j in region s at time t
$v_{j,t}$	The (average) value per click (VPC) of campaign j at time t
$\alpha_{j,t,s}$	The advertising elasticity of campaign j in region s at time t
$\omega(k, k')$	The direct appearance probability of keyword k' under the condition that keyword k appears in a query
$O(j, j')$	The overlapping degree between campaign j and campaign j' in region s at time t
$\gamma(j, j')$	The ad overlapping degree between campaign j and campaign j'
ρ	The response constant
q	The (advertiser's) quality score

Substitution, in our context, refers to the phenomenon wherein two campaigns do not enhance but rather weaken, the influence of each other in the overlapping periods, regions, and contents. The opposite concept is *complementarity,* which refers to the phenomenon in which two campaigns enhance the influence of each other in the overlapping periods, regions, and contents. This research focuses on the substitution relationship between advertising campaigns, because it is a common but critical problem for retailing advertisers, which usually have to decide how to promote a spectrum of products with similar functions. (The complementarity relationship between campaigns and its effects on advertising decisions are beyond the scope of this work.)

The measure of substitution relationship serves as the basis for multicampaign budget planning as proposed in the section "Multicampaign Budgeting over Time." The notations used in this paper are listed in Table 1.

A Three-Dimensional Measure of Substitution Relationship

In sponsored search auctions, an advertiser usually has to simultaneously manipulate several campaigns in a search market. A campaign is composed of several ad groups consisting of a set of keywords and one or more ad copies and is assigned a promotional interval and a set of target regions. In this sense, the overlapping degree between campaigns can be represented with a three-dimensional vector: campaign contents (e.g., keywords and phrases), promotional intervals, and target regions. It is observed that the overlapping degree $O(j,j')$ between two campaigns j and j' is zero if there does not exist overlap from any single dimension. Therefore, the overlapping degree $O(j,j')$ can be given as the product of overlaps from these three dimensions,

$$O(j,j') = I_t(j,j') \times I_s(j,j') \times \gamma(j,j'), \tag{1}$$

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. In this paper, we call $\gamma(j, j')$ the ad overlapping degree, which is modeled as an appearance probability based on a random walk approach.

Let us denote the indicator function $I_A(x)$ as follows:

$$I_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{otherwise.} \end{cases}$$

Then, we give the temporal indicator and the spatial indicator based on the above function.

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

Similarly, let S_j and $S_{j'}$ be target regions of campaign j and campaign j', respectively. The spatial indicator function is given as

$$I_s(j, j') = I_{s_j}(s) I_{s_{j'}}(s).$$

The Ad Overlapping Degree

The ad overlapping degree (γ) indicates how much advertising efforts overlap between two campaigns in sponsored search auctions. Let K_j and $K_{j'}$ be keyword sets of campaigns j and j', respectively. We can obtain frequent item sets of keywords in $K_j \cup K_{j'}$ from keyword tools provided by major search engines (e.g., Google AdWords Keyword Tool, shown in Figure 1). The frequent item set is a popular concept in data mining. By definition, each item set will occur at least as frequently as a predetermined minimum support. In our context, the frequent item set of keywords is a set of keywords used by search users at least once. Let N_k denote the number of frequent item sets including keyword k, and $N_{k,k'}$ denote the number of frequent item sets including both keyword k and keyword k'. Thus, the direct appearance probability of k' under the condition that keyword k appears in a query issued by search users is

$$\omega_{dir}(k, k') = P(k' \mid k) = \frac{N_{k,k'}}{N_k}. \tag{2}$$

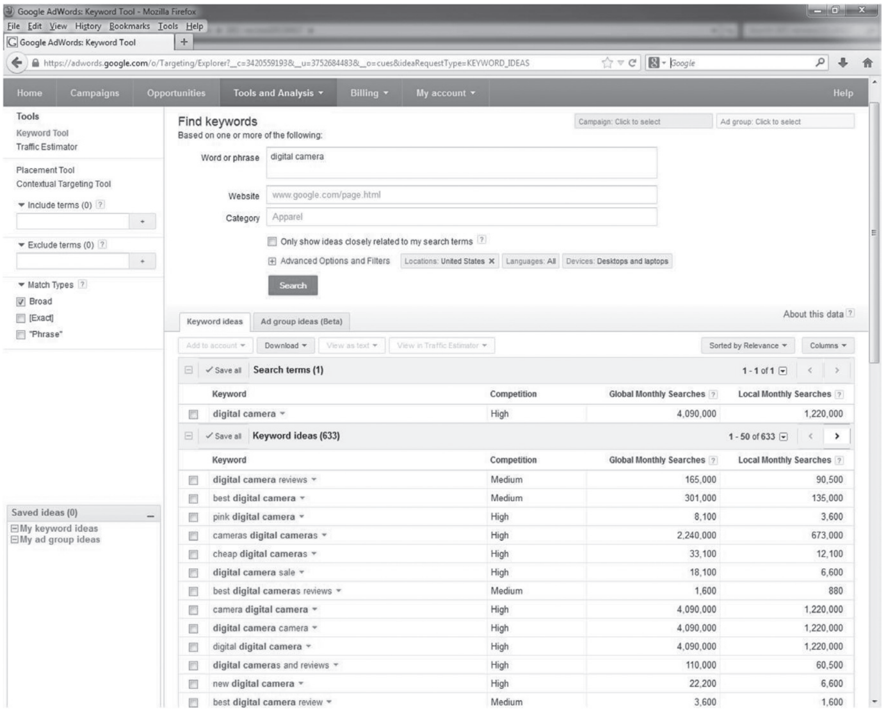

Figure 1. Google AdWords Key Word Tool Showing Suggestions for Key Phrase "Digital Camera"

Note: Screenshot from https://adwords.google.com/o/KeywordTool/.

Let E represent the edge set of the directed graph K. On the one hand, if $\omega_{k,k'} > 0$, then $e(k,k') \in E$. In other words, there exists a direct edge from keyword k to keyword k'. But when there does not exist a direct edge, but a directed path from k to k', we develop a random walk approach [6] to compute the indirect appearance probability, ω_{ind}, that is, the probability starting from k to hit k' in the keyword network. It is given as

$$\omega_{ind}(k,k') = P(l_k = k') = \Sigma_{r:e(k,r)\in E}\beta_{k,r}\mu_{k,r}P(l_r = k'), \tag{3}$$

where $P(l_k = k')$ represents the probability of starting at keyword k to hit keyword k', $\beta_{k,r} = I_E(e(k,r))$ is an indicator function given as

$$\beta_{k,r} = \begin{cases} 1 & \text{if } e(k,r) \in E \\ 0 & \text{otherwise,} \end{cases}$$

and $u_{k,r}$ is the transition probability from keyword k to keyword r, which is equal to $\omega_{dir}(k,r)$ if $\beta_{k,r} = 1$, and 0 otherwise.

We construct a directed graph of keywords (e.g., K) relevant to a given advertiser (or the advertiser's promotional products or services) on which the edge weight is represented by the appearance probability from k to k', for example, $\omega(k,k')$. That is, if $a(k,k') > 0$, there exists a directed edge/path from keyword k to keyword k'.

Then,

$$\zeta(j,j') = \frac{1}{|K_j|}\sum_{k \in K_j}\frac{1}{|K_{j'}|}\sum_{k' \in K_{j'}}\omega(k,k') \tag{4}$$

represents the probability that search users (e.g., potential customers) issuing with keywords in campaign j can also be reached by campaign j', and $\zeta(j,j') \in [0,1]$.

We define the ad overlapping degree between two campaigns as

$$\gamma(j,j') = \frac{d_j\zeta(j,j') + d_{j'}\zeta(j',j)}{d_j + d_{j'}}, \tag{5}$$

where d_j and $d_{j'}$ represent the query demands of campaign j and j', respectively.

An Illustrative Example

Next, we provide an example to illustrate the computation process of the overlapping degree between two campaigns in sponsored search auctions.

Suppose an advertiser has two campaigns (denoted Camp-1 and Camp-2) in a search market. The promotional intervals of Camp-1 and Camp-2 are T_1 and T_2, respectively, and the target regions of Camp-1 and Camp-2 are $S_1 = \{s_1, s_2\}$ and $S_2 = \{s_2, s_3\}$, respectively, as shown in Figure 2(a). The query demands of Camp-1 and Camp-2 are $d_1 = 30$ and $d_2 = 45$, respectively. Figure 2(b) describes co-occurrence relationships among keywords of Camp-1 and Camp-2; the number for a keyword represents the number of frequent item sets including the keyword, and the number for the link between two keywords represents the number of frequent item sets including both of these keywords.

Next, we illustrate the computational process of the ad overlapping degree between Camp-1 and Camp-2.

Step 1: Compute I_t(Camp-1, Camp-2) and I_s(Camp-1, Camp-2)

From Figure 2(a), we can get

$$I_t(\textit{Camp-1},\textit{Camp-2}) = \begin{cases} 1 & \text{if } t \in T_1 \cap T_2 \\ 0 & \text{otherwise} \end{cases}$$

and

$$I_s(\textit{Camp-1},\textit{Camp-2}) = \begin{cases} 1 & \text{if } s \in \{s_2\} \\ 0 & \text{otherwise.} \end{cases}$$

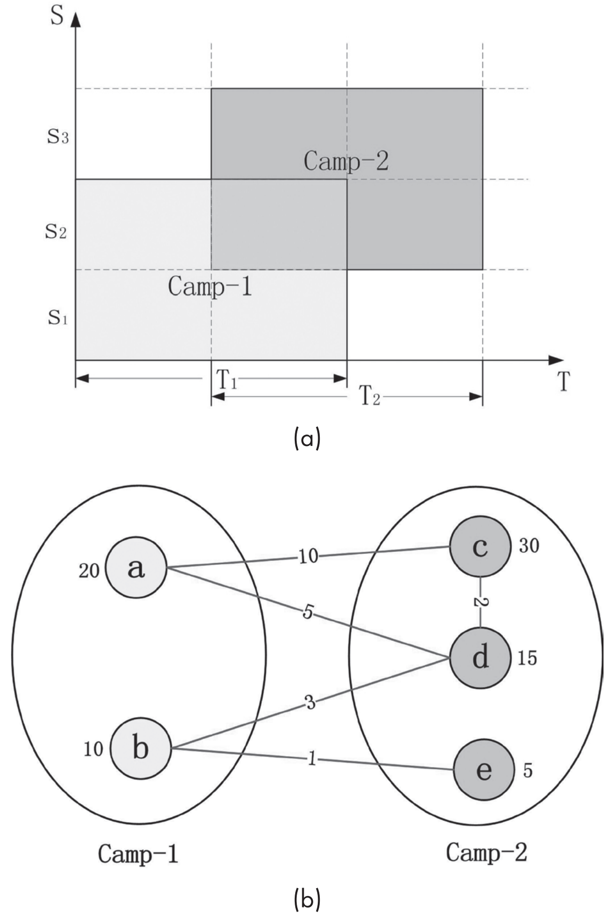

Figure 2. (a) Promotional Intervals of Camp-1 and Camp-2; (b) Co-Occurrence Relationships Among Key Words in Camp-1 and Camp-2

Step 2: Construct a Directed Keyword Graph

From Figure 2(b), we can get

$$N_a = 20,\ N_b = 10,\ N_c = 30,\ N_d = 15,\ N_e = 5,\ N_{a,c} = 10,\ N_{a,d} = 5,$$
$$N_{b,d} = 3,\ N_{b,e} = 1,\ N_{c,d} = 2.$$

The direct appearance probability can be computed according to Equation (2):

$$\omega_{a,c} = \frac{N_{a,c}}{N_a} = 0.5,\ \omega_{c,a} = \frac{N_{a,c}}{N_c} = \frac{1}{3},$$

$$\omega_{a,d} = \frac{N_{a,d}}{N_a} = 0.25,\ \omega_{d,a} = \frac{N_{a,d}}{N_d} = \frac{1}{3},$$

$$\omega_{b,d} = \frac{N_{b,d}}{N_b} = 0.3,\ \omega_{d,b} = \frac{N_{b,d}}{N_d} = 0.2,$$

$$\omega_{b,e} = \frac{N_{b,e}}{N_b} = 0.1,\ \omega_{e,b} = \frac{N_{b,e}}{N_e} = 0.2,$$

$$\omega_{c,d} = \frac{N_{c,d}}{N_c} = \frac{1}{15},\ \omega_{d,c} = \frac{N_{c,d}}{N_d} = \frac{2}{15}.$$

We can construct a directed graph of these keywords with the direct appearance probability as the edge weight, as shown in Figure 3(a). As shown in the figure, although there does not exist a direct edge between some pairs of keywords (e.g., *a* and *e*, *b* and *c*), we can at least find a directed path between them. Thus, we can compute the indirect appearance probability according to Equation (3):

$$\omega_{a,e} = \left(\omega_{a,d} + \omega_{a,c}\omega_{c,d}\right)\omega_{d,b}\omega_{b,e} = \left(0.25 + 0.5 \times \frac{1}{15}\right) \times 0.2 \times 0.1 = \frac{17}{3000},$$

$$\omega_{e,a} = \omega_{e,b}\omega_{b,d}\left(\omega_{d,a} + \omega_{d,c}\omega_{c,a}\right) = 0.2 \times 0.3 \times \left(\frac{1}{3} + \frac{2}{15} \times \frac{1}{3}\right) = \frac{17}{750},$$

$$\omega_{b,c} = \omega_{b,d}\left(\omega_{d,a}\omega_{a,c} + \omega_{d,c}\right) = 0.3 \times \left(\frac{1}{3} \times 0.5 + \frac{2}{15}\right) = 0.09,$$

$$\omega_{c,b} = \left(\omega_{c,a}\omega_{a,d} + \omega_{c,d}\right)\omega_{d,b} = \left(\frac{1}{3} \times 0.25 + \frac{1}{15}\right) \times 0.2 = 0.03.$$

We can obtain a directed graph with the appearance probability as the edge weight, as shown in Figure 3(b).

Step 3: Compute γ(Camp-1, Camp-2)

According to Figure 3(b), we can get

$$\begin{aligned}
&\zeta(\text{Camp-1, Camp-2}) \\
&= \frac{1}{2}\left(\frac{1}{3}\left(\omega_{a,c} + \omega_{a,d} + \omega_{a,e}\right) + \frac{1}{3}\left(\omega_{b,c} + \omega_{b,d} + \omega_{b,e}\right)\right) \\
&= \frac{1}{2}\left(\frac{1}{3}\left(0.5 + 0.25 + \frac{17}{3000}\right) + \frac{1}{3}(0.09 + 0.3 + 0.1)\right) \\
&= \frac{3737}{18000},
\end{aligned}$$

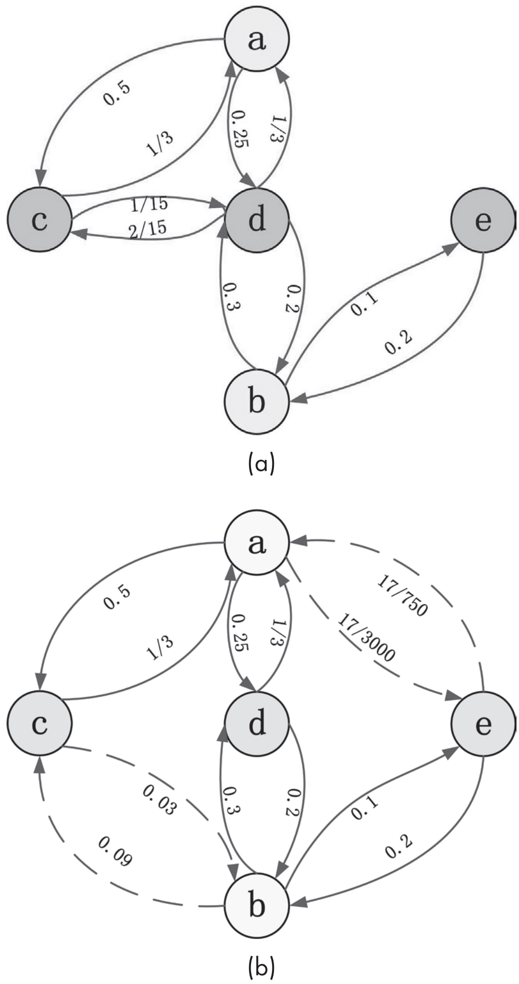

Figure 3. (a) The Initial Directed Key Word Graph; (b) The Final Directed Key Word Graph

$$
\begin{aligned}
&\zeta(\text{Camp-2, Camp-1}) \\
&= \frac{1}{3}\left(\frac{1}{2}\left(\omega_{c,a}+\omega_{c,b}\right)+\frac{1}{2}\left(\omega_{d,a}+\omega_{d,b}\right)+\frac{1}{2}\left(\omega_{e,a}+\omega_{e,b}\right)\right) \\
&= \frac{1}{3}\left(\frac{1}{2}\left(\frac{1}{3}+0.03\right)+\frac{1}{2}\left(\frac{1}{3}+0.2\right)+\frac{1}{2}\left(\frac{17}{750}+0.2\right)\right) \\
&= \frac{1679}{9000}.
\end{aligned}
$$

Then, we can compute the ad overlapping degree between Camp-1 and Camp-2 according to Equation (5):

$$
\begin{aligned}
&\gamma(\text{Camp-1, Camp-2}) \\
&= \frac{d_1\zeta(\text{Camp-1,Camp-2}) + d_2\zeta(\text{Camp-2,Camp-1})}{d_1 + d_2} \\
&= \frac{30 \times \frac{3737}{18000} + 45 \times \frac{1679}{9000}}{30 + 45} \\
&= \frac{4387}{22500} = 0.1950.
\end{aligned}
$$

Step 4: Compute O(Camp-1, Camp-2)

According to Equation (1), we can obtain the overlapping degree between Camp-1 and Camp-2 as follows:

$$
\begin{aligned}
&O(\text{Camp-1,Camp-2}) \\
&= I_t(\text{Camp-1,Camp-2}) I_s(\text{Camp-1,Camp-2}) \gamma(\text{Camp-1,Camp-2}) \\
&= \begin{cases} 0.1950 & \text{if } t \in T_1 \cap T_2, s \in \{s_2\} \\ 0 & \text{otherwise.} \end{cases}
\end{aligned}
$$

Multicampaign Budgeting over Time

Next, we establish a budget planning model for coupled campaigns with substitution relationships in sponsored search auctions.

The Objective

Suppose the advertiser aims to maximize the total payoff from advertising activities. Let $d_{t,s}$ denote the total number of query demands (relevant to an advertiser's promotion activities) in a search market in region s at time t, $\theta_{t,s}$ denote the advertiser's market share in region s at time t, and $\theta_{j,t,s}$ denote the segment of the advertiser's market share by campaign j in region s at time t. Then, the number of potential query demands that can be obtained by campaign j in region s at time t is $d_{t,s}\theta_{j,t,s}$. Let $c_{j,t,s}$ denote the (average) CTR of campaign j in region s at time t, $v_{j,t}$ denote the (average) value per click of campaign j at time t, and $b_{j,t,s}$ denote the budget segment for campaign j in region s at time t. Then, the total payoff for the advertiser can be represented as

$$
\sum_{j=1}^{m} \sum_{s \in S_j} \int_{T_j} e^{-rt} \left(d_{t,s}\theta_{j,t,s} c_{j,t,s} \upsilon_{j,t} - b_{j,t,s} \right) dt,
$$

where e^{-rt} is the discount factor and m is the number of advertising campaigns. Note that the value per click is not a proprietary factor, which is usually computed independently of spatial information (e.g., regions).

The Response Function

The advertising response function is introduced as a formula to compute the cumulative advertising effect for an individual advertiser. In sponsored search markets, an advertiser can make changes to advertising content and strategy at any time in an advertising campaign. In addition, sponsored search advertising has flexibility in terms of keyword selection, bid determination, budget allocation, and advertising schedule, which affects the effectiveness of the advertising budget. To fit search advertising scenarios, Yang et al. [27] extended a variation of the Vidale-Wolfe advertising response function as given in Sethi [22] by introducing the dynamical advertising effort u and quality score q. The Vidale-Wolfe model and its variations can precisely describe the process of how sales evolve over time in response to advertising. The response function in search markets is given as

$$d\theta_{j,t,s}/dt = \rho q u(b,t,s)\sqrt{1-\theta_{j,t,s}},$$

where ρ is the response constant and q is the quality score. The response constant ρ denotes the effectiveness of advertising, for example, response to advertising that acts positively on the unsold market share. In sponsored search auctions, an advertiser's quality score q has significant influences on the capacity to gain market share. Specifically, a higher quality score entitles an advertiser to pay less for each click, so the same amount of advertising budget can result in more market share than that of other advertisers with lower quality scores. The advertising effort $u(b,t,s)$ represents the effective part of advertising budget b. We explore this further in the section "The Budget Planning Model: Solution and Properties."

The Budget Constraint

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,

$$\sum_{j=1}^{m}\sum_{s\in S_j}\int_{T_j} e^{-rt} b_{j,t,s}\,\mathrm{d}t \le B_{\text{market}}.$$

The Budget Planning Model

In summary, the multicampaign budget planning problem can be formulated as

$$\begin{aligned}
&\max \sum_{j=1}^{m}\sum_{s\in S_j}\int_{T_j} e^{-rt}\left(d_{t,s}\theta_{j,t,s}c_{j,t,s}\upsilon_{j,t} - b_{j,t,s}\right)dt\\
&\text{s.t. } \sum_{j=1}^{m}\sum_{s\in S_j}\int_{T_j} e^{-rt} b_{j,t,s}\,dt \le B_{\text{market}}\\
&d\theta_{j,t,s}/dt = \rho q u(b,t,s)\sqrt{1-\theta_{j,t,s}}\\
&b_{j,t,s} \ge 0,
\end{aligned} \tag{6}$$

where $b_{j,t,s}$ is the control variable, $u_{b,t,s}$ is a function of $b_{j,t,s}$ (see the next section), and $\theta_{j,t,s}$ is the state variable.

The Budget Planning Model: Solution and Properties

An advertiser's campaigns in a search market may overlap each other in terms of promotional intervals and target regions but nevertheless not be identical. This makes it difficult to solve the budget planning model shown in Equation (6) because of the variety of overlapping degrees between campaigns and nonuniform descriptions of state variables and control variables. In this section, we study some desirable properties of our budget planning model and discuss possible solutions. Note that we focus on the case with two campaigns in this work. However, our approach can also be applied to cases with more campaigns, with some adaptations.

The Case with Two Campaigns

Consider the case in which an advertiser manipulates two campaigns in a search market. First, the objective function of the budget planning model, formulated in Equation (6), can be written as

$$\sum_{j=1}^{2}\sum_{s\in S}\int_0^T e^{-rt} I_{T_j}(t) I_{S_j}(s)\left(d_{t,s}\theta_{j,t,s}c_{j,t,s}\upsilon_{j,t} - b_{j,t,s}\right)dt.$$

Second, similarly, the budget constraint becomes

$$\sum_{j=1}^{2}\sum_{s\in S}\int_0^T e^{-rt} I_{T_j}(t) I_{S_j}(s) b_{j,t,s}dt \le B_{\text{market}}.$$

Third, the advertising effort depends on whether the two campaigns are independent of each other. According to Little [18], there is an exponential relationship between the budget b and the advertising effort u: $u = b^{\alpha}$, where α denotes the advertising elasticity, which is fixed as a constant in traditional advertisements [8].

In the first case, the two campaigns are mutually independent of each other, that is, $\gamma_{j,j'} = 0$. Then, the advertising effort can be given as

$$u(b,t,s) = \sum_j \left(b_{j,t,s}\right)^{\alpha_{j,t,s}},$$

where $b_{j,t,s}$ represents the budget for campaign j at time t in region s and $\alpha_{j,t,s}$ denotes the advertising elasticity of campaign j at time t in region s.

In the second case, the two campaigns are not independent of each other, that is, $\gamma_{j,j'} > 0$. The substitution relationship between the campaigns leads to crossover effects. This causes part of the budget to be wasted and weakens the advertising effect. The advertising effort can then be given as

$$u(b,t,s) = \sum_j \left(b_{j,t,s}\right)^{\alpha_{j,t,s}} - \sum_j \left(O(j,j')b_{j,t,s}\right)^{\alpha_{j,t,s}},$$

where $O(j,j')$ denotes the proportion of the allocated budget (for these two campaigns) for which the advertising effort is weakened.

Drawing on the preceding discussion, the budget planning model, formulated in Equation (6), for the case with two campaigns can be given as

$$\begin{aligned}
&\max \sum_{j=1}^{m}\sum_{s\in S}\int_0^T e^{-rt} I_{T_j}(t) I_{S_j}(s)\left(d_{t,s}\theta_{j,t,s}c_{j,t,s}\upsilon_{j,t} - b_{j,t,s}\right)dt \\
&\text{s.t. } \sum_{j=1}^{2}\sum_{s\in S}\int_0^T e^{-rt} I_{T_j}(t) I_{S_j}(s) b_{j,t,s}\,dt \le B_{\text{market}} \\
&d\theta_{j,t,s}\big/dt = \rho q u(b,t,s)\sqrt{1-\theta_{j,t,s}} \\
&u(b,t,s) = \sum_{j=1}^{2}\left(I_{T_j}(t) I_{S_j}(s) b_{j,t,s}\right)^{\alpha_{j,t,s}} - \sum_{j=1}^{2}\left(O(j,j')b_{j,t,s}\right)^{\alpha_{j,t,s}} \\
&b_{j,t,s} \ge 0.
\end{aligned} \tag{7}$$

The optimal solution of Equation (7) is $b^*_{j,t,s}$, which represents the optimal budget strategy allocated to campaign j in region s at time t. Then, the optimal budget allocated to campaign j in a finite time horizon (e.g., T) is $\Sigma_s\int_0^T e^{-rt} b^*_{j,t,s}dt$.

The objective function and budget constraint in Model (7) is a special case of the two campaigns in Model (6), as discussed previously. Similarly, $u(b,t,s)$ in Model (7) is also a special case of Model (6).

We next explore a theoretical solution and properties of Model (7) that could provide valuable insights into how to make decisions regarding search advertising budgets.

Properties

From the prior analysis, we can develop the following theorem:

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

$$\sum_{s\in S}\int_0^T e^{-rt}\left(I_{T_1}(t) I_{S_1}(s) b^*_{0,1} + I_{T_2}(t) I_{S_2}(s) b^*_{0,2}\right)dt,$$

the optimal budget allocation strategy is

$$\begin{aligned}
&b_1, b_2 = \arg\min_{b^*_{\lambda,1}, b^*_{\lambda,2}} \lambda \\
&\text{s.t. } \sum_{s\in S}\int_0^T e^{-rt}\left(I_{T_1}(t) I_{S_1}(s) b^*_{\lambda,1}(t,\theta) + I_{T_2}(t) I_{S_2}(s) b^*_{\lambda,2}(t,\theta)\right)dt = B_{\text{market}} \\
&\lambda \ge 0.
\end{aligned} \tag{8}$$

If the total budget B_{market} is larger than

$$\sum_{s\in S}\int_0^T e^{-rt}\left(I_{T_1}(t) I_{S_1}(s) b^*_{0,1} + I_{T_2}(t) I_{S_2}(s) b^*_{0,2}\right)dt,$$

the optimal budget allocation strategy is to invest

$$\sum_{s\in S}\int_0^T e^{-rt}\left(I_{T_1}(t)I_{S_1}(s)b_{0,1}^* + I_{T_2}(t)I_{S_2}(s)b_{0,2}^*\right)dt$$

in the search advertising market.

Theorem 1 provides solutions for the cases with and without budget constraints. This theorem can also be justified because the marginal return on the optimal budget strategy is equivalent to (or approaching) zero at

$$\sum_{s\in S}\int_0^T e^{-rt}\left(I_{T_1}(t)I_{S_1}(s)b_{0,1}^* + I_{T_2}(t)I_{S_2}(s)b_{0,2}^*\right)dt,$$

beyond which the residual budget cannot yield additional revenues. In other words, there exists a producer equilibrium in the case without budget constraints, which is equivalent to the payoff supremum in the case with budget constraints.

Corollary 1: *Let U^* be the optimal payoff of Model (7), and $\bar{U}$ be the payoff 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; then, $U^* > \bar{U}$.*

Corollary 1 indicates that, if an advertiser makes budget planning decisions over two (or more) campaigns independently (i.e., ignoring the overlapping degree), the optimal payoff will decrease. One possible reason is that the advertising effort is more or less weakened when the overlapping degree between campaigns, that is, $O > 0$. The overlapping degree between campaigns heavily influences the optimal budget strategy and corresponding payoff. Thus, advertisers must take the overlapping degree into account when making budget decisions in sponsored search auctions.

Simulations and Experimental Validation

In this section, we design computational simulations and experiments to validate the proposed model and its identified properties. Our experimental evaluation focuses on the following twofold purpose: First, we intend to verify the necessity to consider the overlapping degree (O) in the budget planning approach for several campaigns, and we evaluate our approach by comparing it with a baseline strategy that is commonly used in practice. Second, we prove some desirable properties of our budget model as discussed previously. Specifically, we evaluate our budget planning model with respect to the ad overlapping degree (γ) and the budgeting level and then determine their influences on the optimal budget strategy and the corresponding payoff. Next, we provide details about our experimental setup and some key results.

Data Description

We collect real-world data from search advertising campaigns by an e-business advertiser promoting services across two search markets during the period from September 2008 to August 2010. From this data, we collect information about the advertiser's total advertising budget (B) and relevant budget decisions across these two markets, clicks generated from the advertisements, the average CPC, and search users' activities on the Web site, and so on. Some relevant parameters for our method can be obtained from the statistics derived from past sponsored search campaigns: (1) The potential search demand in a search market can be obtained from keyword research tools provided either by major search engines or by third-party companies such as WordTracker. (2) The value per click and the proportion of effective clicks in a search market can be estimated from historical reports and logs of advertising campaigns and the advertiser's proprietary information. Specifically, the value per click is computed as (*price* – *cost*) * *sales*/*clicks*. The former two factors (i.e., *prices* and *cost* of a product or service) are provided by the advertiser, and the latter two factors (i.e., *sales* and *clicks*) can be obtained from the search advertising report and Web logs. (3) Due to business secrecy and self-protection issues from search engines, it is impossible to obtain the necessary information to compute the quality score. Thus, we measure an advertiser's quality score q according to the relevance between the text in the advertisement and the corresponding landing page, using text-mining techniques. The relevance between the ad text and the landing page can be measured using the cosine function. (4) The advertising elasticity α is instantiated as the normalized profit per unit cost (e.g., the advertiser's ability to make budget decisions).

The frequent item sets of keywords in these two campaigns can be obtained from keyword tools provided by major search engines (e.g., Google AdWords). Based on this information, we can construct a directed keyword graph with the appearance probability as the edge weight. The ad overlapping degree (i.e., $\gamma = 0.11$) can be obtained with the algorithm provided in Equation (5) We also do some approximate treatments on the statistical data in order to provide intelligible experimental settings. Finally, we generate data sets from historical advertising logs to support computational experiments to verify properties of our budget allocation method.

Experimental Results and Analysis

In the following experiments, we take a search advertising scenario: An advertiser manipulates two campaigns that are delivered during different promotional intervals (one from September 1 to September 20, 2009; another from September 10 to September 30, 2009) and in the same target regions. The total advertising budget for these two campaigns is set at 3,000 units.

The Overlapping Degree O

The first experiment concerns the necessity to consider the overlapping degree (O) when formulating a budgeting plan for multiple campaigns in a search

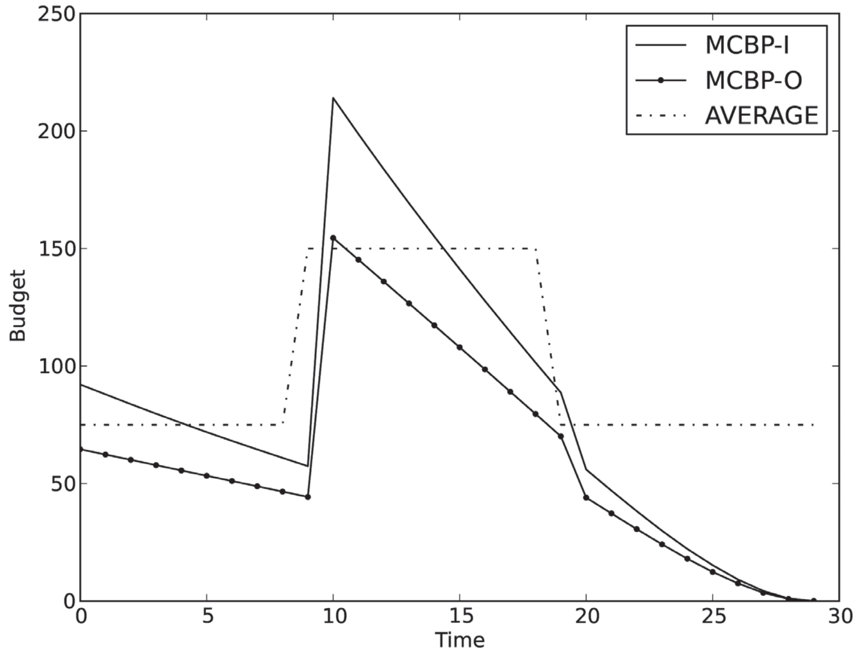

Figure 4. The Optimal Budget over Time by These Three Strategies, MCBP-O, MCBP-I, and AVERAGE

market. We implement our multicampaign budget planning approach (MCBP) as provided in the section "The Budget Planning Model: Solution and Properties" as two strategies: with (MCBP-O) and without (MCBP-I) consideration of the overlapping degree among campaigns. The MCBP-I can be viewed as a baseline strategy for our approach. A second baseline strategy is the AVERAGE strategy, commonly used in practical advertising campaigns. It allocates the budget averagely between campaigns and then over time. The optimal budget and the optimal payoff are illustrated in Figures 4 and 5, respectively. From Figures 4 and 5, we can see the following:

1. The optimal (total) budget allocated to these two campaigns by these three strategies (MCBP-O, MCBP-I, and AVERAGE) is 1,847.17, 2,459.08, and 3,000.00 respectively. Correspondingly, the optimal payoff (i.e., the net profit) is 2,363.70, 2,340.06, and 2,270.74, respectively.
2. The AVERAGE strategy obtains 0.757 payoff per unit budget (i.e., the ratio between the optimal payoff and the total budget). The MCBP-O strategy obtains 1.280 payoff per unit budget, and the MCBP-I strategy obtains 0.952 payoff per unit budget.
3. Both the MCBP-O and MCBP-I strategies outperform the AVERAGE strategy in terms of payoff per unit budget (69.09 percent and 25.76 percent, respectively), which illustrates that our multicampaign budget planning approach can help advertisers to increase the overall payoff.

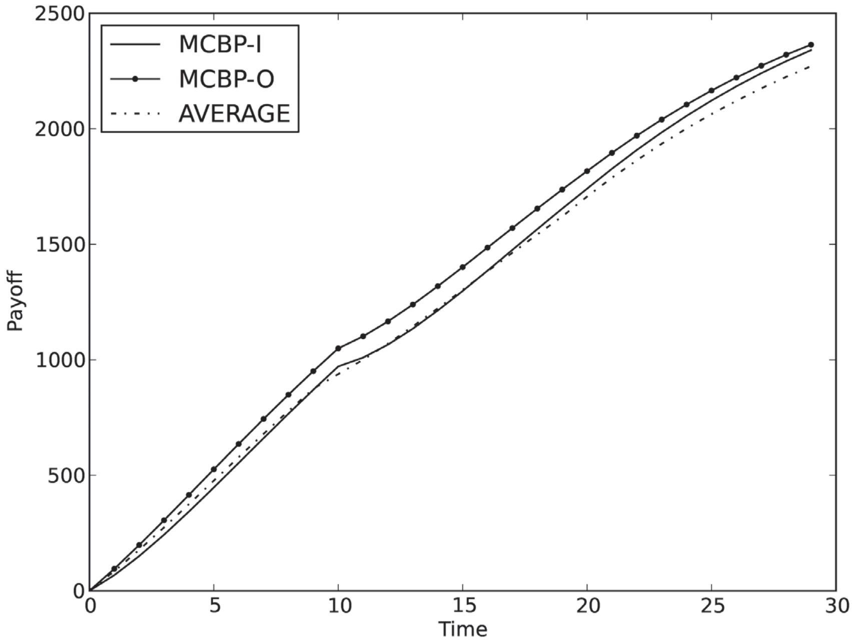

Figure 5. The Optimal Payoff over Time by These Three Strategies, MCBP-O, MCBP-I, and AVERAGE

4. The payoff per unit budget is increased 34.45 percent 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 (i.e., $O > 0$). 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 Ad Overlapping Degree

In the second experiment, we evaluate the influence of the ad overlapping degree (γ) on the optimal budget and the corresponding payoff. We compute optimal budgets and corresponding payoffs under different settings of ad overlapping degrees. That is, the spatial and temporal overlapping degrees are kept fixed (as in the advertising scenario), and the ad overlapping degrees are assigned different values (i.e., $\gamma = 0.0$, $\gamma = 0.1$, $\gamma = 0.2$). Optimal budgets and corresponding payoffs over time in these three settings are illustrated in Figures 6 and 7, respectively. From Figures 6 and 7, we can see the following:

1. For the case with the higher ad overlapping degree (γ), the optimal budget is lower when the campaign overlapping degree $O > 0$ (i.e.,

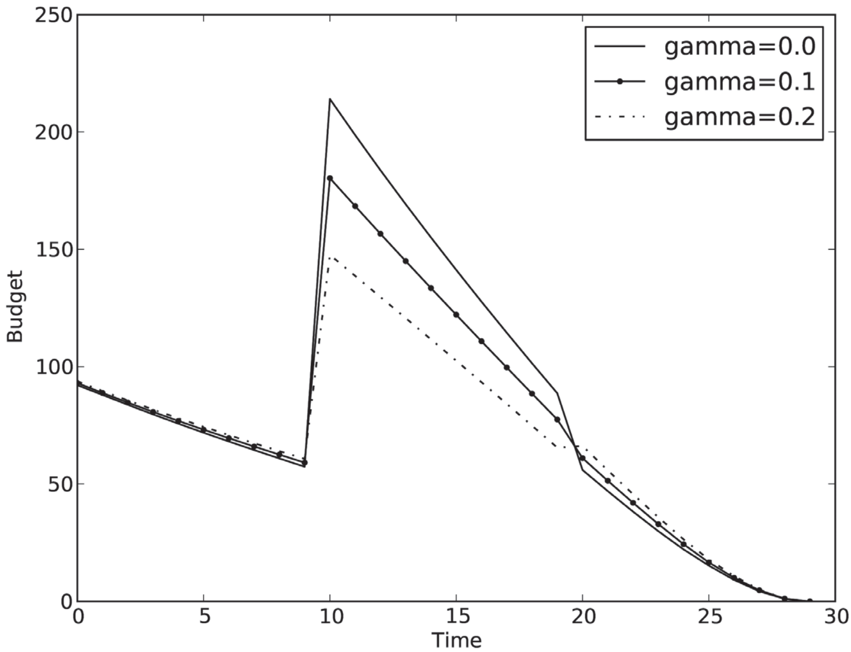

Figure 6. Optimal Budgets over Time with Different Gammas

there exist some overlaps between campaigns) and becomes higher when the overlapping degree $O = 0$ (i.e., there are no overlaps between campaigns). This phenomenon can be explained by the fact that, in the case with the larger γ, more advertising effort is weakened and the optimal budget is less. In other words, it is easier to reach the optimal budgeting level in the case with the larger γ.

2. Concerning the optimal payoff, the case with the larger γ is slightly larger at the initial period, and then its increasing speed becomes lower when the overlapping degree $O > 0$. One possible reason is that the case with a larger γ allocates more budget to advertising campaigns when $O = 0$ (from 1st to 10th); thus, it gets a bit more payoff at the initial stage. When $O > 0$ (from 11th to 20th), both its optimal budget and payoff are lower, and its increasing speed of payoff becomes slower. Then, during the period from 21st to 30th, the case with larger γ again allocates more of the budget to advertising campaigns, but the accumulated payoff is kept lower due to the poor performance in the previous stages.
3. For the three cases, $\gamma = 0.0$, 0.1, and 0.2, the optimal total budget allocated is 2,459.077, 2,281.055, and 2,099.736, respectively. The corresponding optimal payoff is 2,717.684, 2,642.951, and 2,572.598, respectively. Obviously, the case with the larger γ leads to a lower level of optimal budget and optimal payoff. An interesting phenomenon is that the corresponding payoff per unit budget is 1.105,

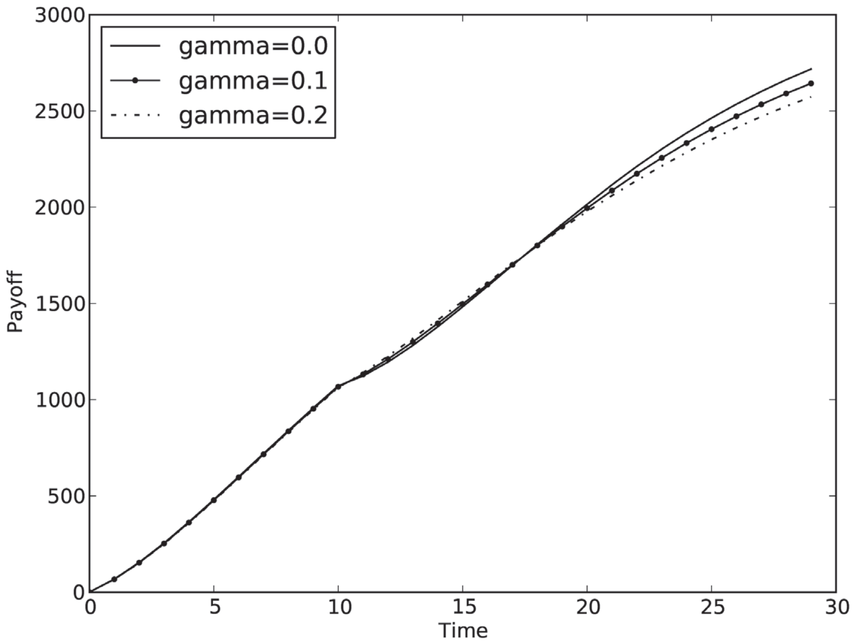

Figure 7. Optimal Payoffs over Time with Different Gammas

1.159, and 1.225, respectively—that is, the payoff per budget unit is larger in the case with the larger γ. A possible reason is that, in the case with the larger γ, the optimal budget is smaller but is effectively distributed and spent during the promotional period. This is also in accordance with the law of diminishing marginal utility. However, with respect to the optimal payoff, advertisers should prefer the case with the smaller γ.

The Budgeting Level B

The third experiment illustrates the relationship between the optimal total budgeting level and the optimal payoff of these two campaigns with different settings of the ad overlapping degree (γ), as in the second experiment. The optimal payoff at different budgeting levels is illustrated in Figure 8. From Figure 8, we can see the following:

1. The optimal payoff grows steadily until reaching the budget cap where the marginal payoff (i.e., the change in additional payoff) is zero when the total budget increases. In other words, there exists a budgeting cap in the case with unlimited budget. The case with larger γ arrives at the budgeting cap earlier, where investing more than the optimal budget will not lead to an increase in optimal payoff.

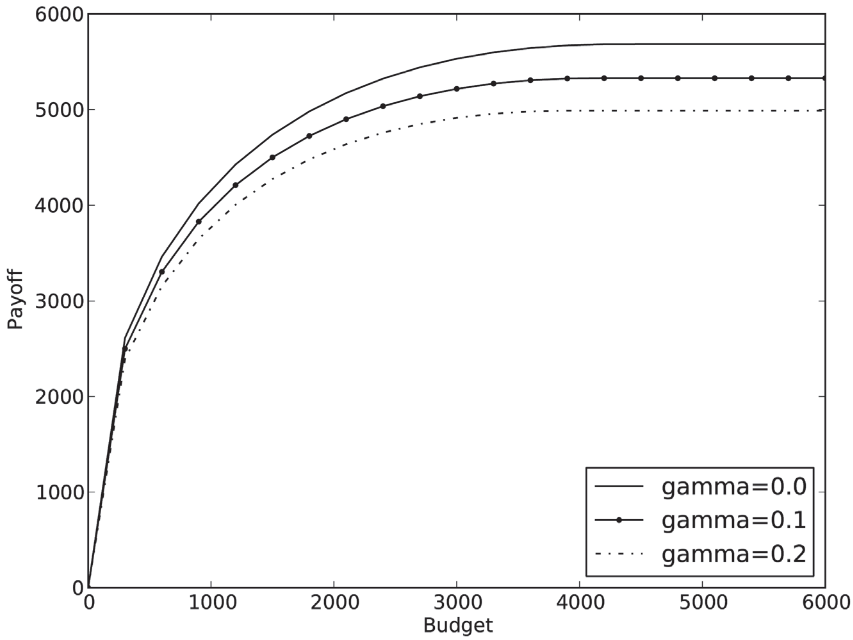

Figure 8. Optimal Payoff at Different Budgeting Levels

2. The optimal payoff in the case with the larger γ is always less than that of cases with a smaller γ.

Discussion

Our work provides valuable managerial insights to advertisers for budget planning for coupled campaigns in search auctions. First, advertisers usually pay less attention to relationships and cross-effects between their own multiple campaigns in a search market, probably due to the fact that it is not easy to measure and manipulate the overlapping degree (*O*). This work provides an explicit measure for the substitution relationships between campaigns in sponsored search auctions. Second, this research indicates that the overlapping degree between campaigns has serious effects on optimal budget strategies at the campaign level. In practice, advertisers should try to reduce the overlapping degree by optimizing advertising structures and contents. Our substitution measure provides a quantitative approach to computing the effects in this process. Third, the larger the overlapping degree between campaigns, the more the advertising effort is weakened and the optimal payoff is less. In this sense, in the case that the overlapping degree is minimized, advertisers should correspondingly determine the optimal budgets over campaigns and make budget planning decisions by using the proposed approaches in order to maximize the expected payoff. Fourth, our normative findings of multicampaign budget planning can also provide valuable insights for similar decision scenarios of advertising budget allocation, such as advertising campaigns across several markets or across different media (or channels).

However, we also realize some shortcomings of our work. First, in this work, we propose a measure of substitution relationship between campaigns. It is necessary to develop a generic measure of relationships (including both substitution and complementarity) between campaigns and to explore crossover effects among campaigns in sponsored search auctions. In contrast to the substitution relationship, which weakens advertising effects, the complementarity relationship involves two campaigns enhancing the influence of each other, which might lead to higher optimal budgets. Second, the ad overlapping degree (γ) takes a graph composed using keywords included in the advertiser's campaigns to compute the appearance probability. However, such a graph represents only a small segment of the set of keywords of interest used by potential customers. Third, this work models spatial and temporal relationships with the indicator function, while ignoring spatial relationships and carryover effects over time. Fourth, our work considers the case for an advertiser with two campaigns. As noted, the case with three or more campaigns leads to more complicated relationships, and thus it demands more flexible budget planning strategies.

Conclusions and Future Work

In this paper, we present a multicampaign budget planning approach using optimal control techniques and carried out under a finite time horizon. Our model takes into account the overlapping degree (i.e., the substitution relationship) between campaigns in search auctions, with respect to three dimensions: target regions, promotional periods, and campaign contents. We discuss some desirable properties and possible solutions to our budget model. Computational experimental studies are made to evaluate our model and its identified properties. Experimental results show that the overlapping degree between campaigns has serious effects on budgeting decisions and advertising performance, and a higher overlapping degree weakens the advertising effort and thus diminishes optimal budgets and payoffs.

More studies on budget-related decisions in sponsored search auctions are needed. We are in the process of extending our model in the following directions: (1) spatial heterogeneity and relationships to capture spatial effects on advertising decisions and performance; (2) the complementarity relationship between campaigns and its effects on budgeting decisions; (3) more flexible budgeting strategies for the case with three or more campaigns in sponsored search auctions; and (4) extension of the analysis to include multiple advertisers within the same business sector of this research.

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