Marketing Science

Practice Prize Paper—PROSAD: A Bidding Decision Support System for Profit Optimizing Search Engine Advertising

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PROSAD: A Bidding Decision Support System for Profit Optimizing Search Engine Advertising

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This paper reports on a large-scale implementation of marketing science models to solve the bidding problem in search engine advertising. In cooperation with the online marketing agency SoQuero, we developed a fully automated bidding decision support system, PROSAD (PRofit Optimizing Search engine ADvertising; see http://www.prosad.de), and implemented it through the agency's bid management software. The PROSAD system maximizes an advertiser's profit per keyword without the need for human intervention. A closed-form solution for the optimized bid and a newly developed "costs-per-profit" heuristic enable advertisers to submit good bids even when there is significant noise in the data. A field experiment demonstrates that PROSAD can increase the return on investment by 21 percentage points and improve the yearly profit potential for SoQuero and its clients by €2.7 million.

1. Introduction

Search engine advertising (SEA) has grown into a multibillion-dollar business that attracts $1 of every $2 spent on online advertising (Chen et al. 2009, Yang and Ghose 2010). The mechanism supporting SEA works as follows (Abou Nabout et al. 2012, Yao and Mela 2008): A consumer types a keyword, such as "cruise vacation," into a search engine (e.g., Google, Bing) and receives two types of results. The lower left-hand portion of the page shows unsponsored search results, whose ranking reflects the relevance assigned to these different results by a search algorithm. On the top right-hand side, sponsored search results appear. Whereas the display of unsponsored search results is free of charge, advertisers pay for each click on their ads that appear among the sponsored search results.

The rankings and prices paid per click depend on keyword auctions, which are generalized, second-price, sealed-bid auctions (Edelman et al. 2007, Varian 2007). In the auctions, advertisers submit bids for a specific keyword by stating their maximum willingness to pay for each click. The search engine provider then weights the submitted bids according to the ad's quality, which it measures using a proprietary quality score (QS), and displays the sponsored search results in decreasing order of weighted bids (Abou Nabout and Skiera 2012, Jerath et al. 2011, Katona and Sarvary 2010). If a consumer clicks on an ad, its advertiser pays the search engine provider an amount equal to the next-highest weighted bid, divided by its own QS. The consumer who clicked on the ad gets redirected to the advertiser's website to place an order or request a sales quote—both cases of potential conversions.

Most SEA campaign managers use rules-based approaches to determine their bid for different keywords. Popular rules include the following:

1. **IF** keyword profit after acquisition costs is greater than €10, **THEN** increase bid by 30%.

2. **IF** rank is worse than rank 5, **THEN** increase bid by 20%.

3. **IF** keyword profit after acquisition costs is smaller than €0, **AND** the number of clicks is more than 100, **AND** rank is better than rank 3, **THEN** decrease bid by 20%.

Such rules help the advertiser make automated bidding decisions, but they suffer several major drawbacks. First, the number of rules can grow quickly and become cumbersome. Second, different rules might offer contradictory bidding suggestions. Third, the choice of the respective parameters in the rules is rather arbitrary (e.g., why should the bid in rule 1 be increased by 30% and not 20%?).

To avoid these drawbacks, advertisers might use profit maximization as a single optimization criterion. We present a decision support system, PROSAD (PRofit Optimizing Search engine ADvertising), that can set bids to maximize profit automatically, using a bidding decision model and a newly developed

"costs-per-profit" heuristic. In a field experiment, we show that the use of PROSAD increases return on investment by 21 percentage points.

2. Related Literature and Desired Properties

Yao and Mela (2011), Agarwal et al. (2011), and Abou Nabout et al. (2012) all offer effective reviews of previous SEA research. Because PROSAD requires empirical data, we focus our review in Table 1 on previous empirical SEA studies.

As Table 1 shows, most studies have focused on estimating response functions (e.g., linking bids to ranks or clickthrough and conversion rates) rather than providing recommendations about advertisers' optimized bid (except for Yang and Ghose 2010 and Yao and Mela 2011). The studies also exert considerable effort capturing heterogeneity across keywords by finding appropriate distributions of parameters and correlations of error terms across response functions. Although they outline how sophisticated modeling and estimation techniques (e.g., Bayesian models, structural models) enable advertisers to capture these effects, the calibration of these functions demands substantial time and human effort. In addition, the models often are tailored to a very specific campaign or industry.

A decision support system that can support a broad range of companies instead needs to apply to various settings: business and consumer contexts, small and large campaigns, expensive or inexpensive keywords. Little (1970, 2004) and Leeflang et al. (2000) describe several other criteria for a decision support system, including simplicity, robustness, adaptivity, completeness on important issues, and cost-benefit considerations. *Simplicity* means that managers can easily understand the decision support system. *Robustness* requires that the decision model never returns unreasonable suggestions, and *adaptivity* implies that the response functions can be updated frequently (e.g., weekly, even daily). *Completeness on important issues* suggests including branding profit, in addition to transactional profit. Finally, *cost-benefit considerations* suggest that the expected benefits exceed the expected costs of the model, including costs to calibrate response functions. Considering the vast number of keywords and moderate profit per keyword, all

Table 1   Review of Empirical Studies on Search Engine Advertising

Study	Data		Modeling and calibration				Recommendation
	Aim	Industry	Estimation technique	Human effort	Automation and robustness	Speed	Optimized bid
Rutz et al. (2011)	Quantifying indirect effects of search engine advertising	Automotive	Bayesian elastic net model	High	No	Slow	No
Yao and Mela (2011)	Impact of searchers', advertisers', and search engine interaction on profit	Music management software	Dynamic structural model	High	No	Slow	Yes
Agarwal et al. (2011)	Impact of rank on revenue and profit	Retail	Hierarchical Bayesian model	High	No	Slow	No
Ghose and Yang (2009)	Impact of keyword attributes on clickthrough and purchase propensities, bid, and rank	Retail	Hierarchical Bayesian model	High	No	Slow	No
Yang and Ghose (2010)	Analysis of the relationship between organic and sponsored search advertising	Retail	Hierarchical Bayesian model	High	No	Slow	Yes
This study	Bidding decision support system to maximize profit	Industrial goods, NGOs, mobile phones, fashion, travel, software, retail	Ordinary least squares	Low	Yes	Fast	Yes

Note. NGOs, nongovernmental organizations.

response functions need to allow for quick calibration with little human intervention, or ideally even automatically.

3. Description of a Bidding Decision Model

3.1. Basic Idea

The bidding decision model links bids to profits and therefore reveals which bid will maximize profit, as Figure 1 shows. The advertiser's bid is the decision variable, which is weighted by ad quality. The weighted bid then determines the ad rank, which affects the number of clicks that the ad receives. The advertiser's acquisition costs per conversion equal the ratio of the bid to the conversion rate (conversion rate = number of conversions/number of clicks, often assumed to be constant, though it could depend on the rank). The number of conversions is also affected by the number of users, the clickthrough rate (= number of clicks/number of searches), and the conversion rate. Finally, the difference between the profit contribution per conversion and the acquisition costs per conversion, multiplied by the number of conversions, yields a keyword's profit after acquisition costs (transactional profit).

3.2. Determination of Optimized Bid

An advertiser aims to maximize its profit after acquisition costs, π_k, by determining the optimized bid per keyword k, with the constraint that Bid_k must be positive and lower than the highest possible bid, which achieves rank 1, Bid_k^1:

$$\underset{Bid_k}{\text{Maximize}} \quad \pi_k(Bid_k) = \pi_k^T(Bid_k) + \pi_k^B(Bid_k)$$

$$= (PC_k - g_k(Bid_k)) \cdot S_k(Bid_k)$$
$$+ \pi_k^B(Bid_k) \tag{1}$$

$$\text{subject to} \quad 0 \le Bid_k \le Bid_k^1. \tag{2}$$

We summarize the variables in Table 2. The advertiser's profit after acquisition costs is the sum of the transactional profit π_k^T and the branding profit π_k^B. As indicated, transactional profit is the difference between the profit contribution per conversion, PC_k, and the acquisition costs per conversion, g_k, multiplied by the number of conversions, S_k. The profit contribution per conversion could be the profit contribution earned through a single purchase (short-term value) or customer lifetime value (long-term value). That is, transactional profit reflects the value of conversions after these users clicked on ads.

The number of conversions S_k that an advertiser acquires by bidding on a keyword k can be calculated by multiplying the number of clicks and the conversion rate CR_k. The number of clicks is simply the number of consumers searching for keyword N_k multiplied by the clickthrough rate CTR_k:

$$S_k(Bid_k) = N_k \cdot CTR_k(Bid_k) \cdot CR_k. \tag{3}$$

The ratio of the bid to the conversion rate yields the acquisition costs per conversion. For the sake of simplicity, we approximate the price per click using the bid (Ghose and Yang 2009); the differences between bids and prices are small in competitive markets (Abou Nabout et al. 2012). Thus, the acquisition costs per conversion g_k are a ratio of the bid to the conversion rate:

$$g_k(Bid_k) = \frac{Bid_k}{CR_k}. \tag{4}$$

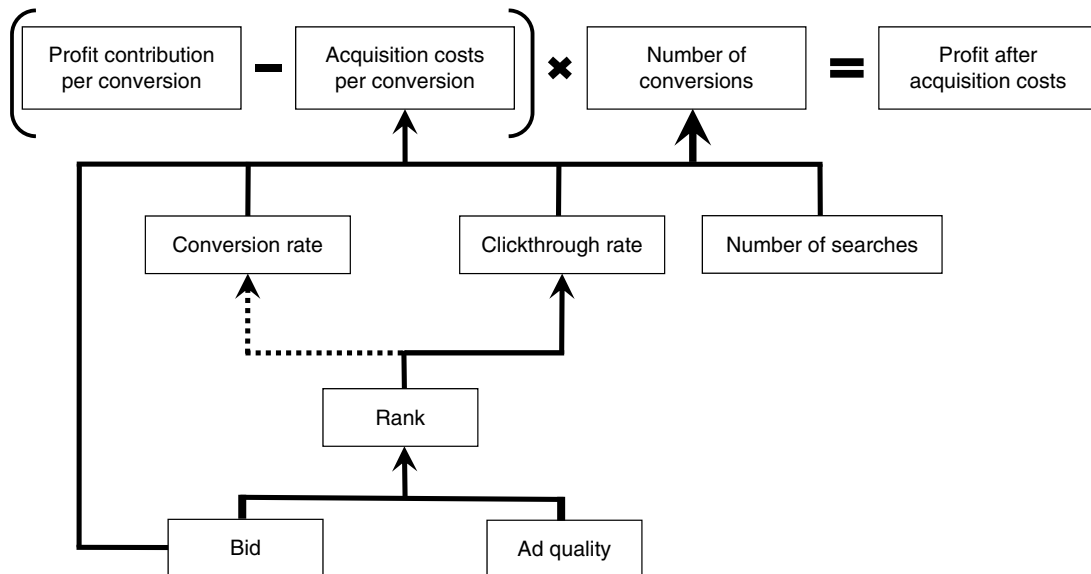**Figure 1   Framework for Linking Bid and Profit**

Table 2   Description of Variables and Parameters

Variable	Description
k	Keyword subscript
Input to decision model	
PC_k	Advertiser's profit contribution per conversion for keyword k
N_k	Number of consumers searching for keyword k
Bid_k^1	Prices per click at rank 1 for keyword k
δ_k	Multiplier reflecting the increase in prices per click for keyword k
$\delta_k - 1$	Percentage increase in prices per click for keyword k
δ_k'	Logarithm of multiplier reflecting the increase in prices per click for keyword k
CTR_k^1	Clickthrough rate at rank 1 of keyword k
ξ_k	Multiplier reflecting the increase in clickthrough rates for keyword k
$\xi_k - 1$	Percentage increase in clickthrough rates for keyword k
ξ_k'	Logarithm of multiplier reflecting the increase in clickthrough rates for keyword k
CR_k	Conversion rate of keyword k
CPM_k	Costs per thousand for keyword k
ω_k	Multiplier reflecting the percentage increase in the branding profit for keyword k
Advertiser's decision variable	
Bid_k	Bid for keyword k
Output of decision model	
$Rank_k$	Rank of keyword k
g_k	Acquisition costs per conversion for keyword k
S_k	Number of conversions for keyword k
π_k^T	Transactional profit for keyword k
π_k^B	Branding profit for keyword k
π_k	Total profit for keyword k

To calculate the number of searchers that clicked on the ad, we assume the click response function is continuous and depends on the rank of the ad, $Rank_k$, which in turn depends on the bid Bid_k. The clickthrough rate increases at better ranks and reaches its highest value at rank 1, captured by CTR_k^1. The multiplier ξ_k reflects the increase in CTR_k from rank $(x+1)$ to rank x. For example, if an ad earns a CTR_k of 10.00% at rank 2 and a CTR_k^1 of 12.60% at rank 1, the percentage increase in CTR_k is 26%, and the corresponding multiplier ξ_k equals 1.26. In line with prior research (Feng et al. 2007), we model the click response function as

$$CTR_k(Bid_k) = \frac{CTR_k^1}{\xi_k^{Rank_k(Bid_k)-1}}. \qquad (5)$$

The price per click depends on the price per click at rank 1, Bid_k^1, and the multiplier reflecting the increase in prices per click from rank $(x+1)$ to rank x, δ_k. The prices per click need to be positive and increase

exponentially at better ranks (Ganchev et al. 2007). Thus,

$$Bid_k = \frac{Bid_k^1}{\delta_k^{Rank_k(Bid_k)-1}}. \qquad (6)$$

The rank function is the inverse of the price function from Equation (6):

$$Rank_k(Bid_k) = 1 - \frac{\ln(Bid_k/Bid_k^1)}{\ln(\delta_k)}. \qquad (7)$$

By combining Equations (3)–(7), we recognize that the advertiser's transactional profit for keyword k is

$$\pi_k^T(Bid_k) = \left(PC_k - \frac{Bid_k}{CR_k}\right) \cdot N_k \cdot CTR_k(Bid_k) \cdot CR_k. \qquad (8)$$

Some advertisers do not concentrate only on transactional profits of SEA, or π_k^T, so we also consider branding profit, or π_k^B, which captures the perception generated by the display of an ad in the sponsored search results. For this measure, the cost per thousand CPM_k equals 0 if the advertiser believes that SEA does not offer significant branding profit. We assume branding profit increases exponentially with better ranks, so the multiplier ω_k reflects the increase in the branding profit from rank $(x+1)$ to rank x:

$$\pi_k^B(Bid_k) = \frac{N_k \cdot CPM_k}{\omega_k^{Rank_k(Bid_k)-1} \cdot 1,000}. \qquad (9)$$

Inserting Equations (3)–(7) into Equations (8) and (9), we uncover profit after acquisition costs related to the bid for keyword k, as in Equation (10). It equals the sum of transactional and branding profit and results in the following decision model:

$$\begin{aligned}
\underset{Bid_k}{\text{Max}} \quad \pi_k(Bid_k) = &\left(PC_k - \frac{Bid_k}{CR_k}\right) \\
&\cdot N_k \cdot CTR_k^1 \cdot \xi_k^{\ln(Bid_k/Bid_k^1)/\ln(\delta_k)} \cdot CR_k \\
&+ \omega_k^{\ln(Bid_k/Bid_k^1)/\ln(\delta_k)} N_k \cdot \frac{CPM_k}{1,000},
\end{aligned} \qquad (10)$$

$$\text{subject to} \quad 0 \le Bid_k \le Bid_k^1. \qquad (11)$$

The nonlinearities in the rank, clickthrough rate, and branding profit functions do not allow for a closed-form solution for the optimized bid from Equations (10) and (11). However, we can use the Newton search method to compute the optimized bid per keyword.

If the branding profit is 0, the Kuhn–Tucker first-order optimality conditions instead can solve Equations (10) and (11). The closed-form solution for the optimized bid Bid_k^* depends on the profit contribution per conversion PC_k, the conversion rate CR_k, and δ_k' and ξ_k', which are logarithms of the multipliers in

prices per click, or δ_k, and the clickthrough rates, ξ_k, such that $\delta_k' = \ln(\delta_k)$, and $\xi_k' = \ln(\xi_k)$. In turn,

$$Bid_k^* = \begin{cases} \dfrac{PC_k \cdot CR_k \cdot \xi_k'}{\delta_k' + \xi_k'} & \text{if } Bid_k^* < Bid_k^1, \\[2mm] Bid_k^1 & \text{if } Bid_k^* \geq Bid_k^1. \end{cases} \quad (12)$$

Because rank 1 is the highest possible rank, we also consider a boundary solution: if the optimized bid is lower than the highest possible bid for rank 1 ($Bid_k^* < Bid_k^1$), the resulting rank is worse than rank 1. If the optimized bid is higher than or equal to the bid at rank 1 ($Bid_k^* \geq Bid_k^1$), the ad is displayed at rank 1.

Inserting the optimized bid into Equation (4) and the corresponding result into Equations (7), (5), and (3), we determine the optimized acquisition costs per conversion g_k and the optimized number of conversions S_k:

$$g_k(Bid_k^*) = \begin{cases} \dfrac{PC_k \cdot \xi_k'}{\delta_k' + \xi_k'} & \text{if } Bid_k^* < Bid_k^1, \\[2mm] \dfrac{Bid_k^1}{CR_k} & \text{if } Bid_k^* \geq Bid_k^1, \end{cases} \quad (13)$$

and

$$S_k(Bid_k^*)$$

$$= \begin{cases} N_k \cdot CR_k \cdot CTR_k^1 \\ \quad \cdot \left[\dfrac{PC_k \cdot CR_k \cdot \xi_k'}{Bid_k^1 \cdot (\delta_k' + \xi_k')} \right]^{\xi_k'/\delta_k'} & \text{if } Bid_k^* < Bid_k^1, \\[2mm] N_k \cdot CR_k \cdot CTR_k^1 & \text{if } Bid_k^* \geq Bid_k^1. \end{cases} \quad (14)$$

3.3. Optimized Costs per Profit
The optimized bid in Equation (12) is the investment per click; it depends on the product of the profit contribution per conversion and the conversion rate, $PC_k \cdot CR_k$ (i.e., return per click). Dividing Equation (12)

by $PC_k \cdot CR_k$ and rearranging the terms yields an advertiser's optimized share of acquisition costs at the profit contribution per conversion, or "costs per profit," CPP:

$$CPP(Bid_k^*) = \dfrac{Bid_k^*}{PC_k \cdot CR_k}$$

$$= \dfrac{g_k(Bid_k^*)}{PC_k} = \begin{cases} \dfrac{\xi_k'}{\delta_k' + \xi_k'} & \text{if } Bid_k^* < Bid_k^1, \\[2mm] \dfrac{Bid_k^1}{PC_k \cdot CR_k} & \text{if } Bid_k^* \geq Bid_k^1. \end{cases} \quad (15)$$

As long as the optimized bid is lower than the bid at rank 1, the optimized costs per profit depend only on percentage increases in prices per click and clickthrough rates within ranks, as reflected by the multipliers δ_k and ξ_k, respectively. The optimized costs per profit decrease with ascending percentage increases in prices per click. The intuition is as follows: if the percentage increase in prices is high, the advertiser can bid substantially lower for worse ranks, which strongly reduces the acquisition costs per conversion and results in lower optimized costs per profit. A greater percentage increase in the clickthrough rates within ranks has the opposite effect: if the percentage increase in clickthrough rates is high, the number of clicks diminishes substantially within ranks, which makes better ranks more attractive. Then the advertiser submits higher bids, which leads to higher optimized costs per profit.

According to Equation (15), if the percentage increase in prices equals the percentage increase in clickthrough rates, the optimized costs per profit are 50% (e.g., $\ln(1.25)/(\ln(1.25) + \ln(1.25)) = 0.50$). Using four empirical data sets, we reveal that the mean percentage increase in prices per click lies between 52.93% and 93.16% (median: 46.55%–87.01%); in clickthrough rates, it ranges between 48.42% and 73.63% (median: 46.13%–70.31%). Table 3 uses these values to calculate the respective optimized costs per profit: 50% is a good guess.

Table 3   Percentage Increases in Prices per Click and Clickthrough Rates

		Fashion (%)		Mobile phones (%)		Industrial goods (%)		Travel (%)	
		Price(%) $(\delta_k - 1)$	CTR $(\xi_k - 1)$	Price $(\delta_k - 1)$	CTR $(\xi_k - 1)$	Price $(\delta_k - 1)$	CTR $(\xi_k - 1)$	Price $(\delta_k - 1)$	CTR $(\xi_k - 1)$
Percentage	Mean	67.28	73.18	63.28	73.63	93.16	57.73	52.93	48.42
increases	Median	64.68	70.31	60.32	57.71	87.01	56.59	46.55	46.13
Optimized costs per profit (CPP^*)		52.09		48.89		39.41		49.77	

Notes. $N = 90$ in each industry. Both multipliers reflecting the increase in prices per click and *CTR* are typically larger than 1. For example, a percentage increase $\xi_k - 1$ of 50% indicates a multiplier of 150%, inserted into Equation (15). The same is true for the percentage increase $\delta_k - 1$. To calculate the optimized costs per profit, we use the median percentage increases in *CTR* and prices per click, because the mean values might be too heavily influenced by outliers.

4. Calibration of Response Functions

4.1. Estimation of Price and Click Response Functions

The quick automatic calibration of the price response function (Bid_k^1 and δ_k) and the click response function (CTR_k^1 and ξ_k) is challenging, because it requires a robust, fast estimation procedure. As a consequence, we use regressions that estimate a response function for each keyword separately. Thus, in favor of a fast estimation approach, we do not apply the simultaneous equation model proposed by Ghose and Yang (2009), which puts more emphasis on accounting for potential endogeneity of rank.

In addition, the estimation procedure needs to deal with unreasonable parameter values, which might reflect noise in the data. Search engine providers typically inform advertisers about prices per click, ranks, number of consumers searching for a keyword, number of clicks, number of conversions, and the QS of their own SEA campaigns. However, advertisers do not receive competitors' data. That is, an advertiser knows its own price for a keyword at time t and rank x but not the price for that keyword at any other rank or time. We thus need to control for differences across time in prices and QS (Abou Nabout and Skiera 2012).

We model the price of keyword k at time t as dependent on its rank, time, and QS, and we estimate the keyword-specific parameters with ordinary least squares regressions:

$$\ln(Bid_{kt}) = \alpha_k + \beta_{1k} \cdot Rank_{kt} + \beta_{2k} \cdot t$$
$$+ \beta_{3k} \cdot QS_{kt} + \varepsilon_{kt}, \tag{16}$$

where $\ln(Bid_{tk})$ denotes the logarithm of the bid for keyword k at time t. Thus, we can estimate the above regression for every keyword at different points in time and do not need keyword attributes as proxies to account for unobserved heterogeneity of individual keyword (the same applies to Equation (17)). As the appendix outlines, the multiplier reflecting the increase in prices per click δ_k equals

$$\delta_k = 1/\exp(\beta_{1k}). \tag{17}$$

Because prices decrease in worse ranks, β_{1k} is likely negative, and δ_k should be greater than 1. Similarly, we can model the click response function as dependent on rank, time, and QS:

$$\ln(CTR_{kt}) = \gamma_k + \varphi_{1k} \cdot Rank_{kt} + \varphi_{2k} \cdot t$$
$$+ \varphi_{3k} \cdot QS_{kt} + \omega_{kt}, \tag{18}$$

where $\ln(CTR_{tk})$ denotes the logarithm of the *CTR* for keyword k at time t. As the appendix shows, the multiplier reflecting the increase in clickthrough rates is given by

$$\xi_k = 1/\exp(\varphi_{1k}). \tag{19}$$

Similar to the multiplier reflecting the increase in prices per click, φ_{1k} is negative, and ξ_k is greater than 1.

4.2. Outline of Heuristic

We check whether the calibrations of the price and click response functions are successful, such that they lead to reasonable values for percentage increases in clickthrough rates and prices per click. A negative percentage increase would be inconsistent with theory and extant results (Agarwal et al. 2011, Ghose and Yang 2009), because it suggests higher clickthrough rates or prices per click for worse ranks. Missing data, too few observations, measurement errors, or omitted variables could produce such unreasonable values, and thus poor bids.

If the calibration of the response function yields reasonable values (87.5% of cases), we solve Equations (10) and (11) to determine the optimized bid; otherwise, we use the heuristic that costs per profit should be 50%, because the percentage increases in clickthrough rates and prices per click are frequently equal (see Table 3). Thus, we determine a heuristic bid:

$$Bid_k^{Heuristic} = 50\% \cdot PC_k \cdot CR_k. \tag{20}$$

The beauty of this heuristic is its simplicity, which reflects our finding that only percentage increases in clickthrough rates and prices per click influence the optimized costs per profit. The simple heuristic also guarantees that the acquisition costs per conversion do not exceed the profit contribution per conversion. Although such a requirement clearly should be fulfilled, our experience reveals that it is frequently violated in practice.

5. Application of PROSAD

SoQuero (http://www.soquero.de) is a Frankfurt-based online advertising agency that manages SEA campaigns for more than 40 advertisers (e.g., Best Western, Mettler-Toledo, Royal Caribbean). We implemented PROSAD (http://www.prosad.de) in SoQuero's bid management software, to be employed in the daily management of campaigns that feature an average of 2,000 keywords. The system automatically calibrated response functions and suggested optimized bids that a campaign manager may accept or discard.

Clients often are hesitant to participate in field experiments and tend to reject suggested bids, which makes it difficult to evaluate the financial impact across campaigns. However, we convinced a small client, conducting a nationwide campaign for toys and kindergarten materials, to rely on PROSAD for 20 keywords over a period of 10 weeks. In the field

experiment, the client first managed the campaign itself without PROSAD, then allowed SoQuero to manage 20 keywords using PROSAD. To ensure that changes in the advertiser's clickthrough and conversion rate did not result from changes in the ad creative or landing page, we kept both the ad creative and landing page constant over time. The results of the field experiment therefore include weekly information about the numbers of searches, clicks, and conversions; average cost per click; average rank; acquisition costs; and the profit after acquisition costs for each keyword, as we show in Table 4.

Without PROSAD, the 20 keywords generated an overall loss of −€2.69 (average per keyword = −€0.13); they earned a profit of +€124.85 (average per keyword = +€6.24) with PROSAD. The client bid too high on most keywords, which our experience suggests is a common phenomenon. These high bids resulted in overly high acquisition costs that diminished profit after acquisition costs, though the profit before acquisition costs was considerably higher before PROSAD's application. The field experiment thus suggests that acquisition costs can be reduced by 38% (= (48.78 − 30.05)/48.78), and return on investment increases from 0% (= €48.65/€48.78 − 1) to 21% (= €36.29/€30.05 − 1).

These results reflect the entire 10-week observation period. During that time, an average keyword yielded an additional profit of €6.37 with PROSAD. Over a year, the average keyword therefore would realize an additional profit of €33.12. Although this value may seem small or even negligible, the vast number of keywords included in most campaigns (e.g., 2,000 in SoQuero campaigns) suggests a substantial impact. SoQuero manages 40 campaigns on behalf of its clients each year, so the annual profit potential of PROSAD for SoQuero and its clients is about €2.7 million (= €33.12 · 2,000 · 40).

Table 4   Results of Field Experiment

Average values per keyword	Without PROSAD	With PROSAD
Number of keywords	20	20
Number of searches	4,510.60	4,510.60[a]
Number of clicks	185.30	107.58
CTR (%)	4.11	2.39
CPC (€)	0.19	0.13
Rank	2.97	3.78
Number of conversions	3.50	1.12
Conversion rate (%)	0.08	0.02
Profit before acquisition costs (€)	48.65	36.29
Total acquisition costs (€)	48.78	30.05
Profit after acquisition costs (€)	−0.13	+6.24
Return on investment (%)	0	21

Note. CPC, cost per click.

[a]To ensure the comparabiliy of the two experimental groups, we set the number of searches "With PROSAD" to be equal to the number of searches "Without PROSAD." All other variables were adjusted by actual clickthrough and conversion rates.

The simplicity of our modeling approach means that it does not take competitive reactions into account. If competitors adjust their bids in response to a change in the focal advertiser's bid, the percentage increase in prices per click changes. Is a weekly calibration of the response functions then sufficient? In the field experiment, PROSAD placed optimized bids at the beginning of the week; competitors might react after the second day of the week, at the earliest. We thus compare ranks and prices per click of the first two versus the last two days of the week but find no statistically significant difference.[1] That is, competitive reactions to changes in the focal advertiser's bid do not appear to occur within a single week.

Another drawback related to the simplicity of our modeling approach is that we do not model the link between clickthrough rate and QS, though an increase (decrease) in the optimized bid might lead to a better (worse) rank and thus a higher (lower) clickthrough rate, which in turn might lead to a better (worse) QS. Then the rank might improve (worsen) even further, and the price might decrease (increase) (see Abou Nabout and Skiera 2012). To evaluate this drawback, we analyze by how much and how quickly the QS changes in response to changes in the clickthrough rate using a fixed effects model of different lag structures of clickthrough rate on QS. None of the lags of the clickthrough rate had a significant impact on QS; the low impact of this drawback corresponds with the findings of Abou Nabout and Skiera (2012) that QS changes occur just once every six months on average. However, prices per click and clickthrough rate changed, on average, 22 times during the same observation period.

6.   Summary

We have reported on a large-scale implementation of marketing science models to solve the bidding problem in SEA. In cooperation with SoQuero, an online marketing agency, we have developed the PROSAD (PRofit Optimizing Search Engine ADvertising) bidding decision support system and implemented it in the agency's bid management software. PROSAD can automatically determine optimized bids that maximize the advertiser's profit. It estimates all response functions using ordinary least squares, so the calibration is rapid. Our field experiment shows that PROSAD not only increases the return on investments in SEA by 21 percentage points but also better captures the trade-off between the number of conversions and the money spent to acquire those conversions.

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[1] The results are robust to other combinations, such as the first versus the last four days or the first two versus last three days of the week.

We acknowledge several limitations to our study. First, we do not consider indirect effects of SEA (Chan et al. 2011, Rutz and Bucklin 2011, Rutz et al. 2011). Such effects might lead to situations in which SEA performance is either under- or overstated. For instance, branded keywords usually convert at an exceptionally high rate, but they do not actually initiate the customer journey—their performance is overstated in that case. Yet they might also generate sales in off-line channels, in which case their performance is understated. In addition, we are not able to account for intraday variation in rank because Google and other search engines only provide advertisers with average ranks and prices per day. These intraday variations increase noise in the data so that future research should develop better instruments to track these variations.

Appendix

In the main text, Equation (5) describes the click response function:

$$CTR_k(Bid_k) = \frac{CTR_k^1}{\xi_k^{(Rank_k(Bid)-1)}} \qquad (A1)$$

Rewriting this equation yields

$$\begin{aligned}
CTR_k(Bid_k) &= CTR_k^1 \cdot \xi_k \cdot \left(\frac{1}{\xi_k}\right)^{Rank_k(Bid_k)} \\
&= CTR_k^1 \cdot \xi_k \cdot exp\left(\ln\left[\frac{1}{\xi_k}\right] \cdot Rank_k(Bid_k)\right) \\
&= \gamma_k' \cdot exp\left(\phi_{1k} \cdot Rank_k(Bid_k)\right), \qquad (A2)
\end{aligned}$$

where $\gamma_k' = CTR_1^k \cdot \xi_k$ and $\phi_{1k} = \ln[1/\xi_k]$. Consequently, $\xi_k = 1/exp(\phi_{1k})$. Rearranging the terms in Equation (6) from the main text, which describes the price response function, yields

$$\begin{aligned}
Bid_k = \frac{Bid_k^1}{\delta_k^{(Rank_k(Bid_k)-1)}} &= Bid_k^1 \cdot \delta_k \cdot \left(\frac{1}{\delta_k}\right)^{Rank_k(Bid_k)} \\
&= Bid_k^1 \cdot \delta_k \cdot \exp \cdot \left(\ln\left[\frac{1}{\delta_k}\right] \cdot Rank_k(Bid_k)\right) \\
&= \alpha_k' \cdot \exp(\beta_k \cdot Rank_k(Bid_k)), \qquad (A3)
\end{aligned}$$

where $\alpha_k' = Bid_k^1 \cdot \delta_k$ and $\beta_{1k} = \ln[1/\delta_k]$. Therefore, $\delta_k = 1/exp(\beta_{1k})$.

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