

Chapter 3

Current Issues in Keyword Auctions

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Abstract

Search engines developed a unique advertising model a decade ago that matched online users with short-text advertisements based on users' search keywords. These keyword-based advertisements, also known as "sponsored links," are the flagship of the thriving Internet advertising business nowadays. Relatively unknown to online users, however, is the fact that slots for search engine advertisements are sold by a special kind of auctions which we call "keyword auctions." As the most successful online auctions since eBay's business-to-consumer auctions, keyword auctions form the backbone of the multibillion dollar search advertising industry. Owing to their newness and significance, keyword auctions have captured attention of researchers from information systems, computer science, and economics. Many questions have been raised, including how to best characterize keyword auctions, why keyword auctions, not other selling mechanisms, are used, and how to design keyword auctions optimally. The purpose of this chapter is to summarize the current efforts in addressing these questions. In doing so, we highlight the last question, that is, how to design effective auctions for allocating keyword advertising resources. As keyword auctions are still new, there are still many outstanding issues about keyword auctions. We point out several such issues for future research, including the click-fraud problem associated with keyword auctions.

1 Introduction

Keyword advertising is a form of targeted online advertising. A basic variation of keyword advertising is “sponsored links” (also known as “sponsored results” and “sponsored search”) on search engines. Sponsored links are advertisements triggered by search phrases entered by Internet users on search engines. For example, a search for “laptop” on Google will bring about both the regular search results and advertisements from laptop makers and sellers. Figure 1 shows such a search-result page with sponsored links at the top and on the side of the page. Another variation of keyword advertising is “contextual advertising” on content pages. Unlike sponsored links, contextual advertisements are triggered by certain keywords in the content. For example, a news article about “Cisco” is likely to be displayed with contextual advertisements from Cisco network equipment sellers and Cisco training providers.

Both sponsored links and contextual advertisements can target online users who are most likely interested in seeing the advertisements. Because of its superior targeting ability, keyword advertising has quickly gained popularity among marketers, and has become a leading form of online advertising. According to a report by Interactive Advertising Bureau (2007)

Google [Advanced Search](#) [Preferences](#)

[Web](#) [News](#) [Products](#) Results 1 - 10 of about 110,000,000 for **laptop** (definition). (0.45 seconds)

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Fig. 1. Search-based keyword advertising.

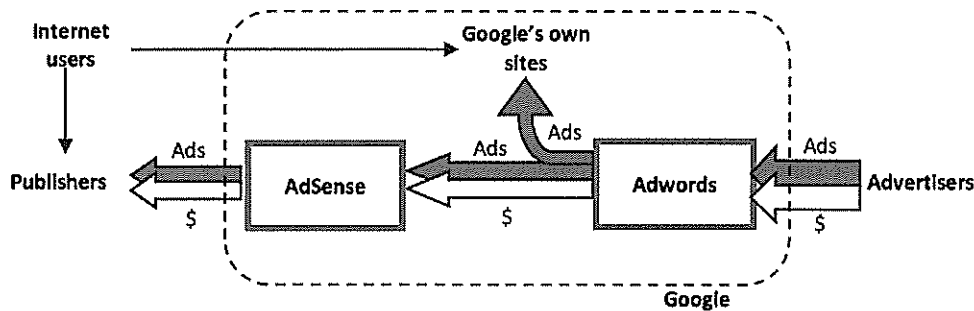


Fig. 2. Google's Adwords and AdSense programs.

and PricewaterhouseCoopers, keyword advertising in the United States reached \$6.8 billion in total revenue in 2006. eMarketer (2007) predicts the market for online advertising will rise from \$16.9 billion in 2006 to \$42 billion in 2011, with keyword advertising accounting for about 40% of the total revenue.

A typical keyword advertising market consists of advertisers and publishers (i.e., websites), with keyword advertising providers (KAPs) in between. There are three key KAPs in the U.S. keyword advertising market: Google, Yahoo!, and MSN adCenter. Figure 2 illustrates Google's keyword-advertising business model. Google has two main advertising programs, Adwords and AdSense. Adwords is Google's flagship advertising program that interfaces with advertisers. Through Adwords, advertisers can submit advertisements, choose keywords relevant to their businesses, and pay for the cost of their advertising campaigns. Adwords has separate programs for sponsored search (Adwords for search) and for contextual advertising (Adwords for content). In each case, advertisers can choose to place their advertisements on Google's site only or on publishers' sites that are part of Google's advertising network. Advertisers can also choose to display text, image, or, more recently, video advertisements.

AdSense is another Google advertising program that interfaces with publishers. Publishers from personal blogs to large portals such as CNN.com can participate in Google's AdSense program to monetize the traffic to their websites. By signing up with AdSense, publishers agree to publish advertisements and receive payments from Google. Publishers may choose to display text, image, and video advertisements on their sites. They receive payments from Google on either a per-click or per-thousand-impressions basis.¹ AdSense has become the single most important revenue source for many Web 2.0 companies.

This chapter focuses on keyword auctions, which are used by KAPs in selling their keyword advertising slots to advertisers. A basic form of

¹Google is also beta-testing a per-action based service in which a publisher is paid each time a user carries out a certain action (e.g., a purchase).

keyword auction is as follows. Advertisers choose their willingness-to-pay for a keyword phrase either on a per-click (pay-per-click) or on per-impression (pay-per-impression) basis. An automated program ranks advertisers and assigns them to available slots whenever a user searches for the keyword or browses a content page deemed relevant to the keyword. The ranking may be based on advertisers' pay-per-click/pay-per-impression only. It may also include other information, such as their historical click-through-rate (CTR), namely the ratio of the number of clicks on the advertisement to the number of times the advertisement is displayed. Almost all major KAPs use automated bidding systems, but their specific designs differ from each other and change over time.

Keyword auctions are another multibillion-dollar application of auctions in electronic markets since the celebrated eBay-like business-to-consumer auctions. Inevitably, keyword auctions have recently gained attention among researchers. Questions have been raised regarding what a keyword auction is, why keyword auctions should be used, and how keyword auctions should be designed. Some of these questions have been addressed over time, but many are still open. The purpose of this chapter is to summarize the current efforts in addressing these questions. In doing so, we focus mainly on the third question, that is, how to design effective auctions for allocating keyword advertising resources. We also point out several issues for future research.

We will examine keyword auctions from a theoretical point of view. The benefits of conducting a rigorous theoretical analysis on real-world keyword auctions are two-fold. On one hand, we hope to learn what makes this new auction format popular and successful. On the other hand, by conducting a theoretical analysis on keyword auctions, we may be able to recommend changes to the existing designs.

The rest of the chapter is organized as follows. Next, we discuss the research context by briefly reviewing the history of keyword advertising and keyword auctions. In Section 3, we introduce a few popular models of keyword auctions. In Section 4 and Section 5, we focus on two design issues in keyword auctions, namely, how to rank advertisers and how to package advertising resources. In Section 6, we discuss a threat to the current keyword-advertising model—click fraud. We conclude this chapter in Section 7.

2 A historical look at keyword auctions

Keyword advertising and keyword auctions were born out of practice. They were fashioned to replace the earlier, less efficient market mechanisms and are still being shaped by the accumulative experiences of the keyword advertising industry. In this subsection, we chronicle the design of keyword advertising markets and keyword auctions, and show how they evolved.

2.1 Early Internet advertising contracts

In early online advertising, advertising space was sold through advance contracts. These contracts were negotiated on a case-by-case basis. As such negotiations were time-consuming, advertising sales were limited to large advertisers (e.g., those paying at least a few thousand dollars per month). These advertising contracts were typically priced in terms of the number of thousand-page-impressions (cost-per-mille, or CPM). CPM pricing was borrowed directly from off-line advertising, such as TV, radio, and print, where advertising costs are measured on a CPM basis. The problem with CPM pricing is that it provides no indication as to whether users have paid attention to the advertisement. Advertisers may be concerned that their advertisements are pushed to web users without necessarily generating any impact. The lack of accountability is reflected in the saying among marketing professionals: “I know that I waste half of my advertising budget. The problem is I don’t know which half.”

2.2 Keyword auctions by GoTo.com

In 1998, a startup company called GoTo.com demonstrated a new proof-of-concept search engine at a technology conference in Monterey, California. At that time, all other search engines sorted search results based purely on algorithm-assessed relevancy. GoTo.com, on the other hand, devised a plan to let advertisers bid on top positions of the search result. Specifically, advertisers can submit their advertisements on chosen words or phrases (“search terms”) together with their pay-per-click on these advertisements. Once the submitted advertisements are validated by GoTo.com’s editorial team, they will appear as a search result. The highest advertiser will appear at the top of the result list, the second-highest advertiser will appear at the second place of the result list, and so on. Each time a user clicks on an advertisement, the advertiser will be billed the amount of the bid.

GoTo.com’s advertising model contains several key innovations. First, advertising based on user-entered search terms represents a new form of targeted advertising that is based on users’ behavior. For example, a user who searches “laptop” is highly likely in the process of buying a laptop. Keyword-based search engine advertising opens a new era of behavioral targeted advertising. Second, by billing advertisers only when users click on the advertisements, GoTo.com provides a partial solution to a longstanding issue of lack of accountability. Clicking on an advertisement indicates online users’ interests. Therefore, pay-per-click represents a significant step toward more accountable advertising.

The ability to track behavioral outcomes such as clicks is a crucial difference between online advertising and its off-line counterparts. The act

of clicking on an advertisement provides an important clue on advertising effectiveness. Accumulated information on clicking behavior can be further used to fine-tune advertisement placement and content. In such a sense, pay-per-click is a significant leap from the CPM scheme and signifies the huge potential of online advertising.

Finally, the practice of using auctions to sell advertising slots on a continuous, real-time basis is another innovation. These real-time auctions allow advertisements to go online a few minutes after a successful bidding. As there is no pre-set minimum spending, auction-based advertising has the advantage of tapping into the “long tail” of the advertising market, that is, advertisers who have small spending budgets and are more likely to “do-it-yourself.”

GoTo.com was re-branded as Overture Services in 2001 and acquired by Yahoo! in 2003. During the process, however, the auction mechanism and the pay-per-click pricing scheme remained largely unchanged.

2.3 Subsequent innovations by Google

Google, among others, made several key innovations to the keyword advertising business model. Some of these have become standard features of today’s keyword advertising. In the following, we briefly review these innovations.

2.3.1 Content vs. advertising

The initial design by GoTo.com features a “paid placement” model: paid advertising links are mixed with organic search results so that users cannot tell whether a link is paid for. Google, when introducing its own keyword advertising in 1998, promoted a “sponsored link” model that distinguished advertisements from organic search results. In Google’s design, advertisements are displayed on the side or on top of the result page with a label “sponsored links.” Google’s practice has been welcomed by the industry and policy-makers and has now become standard practice.

2.3.2 Allocation rules

Google introduced a new allocation rule in 2002 in its “Adwords Select” program in which listings are ranked not only by bid amount, but also by CTR (later termed as “quality score”). Under such a ranking rule, paying a high price alone cannot guarantee a high position. An advertiser with a low CTR will get a lower position than advertisers who bid the same (or slightly lower) but have higher CTRs. In 2006, Google revised its quality score calculation to include not only advertisers’ past CTRs but also the quality of their landing pages. Advertisers with low quality scores are required to pay a high minimum bid or they will become inactive.

Google's approach to allocation gradually gained acceptance. At the beginning of 2007, Yahoo! conducted a major overhaul of its online advertising platform that considers both the CTRs of an advertisement and other undisclosed factors. Microsoft adCenter, which came into use only at the beginning of 2006, used a ranking rule similar to Google's Adwords. Before that, all of the advertisements displayed on the MSN search engine were supplied by Yahoo!

2.3.3 Payment rules

In the keyword auctions used by GoTo.com, bidders pay the amount of their bids. This way, any decrease in one's bid will result in less payment. As a result, bidders have incentives to monitor the next highest bids and make sure their own bids are only slightly higher. The benefits from constantly adjusting one's bid create undesirable volatility in the bidding process. Perhaps as a remedy, Google used a different payment rule in their Adwords Select program. In Adwords Select, bidders do not pay the full amount of their bids. Instead, they pay the lowest possible to remain above the next highest competitor. If the next highest competitor's bid drops, Google automatically adjusts the advertiser's payment downward. This feature, termed as "Adwords Discounter," is essentially an implementation of second-price auctions in a dynamic context. One key advantage of such an arrangement is that bidders' payments are no longer directly linked to their bids. This reduces bidders' incentive to game the system. Recognizing this advantage, Yahoo! (Overture) also switched to a similar payment rule. We discuss further the implications of different payment rules in Section 3.

2.3.4 Pricing schemes

As of now, Google's Adwords for search offers only pay-per-click advertising. On the other hand, Adwords for content allows advertisers to bid either pay-per-click or pay-per-thousand-impression. Starting spring 2007, Google began beta-testing a new billing metric called pay-per-action with their Adwords for content. Under pay-per-action metric, advertisers pay only for completed actions of choice, such as a lead, a sale, or a page view, after a user has followed through the advertisement to the publisher's website.

2.4 Beyond search engine advertising

The idea of using keywords to place most relevant advertisements is not limited to search engine advertising. In 2003, Google introduced an "AdSense" program that allows web publishers to generate advertising revenue by receiving advertisements served by Google. AdSense analyzes publishers' web pages to generate a list of most relevant keywords, which are subsequently used to select the most appropriate advertisements for

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Fig. 3. Context-based keyword advertising.

these pages. Figure 3 shows an example of contextual advertising in Gmail. The order of advertisements supplied to a page is determined by Adwords auctions. The proceeds of these advertisements are shared between Google and web publishers. Yahoo! has a similar program called Yahoo! Publisher Network.

KAPs also actively sought expansion to domains other than Internet advertising, such as mobile devices, video, print, and TV advertising. Google experimented with classified advertising in the *Chicago Sun-Times* as early as fall 2005. In February 2006, Google announced a deal with global operator Vodafone to include its search engine on Vodafone Live! mobile Internet service. In April 2007, Google struck a deal with radio broadcaster Clear Channel to start supplying less than 5% of the advertising inventory across Clear Channel's 600+ radio stations. During the same month, Google signed a multiyear contract with satellite-TV provider EchoStar to sell TV advertisement spots on EchoStar's Dish service through auctions.

3 Models of keyword auctions

In this section we discuss several models of keyword auctions. The purpose of these models is not to propose new auction designs for keyword-advertising

settings but to capture the essence of keyword auctions accurately. The value of these models lies in that they allow the real-world keyword auctions to be analyzed in a simplified theoretical framework.

We start by describing the problem setting. There are n advertisers bidding for m ($\leq n$) slots on a specific keyword phrase. Let c_{ij} denote the number of clicks generated by advertiser i on slot j . In general, c_{ij} depends both on the relevance of the advertisement and on the prominence of the slot. In light of this, we decompose c_{ij} to an advertiser (advertisement) factor (q_i) and a slot factor (δ_j).

$$c_{ij} = \delta_j q_i \quad (1)$$

We interpret the advertiser factor q_i as the advertiser i 's CTR. For example, everything else being equal, a brand-name advertiser may attract more clicks and thus have a higher CTR than a non-brand-name advertiser. We interpret the slot factor δ_j as the *click potential* of the slot. For example, a slot at the top of a page has higher click potential than a slot at the bottom of the same page.

Each advertiser has a valuation-per-click v_i . As in most research, we assume that advertisers know their own valuation-per-click. Though in reality, advertisers may have to learn over time their valuation-per-click from the outcome of the keyword advertising.

Each advertiser submits a bid b that is the advertiser's maximum willingness-to-pay per click for the keyword phrase. Each time a user initiates a search for the keyword phrase or requests a content page related to the keyword phrase, the auctioneer (KAP) will examine the bids from all participating advertisers and determine which advertisements should be displayed and in which order according to an *allocation rule*. If a user clicks on a particular advertisement, the advertiser will be charged a price determined by the *payment rule* of the keyword auction (which we will explain shortly).

The allocation rule and the payment rule used in keyword auctions are different across different KAPs. For example, until recently, Yahoo! ranked advertisers strictly by the prices they bid, and advertisers paid the amount they bid. On the other hand, Google ranks advertisers based on their prices and their CTRs, and advertisers pay the lowest price that keeps the advertiser above the next highest-ranked advertiser. We distinguish the following models of keyword auctions by different allocation or payment rules used.

3.1 Generalized first-price auction

In the early days of keyword auctions, bidders paid the price they bid. Such a format is termed "generalized first-price (GFP)" auctions because they essentially extended the first-price auctions to a multiple-object

setting. However, people soon discovered that GFP auctions could be instable in a dynamic environment where bidders can observe and react to other bidders' latest bids as often as they can. For instance, let us assume that there are two slots and two advertisers, 1 and 2, with valuations per click of \$2 and \$1 only. Assume the minimum bid is \$0.10 and slot 1 generates twice the number of clicks that slot 2 generates. Obviously, it is the best for advertiser 1 to bid 1 cent higher than advertiser 2. It is also best for advertiser 2 to bid 1 cent higher than advertiser 1 till advertiser 1 reaches \$0.55 or higher, in which case advertiser 2 is better off bidding just the minimum bid \$0.1. So the two advertisers will form a bidding cycle that escalates continuously from the minimum bid to \$0.55 and starts over again from there.

Zhang and Feng (2005) and Asdemir (2005) show that the cyclic bidding pattern illustrated existed in Overture. The cyclic bidding is harmful in three ways. First, the frequent revision of bids requires additional computing resources that can slow down the entire auction system. Second, as shown by Zhang and Feng (2005), the oscillation of prices (because of the bidding cycle) can dramatically reduce KAP's revenue. Third, GFP auctions are biased toward bidders who can attend and revise their bids more often. Such a bias may be perceived as unfair.

3.2 Generalized second-price auction

Edelman et al. (2007) and Varian (2007) study a generalized second price (GSP) auction that captures Google's payment rule. In GSP auctions, advertisers are arranged in descending order by their pay-per-click bids. The highest-ranked advertiser pays a price that equals the bid of the second-ranked advertiser plus a small increment; the second-ranked advertiser pays a price that equals the bid of the third-ranked advertiser plus a small increment, and so on. For example, suppose there are two slots and three advertisers {1, 2, 3} who bid \$1, \$0.80, and \$0.75, respectively. Under the GSP rule, advertiser 1 wins the first slot, and advertiser 2 wins the second slot. Assuming that the minimum increment is ignorable, advertisers 1 and 2 should pay \$0.80 and \$0.75 per click, respectively (Table 1).

Table 1
Payments under generalized second-price auctions

Advertiser	Bid (\$)	Slot assigned	Pay-per-click
1	1	1	0.80
2	0.8	2	0.75
3	0.75	–	–

Table 2
Payments under the VCG mechanism

Advertiser	Bid (\$)	Slot assigned	Pay-per-click
1	1	1	0.775
2	0.8	2	0.75
3	0.75	–	–

One notable feature of GSP auctions is that advertisers' payments are not directly affected by their own bids. This feature is also present in the well-known Vickrey-Clarke-Grove (VCG) mechanism. Under the VCG mechanism, each player's payment is equal to the opportunity cost the player introduces to other players. To illustrate, in the earlier example, the VCG payment of advertiser 1 should equal the reduction in advertisers 2 and 3's total valuation because of 1's participation. Let us assume that all advertisers have the same CTR (normalized to 1), and all bids in Table 2 reflect advertisers' true valuation-per-click. Let us also assume that the first slot has a (normalized) click potential of 1, and the second slot has a click potential of 0.5. Without advertiser 1, advertisers 2 and 3 will be assigned to the two slots, generating a total valuation of $0.8 \times 1 + 0.75 \times 0.5 (= 1.175)$. With advertiser 1, advertiser 2 is assigned to the second slot, and advertiser 3 is not assigned a slot, generating a total valuation of $0.8 \times 0.5 (= 0.4)$. The VCG mechanism suggests that advertiser 1 should pay $(1.175 - 0.4)/1 = 0.775$ per click. Similarly, we can calculate the VCG payment for advertiser 2. Table 2 illustrates the slot allocation and payments under the VCG rule. Clearly, GSP is not a VCG mechanism. Advertisers pay higher prices (except the lowest-ranked winner) under the GSP than under the VCG, provided that they bid the same prices.²

Edelman et al. (2007) show that GSP has no dominant-strategy equilibrium, and truth-telling is not an equilibrium. However, the corresponding generalized English auction has a unique equilibrium, and in such an equilibrium, bidders' strategies are independent of their beliefs about other bidders' types. These findings suggest that GSP auctions do offer a certain degree of robustness against opportunism and instability.

The above results are obtained in the somewhat restrictive assumption that bidders differ on a single dimension (valuation per click). The reality is that advertisers at least differ on both valuation per click and CTRs. This fact has motivated Google, and later Yahoo! and MSN adCenter, to rank advertisers based on both bid prices and CTRs. In such a sense, GSP is accurate about Google's payment rule but not its allocation rule. In the next subsection, we discuss an auction framework that captures the allocation rules of keyword auctions.

²This is not to say that GSP generates higher revenue than VCG because advertisers may bid differently under the two mechanisms.

3.3 Weighted unit-price auction

Weighted unit-price auction (WUPA) has been studied in Liu and Chen (2006) and Liu et al. (2009). The WUPA is motivated by the fact that Google allocates slots based on a score rule that is a function of advertisers' unit-price bids. While Google does not fully disclose their scoring formula, Search-Engine Watch reported that the formula used by Google is (Sullivan, 2002)

$$\text{Score} = \text{Willingness-to-pay per click} \times \text{CTR} \quad (2)$$

In 2006, Google updated its ranking rule by replacing CTR in the above formula with a more comprehensive "quality score," which takes into account advertisers' CTRs as well as other information such as the quality of their landing pages. In the updated ranking rule, CTR remains a primary consideration in an advertiser's "quality score."

The idea of using a scoring rule to synthesize multidimensional criteria is not new. "Scoring auctions" have been used in procurement settings (Asker and Cantillon, 2008; Che, 1993) where suppliers (bidders) submit multi-dimensional bids, such as price p and quality q , and are ranked by a scoring function of the form $s(p, q) = \phi(q) - p$. A score rule is also used in "tender auctions" (Ewerhart and Fieseler, 2003) where a buyer (the auctioneer) requests suppliers to bid a unit price for each input factor (e.g., labor and materials) and ranks suppliers by the weighted sum of their unit-price bids. However, a weighted unit-price score rule is never used on such a large scale. The scoring rule used in keyword auctions is also different from procurement auctions and tender auctions. Therefore, the weighted unit-price auction as a general scoring auction format is not previously studied.

The specifics of the WUPA framework are as follows. The auctioneer assigns each advertiser a score s based on the advertiser's bid and information on the advertiser's future CTR.

$$s = wb \quad (3)$$

where w is a weighting factor assigned to the advertiser based on their expected future CTRs. The auctioneer allocates the first slot to the advertiser with the highest score, the second slot to the advertiser with the second-highest score, and so on.

As with the price-only allocation rule, WUPA can also have "first-score" and "second-score" formats. Under the "first-score" rule, each advertiser pays a price that "fulfills" the advertiser's score. This is equivalent to saying that advertisers need to pay the prices they bid. Under the "second-score" payment rule, each advertiser pays the lowest price that keeps the advertiser above the next highest advertiser's score. For example, suppose there are only two types of expected CTRs, high and low. Suppose also the weighting factor for high-CTR advertisers is 1 and for low-CTR advertisers is 0.5.

Table 3
Payments under first- and second-score WUPAs

Advertiser	Bid	CTR	Score	Slot assigned	Pay-per-click	
					First-score	Second-score
1	1	Low	0.5	–	–	–
2	0.8	High	0.8	1	0.8	0.75
3	0.75	High	0.75	2	0.75	0.5

Continuing with the earlier examples, we assume the expected CTRs of advertisers 1, 2, and 3 are low, high, and high, respectively. Table 3 illustrates the winning advertisers under the WUPA and the price they pay-per-click under the first-score and second-score rules, respectively.

Liu et al. (2009) show that in an incomplete-information setting (i.e., advertisers do not know other advertisers' valuation-per-click or expected CTRs), the first-score and second-score WUPAs are equivalent in expected revenue. The first-score WUPAs have a unique Bayesian-Nash equilibrium and the equilibrium can be explicitly solved. As in GSP auctions, the second-score WUPAs do not have a truth-telling equilibrium except when there is only one slot. In Section 4, we discuss the implications of different ranking rules.

4 How to rank advertisers

Yahoo is strictly capitalistic—pay more and you are number one. Google has more socialist tendencies. They like to give their users a vote.

—Dana Todd, SiteLab International

This quote summarizes an interesting dichotomy in Yahoo! and Google's approaches to advertiser ranking. Yahoo! (Overture), the pioneer in keyword auctions, ranked advertisers purely based on their willingness-to-pay. On the other hand, Google, the now-leading player, invented a design that ranks advertisers by the product of per-click prices they bid and their historical CTRs. What exactly is the significance of different ranking approaches? Vise and Malseed (2005), authors of *The Google Story*, noted that Google displays a “socialist tendency” because in Google's approach, advertisements that Internet users frequently click on are more likely to show up in top positions. Authors from academia, on the other hand, have searched for answers along the lines of revenue-generation and resource-allocation efficiency. A few authors, such as Feng et al. (2007) and Lahaie (2006), studied Google's and Yahoo!'s approaches strictly as a ranking issue. Liu and Chen (2006) embedded the ranking problem in a larger issue of how to use bidders' past-performance information. After all, what

Google uses is the information on advertisers' past CTRs, which essentially signals their abilities to generate clicks in the future. In fact, KAPs can also impose differentiated minimum bids for advertisers of different historical CTRs, which is what Google is doing now. This later use of past-performance information is studied in Liu et al. (2009).

Three main questions are associated with different rank rules. What is the impact of adopting different ranking rules on advertisers' equilibrium bidding? On KAP's revenue? And on resource-allocation efficiency? The revenue and efficiency criteria may matter at different stages of the keyword advertising industry. At the developing stage of the keyword advertising market, it is often sensible for KAPs to use efficient designs to maximize the "total pie." After all, if advertisers see high returns from their initial use, they are likely to allocate more budgets to keyword advertising in the future. On the other hand, as the keyword advertising market matures and market shares stabilize, KAPs will more likely focus on revenue. Several authors in economics, information systems, and computer science have approached these questions.

Feng et al. (2007) are the earliest to formally compare the ranking rules of Google and Yahoo! One focus of their study is the correlation between advertisers' pay-per-click and the relevance of their advertisements to the keywords. With numerical simulation, they find that Google's ranking mechanism performs well and robustly across varying degrees of correlation, while Yahoo!'s performs well only if pay-per-click and relevance are positively correlated. Those observations are sensible. Intuitively, an advertiser's contribution to the KAP's revenue is jointly determined by the advertiser's pay-per-click and the number of clicks the advertiser can generate (i.e., relevance). When pay-per-click is negatively correlated with relevance, ranking purely based on pay-per-click tends to select advertisers with low revenue contribution, which can result in a revenue loss for KAPs. However, their study has certain limitations. Instead of solving the auction model, they simplify by assuming that bidders will bid truthfully under Google's mechanism.

Lahaie (2006) compares Google's and Yahoo!'s ranking rules based on an explicit solution to the auction-theoretic model. He finds that Google's ranking rule is efficient while Yahoo!'s is not. Yahoo!'s ranking is inefficient because, as we mentioned earlier, high bid does not necessarily mean high total valuation because total valuation also depends on relevance. In contrast, Google's ranking rule is efficient. He also shows that no revenue ranking of Google's and Yahoo!'s ranking mechanism is possible given an arbitrary distribution over bidder values and relevance. His findings are consistent with results derived in a weighted unit-price auction framework by Liu and Chen (2006) and Liu et al. (2009), which we discuss next.

While both Feng et al. (2007) and Lahaie (2006) focus on two specific cases: Yahoo!'s price-only ranking rule and Google's ranking rule, Liu

and Chen (2006) and Liu et al. (2009) study weighted unit-price auctions (WUPAs), which encompass Yahoo! and Google's ranking rules. Under WUPAs, advertisers bid on their willingness-to-pay per click (or unit-price), and the auctioneer weighs unit-price bids based on advertisers' expected CTRs. Liu and Chen (2006) consider a single slot setting. Liu et al. (2009) extend to a more general multiple slot setting and study both ranking rules and minimum-bid rules.

As in Section 3, advertiser i , if assigned to slot j , will generate $c_{ij} = \delta_j q_i$ clicks, where δ_j is a deterministic coefficient that captures the prominence of slot j . $\delta_1 \geq \delta_2 \dots \geq \delta_m$ and $\delta_1 = 1$. q_i is a stochastic number that captures the advertiser i 's CTR.

A key assumption of the WUPA framework is that the KAP has information on advertisers' future CTRs. This assumption is motivated by the fact that e-commerce technologies allow KAPs to track advertisers' past CTRs and predict their future CTRs. The KAP can make the ranking of advertisers depend on both their pay-per-click and their expected CTRs. In particular, the KAP assigns each advertiser a score $s = wb$, where the weighting factor w is determined by the advertiser's expected CTR. If the advertiser has high-expected CTR, then the weighting factor is 1. If the advertiser has low expected CTR, then the weighting factor is w_l .

Liu et al. (2009) study WUPAs in an incomplete information setting. They assume that each advertiser has a private valuation-per-click v , $v \in [\underline{v}, \bar{v}]$. The distributions of valuation-per-click, $F_h(v)$ (for high-CTR advertisers) and $F_l(v)$ (for low-CTR advertisers), are known to all advertisers and the KAP. The probabilities of being a high-CTR advertiser, α , and a low-CTR one, $1-\alpha$, are also known to all advertisers and the KAP. Furthermore, we denote Q_h and Q_l as the expected CTRs for a high-CTR advertiser and a low-CTR advertiser, respectively. It is assumed that $Q_h > Q_l$.

Suppose advertisers' payoff functions are additive in their total valuation and the payment. Under the first-score payment rule (see Section 3),³ the payoffs for a low-CTR advertiser and a high-CTR advertiser are, respectively,

$$U_l(v, b) = Q_l(v - b) \sum_{j=1}^m \delta_j \Pr\{w_l b \text{ ranks } j\text{th}\} \quad (4)$$

$$U_h(v, b) = Q_h(v - b) \sum_{j=1}^m \delta_j \Pr\{b \text{ ranks } j\text{th}\} \quad (5)$$

Liu et al.'s analysis generates several insights. First, their analysis illustrates how ranking rules affects equilibrium bidding. The ranking rule affects how low- and high-CTR advertisers match up against each other in equilibrium. Specifically, weighting factors for low- and high-CTR

³In this model setting, a first-score auction is revenue-equivalent to a second-score auction.

advertisers determine the ratio of valuation-per-clicks between a low-CTR advertiser and a high-CTR advertiser who tie in equilibrium. For example, if the low-CTR advertisers are given a weighting factor of 0.6, and the high-CTR advertiser, 1, a low-CTR advertiser with valuation-per-click 1 will tie with a high-CTR advertiser with valuation-per-click 0.6 in equilibrium. Furthermore, high-CTR advertisers' with valuation-per-click higher than 0.6 out-compete all the low-CTR advertisers, and therefore compete only with other high-CTR competitors. As a result, these high-CTR advertisers will bid markedly less aggressively than high-CTR advertisers with valuation-per-click lower than 0.6.

Second, they identify the efficient ranking rule under the WUPA framework. Here efficiency is measured by the total expected valuation realized in the auction. The efficient ranking rule under the WUPA framework is remarkably simple: The KAP should weigh advertisers' pay-per-click by their expected CTRs, as if they bid their true valuation-per-click (while in fact they generally do not).

Third, they characterize the revenue-maximizing ranking rule under the WUPAs. The revenue-maximizing ranking rule may favor low- or high-CTR advertisers relative to the efficient ranking rule. When the distribution of valuation-per-click is the same for high- and low-CTR advertisers, the revenue-maximizing ranking rule should always favor low-CTR advertisers (relative to the efficient design). But when the valuation distribution of low-CTR advertisers become less "disadvantaged," the revenue-maximizing ranking rule may instead favor high-CTR advertisers (relative to the efficient design).

Besides the above-mentioned research on ranking rules, Weber and Zheng (2007) study the revenue-maximizing ranking rule in a setting that resembles "paid placement." They study a model where two competing firms can reach their customers through sponsored links offered by a search engine intermediary. Consumers differ in "inspection cost" (cost incurred when they click on a sponsored link to find out the surplus they can get from purchasing the product). Thus, some consumers may inspect only the first link, while others inspect both before making a purchase decision. To get the higher position, firms can offer a payment b to the search engine each time a consumer clicks on their product link (their "bids"). The search engine's problem is to choose how to rank the firms, given the consumer surplus u generated by two firms (assumed known to the search engine) and their bids b . The authors study an additive ranking rule

$$s(b, u; \beta) = \beta u + (1 - \beta)b \quad (6)$$

where the parameter β is the focal design factor. They find that the revenue-maximizing ranking design should put nonzero weight on firms' bid b . In other words, search engines have incentive to accept "bribes" from advertisers to bias the ranking of product links.

5 How to package resources

Keyword auctions maintain that bidders simply bid their willingness-to-pay per click (thousand-impression, action) and are assigned to slots by an automatic algorithm, with higher-ranked advertisers receiving a better slot (more exposure). This is different from a fixed-price scheme, where sellers specify a menu of price-quantity pairs for buyers to choose from, and from traditional divisible-good auctions where sellers need not specify anything and buyers bid both price and quantity they desire. In a sense, keyword auctions strike a middle ground between the fixed-price scheme and traditional divisible-good auctions: in keyword auctions, the buyers (advertisers) specify prices they desire, and the seller (the KAP) decides the quantities to offer. Given the unique division of tasks in keyword auction settings, how to package resources for auctioning becomes an important issue facing KAPs.

Before we address the issue of resource packaging, it is useful to clarify what we mean by resource in keyword auctions and why resource packaging is a practical issue. What KAPs sell to advertisers is impressions. Each time a page is requested by an Internet user, all advertisements on this page get an impression. Though keyword advertising is often priced by the number of clicks or “actions” (e.g., purchases), KAPs can always re-allocate impressions from one advertiser to another but cannot do the same with clicks or actions. Therefore, impression is the ultimate resource controlled by KAPs.

Although slots on the same page generate the same number of impressions, they may not be equal to advertisers. For example, an advertising slot is noticed more often if it is at the top of a page than at the bottom of the page. Other factors can also affect how often a slot is noticed, such as its geometric size, the time of the day it is displayed, and whether the deployment website is frequented by shoppers. One way to address these differences in page impressions is to substitute raw impressions with standardized effective exposure, which weighs impressions differently based on how much value it can deliver to an average advertiser. For example, if the effective exposure generated by one page impression at the top of a page is 1, then the effective exposure, generated by one page impression at the bottom of the page might be 0.3. In the following we study the packaging of effective exposures rather than raw page impressions.⁴

With the notion of effective exposure, a keyword auction goes like this. The KAP packages the available effective exposure into several shares,

⁴A recommendation based on effective exposure can be transparently translated into a recommendation based on raw page impressions. This is because KAPs can always tailor the exposure allocated to an advertisement by randomizing its placement between different slots, varying the timing and length of its appearance, and/or selecting the number of websites for the advertisement to appear.

ordered from large to small. Advertisers will be assigned to shares by their rankings, with the highest-ranked advertiser receiving the largest share, the second-highest-ranked advertiser receiving the second-largest share, and so on. A resource packaging problem in such a setting is to decide how many shares to provide and the size of each share to maximize total revenues. We call this problem a share-structure design problem.

The share-structure design problem is relevant to KAP's day-to-day operations. The demand and supply of keyword advertising resources are highly dynamic. On one hand, the supply of advertising resources fluctuates as new websites join KAPs' advertising network, and existing websites may lose their draw of online users. On the other hand, the demand for advertising on particular keywords shifts constantly in response to changes in underlying market trends. Therefore, KAPs must constantly adjust their share structures to maximize their total revenue. To do so, KAPs need a good understanding of the share structure design problem. Given that KAPs have become managers of tremendous advertising resources, the issue of share structure design is critical to their success.

5.1 *The revenue-maximizing share structure problem*

Chen et al. (2006, 2009) address the issue of revenue-maximizing share structures with the following specifications. There are n risk-neutral advertisers (bidders). The KAP (auctioneer) packages total effective exposure (normalized to 1) into as many as n shares arranged in a descending order, $s_1 \geq s_2 \geq \dots \geq s_n$. A share structure refers to vector $\mathbf{s} = (s_1, s_2, \dots, s_n)$. Table 4 shows some examples of share structures and their interpretations.

Bidders' valuation for a share is determined by the size of the share (s) and a private parameter (v), called the bidder's type. v is distributed according to a cumulative distribution function $F(v)$ on $[\underline{v}, \bar{v}]$, with density $f(v)$. Bidders' valuation of a share take the form of $vQ(s)$, where $Q(\cdot)$ is an increasing function.

Bidders are invited to bid their willingness-to-pay per unit exposure (or unit price), and all shares are allocated at once by a rank-order of bidders' unit-price bids.⁵ Bidders pay the price they bid.⁶ Each bidder's expected payoff is the expected valuation minus expected payment to the auctioneer. Denote $p_j(b)$ as the probability of winning share j by placing bid b . The

⁵Google ranks advertisers by a product of their willingness-to-pay per click and a click-through-rate-based quality score, which can be loosely interpreted as advertisers' willingness-to-pay per impression (see Liu and Chen (2006) for a more detailed discussion). Yahoo! used to rank advertisers by their willingness-to-pay per click only, but recently switched to a format similar to Google's. Our assumption that bidders are ranked by their willingness-to-pay per unit exposure is consistent with both Google's approach and Yahoo!'s new approach.

⁶The expected revenue for the auctioneer is the same if bidders pay the next highest bidder's price.

Table 4
Examples of share structures

s	Interpretation
(1, 0, 0, 0)	The highest bidder gets all effective exposures
(0.25, 0.25, 0.25, 0.25)	Top 4 bidders each get one-fourth of the total effective exposures
(0.4, 0.2, 0.2, 0.2)	The top bidder gets 40% of the total effective exposures. The 2nd–4th highest bidders each get 20% of the total effective exposures

expected payoff of a bidder of type v is

$$U(v, b) = \sum_{j=1}^n p_j(b)(vQ(s_j) - bs_j) \quad (7)$$

The auctioneer's revenue is expected total payments from all bidders.

$$\pi = nE \left[b \sum_{j=1}^n p_j(b)s_j \right] \quad (8)$$

Bidders maximize their expected payoff by choosing a unit price b . The auctioneer maximizes the expected revenue by choosing a share structure s .

5.2 Results on revenue-maximizing share structures

Chen et al. (2009) showed that the auctioneer's expected revenue in the above setting is written as

$$\pi = n \sum_{j=1}^n Q(s_j) \int_{\underline{v}}^{\bar{v}} P_j(v) \left[v - \frac{1 - F(v)}{f(v)} \right] f(v) dv \quad (9)$$

where

$$P_j(v) \equiv \binom{n-1}{n-j} F(v)^{n-j} (1 - F(v))^{j-1} \quad (10)$$

is the equilibrium probability for a bidder of type v to win share j .

We denote

$$\alpha_j \equiv n \int_{\underline{v}}^{\bar{v}} P_j(v) \left[v - \frac{1 - F(v)}{f(v)} \right] f(v) dv, \quad j = 1, 2, \dots, n \quad (11)$$

The expected revenue (Eq. (9)) can be written as

$$\pi = \sum_{j=1}^n \alpha_j Q(s_j) \quad (12)$$

Here α_j is interpreted as the return coefficient for the j th share.

Chen et al. (2009) showed that the revenue-maximizing share structures may consist of plateaus—a plateau is a set of consecutively ranked shares with the same size. For example, the third example in Table 4 has two plateaus: the first plateau consists of the first share (of size 0.4); the second plateau consists of the second to the fourth share (of size 0.2). Chen et al. (2009) showed that the starting and ending ranks of plateaus in the revenue-maximizing share structure are determined only by the distribution of bidders' type. Based on their analysis, the optimal starting/ending ranks of plateaus and the optimal sizes of shares in each plateau can be computed using the following algorithm.

1. Compute return coefficients $\{a_j\}$, $j = 1, \dots, n$.
2. Let j_k denote the ending rank of k -th plateau. $j_0 \leftarrow 0$ and $k \leftarrow 1$.
3. Given j_{k-1} , compute $j_k \leftarrow \arg \max_{j \in \{j_{k-1}+1, \dots, n\}} \{(1/(j - j_{k-1})) \sum_{l=j_{k-1}+1}^j \alpha_l\}$.
4. If $j_k = n$, $K \leftarrow k$ (K denotes the total number of plateaus) and continue to step 5. Otherwise, $k \leftarrow k + 1$, go to step 3.
5. Compute the average return coefficient $\bar{\alpha}_k \leftarrow (1/(j_k - j_{k-1})) \sum_{l=j_{k-1}+1}^{j_k} \alpha_l$, for plateau $k = 1, \dots, K$.
6. Solve the following nonlinear programming problem for the sizes of shares (z_1, z_2, \dots, z_K) in all plateaus:

$$\begin{aligned} & \max \sum_{k=1}^K (j_k - j_{k-1}) \bar{\alpha}_k Q(z_k) \\ & \text{subject to : } \sum_{k=1}^K (j_k - j_{k-1}) z_k = 1 \text{ and } z_1 \geq z_2 \geq \dots \geq z_K \geq 0 \end{aligned}$$

A share structure becomes steeper if we allocate more resources to high-ranked shares and less to low-ranked ones. In Table 4, the steepest share structure is (1, 0, 0, 0), followed by (0.4, 0.2, 0.2, 0.2), and then by (0.25, 0.25, 0.25, 0.25). Chen et al. (2009) obtained several results on how the revenue-maximizing share structures should change in steepness when the underlying demand or supply factors change. First, as bidders' demands become less price-elastic (as the valuation function $Q(\cdot)$ becomes more concave), the auctioneer should use a less steep share structure. When bidders have perfectly elastic demand (i.e., the bidder's valuation $Q(\cdot)$ is a

linear function), the auctioneer should use the steepest share structure, winner-take-all. The following example illustrates the above finding.

Example 1. Let the number of bidder be six and the type distribution be an (truncated) exponential distribution on $[1, 3]$. When $Q(s) = s$, the revenue-maximizing share structure is $(1, 0, 0, 0, 0, 0)$ (winner-take-all). When $Q(s) = \sqrt{s}$, the revenue-maximizing share structure is $(0.51, 0.25, 0.13, 0.07, 0.03, 0.01)$. When $Q(s) = s^{1/4}$, the revenue-maximizing share structure is $(0.40, 0.25, 0.16, 0.10, 0.06, 0.03)$. Figure 4 plots the first to the sixth shares under three different valuation functions. The figure shows that the revenue-maximizing share structure becomes flatter when bidders' demand becomes less price-elastic.

A change in the type distribution affects the revenue-maximizing share structure through the return coefficients α_j 's. In the case of "scaling" (all bidders' valuation is multiplied by a common factor), all return coefficients are also scaled, and the revenue-maximizing share structure should remain the same. When the type distribution is "shifted" to the right (i.e., every bidder's v increases by the same amount), the return coefficient for a low-ranked share increases by a larger proportion than the return coefficient for a high-ranked share does, and thus the revenue-maximizing share structure becomes less steep.

Example 2. Continue with Example 1. Fix $Q(s) = \sqrt{s}$. When the type distribution is shifted to $[5, 7]$, the revenue-maximizing share structure becomes $(0.24, 0.19, 0.17, 0.15, 0.13, 0.12)$. Figure 5 shows that the revenue-maximizing share structure becomes flatter when the type distribution is shifted from $[1, 3]$ to $[5, 7]$.

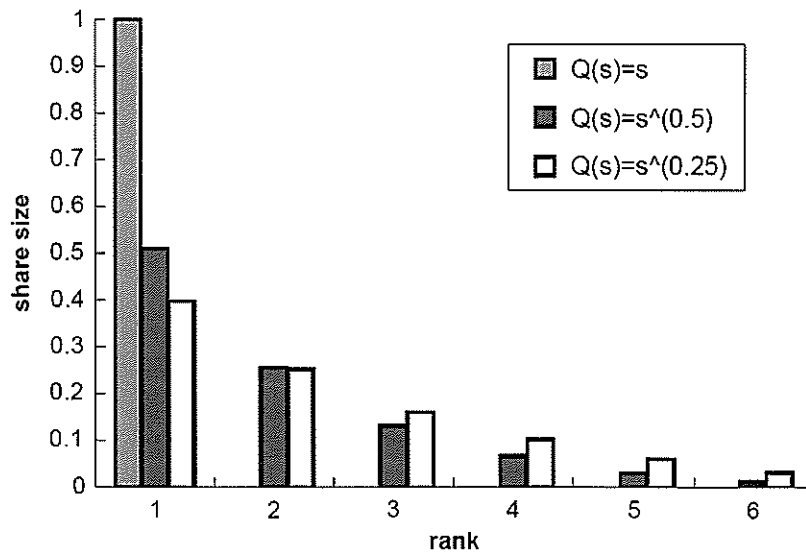


Fig. 4. Effect of price elasticity of demand.

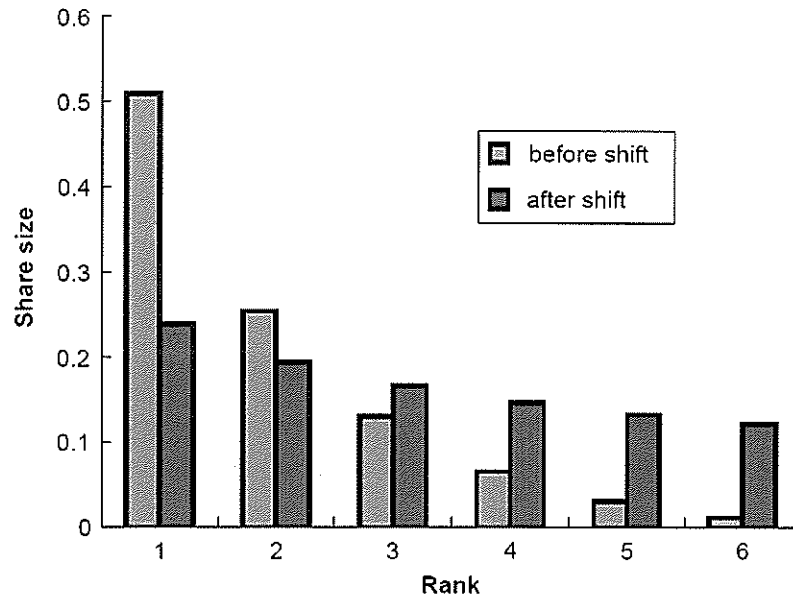


Fig. 5. Effect of type distribution.

Another factor studied in Chen et al. (2009) is the effect of increasing total resources available. They showed that when total resource increases, all shares will increase, but whether the share structure (in terms of percentages of the total resources) becomes flatter or steeper depends on how bidders' price elasticity increases or decreases with the resources assigned. When bidders' price elasticity increases in the amount of resources allocated, the KAP should increase high-ranked shares by a larger percentage. When bidders' price elasticity of demand decreases, the KAP should increase low-ranked shares by a larger percentage.

The above results highlighted the importance of advertisers' price elasticity of demand and the competitive landscape (as determined by the distribution of bidders' types). Generally speaking, when bidders become more price-elastic, the share structure should be steeper; when the competition between bidders is fiercer, the share structure should be flatter.

5.3 Other issues on resource packaging

The resources managed by KAPs have expanded significantly since the advent of keyword advertising. Leading KAPs have developed vast advertising networks of thousands of websites. Meanwhile, they are also actively seeking expansion to other media, including mobile devices, radio, and print advertising. The issue of resource packaging will only become more important when KAPs manages more advertising resources.

The earlier research addressed only a small part of a larger resource-packaging problem. There are a few interesting directions for future research on the issue of resource packaging. First, Chen et al.'s (2009) framework assumes bidders share a common valuation function Q . A more general setting is that bidders' valuation functions are also different. For example, bidders with highly elastic demand and bidders with inelastic demands may coexist. Feng (2008) studies a setting in which bidders differ in price elasticities, but her focus is not on the share structure design.

Another interesting direction is to compare keyword auctions with alternative mechanisms for divisible goods such as the conventional discriminatory-price and uniform-price auctions (Wang and Zender, 2002; Wilson, 1979), in which bidders not only bid on prices but also on the quantity desired. The study on revenue-maximizing share structure facilitates such comparison because one would need to pick a revenue-maximizing share structure for keyword auctions to make a meaningful comparison.

Also, it is interesting to study the optimal mechanism for allocating keyword-advertising resources. Different mechanisms may be evaluated along the lines of the auctioneer's revenue, the allocation efficiency, and whether the mechanism encourages bidders to reveal their true valuation. Bapna and Weber (2006) study a mechanism that allows bidders to specify their "demand curves," rather than just one price. They consider a more general setting in which multiple divisible goods are offered and bidders may have multidimensional private information. More specifically, they consider n bidders that have valuation for fractional allocations of m slots. For a fraction $x_i = (x_i^1, \dots, x_i^m)$ allocated, bidder i 's utility is $v_i(x_i; \eta_i)$, where η_i represents bidder i 's private information, or type. The auctioneer first announces its mechanism, which includes a fixed m -dimensional price vector $p = (p^1, \dots, p^m)$. Then each bidder submits a bid function $b_i(\cdot; \eta_i)$. The bidder's bids are considered as discounts that will be subtracted from the payment implied by the posted price schedule. Under such a setting, Bapna and Weber show that such a mechanism has a dominant-strategy incentive-compatible equilibrium in which a bidder's equilibrium bids do not depend on the knowledge of type distribution, the number of bidders, or other bidders' payoff functions.

6 Click fraud

The keyword advertising industry has been extraordinarily successful in the past few years and continues to grow rapidly. However, its core "pay-per-click" advertising model faces a threat known as "click fraud." Click fraud occurs when a person, automated script, or computer program imitates a legitimate user of a web browser clicking on an advertisement, for the purpose of generating a click with no real interest in the target link. The

consequences of click fraud include depleting advertisers' budgets without generating any real returns, increasing uncertainties in the cost of advertising campaigns, and creating difficulty in estimating the impact of keyword advertising campaigns. Click fraud can ultimately harm KAPs because advertisers can lose confidence in keyword advertising and switch to other advertising outlets. Both industrial analysts and KAPs have cited click fraud as a serious threat to the industry. A Microsoft AdCenter spokesperson stated, "Microsoft recognizes that invalid clicks, which include clicks sometimes referred to as 'click fraud,' are a serious issue for pay-per-click advertising."⁷ In its IPO document, Google warned that "we are exposed to the risk of fraudulent clicks on our ads."⁸ While no consensus exists on how click fraud should be measured, "most academics and consultants who study online advertising estimate that 10% to 15% of advertisement clicks are fake, representing roughly \$1 billion in annual billings" (Grow and Elgin, 2006).

Click fraud has created a lingering tension between KAPs and advertisers. Because advertisers pay for valid click they receive, it is critical for advertisers not to pay for clicks that are invalid or fraudulent. The tension arises when advertisers and KAPs cannot agree on which clicks are valid. KAPs often do not inform advertisers which clicks are fraudulent clicks, citing the concern that click spammers may use such information against KAPs and undermine KAPs' effort to fight click fraud. Also, KAPs may have financial incentives to charge advertisers for invalid clicks to increase their revenues. Such incentives may exist at least in a short run. A few events illustrate the tension between advertisers and KAPs. In June 2005, Yahoo! settled a click-fraud lawsuit and agreed to pay the plaintiffs' \$5 million legal bills. In July 2006, Google settled a class-action lawsuit over alleged click fraud by offering a maximum of \$90 million credits to marketers who claim they were charged for invalid clicks.

Before we proceed, it is useful to clarify the two main sources of fraudulent clicks. The first is from competing advertisers. Knowing that most advertisers have a daily spending budget, an advertiser can initiate a click-fraud attack on competitors to drain their daily budgets. Once the competitors' daily budgets are exhausted, their advertisements will be suspended for the rest of the day, so the attacker can snag a high rank at less cost.

The second and more prevalent source of click fraud comes from publishers who partner with KAPs to display keyword advertisements. Many publishers earn revenue from KAPs on a per-click basis. Therefore, they have incentives to inflate the number of clicks on the advertisements displayed on their sites. This became a major form of click fraud after KAPs expanded keyword advertising services to millions of websites,

⁷<http://news.com.com/2100-10243-6090939.html>

⁸<http://googleblog.blogspot.com/2006/07/let-click-fraud-happen-uh-no.html>

including many small and obscure websites that are often built solely for advertising purposes.

One argument is that click fraud is not a real threat. This line of argument underlines current Google CEO Eric Schmidt's comment on click fraud.⁹

Let's imagine for purposes of argument that click fraud were not policed by Google and it were rampant ... Eventually, the price that the advertiser is willing to pay for the conversion will decline, because the advertiser will realize that these are bad clicks, in other words, the value of the ad declines, so over some amount of time, the system is in fact self-correcting. In fact, there is a perfect economic solution which is to let it happen.

Research also shows that Google's keyword auction mechanisms resist click fraud (Immorlica et al., 2005; Liu and Chen, 2006). The reason is that advertisers who suffer from click fraud also gain in their CTR rating, which works in their favor in future auctions (recall that Google's ranking mechanism favors advertisers with high historical CTRs).

While the above arguments have merits, they also have flaws. The first argument works best when the click-fraud attack is predictable. When the attack is unpredictable, advertisers cannot effectively discount its impact. Also, unpredictable click fraud creates uncertainties for advertisers, which can make keyword advertising unattractive. As to the second argument, while receiving fraudulent clicks has positive effects under the current system, it is unclear whether the positive effects can dominate the negative ones.

In what follows, we discuss measures to detect and to prevent click fraud. Detection efforts such as online filtering and off-line detection reduce the negative impact of fraudulent clicks. Preventive measures such as using alternative pricing or a new rental approach can reduce or eliminate incentives to conduct click fraud.

6.1 Detection

6.1.1 Online filtering

A major tool used in combating click fraud is an automatic algorithm called "filter." Before charging the advertisers, major KAPs use automatic filter programs to discount suspected fraudulent clicks as they occur. Such filters are usually rule-based. For example, if a second click on the advertisement occurs immediately after a first click, the second click ("the doubleclick") is automatically marked as invalid, and the advertiser will not pay for it. KAPs may deploy multiple filters so that if one filter misses a fraudulent click, another may still have a chance to catch it. Tuzhilin (2006) studied filters used by Google and stated that Google's effort in filtering out invalid clicks is reasonable, especially after Google started to consider doubleclicks as invalid clicks in 2005.

⁹<http://googleblog.blogspot.com/2006/07/let-click-fraud-happen-uh-no.html>

While some fraudulent clicks are easy to detect (e.g., doubleclicks), others are very difficult. For example, it is virtually impossible to determine whether a click is made by a legitimate Internet user or by a laborer hired cheaply in India to click on competitors' advertisements.¹⁰ The current filters are still simplistic (Tuzhilin, 2006). More sophisticated and time-consuming methods are not used in online filters because they do not work well in real-time. As a result, current filters may miss sophisticated and less-common attacks (Tuzhilin, 2006). The fact that advertisers have requested refunds or even pursued lawsuits over click fraud indicates that filter programs alone cannot satisfyingly address the click fraud problem.

6.1.2 Off-line detection

Off-line detection methods do not have the real-time constraint. Therefore an off-line detection team can deploy more computationally extensive methods, and consider a larger set of clicking data and many other factors (such as conversion data). Off-line detection can be automatic or manual. Google uses automated off-line detection methods to generate fraud alerts and to terminate publishers' accounts for fraudulent click patterns. Automatic off-line detection methods are pre-programmed; thus they cannot react to new fraud patterns. Google also uses manual off-line detection to inspect click data questioned by advertisers, alert programs, or internal employees. While such manual detection is powerful, it is hardly scalable. Unlike online filtering, off-line detection does not automatically credit advertisers for invalid clicks. However, if a case of click fraud is found, advertisers will be refunded.

6.2 Prevention

First of all, KAPs may prevent click fraud by increasing the cost of conducting click fraud. KAPs have taken several other steps in discouraging click spammers, including (Tuzhilin, 2006):

- Making it hard for publishers to create duplicate accounts or open new accounts after the old accounts are terminated,
- Making it hard for publishers to register using false identities, and
- Automatically discounting fraudulent clicks so that click spammers are discouraged.

All of the above prevention efforts rely on a powerful click-fraud detection system. However, a powerful and scalable click-fraud system is very difficult, if not impossible, to develop. The above prevention efforts are dwarfed if sophisticated click spammers can pass the detection.

¹⁰<http://timesofindia.indiatimes.com/articleshow/msid-654822,curpg-1.cms>

6.2.1 *Alternative pricing*

Pay-per-click is susceptible to click fraud because clicks can be easily falsified. Witnessing this, some suggest different pricing metrics, such as pay-per-action (e.g., pay-per-call and pay-per-purchase), as a remedy to click fraud. Because purchases and calls are much more costly to falsify, switching to a pay-per-action or pay-per-call pricing scheme will overcome the click-fraud problem.

Pay-per-action pricing is unlikely a remedy for all advertisers. Sometimes outcome events such as purchases are hard to track or define (e.g., should KAPs count a purchase if it is made the next day after the customer visited the link?). Other times, advertisers may be reluctant to share purchase information with KAPs. Finally, different advertisers may be interested in different outcome measures. For example, direct marketers are more interested in sales, while brand advertisers may be interested in the time Internet users spend on their websites.

One may suggest going back to the pay-per-impression model to prevent click fraud. However, pay-per-impression is subject to fraud of its own kind: knowing that advertisers are charged on per-impression basis, a malicious attacker can request the advertising pages many times to exhaust the advertisers' budgets; similarly, publishers can recruit viewers to their websites to demand higher revenue from KAPs. Goodman (2005) proposed a pricing scheme based on percentage of impressions. The assumption is that if attackers systematically inflate impressions, advertisers will pay the same amount because they still receive the same percentage of all impressions. While this proposed pricing scheme addresses the click-fraud problem to a large extent, it also has some consequences. For example, such a pricing scheme will not automatically adjust to the changes in overall legitimate traffic. As a result, web publishers have no incentives to increase the popularity of their websites. Also, the pay-per-percentage-impression pricing imposes all risks on advertisers. In general, advertisers are more risk-averse than KAPs, and it is often revenue-maximizing for KAPs to absorb some of the risks.

6.2.2 *Rental model*

Another possible remedy is a rental model in which advertisers bid on how much they are willing to pay per hour exposure. Clearly, such a pricing model is immune to the click-fraud problem. The rental model can be implemented in different ways. One way is to ask each advertiser to bid on each slot, and KAPs will assign the slot to the highest bidder. Alternatively, KAP can ask advertisers to bid on the first slot only, provided that they agree on receiving other slots at a discounted price proportional to their bid for the first slot. Such a rental model can be valuable when advertisers have a reasonable idea about how much exposure they can get from a particular slot. Of course, when the outcome is highly uncertain, a rental model also exposes advertisers to grave risks.

In sum, a single best solution to the click-fraud problem may not exist. While alternatives to pay-per-click advertising may remove incentives to conduct click fraud, they often come with other costs and limitations. Clearly, future keyword auction designs must take into account the click-fraud problem.

7 Concluding remarks

In this chapter, we review the current research on keyword advertising auctions. Our emphasis is on keyword-auction design. Keyword auctions are born out of practice and have unique features that previous literature has not studied. Keyword auctions are still evolving, giving us an opportunity to influence future keyword-auction designs. Given the central position of search and advertising in online worlds, research on keyword auctions holds important practical values.

It is worth noting that keyword auctions as a mechanism for allocating massive resources in real-time are not limited to online advertising settings. Other promising areas of application of keyword auctions include grid-computing resources, Internet bandwidth, electricity, radio spectrum, and some procurement areas. In fact, Google filed a proposal on May 21, 2007, to the Federal Communications Commission calling on using keyword-auction-like mechanisms to allocate radio spectrum. In the proposal, Google argued that a keyword-auction-like real-time mechanism would improve the fairness and efficiency of spectrum allocation and create a market for innovative digital services. As keyword auctions as a general mechanism are proposed and tested in other settings, several important questions arise. For example, what conditions are required for keyword auctions to perform well? And what needs to be changed for keyword auctions to apply in new settings?

This chapter focuses on design issues within keyword advertising settings. It would also be interesting to compare keyword auctions with various other alternative mechanisms in different settings. It is not immediately clear whether keyword auctions are superior to, for instance, dynamic pricing or a uniform-price auction where bidders bid both price and quantity. More research must be done to integrate the brand-new keyword auctions into the existing auction literature. We believe research in such a direction will yield new theoretical insights and contribute to the existing auction literature.

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