Competition and Fraud in Online Advertising Markets

Bob Mungamuru[1] and Stephen Weis[2]

[1] Stanford University, Stanford, CA, USA 94305
[2] Google Inc., Mountain View, CA, USA 94043

Abstract. An economic model of the online advertising market is presented, focusing on the effect of ad fraud. In the model, the market is comprised of three classes of players: publishers, advertising networks, and advertisers. The central question is whether ad networks have an incentive to aggressively combat fraud. The main outcome of the model is to answer this question in the affirmative.

1 Introduction

Advertising fraud, particularly click fraud, is a growing concern to the online advertising industry. At first glance, however, the incentives regarding fighting fraud seem somewhat perverse. If an advertiser is billed for clicks that are fraudulent, the ad network's revenues increase. As such, is it even in an ad network's interest to fight fraud at all? Would it make more sense for an ad network to just let fraud go unchecked? If not, can an advertising network actually gain a market advantage by aggressively combating fraud? In this paper, we address these questions by studying the economic incentives related to combating fraud, and how these incentives might translate into behavior.

An economic analysis of ad fraud is interesting because, unlike many online security threats, ad fraud is primarily motivated by financial gain. Successfully committing ad fraud yields direct monetary gains for attackers at the expense of the victims. The threat of fraud to the advertising business model and the technical challenge of detecting fraud have been topics of great concern in the industry (e.g., [5, 6]). There have been many informal conjectures in online forums and the media attempting to answer the questions we have posed above. The arguments, while sometimes intuitive, generally are not backed by a sound economic analysis. Thus, the conclusions arrived at differ widely. To date, there has been little formal analysis of the economic issues related to fraud. This work attempts to fill this gap by performing just such an analysis.

Conducting an economic analysis of the online advertising market is difficult because faithful models of the market can quickly become intractable. For example, a content publisher's type includes, among other things, the volume of traffic they receive, the quality of their content, and their user demographics and interests. Advertisers can be differentiated by the size of their advertising budgets, their valuation of traffic that they receive through online ads, the quality of their campaign, and their relevance to particular demographics. Ad networks can differ in their ability to detect ad fraud, as well as the quality and relevance of their ad serving mechanisms. Our goal is to construct and analyze a simplified model that hones in on the effect of fighting fraud.

This paper will focus solely on *click fraud* in pay-per-click advertising systems. Click fraud refers to the act of clicking on advertisements, either by a human or a computer, in an attempt to gain value without having any actual interest in the advertiser's website. Click fraud is probably the most prevalent form of online advertising fraud today [2–4]. There are other forms of ad fraud[3] that will not be addressed here.

We begin by describing a simplified model of the pay-per-click online advertising market as a game between publishers, advertising networks and advertisers. We then predict the steady-state behaviour of the players in our model. Our conclusions can be summarized as follows:

1. It is not in an ad network's interest to let fraud go unchecked.
2. Ad networks can, indeed, gain a competitive edge by aggressively fighting fraud.
3. When ad networks fight fraud, it is the high-quality publishers that win.

For brevity's sake, we don't delve too deeply into the mathematical details of our model in this paper. We state the results and predictions of our model without proof, focusing instead on their intuitive content.
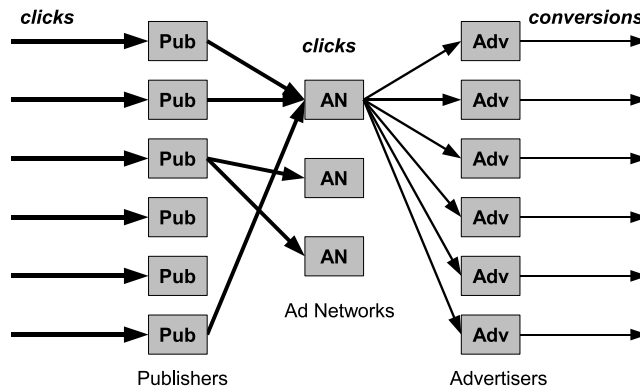
2   Model

In *pay-per-click advertising systems*, there are three classes of parties involved: publishers, ad networks and advertisers. *Publishers* create online content and display advertisements alongside their content. *Advertisers* design advertisements, as well as bid on *keywords* that summarize what their target market might be interested in. *Advertising networks* act as intermediaries between publishers and advertisers by first judging which keywords best describe each publisher's content, and then delivering ads to the publisher from the advertisers that have bid on those keywords. For example, an ad network might deduce that the keyword "automobile" is relevant to an online article about cars, and serve an ad for used car inspection reports.

When a user views the publisher's content and clicks on an ad related to a given keyword, she is redirected to the advertiser's site – we say that a *click-through* (or, *click* for short) has occurred on that keyword. The advertiser then pays a small amount to the ad network that delivered the ad. A fraction of this amount is in turn paid out to the publisher who displayed the ad. The exact amounts paid out to each party depend on several factors including the advertiser's bid and the auction mechanism being used. Advertisers are willing to pay for click-throughs because some of those clicks may turn into *conversions*[4], or "customer acquistions". The publishers and ad networks, of course, hope that users will click on ads because of the payment they would receive from the advertiser. The market for click-throughs on a single keyword can be thought of as a "pipeline", as illustrated in Figure 1 – click-throughs are generated on publishers' pages, which are distributed amongst advertisers via the ad networks, with the hope that some of the clicks turn into conversions.

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[3] See [1] for a detailed discussion of the various types of ad fraud.

[4] The definition of a conversion depends on the agreement between the advertiser and the ad network, varying from an online purchase to joining a mailing list. In general, a conversion is some agreed-upon action taken by a user.

Fig. 1. The online advertising market.

Apart from ad delivery, advertising networks serve a second important function, namely, trying to filter out invalid clicks. *Invalid clicks* can be loosely defined[5] as click-throughs that have zero probability of leading to a conversion. Invalid clicks include fraudulent click-throughs as well as *unintentional clicks*. For example, if a user unintentionally double-clicks on an ad, only one of the two clicks has a chance at becoming a conversion, so the other click is considered invalid. Going forward, we will speak of valid and invalid clicks, rather than "legitimate" and "fraudulent" clicks. In practice, advertisers are never billed for clicks that ad networks detect as invalid. Ad networks will, of course, make mistakes when trying to filter out invalid clicks. In particular, their filters may produce *false negatives* by identifying invalid clicks as valid, and *false positives* by identifying valid clicks as invalid. Ad networks differ in how effectively they are able to filter, as well as how aggressively they choose to filter. Our goal is to study how filtering effectiveness and aggressiveness affects an ad network in the market.

In some cases, a publisher and an ad network are owned by the same business entity. For example, major search engines often display ads next to their own search results. Similarly, a publisher and an advertiser can be owned by the same entity. Online newspapers are a common example. In our model, even if a publisher and an ad network are owned by the same entity, they will nevertheless both act independently. Consequently, the model may predict some behaviors that, while economically rational, are unlikely to occur in practice. For example, a real-world entity that owns both a publisher and an ad network is unlikely (for strategic reasons) to display ads from a rival ad network on its properties, even if it might yield an immediate economic advantage.

2.1 Player Types

We model the online advertising market as an infinite-horizon dynamic game between publishers, ad networks and advertisers. Publisher i's type is a triple (V_i, r_i, β_i) where

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[5] It is still a topic of some debate what the exact definition of an invalid click should be.

$V_i \in [0, \infty)$ is the volume of clicks on i's site per period, $r_i \in [0, 1]$ is the fraction of i's clicks that are valid and $\beta_i \in [0, 1]$ is the fraction of i's valid clicks that become conversions. For example, if $V_i = 10000$, $r_i = 0.7$ and $\beta_i = 0.2$, then publisher i has 7000 valid clicks per period of which 1400 convert. Advertiser k's type is (y_k, R_k), where $y_k \in [0, \infty)$ is the revenue generated by k on each conversion, and $R_k \in (0, \infty)$ is their target *return on investment* (ROI). For example, if $y_k = \$100$ and $R_k = 2$, then advertiser k would be willing to pay at most \$50 per converted click-through.

Ad network j's type is $\alpha_j \in [0, 1]$. The parameter α_j describes the effectiveness of ad network j's invalid click filtering i.e., its *ROC curve*[6]. In particular, we assume that if ad network j is willing to tolerate a false positive rate of $x \in [0, 1)$, they can achieve a true positive rate of x^{α_j}. Therefore, if $\alpha_1 < \alpha_2$, we can say that ad network 1 is more effective at filtering ad network 2. If $\alpha_j = 0$, it means j is "perfect" at filtering (i.e., j can achieve a true positive rate of 1 with an arbitrarily small false positive rate), whereas at the other extreme, $\alpha = 1$ means j is doing no better than randomly guessing. The parameter α_j captures the concave shape of typical real-world ROC curves.

2.2 Decision Variables

At the start of each period t, publishers decide which ad networks' ads to display, or equivalently, how to allocate their "inventory" of click-throughs across the ad networks. Publisher i chooses $c_{i,j,t} \in [0, 1]$ $\forall j$ such that $\sum_j c_{i,j,t} = 1$, where $c_{i,j,t}$ is the fraction of i's click-throughs that i allocates to j. In the earlier example with $V_i = 10000$, $c_{i,j,t} = 0.2$ means i sends 2000 clicks to j in period t. We assume that publisher i will choose $c_{i,j,t}$ such that their expected profit in period t is maximized.

Simultaneously, advertiser k chooses $v_{k,j,t} \in [0, \infty)$ $\forall j$, which is their valuation of a click (on this keyword) coming from ad network j. If j is using a truthful auction mechanism to solicit bids on click-throughs, $v_{k,j,t}$ will also be k's bid for a click. We assume that advertisers submit bids on each ad network (i.e., they choose $v_{k,j,t}$) such that their period-t ROI on every ad network is R_k.

Having observed $c_{i,j,t}$ $\forall j$ and $v_{k,j,t}$ $\forall k$, ad network j then chooses $x_{j,t} \in [0, 1)$, which is j's false positive rate for invalid click filtering. Recall that the true positive rate would then be $x_{j,t}^{\alpha_j}$. For example, if $\alpha_j = 0.5$ and $x_{j,t} = 0.25$, then j's period-t false positive rate would be 0.25 and the true positive rate would be $\sqrt{0.25} = 0.5$. There is a tradeoff involved here. If $x_{j,t}$ is high (i.e., filtering more aggressively), j will detect most invalid clicks, but the cost is that more valid clicks will be given to advertisers for "free". Conversely, if $x_{j,t}$ is low (i.e., filtering less aggressively), ad net j and its publishers will get paid for more clicks, but advertisers will be charged for more invalid clicks. Ad networks compete with each other through their choice of $x_{j,t}$. We assume that ad networks choose $x_{j,t}$ such that their infinite-horizon profits are maximized.

3 Equilibria

We now consider the *steady-state* behaviour of the players in our model i.e., $x_{j,t} = x_j$, $c_{i,j,t} = c_{i,j}$ and $v_{k,j,t} = v_{k,j}$.

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[6] ROC is an acronym for *Receiver Operating Characteristic*.

Theorem 1. *Suppose there are $J \geq 2$ ad networks, and $\alpha_1 < \alpha_2 \leq \alpha_j \ \forall j \geq 2$. Then, the following is true in any subgame-perfect Nash equilibrium:*

1. *For every decision profile $\mathbf{x} \in [0, 1)^J$, there exists a j^* such that $c_{i,j^*} = 1 \ \forall i$.*
2. *There exists an $x^* > 0$ such that if ad network 1 chooses any $x_1 > x^*$, then $c_{i,1} = 1 \ \forall i$, irrespective of what the other ad networks choose.*
3. *As $\alpha_1 - \alpha_2 \to 0$, $x^* \to 1$.*
4. *As $x^* \to 1$, low-quality publishers get a diminishing fraction of the total revenue.*

Thus, it is a dominant strategy for ad network 1 to filter at a level x_1 greater than x^*, and win over the entire market as a result.

The intuition behind Theorem 1 is as follows. Recall that $\alpha_1 < \alpha_2 \leq \alpha_j \ \forall j \geq 2$ implies that ad network 1 is the most effective at filtering invalid clicks, and ad network 2 is the second-most effective. Part 1 says that for any $\{x_1, \ldots, x_J\}$, all publishers (even the low-quality ones) will send their clicks to the same ad network. Part 2 says that since ad network 1 is the most effective at filtering, all publishers will choose ad network 1, as long as they filter more aggressively than than x^*. Ad network 1 will be indifferent between $x \in [x^*, 1)$. Part 3 says that as ad network 1's technology lead narrows, they must be increasingly aggressive in order to win over the market. Part 4 is intuitive, since filtering aggressively penalizes low-quality publishers most heavily.

4 Conclusion

Theorem 1 implies that, indeed, letting fraud go unchecked (i.e., choosing $x_j = 0$) is suboptimal. Moreover, the ad network that can filter most effectively (i.e., lowest α_j) does have a competitive advantage – a very dramatic one, in this simplified case. In the real world, obviously no ad network is earning 100% market share. On the other hand, publishers in the real world do often choose the most profitable ad network, and would switch to a different ad network if revenue prospects seemed higher and switching were frictionless. So, to the extent that players act purely rationally, we conjecture that our predictions would hold true in practice. Accounting for differences between ad networks in revenue sharing, ad targeting and "quality-based pricing" may explain deviations from Theorem 1, and would be a promising extension to our model.

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