
Research paper

Characterizing fraud and its ramifications in affiliate marketing networks

Peter Snyder,^{1*} and Chris Kanich¹

¹University of Illinois at Chicago, Chicago, Illinois, USA

*Corresponding Author: E-mail: psnyde2@uic.edu

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Abstract

Cookie stuffing is an activity which allows unscrupulous actors online to defraud affiliate marketing programs by causing themselves to receive credit for purchases made by web users, even if the affiliate marketer did not actively perform any marketing for the affiliate program. Using 2 months of HTTP request logs from a large public university, we present an empirical study of fraud in affiliate marketing programs. First, we develop an efficient, decision-tree based technique for detecting cookie-stuffing in HTTP request logs. Our technique replicates domain-informed human labeling of the same data with 93.3% accuracy. Second, we find that over one-third of publishers in affiliate marketing programs use fraudulent cookie-stuffing techniques in an attempt to claim credit from online retailers for illicit referrals. However, most realized conversions are credited to honest publishers. Finally, we present a stake holder analysis of affiliate marketing fraud and find that the costs and rewards of affiliate marketing program are spread across all parties involved in affiliate marketing programs.

Key words: affiliate marketing, cybercrime, machine learning.

Introduction

Despite the size of the online display advertising market, there are still alternative revenue opportunities for free-to-access web services. Along with models like freemium and crowdfunding, affiliate advertising is a prevalent method of creating revenue for a free website. As with any online revenue generation scheme, there are opportunities for bad actors on the Internet to defraud affiliate networks for what is potentially a substantial sum. What we don't yet understand is how prevalent and successful this fraud is. Understanding its effect on the market can inform technical solutions to the problem as well as provide motivation for how many resources should be committed to finding solutions.

Online affiliate marketing is a commercial system in which an online retailer attempts to increase traffic to their site—and hopefully their sales—by compensating third parties to promote the retailer's goods and services. Many large online businesses run affiliate marketing programs, with some of the largest run by Amazon.com, GoDaddy, eBay and WalMart [1–4].

Dishonest parties try to subvert these systems for personal gain. Affiliate marketing fraud occurs when a dishonest party hacks a

website, leaves a spam comment, or simply adds some code to an unrelated page which causes visitors to also visit the fraudster's affiliate link. Online retailers then pay the most recent affiliate for generating any successive sales, even if the user was completely unaware of loading the fraudster's affiliate link. This fraud has the potential not only to provide substantial revenue to the fraudster, but can also cause the affiliate program to pay a commission when no legitimate advertising was happening.

Most damaging, however would be the effect on the revenue model itself: because only the most recent affiliate gets credited for each sale, sufficiently successful attackers could reduce the revenue for legitimate affiliate advertisers so much that the entire business model no longer works, putting both those free sites out of business and further limiting the ways in which free content can be subsidized online. Understanding the technical methods that these attackers use, as well as how damaging they actually are to the business model, is key to understanding the full effects of affiliate marketing fraud.

In the course of investigating this phenomenon, this article makes three contributions. First, we describe an automated

technique for detecting affiliate marketing fraud based on analyzing HTTP request headers with approximately 93.3% accuracy. Second, we provide measurements of how frequently affiliate marketing fraud occurs relative to valid affiliate marketing activities. And third, we provide an analysis of the costs and benefits of affiliate marketing fraud, and find that the benefits and costs of affiliate marketing fraud are spread among all parties involved in affiliate marketing programs.

Related work

Our work exists alongside a wealth of research into the role of cybercrime and fraud in online economic activity. To name several examples, Edelman and Brandi [5] looked into the organization and functioning of affiliate marketing programs, including the role that fraud plays in these systems. Dave et al. [6] developed a successful method for detecting click-fraud in advertising networks by looking for publishers who deviate from an expected baseline profit-per-user. Clayton and Mansfield [7] investigated the frequency of, and motivations behind, parties providing false information to the WHOIS system when registering domains, and found that the practice was common among domains affiliated with illegal activities. Chachra et al. [8] empirically measured how, and how often, malicious parties abused domains and web services to circumvent domain-based black-listing systems. They found that malicious parties regularly do so by piggy-backing their services on-top of popular and trusted domains, which are unfeasible to blacklist. Kanich et al. [9] measured the effectiveness of, and returns to, selling illegal pharmaceuticals promoted by through botnet produced spam campaigns. Moore and Edelman [10] found that affiliate marketing fraud was a common method of monetizing typosquatted domains. Chachra et al. [11] measured the frequency of affiliate marketing fraud using a browser extension and found that large affiliate networks are targeted significantly more than online retailer-run affiliate programs.

A primary aim of this work is to provide a stakeholder analysis of affiliate marketing fraud. Our work builds on similar analyses that have been conducted for other types of crime and fraud. Peacock and Friedman [12] studied how the costs of payment card theft are distributed between cardholders, the banks representing card holders, banks representing merchants, the merchant, and the card network in general. They found that cardholders bare a minimum amount of risk, while merchants are most negatively affected. Kshetri [13] applied a similar analysis to click-fraud and teased apart how the behavior affected the party committing the fraud, the advertiser, and the pay-per-click network operator. Khan et al. [14] also carried out a stakeholder analysis of typo-squatting, and found that despite the presence of fraud, the practice was often beneficial for all involved parties: web users, valid domain holders and typo-squatters.

Finally, a fundamental part of our methodology is inferring user intent based on HTTP header data. Schneider et al. [15] enumerated many of the difficulties of performing any analysis based on HTTP traces, including dealing with HTTP pipelining, incorrect advertised content types, and wrongly provided content length fields. Xie et al. [16] provide a method for inferring and rebuilding user browsing sessions based on collections of HTTP requests. Most relevant to our work is their focus on the HTTP referrer field and timestamp information. Neasbitt et al. [17] built on this research in their work on reconstructing browser sessions from HTTP request logs. Their work uses an instrumented browser and replayed parts of the HTTP

logs to deal with ambiguities in the methods used by Xie and our work, and in effect represents a trade off between accuracy and performance.

Background

Modern website monetization programs have become increasingly complex. Here we provide an overview of the relevant actors in the space, as well as define terms which we will use for the remainder of the article.

Affiliate marketing programs

Affiliate marketing programs are programs set up by online retailers to increase their sales. While these are run by both on-and-offline businesses, this article only considers on-line programs. Affiliate marketing programs consist of three main parties, online retailers that set up the programs to increase the sales of their products, publishers which promote the online retailers' sites and products in exchange for compensation from the retailer, and web users, which are the target of the affiliate marketing programs. Online retailers hope that when web users visit websites run by publishers, the publishers will convince some web users to visit the online retailer's web site and make purchases.

Online retailers, like traditional businesses, must promote themselves and their products to generate sales, stay in business, and make a profit. However, for online retailers the need for marketing is arguably intensified by the Internet's low barriers to entry and relative lack of geographic restrictions, both of which result in greater competition and greater difficultly retaining consumers.

One technique online retailers use is affiliate marketing, where the retailer outsources some of the marketing work to third-parties on the Internet. These sites—publishers—then take on some of the responsibility for promoting the goods and products of the online retailer. In exchange, the online retailer agrees to share a portion of the profits resulting from the publisher's promotion with the publisher. Amazon, GoDaddy, eBay and Walmart run the largest affiliate marketing programs on the web, with Amazon's being by far the most popular.

Because retailers generally only pay publishers when sales occur, affiliate marketing programs are generally low risk endeavors for online retailers. The challenge for an online retailer in setting up an affiliate marketing program is instead in two other areas, (i) ensuring that the correct third party is credited for sales that publisher generated, and (ii) only paying publishers for sales that they are responsible for (i.e. to not share sales that would have happened even without the publisher's promotion). In the former case, the goal is to maintain fair and ongoing relationships with promoting publishers; in the second, profit maximization by minimizing the payouts of the affiliate marketing program.

Publishers are the third-party websites that participate in affiliate marketing programs by directing visitors—and potential customers—to the online retailer's website. Honest publishers do this in many ways, such as including links on their websites or newsletters, promoting and linking to products on the online retailer's website, or the online retailer's website itself. If any web users visit these links, traveling from a web property the publisher controls to the online retailer's site, and then make a purchase on the online retailer's site, the online retailer pays the publisher a portion of the sale in compensation.

Finally, web users are anyone on the Internet using a commodity web browser to interact with the web. These interactions might

include visiting web pages controlled by publishers or making purchases from online retailers. As a group they are the indirect target of online retailers' marketing efforts; online retailers hope that affiliate marketing programs will result in more web users making purchases from the online retailers.

General implementations

Though each affiliate marketing program studied in this article differs in the details, each is implemented in a similar manner. Online retailers build and maintain the infrastructure for the affiliate marketing program, including means to track which publishers delivered which web users, web portals for publishers to monitor their credit, and so on. Parties wishing to monetize their web sites register with the online retailers through these web portals to become publishers. The online retailer then provides each publisher with an affiliate identifier, which the publisher uses to identify herself to the online retailer going forward. Whenever the publisher creates links or directs traffic to the online retailer, she does so by combining her affiliate identifier, the online retailer's domain, and a path provided by the online retailer to create an affiliate link. Any web users who come to the online retailer's site using an affiliate link will have an HTTP cookie set in their browser, identifying the web user as having come from the publisher. The web user is then able to use the online retailer's site and make purchases as normal.

When the web user makes a purchase on the online retailer's site, the online retailer checks to see if the web user has an HTTP cookie identifying them as having come from a publisher. If so, the publisher receives a portion of the sale price as compensation for "delivering" the shopper to the online retailer.

Illustrative example

To better understand how this is carried out in practice, consider the following example. Asher runs a website where he reviews movies. Asher decides he would like to make money from his site, so he becomes a publisher in an affiliate marketing program by Amazon, an online retailer. Amazon provides Asher with an affiliate identifier, such as "Asher123", which he uses to identify his visitors in the program.

In Amazon's affiliate marketing program, Asher is only paid when a web user visiting Asher's site clicks on a link, travels to Amazon, and makes a purchase on Amazon's site. To encourage his visitors to do this, Asher edits his site to add a link to Amazon next to each movie review. This link might read "purchase this movie on Amazon." Clicking the link would then take the web user to an affiliate link on Amazon's site, such as `http://amazon.com/example-movie?publisher=Asher123`, indicating to Amazon that the user came from Asher's site.

Mark is a web user visiting Asher's site. He sees one of the links Asher created and clicks on it. Mark is then taken to Amazon, but at a URL containing Asher's affiliate identifier, identifying to Amazon that Mark was directed by Asher. Amazon receives this request and responds by recording that Mark's browser visited Amazon due to a link from Asher's site (When a web browser makes a request to a URL, the web server listening to that URL respond with a Set-Cookie header, instructing the web browser to return a given key-value pair on all subsequent requests to the same domain. This allows web servers to keep track of users between different web requests. In the case of affiliate marketing programs, cookies are also used to keep track of which publishers delivered with web users. Cookie stuffing is called as such because this functionality is typically implemented by setting a special cookie in the user's browser:

the fraudster is then thought to be "stuffing" it into the browser, unbeknownst to the user and possibly displacing an honest affiliate. Amazon's implementation does not change anything about the user's session cookie (a unique identifier generated for all visitors to the site), but rather stores this session-to-affiliate mapping server side.)

Mark might then browse around Amazon, or even leave his computer and continue shopping a few hours later. Mark eventually adds several items to his shopping cart and makes his purchase. When Amazon is processing the purchase, Amazon notices that Mark had recently clicked through to Amazon via a link from Asher's site. Amazon would then credit Asher a portion of Mark's purchases, using a formula based on the types and number of products being purchased [18].

Affiliate marketing fraud

The above example describes how an online retailer intends an affiliate marketing program to work. In practice, malicious users try to defraud the system, attempting to receive credit for sales they did not generate. This process is called affiliate marketing fraud, and it occurs when a fraudulent publisher tricks a web user's browser into visiting a page on the online retailer's site that the web user did not intend to visit, or in some cases, even realize their browser visited. These links cause the online retailer to record that the publisher generated the "sales lead," and gives the fraudulent publisher credit for any purchases the web user might make.

There are many ways this is done in practice. One common way is for a fraudulent publisher to control a website, or have broken into a website they do not control. The fraudulent publisher could then add a hidden *iframe* element to the site, and set this *iframe* to an affiliate link on the online retailer's domain. The fraudulent party would set the affiliate link to include their affiliate identifier, causing the online retailer to treat this request as though the fraudulent publisher encouraged the web user to visit the online retailer.

Thus, when the web user's browser renders the page that the fraudulent publisher has manipulated, the browser will also render the embedded *iframe*, resulting in a new request from the web user's browser to the online retailer's site. When the online retailer processes this web request, they will again set a cookie on the web user's browser, now giving the fraudulent publisher credit for delivering the web user and possibly overwriting any record that the web user was previously referred by an honest publisher.

The online retailer is generally unable to determine if the web user intended to visit the online retailer, and thus gives the fraudulent publisher credit for any purchases made by the web user. This behavior is "fraudulent" because it does not reflect the intent of the web user, and likely does not result in additional sales for the online retailer, yet results in the fraudulent publisher being paid.

Other common ways malicious parties carry out affiliate marketing fraud includes Flash objects that spawn new pages in the background, javascript redirects (either directly included or through XSS), or through malware installed on a web user's machine that opens pages on the online retailer's site carrying the fraudulent publisher's affiliate identifier. Note that regardless of the delivery mechanism, the fraudster must cause the web user's browser to visit the fraudster's affiliate link, otherwise the fraudster will not be credited for the sale.

Data

To better understand affiliate marketing fraud, we looked at many affiliate marketing programs run by popular online retailers. We

Table 1. Extracted regular expressions for the five most frequently observed programs (in PCRE format)

Online Retailer	Domains	Cookie Setting URL
Amazon	(www\.)amazon\.com	?(?:.*(dp gp)/.)*? [&?]tag=
GoDaddy	^godaddy\.*	(?:& \? ;);isc=
imlive.com	^imlive\.com\$	(?:& \? ;);wid=
wildmatch.com	^wildmatch\.com\$	(?:& \? ;);wid=
eroticasians.com	\.eroticasians\.com\$	\?t T=
Online Retailer	Conversion URL	
Amazon	*handle-buy-box*	
GoDaddy	*domains/domain-configuration\.aspx*	
	hosting/web-hosting-config-new\.aspx	
	ssl/ssl-certificates-config\.aspx	
	hosting/vps-hosting-config\.aspx	
imlive.com	*savebillclickout\.ashx*	
wildmatch.com	*/join/*	
eroticasians.com	*signup.html*	
Online Retailer	Affiliate Identifier	Session ID (for cookie data)
Amazon	tag = (.*)?(?:& \$)	session-token = ([\;]+)
GoDaddy	cvosrc = (.*)?(?:& \$)	visitor = ([\;]+)
imlive.com	wid WID = (.*)?(?:& \$)	spvdr = ([\;]+)
wildmatch.com	wid WID = (.*)?(?:& \$)	vi = ([\;]+)
eroticasians.com	t = (.*)?(?:& \$)	ntc = ([\;]+)

then looked at the incidence of affiliate marketing activity in real-world HTTP request headers. This section describes the size, structure and source of the data used in this analysis, followed by a detailed explanation of how the raw log data was processed into data structures used in the analysis described in the next section.

Affiliate marketing programs

Six affiliate marketing networks were analyzed in this research. These included the largest affiliate marketing programs identified in our dataset, run by Amazon and GoDaddy, as well as four affiliate marketing networks covering 164 individual affiliate marketing programs: The ClickCash network, consisting of 6 sites at the time the data was collected, the MoreNiche network, consisting of 9 sites, the PussyCache network, consisting of 8 sites, and the Sextronics network, encompassing 141 sites.

We selected these programs because they are large parties in the affiliate marketing economy, particularly Amazon and GoDaddy. A large volume of traffic to these sites was carried over unsecured HTTP connections during January and February of 2014, which allowed us to follow the related affiliate marketing activity in our dataset. Additionally, these parties use regular affiliate identifiers and predictable patterns in their affiliate links, which make it possible to extract the affiliate marketing activity from the structure of the URLs requested, without needing any information held in secret at the online retailers.

Only a subset of online affiliate marketing programs meets the above conditions. Other popular affiliate marketing programs, including Commission Junction and Google Affiliate Network, were examined but were not able to be included in this work. This was for a variety of reasons, including using non-predictable URLs in affiliate links and conversion URLs

(which made detecting referrals and purchases infeasible) and carrying the majority of their traffic over HTTPS (which resulted in traffic in these networks from being omitted from our dataset).

As such, this work measures only a subset of the affiliate marketing economy. However, the substantial size of the affiliate

marketing programs selected make us confident that we are capturing a large portion of affiliate marketing activity in terms of economic activity, if not in terms of parties involved. Thus, while we cannot estimate the absolute amount of affiliate marketing activity in our dataset, the findings in this article constitute a lower bound.

Our goal was to measure, for each affiliate marketing program analyzed, how frequently web users visited affiliate marketing links, received affiliate marketing tracking cookies, and made purchases from online retailers. We also wanted to understand the ratio of honest versus fraudulent activity occurring in each network.

To do so, we registered as a publisher in each affiliate marketing program and created regular expressions to match both the affiliate links and the contained affiliate identifiers in each system. We also extracted regular expressions to detect URLs indicating a web user was making a purchase from an online retailer. We refer to these as conversion URLs. These patterns are included in [Table 1](#).

For online retailers that served most of their site's content over HTTP, but which directed users to HTTPS connections for the checkout process (most significantly in our dataset, Amazon and GoDaddy), we used the URL for the "add to cart" or equivalent pages as proxies for conversion URLs. As is explained in further detail below, this was done because our data set does not include any requests made over HTTPS. Conversion URLs that occurred close together in time (within an hour of each other) were coalesced into a single event. We refer to these events—visiting a conversion URL for online retailers that do not force HTTPS, or visiting an "add to cart" URL for online retailers to do—as conversion events. While this method will result in over counting the number of purchases made from online retailers because not all conversion events result in purchases, we believe that this is the best possible approximation given the data available ([Table 6](#)).

HTTP logs

Raw data

We conducted this research on HTTP request logs taken from a large East coast university in the United States. The size and dates of

Table 2. Counts of http request records

Date	Count	Size
January 2014	895 722435	240G
February 2014	1 440 677 533	420G
Total	2 336 399 968	660G

these request logs are described in Table 2. Each record in the HTTP logs included the following fields.

- requester IP address;
- User Agent header;
- the IP of the host the request is being sent to;
- the domain and the path of the resource being requested;
- timestamp;
- returned HTTP status code;
- the HTTP referrer (if available).

We processed this raw data as follows. First, we reduced the data set by removing all logs documenting requests for any-non HTML or text asset, based on the returned MIME type, with the notable exception of HTTP redirect responses, which were also retained. The remaining logs were processed into trees, each representing part of a browsing session by a user on the network. We refer to these trees going forward as browsing-session trees.

Browsing sessions as trees

Conceptually, each time a web user opens her web browser, the set of visited pages can be thought of as forming a tree, with any URL typed into the browser's URL field forming the root of a tree. These "typed" URLs are roots of each tree because they are "initial" requests, not the result of visiting any "parent" page. All links clicked on from any of these root pages take users to a child page, adding a child-node to the browsing-session tree. These child-requests in turn lead to their own child-requests and so on, resulting in a tree of arbitrary depth and complexity. Because users can click the "back" button and click on a different link, or open different links from the same page in a new tab or window, each node can have multiple children. In this conception, starting a new browsing session equates to constructing a new parallel tree of requests, with the first page visited in the new window forming the root of the new tree.

Parsing the original log records into browsing-session trees eased analyzing a user's behavior in several ways. First, having a tree structure made it trivial to find the series of requests that brought a web user to a given page. Instead of needing to search through a massive flat file, answering this question with a browsing-session tree only required following the path from a request (a node) in the tree to the root of the tree. Similarly, understanding how long it took a user to move between pages also becomes trivial. It could be calculated by taking the difference between the timestamp of a request node and that of its parent node.

Building browsing session trees

The flat log records were converted into browsing-session trees in the following manner. First, HTTP request records were grouped by (requester IP, user agent) pairs. Each resulting group of records roughly corresponded to an individual web user. We found IP aliasing to not be an issue in the network in question. Out of 19 985 observed pairs of IP addresses and user agent strings, we never observed multiple user agents using the same IP address at the same time.

Second, each group of records was ordered chronologically.

Third, the following algorithm was followed for each group of records. First, allocate an empty set for each web user. This set will be used to store trees describing this web user's browser sessions. Second, consider each request, earliest to latest. If a record has an HTTP referrer, check to see if it matches any of the URLs of any record in any of the browsing-session trees in the user's tree-set (within a time window which we set to 5 min). If yes, add the current record to the tree as a child of the matching record. Otherwise, if the record does not have an HTTP referrer, or if the record's HTTP referrer could not be matched to an existing node, add a new browsing-session tree to the user's tree-set, and set the record as the root of the new tree. Once this process has been carried out for each record, all records will be assigned to a tree describing a browsing session for this user.

Finally, to further reduce the working set, each tree was examined to see if it contains any records associated with either an affiliate link or a conversion URL for any affiliate marketing program under consideration, using the regular expressions extracted and discussed previously. If the tree does not include any such requests, it is removed from further consideration, since these trees trivially did not include any relevant affiliate marketing activity.

Measurement ethics

This research was conducted on organic user metadata, and thus the ethics of this collection and analysis is a primary concern. We received Institutional Review Board (IRB) approval for this research, under the grounds that the research has minimal potential for harm, and that the potential increase in understanding cybercrime offers potential beneficence for network users. Furthermore, whenever potentially private data was no longer necessary for analysis, a hashed version of the information was used in place of the raw data so that manual inspection was not performed on the raw sensitive information. Further discussion of measurement ethics in this type of environment can be found in [19].

Validation

The data processing described previously in this section made a very large unsorted collection of HTTP request logs into trees representing individual browsing sessions tied together by HTTP referrer header values. While effective for our purposes, this process was imperfect: web browsers omit the HTTP referrer header in some cases (such as when the user is visiting or leaving a site requested over HTTPS, or when a web page's "content security policy" [20] is set as such), which can cause our approach to split a logical browsing session over multiple trees. However, based on manual inspection and findings from prior work on recreating browser session from HTTP requestsxxii we do not believe that this limitation meaningfully impacted the accuracy of our analysis or affiliate marketing fraud detection techniques.

This work exists in a different context than [21] though; that work focused on recreating browsing sessions for general HTTP request logs, and the sessions being modeled were unlikely to be taking steps to frustrate the researchers. In the case of affiliate marketing fraud, there is the possibility for some fraudulent parties to take steps to cloak their activities and attempt to evade detection. This could be done by employing any of the previously discussed methods for suppressing or removing HTTP referrer headers. Doing so would prevent us from linking affiliate identifiers to their referring sites, and thus not allow us to apply our decision tree classifier to the referral.

To get a worst case estimate of how much evasion occurs in our dataset, we measured how many affiliate identifiers we could associate with a referring URL. A large percentage of unassociable affiliate identifiers could indicate that fraudulent partners were taking steps to hide their referrals by suppressing HTTP referrer headers (though note that there are also benign reasons HTTP referrer headers may be absent in HTTP requests).

This was not the case in our dataset though. We were able to associate the vast majority (92.9%) of observed affiliate identifiers with referring URLs. This suggests a low amount of detection-evasion in our data set.

Limitations and qualifications

In this subsection we note some qualifications and caveats for interpreting the results in this article. First, this work covers on the affiliate marketing programs for which we were able to collect data. While this includes some of the largest affiliate marketing programs (most notably, Amazon's), it does not include all affiliate marketing programs. It is possible that the rates of fraud in the programs were not able to measure difference from the rates of fraud in the programs we were able to measure.

Second, this study draws on data taken from two of internet usage at a United States university taken during winter. It is possible that non-university internet users experience affiliate marketing fraud at different rates than web users in general, or that affiliate marketing fraud happens less often during the winter than other times during the year. If either were the case, it could cause our approach to under represent the amount of fraud in affiliate marketing programs.

Additionally, it is possible that some fraudulent partners may take steps to avoid detection beyond what we anticipate in this work. For example, they may inject delays in the redirection process, which would cause our classification algorithm to miss the fraudulent behavior, and thus undercount the amount of fraud in these systems. While this is possible, we expect that these types of evasion strategies are rare, since the more delays the fraudulent partner injects in the referral process, the less frequently the referral process will succeed, since web users could browse away before the redirection process completes. However, we note and acknowledge the possibility that more sophisticated evasion techniques would cause us to under report fraud.

Measurements

Fraud detection

Measuring fraudulent activity in affiliate marketing programs requires inferring the intent of the web user based on the time and content of their HTTP requests. We developed a decision tree classifier that labels HTTP requests to affiliate links as either “fraudulent” or “honest”, reflecting the intent—or lack thereof—of the web user behind those requests. Our classifier replicated trained human labeling of the same data with 93.3% accuracy, a false positive rate (i.e. an incorrect label of “fraudulent”) of 1.5%, and a false negative rate (i.e. an incorrect labeling of “valid”) of 5.2%. The classifier requires minimal network activity (a maximum of one request per domain), and otherwise requires no data beyond what is in the HTTP request logs. We detail in the following sections how we generated and evaluated this classifier, followed by how we applied the classifier to our data to measure fraudulent affiliate marketing activity.

Training data

We built our classifier based on a subset of our data (a subset of the January 2014 data), and ran our classifier on the remaining data

(the remaining January 2014 records as well as data from February of the same year). 1141 browsing-session trees from the January data that contained affiliate links were manually inspected to determine if the request looked to be the result of user intent, or if the request appeared fraudulently generated.

We had labeled each affiliate link request by examining the surrounding requests in each browsing-session tree and manually visiting each page that referred a web user to an affiliate link (the parent of the affiliate link node in the browsing-session tree). We label a request as fraudulent if any of the following apply:

- without any interaction a new window to an affiliate link was visited;
- the current window was redirected to the same;
- an affiliate link was requested in an iframe;
- a flash element made a cross domain request to an affiliate link
- a request was made in any other way (such as an image or script reference) to an affiliate link without interaction

In many cases we were not able to access the content of the referring page, or there was no longer a reference to the affiliate link on the referring page. Given the age of the data at time of examination (the hand-labeling was done in October and November of 2014, the examined requests were made in January 2014) this could have occurred for a wide variety of reasons, such as site redesigns, domain expirations, or changes to content.

In cases where we were not able to find a reference to the affiliate link, and thus could not recreate the steps that caused the web user to arrive at the affiliate link from the referring page, we had to make a best effort estimate based on characteristics of the browsing-session tree. We based our decisions in these cases on whether there were request patterns in the browsing-session tree that appeared “suspicious”, or out of what standard, user-initiated browsing patterns look like. Examples of such suspicious patterns include web users being redirected to the affiliate link's site almost instantly (faster than would have been possible for them to read, and maybe even fully render, the page), or referrals coming from domains with nonsensical, machine generated domains which themselves had no referrer.

To minimize the chances of false positives (e.g. false “fraudulent” labels), we rounded all decisions strongly towards “honest,” thus maintaining a high burden of suspiciousness for any “fraudulent” labelings.

Fraud classifier

Once we hand labeled the January data set, we built a classifier that would accurately approximate the human labels for the rest of our data, the remaining January records and the larger set of requests made in February 2014. We did so by generating a simple decision tree algorithm that was able to match the human generated labels 93.3% of the time. Our decision tree consists of three boolean questions.

Referrer time

We measured the amount of time that occurred between the affiliate link being visited and the parent request in the browsing-session tree. This measure represents the amount of time that the web user spent on the referring page before clicking on a link, or otherwise visiting the online retailer's page. Note that if an affiliate link did not have a detected referrer, and thus no parent in its containing browsing-session tree, it was removed from consideration and did not receive either an “honest” or “fraudulent” label. Our decision tree treats values of less than 2 s as suggesting fraud.

Table 3. Measures of how frequently each affiliate marketing programs is requested by a web user

Retailer	Requests	Unique
Amazon	2 663 574	87 654
GoDaddy	7320	364
imlive.com	731	194
wildmatch.com	3	1
eroticasians.com	3	1
Total for 166 programs	2 671 808	88 257

Time spent on online retailer's site

This feature captured the amount of time the web user continued browsing the online retailer's site after requesting the affiliate link. Low values here indicate that the user quickly closed the window or tab depicting the online retailer's site, or never noticed it in the first place. This measure was taken by calculating the maximum time that occurred between the affiliate link and any leaf nodes below it in the browsing-session tree. Our decision tree treats values of less than two seconds as suggesting fraud.

Does the referring domain offer HTTPS?

A HTTPS request was made to port 443 for each domain that referred a web user to an affiliate link. If the server responded with a valid HTTPS connection, and the certificate offered in that request had a PKI root in Mozilla's set of trusted root certificates [22], the referring domain was treated as offering HTTPS. If a referring domain gave any valid response to an HTTPS request, our decision tree treated it as indicating no fraud.

If the answer to the first two questions was less than 2 s, and if the answer to the third decision was "no", then the affiliate link request was treated as "fraudulent." In all other cases the request was treated as "honest." Put differently, if (i) a web user spent less than 2 s on the referring page before visiting the affiliate link, and (ii) spent less than 2 s on the online retailer's site after visiting the affiliate link, and (iii) the referring domain did not offer HTTPS, we classified the referral as "fraudulent." All other referrals were labeled "honest."

The above classifier was evaluated using standard 3-fold cross-validation, with each of the hand-labeled records being assigned randomly to one of three groups. This decision tree classifier reproduced the hand labeled values 93.3% of the time.

Measuring affiliate marketing activity

Using our dataset and the above fraud detection mechanism, we were able to make several measurements which are helpful for understanding affiliate marketing programs, and the role that fraud plays in them.

Retailer popularity

First, we measured how frequently each retailer appeared in our data set, and how many sessions web users created with them. We derived the first count by summing the number of requests to each online retailer in the network trace that returned an HTML document. This number is presented in the "Requests" column in Table 3.

Similarly, we captured the number of browsing sessions initiated with each online retailer by counting the number of browsing-session trees. These counts are included in the "Unique Sessions" column of Table 3.

One limitation to note is that while this number is linearly related to the number of visitors to these services, it will be

Table 4. Number of publishers in most popular affiliate marketing programs

Retailer	Honest	Fraudulent	Total
Amazon	2268	1396	3664
GoDaddy	5	19	24
imlive.com	4	7	11
wildmatch.com	0	1	1
eroticasians.com	1	0	1
Total for 166 programs	2281	88257	3707

Table 5. Counts of referrals in most popular affiliate marketing programs

Retailer	Honest	Fraudulent	Total
Amazon	12 870	2782	15 652
GoDaddy	399	98	497
imlive.com	9	13	22
wildmatch.com	0	1	1
eroticasians.com	2	0	2
Total for 166 programs	13 283	2897	16 180

significantly larger than the actual number of individuals who use the service, as repeat visitors who do so in different sessions will be counted as different events.

Publishers

We also measured the number of publishers appearing in our dataset, grouped by affiliate marketing program. Since each publisher is given their own affiliate identifier, and each affiliate identifier must appear in an affiliate link for the publisher to be participating in the program, we detected the number of publishers in our data set by counting the number of unique affiliate identifiers appearing in affiliate links for each program. This number is included in the "Total" column of Table 4.

We then separated this measure into "honest" and "fraudulent" publishers. Fraudulent publishers are publishers that direct web users to affiliate links without the web user's intent. For our measures, "fraudulent" behavior is toxic; if a publisher is associated with both honest and fraudulent referrals, it is counted as a "fraudulent" publisher in these measures. Honest publishers are simply those that are not associated with any "fraudulent" referrals in our dataset.

A caveat to our approach is that it might over count the number of actual participants in these systems. Since individuals and companies can create multiple publisher accounts, any party can acquire multiple affiliate identifiers. While intuitively we can assume that "fraudulent" publishers are more likely than honest parties to create multiple accounts—whether to avoid detection, respond to account closures, or otherwise—the option is nevertheless present for both types of publishers. The presented numbers should therefore be treated as an upper bound on the number of observed publishers.

Affiliate marketer referrals

We also measured the number of times affiliate links were visited. This measure is an important part of understanding how significant an affiliate marketing program is to an online retailer. This measure was found by simply summing the number of affiliate links found in the data set for each affiliate marketing program. This number is included in the "Total" row of Table 5.

Table 6. Counts of conversion events in the most commonly observed affiliate marketing programs

Retailer	Conversion Events	Affiliate Conversions	Honest	Fraudulent	Stolen
Amazon	15 624	955	781	174	0
GoDaddy	26	8	8	0	0
imlive.com	0	0	0	0	0
wildmatch.com	0	0	0	0	0
eroticasians.com	0	0	0	0	0
Total for 166 programs	15 650	963	789	174	0

We then distinguished fraudulent from honest referrals by using the techniques described in the subsection 'Fraud detection'. By combining the hand-generated January validity labels with the machine classified data, we get a complete labeling of all affiliate link requests as being generated by either valid user intent ("honest") or manipulated browser activity ("fraudulent").

Conversion events

Finally, we determined the number of conversion events made with the tracked online retailers, and distinguished which conversions were a result of honest or fraudulent affiliate marketing. We also measured how often credit for affiliate-marketing-generated sales was stolen from an honest publisher by a fraudulent one.

First, we approximated the number of times web users were converted by an online retailer. For online retailers who have HTTPS protected checkout pages, we instead counted the number of sessions during which a web user added an item to their cart. This count, included in the "Conversion Events" column of Table 6, was found by counting the number of conversion events (as defined in the subsection 'Affiliate marketing programs') for each online retailer.

Next, we measured the number of conversion events credited to each affiliate marketing program. Conceptually this is the count of the number of conversions that were made by web user carrying affiliate marketing cookies. In practice though, this was made difficult by the fact that some online retailers (most significantly Amazon) track which publisher referred which web user server side, instead of directly in cookie values. Most examined affiliate marketing programs assign a cookie stating which publisher the web user came from (ex *affiliate=Example123*). Amazon differs by treating the referring publisher as part of the web user's larger session data. As a result, determining whether a web user making a purchase on Amazon came from a publisher required looking at Amazon requests in the web user's browsing session.

To account for these online retailers, we examined the web user's activities before each conversion event. Due to anecdotal evidence within the affiliate marketing community, we set the "timeout" after which an affiliate does not receive credit for a sale at 24 h. Thus, if the web user visited an affiliate link within 24 h of visiting the conversion event, we credited the affiliate marketing associated with the most recent affiliate link for the purchase. Otherwise, if the web user did not visit any affiliate links in the hour before the conversion event, we treated the conversion as not being part of the affiliate marketing program. The count of how many conversion events were credited to an affiliate marketing is included in the "Affiliate Conversions" column of Table 6.

We determined which conversions were credited to a fraudulent publisher by first extracting all conversion events from the data set. Then we considered the preceding time-window during which the online retailer would give the publisher credit for the conversion. If the web user visited no affiliate links in this time frame, the

conversion was treated as if it was made without an affiliate marketing cookie. If the most recent affiliate link was labeled as "honest", then the conversion event was attributed to an honest publisher, and included in the "Honest" column of Table 6. Conversely, if the most recent affiliate link was labeled as "fraudulent", it was included in the "Fraudulent" column of the same table.

Finally, we calculated the number of conversion events that were credited to a fraudulent publisher which would have otherwise been credited to an honest publisher. We call these events affiliate marketing thefts, since they represent instances where a fraudulent publisher party "stole" credit for a conversion from an honest publisher. We detected these events by taking the same 24-h window described in the previous paragraph and looking for instances where a conversion event was credited to a fraudulent publisher, but where the window also contained honest affiliate links. In the 2 months of data we examined, we did not find any instances of affiliate marketing theft, as is documented in the "Stolen" column of Table 6.

Analysis

Here we use the data and measurements described in the previous sections to better understand the affiliate marketing ecosystem and the different actors in it.

Market analysis

Our measurements of affiliate marketing programs reveal several interesting aspects of these markets. First is that there are a large number of fraudulent publishers in these systems. In the largest affiliate marketing program observed, Amazon's, over one-third of the observed publishers engage in "cookie-stuff". In the case of the second largest observed affiliate marketing program, GoDaddy's, the case is even more dramatic, with the majority of observed publishers carrying out fraudulent activity. From the data we have, we conclude that a significant portion of parties participating in affiliate marketing programs are engaging in deceptive activities.

Fraudulent publishers are less successful than honest publishers. While the number of fraudulent publishers is large, they are underrepresented in conversion events completed at online retailers. For example, even though 38.1% of Amazon's affiliate partners were engaged in fraud, only 18.2% of conversion events were associated with a fraudulent affiliate identifier. In the case of GoDaddy, the numbers are even more lopsided, with 79.1% of observed partners participating in cookie-stuffing, but resulting in no purchases.

As Figure 1 shows, a relatively small number of domains contribute the majority of affiliate marketing referrals, and the majority of domains appear only once in the data. Relatively well known websites, such as *gizmodo.com*, *slick-deals.com*, *thewirecutter.com* and *dealmoon.com* refer a large number of visitors to online retailers. As these are all specifically deal focused websites which explicitly link to products throughout the site, it's very unlikely that they would have any reason to commit cookie stuff.

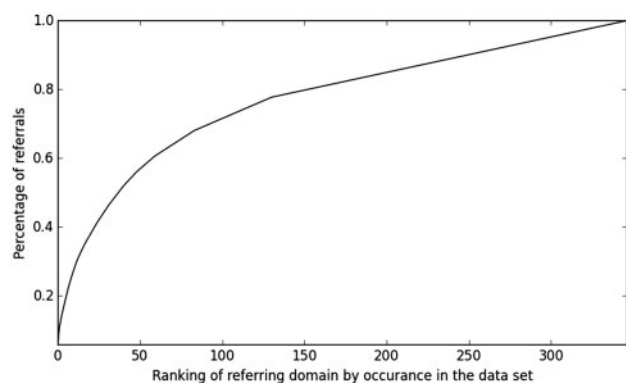


Figure 1. Number of referrals credited to each domain against each domain's frequency in dataset.

Finally, the market for affiliate marketing programs is dominated by a very small number of parties. Though we examined 166 affiliate marketing programs, the largest online retailer, Amazon, captured over 98% of affiliate marketing-produced conversion events, and the top two observed online retailers combined captured every conversion event observed.

Stakeholder analysis

The costs and benefits of affiliate marketing fraud are not distributed equally across all participants in the affiliate marketing system. This section attempts to provide a breakdown of how fraud affects each relevant party.

Web users

In most affiliate marketing programs, web users pay the same amount, whether or not their purchase is part of an referral. In terms of purchase price, web users are unaffected by affiliate marketing fraud.

Web users may be affected by affiliate marketing fraud in less direct ways though. For example, it is possible that fraud in affiliate marketing programs reaches a threshold where it is no longer profitable for the organizing online retailers, resulting in programs closing. Were this to happen, it could pose a substantial cost to web users, as one common role of affiliate marketing is to subsidize free content online. If affiliate partners suddenly lost the income provided by affiliate marketing, a large amount of now-free content might move behind paywalls, or might not be produced at all.

There have been cases of online retailers closing down affiliate marketing programs, due at least in part to fraud [23, 24]. It is not possible for us to determine the degree to which fraud led to the end of these programs, but we expect fraud to have played some role in each decision. Given the limitations of our data and the focus of this work, we cannot determine how large of a role fraud has played in the shutting down of these programs.

A final possible cost that fraud imposes on web users is that gains to online retailers from affiliate marketing programs could be used by those companies to offer possible price-reductions to shoppers. Affiliate marketing fraud may thus impose costs on web users indirectly in the form of forgone price reductions. Similarly, if fraud causes an online retailer to lose money from investments in the program, the retailer may choose to pass those losses on to the consumer in the form of higher prices, though market competition may also prevent the retailer from doing so. The effect of affiliate marketing

fraud on the prices of goods sold by online retailers is beyond the scope of this work, but is noted for completeness.

Finally, the methods used by fraudulent affiliate partners affect web users in other, less-direct ways. For example, the methods fraudulent partners use to target web users (malware, hidden, *iframes*, automated redirects, and other forms of browser manipulation) can cause users problems, ranging from minor annoyance to machine compromise. However, the tools fraudulent partners use to redirect users to affiliate links are not inherently harmful; in this narrow regard, affiliate marketing fraud is more a way that fraudulent parties can monetize machines that have already been harmed, instead of harmful to web users itself.

Fraudulent publishers

Not surprisingly, fraudulent publishers benefit the most from affiliate marketing fraud. They benefit whenever a purchase is made on an online retailer's site by a web user carrying the fraudulent publisher's cookie. For Amazon, for example, this amount is between 1 and 10% of the price of each product purchased in each manipulated sale [25]. If a fraudulent publisher is able to redirect a large number of web users, or is able to target the browsers of web users who are likely to make disproportionately large purchases, the affiliate marketing fraud can provide a large return to the fraudster.

The costs a fraudulent publisher faces are minimal. While there may be some initial fixed cost in gaining control of site web users visit—purchasing a hacked site, investing time to find a site vulnerable to XSS injection, generating content users desire, etc.—the marginal cost for each additional redirected web user is nearly zero to the fraudulent party. Similarly, attacks used to redirect browsers may be automatable, further driving down the marginal cost of the attack. Fraudulent publishers must also have the ability to receive funds from their chosen affiliate program, either in their own personal financial account or an account they control.

Fraudulent publishers also face possible costs of detection. If an online retailer detects that an affiliate marketing account is being used for fraudulent activity, the online retailer may choose to cancel the affiliate account, and the fraudulent publisher would then lose some unrealized revenue. There have been observed cases of online retailers closing accounts of fraudulent publishers [26, 27], though since most account closures are not likely publicized, we are unable to measure how frequently online retailers close accounts for fraud.

However, this does not shut down the traffic stream the fraudulent publisher was using, and if they still have control over the site, they can easily target a different site to extract revenue from the visitors (perhaps even using something more malicious like a drive-by download). This suggests that the costs a fraudulent publisher faces if detected are not total, since they can monetize their infrastructure in other ways.

Finally, a fraudulent publisher may also face legal repercussions, both private and criminal [28–30]. While the number of legal actions against fraudulent publishers seems small when compared against the large amount of fraud occurring in these markets, the magnitude of the cost of legal action to the fraudulent party may be substantial, including some fraudulent parties serving jail time.

Honest publishers

While it's unlikely that there are any benefits for honest publishers, they certainly stand to lose something in the face of affiliate marketing fraud. Honest parties face the possibility of having their referrals "stolen" by a dishonest party, thereby depriving the honest publisher of the compensation they expected. While affiliate marketing theft

was never observed in our data, it is a clear possibility, and given a large enough amount of data we expect instances of affiliate marketing theft would be found. Acknowledging that though, the costs to honest publishers appears to be much more theoretical than practical; we expect the realized costs to honest publishers are minimal.

Online retailers

Online retailers are the only party in the affiliate marketing system where the balance of costs and benefits of fraud is ambiguous. Online retailers are harmed by the additional payouts made to fraudulent affiliate partners. If the fraudulent affiliates are claiming credit for sales that would have occurred regardless of the fraudulent marketer's actions, then the fraction of the sale the online retailers must share with the fraudulent parties is pure cost. However, if the web users referred by the fraudulent publishers make purchases that otherwise would not have been made, then the affiliate marketer's fee is likely dwarfed by the additional revenue the sale brought the online retailer.

Of the four parties in the affiliate marketing system, online retailers are unique in facing both real costs and benefits. The net benefit to online retailers will depend on several business specific factors, and is beyond the scope of this analysis.

Conclusions

This article describes a large scale investigation of the role and frequency of fraud in affiliate marketing programs. We developed an efficient, automated approach for detecting fraud with 93.3% accuracy based on HTTP request logs. Using this approach, we measured the honest and fraudulent activity of 166 affiliate marketing programs across six affiliate marketing networks in 2.3 billion HTTP requests. These measurements allowed us to estimate the gains and losses of the four classes of participants with a financial interest in the market: web users, honest publishers, fraudulent publishers, and online retailers who run affiliate marketing programs.

In our dataset, two affiliate marketing programs were dominant, with the programs run by Amazon and GoDaddy accounting for more than 99.9% of observed affiliate marketing activity. A significant proportion of the publisher accounts in these programs appear to be engaged in fraud (38.1%). However, the fraudulent accounts are less successful than their honest counterparts in generating referrals (17.8% of referrals appear fraudulent), and less successful in generating referrals that end up making purchases (18.1% of observed conversion events were performed by web users carrying the affiliate identifier of a fraudulent publisher).

While this data is limited in scope due to collection artifacts (e.g. the lack of HTTPS data), the proportions between each type of affiliate marketing event allow us to provide a stakeholder analysis of affiliate marketing fraud and to identify how each party involved in affiliate marketing fraud is hurt or benefited by the activity. Although legitimate marketers could possibly be harmed by affiliate marketing fraud, we did not observe any such cases in this work. Only one of the four parties involved—the online retailer running the affiliate marketing program—faces substantial negative effects, and even these costs may be overwhelmed by the additional traffic and sales generated. We also identified other costs of affiliate marketing fraud, such as the possible collapse of affiliate marketing programs and the free content that affiliate marketing programs fund.

More generally, we find that stakeholder analysis is useful for putting a perspective on the harms involved in cybercrime. Performing this analysis on other attack or fraud schemes could aid the community in better understanding what types of deceptive and fraudulent behavior generate public costs, and thus where researcher effort can be focused to maximize societal benefit. Conversely, we expect that stakeholder analysis of other cybercrime activities may reveal that most of the negative externalities due to the fraudulent activity are actually quite marginal, and thus these problems are of lower concern for researcher effort.

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