

FP-Inconsistent: Detecting Evasive Bots using Browser Fingerprint Inconsistencies

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Abstract—As browser fingerprinting is increasingly being used for bot detection, bots have started altering their fingerprints for evasion. We conduct the first large-scale evaluation of evasive bots to investigate whether and how altering fingerprints helps bots evade detection. To systematically investigate evasive bots, we deploy a honey site incorporating two anti-bot services (DataDome and BotD) and solicit bot traffic from 20 different bot services that purport to sell “realistic and undetectable traffic.” Across half a million requests from 20 different bot services on our honey site, we find an average evasion rate of 52.93% against DataDome and 44.56% evasion rate against BotD. Our comparison of fingerprint attributes from bot services that evade each anti-bot service individually as well as bot services that evade both shows that bot services indeed alter different browser fingerprint attributes for evasion. Further, our analysis reveals the presence of inconsistent fingerprint attributes in evasive bots. Given evasive bots seem to have difficulty in ensuring consistency in their fingerprint attributes, we propose a data-driven approach to discover rules to detect such inconsistencies across *space* (two attributes in a given browser fingerprint) and *time* (a single attribute at two different points in time). These rules, which can be readily deployed by anti-bot services, reduce the evasion rate of evasive bots against DataDome and BotD by 48.11% and 44.95% respectively.

1. Introduction

The proportion of bots on the web is on the rise [1]. As of 2023, bots constitute around 47.5% of online traffic [2], with 63.6% of those being bots that engage in malicious activity. Fraudsters employ such bots to launch a multitude of attacks [3, 4, 5, 6, 7] which results in of dollars of loss to the industry. To counter such attacks, anti-bot services aim to detect and block bot traffic. Prior research has shown that anti-bot services employ browser fingerprinting to detect bots without disrupting the user experience of legitimate

users [8, 9]. Browser fingerprints capture attributes of the web browser sending web requests and anti-bot services attempt to use differences in these attributes to distinguish bots from real users [10].

Blackhat marketplaces [11, 12, 13], however, advertise realistic and undetectable bot traffic as a service. The traffic from such services constitute impression fraud and serve to artificially boost website engagement for monetization [3, 14, 15]. We surmise that the bots from these services are likely manipulating their browser attributes, which are used by anti-bot services for detection, to alter their fingerprints [16, 17] for evasion. We refer to such bots as *evasive* bots and their fingerprints as *evasive* fingerprints. It is imperative to characterize evasive bots and their fingerprints to devise countermeasures against them to bolster bot detection.

Prior research has studied bot fingerprints by employing their own bots [8, 18] or by focusing on naturally discovered bots on their honey sites [19]. Thus, this work does not capture the evasive fingerprints used by bots seeking to evade detection in the wild. Wu et al. performed a large scale characterization of the differences between human and bot fingerprints in the wild [10]. However, they did not characterize evasive bots since they treat their bot detection system decisions as ground-truth to distinguish between the fingerprints of bots and real users. Thus, they are unable to identify evasive bots that evade their bot detection system.

To fill this gap, we perform the first large-scale measurement of evasive bots that are able to evade anti-bot services. To ensure reliable ground-truth, we use a honey site architecture to selectively drive traffic from different bot services from blackhat marketplaces to different instances of our honey site. Our honey site is designed such that the requests recorded at each instance is mapped to the corresponding bot service from whom we purchased traffic. These operators advertise their traffic as being realistic and natural, indicating that they likely employ evasive bots to ensure that they

do not get detected. We integrate two commercial bot detection services (DataDome and BotD) on our honey site for bot detection.

We receive 507,080 requests from 20 different bot services, with DataDome and BotD detected 55.44% and 47.07% of these requests respectively. We systematically analyze fingerprint attributes from different bot services to identify different sets of attributes that are effective at evading DataDome and BotD individually as well as attributes that are effective at evading both anti-bot services. Our analysis reveals spatial inconsistencies (among the different attributes of a given request) and temporal inconsistencies (across requests originating from the same device). These were egregious inconsistencies that cannot exist for real users, thereby making them outright signatures to detect bots.

We use insights from our analysis to develop FP-Inconsistent, a data-driven, semi-automatic approach to discover inconsistencies in browser fingerprint attributes for more reliable bot detection. FP-Inconsistent relies on the fundamental understanding that real devices can only have limited number of hardware and software configurations that are reflected in browser fingerprint attributes. Evasive bots, in their attempt to evade detection, proliferate large number of invalid or extraneous configurations. FP-Inconsistent leverages this mismatch between expected and observed number of configurations to identify potential inconsistencies among evasive bot fingerprints. It does so by calculating the number of configurations for pairs of evasive bot fingerprint attributes, and identifying inconsistencies among attribute pairs that exhibit higher than expected number of configurations. Using this approach, we generate inconsistency rules that can be readily deployed by anti-bot services. While prior research has proposed the use of inconsistencies for bot detection [8, 20], it mainly relies on one-off anecdotes to define inconsistencies which does not scale because it is not data-driven. FP-Inconsistent is the first technique to systematize the generation of inconsistency based rules for bot detection. Our evaluation shows the rules generated by FP-Inconsistent are able to achieve 48.11% and 44.95% reduction in requests that evade DataDome and BotD respectively. We open source our rules for public use at [this link](#).

Our key contributions are:

- A **large-scale analysis of browser fingerprint attributes** for evasive bots that are able to evade anti-bot services.
- A **data-driven approach to discover inconsistencies in browser fingerprint attributes** for detecting evasive bots.
- A novel use of **honey site architecture to establish reliable ground-truth** for evasive bots.

2. Background and Related Work

2.1. Evaluation of bot detection services

Anti-bot services on the web generally employ machine learning to determine if an incoming request was sent by a human or a bot[21]. These services rely on several signals captured through different browser APIs, request headers, and behavior characteristics on a website[8]. Prior research has attempted to measure the accuracy of anti-bot services and understand their detection techniques. Azad et al. [18] analyzed 15 different anti-bot services, 14 of which used fingerprinting to detect bots. These services employ modern techniques such as WebGL and Canvas-based fingerprinting. They also detect inconsistencies in the collected bot fingerprints to determine if a request is from a bot or a human. We show in this paper (Section 7) that commercial anti-bot services can be more extensive in using inconsistencies to improve bot detection.

Azad et al. also tried to evaluate the performance of these services by deploying their own bots and measuring their evasiveness. They found that while most services were able to catch their "Basic Bots", more advanced bots, through either protection against fingerprinting scripts or employing fingerprints that are less common, were able to evade detection.

2.2. Analysis of bot traffic in the wild

Xigao et. al [19] studied the prevalence of "malicious" bots in the wild. They rely on the behavior of bots (indulging in credential stuffing, not honoring bots.txt etc) to characterize them as malicious. Such characterization is not applicable for bots indulging in impression fraud since these bots don't display any specific behavior that can be leveraged for detection. One drawback of their approach is lack of a mechanism to entice evasive bots to visit their honey sites. While it is impossible for humans to accidentally land on their sites, the bots that visit the websites are also not likely to be evasive bots.

Wu et. al[10] analyzed browser fingerprints from 36 billion requests on 14 commercial websites. Their analysis shows that adversarial bots (bots which change their fingerprints to avoid detection) have significantly different properties compared to benign bots. They found an overlap of only 1.6% of fingerprints between adversarial and benign bots. They also found that adversarial bots are involved in several different attack types, such as content scraping, fraudulent transactions, and credential stuffing. While Wu et. al conducted the largest study (at the time of writing) of bots in wild, their ground truth relies on decisions by F5 Inc.[22], a commercial anti-bot service. We show in this paper that evasive bots have high evasion rates against anti-bot

services (Section 5), identifying the need to have a more robust mechanism to collect ground-truth. Next, we discuss some of the challenges affecting bot detection.

2.3. Challenges in bot detection

Detecting bots, especially those actively trying to evade detection, is a difficult task. Adversaries using bots employ various evasion techniques to bypass bot detection systems. We discuss some of the common evasion techniques employed by bots.

Polymorphism: Bots employ techniques such as morphing their User-Agent or other attributes [18] (i.e., fingerprints) to appear as benign website visitors. Prior research on bot detection has shown that morphing fingerprints can result in successful evasion. Iliou et. al [23] showed that while machine learning algorithms can detect simple bots with a precision and recall of 95% and 97% respectively, more advanced bots, i.e. bots that change their fingerprints, result in a drop in accuracy to only 55%.

Behavioral Mimicry: Bots also simulate human-like behavior to evade behavioral analysis systems, including mimicking mouse movements, keystrokes, browsing patterns, and human text input [24]. Bot detection systems use these movements as “Human Interactive Proofs (HIPs)” [25, 26] to determine if a website visitor is a bot or a human. Jing et. al. [27] showed the development of a bot framework that employs behavioral mimicry. This framework enables bots to generate application-level events, such as keystrokes and mouse clicks, that closely resemble human actions to evade detection mechanisms. By analyzing inter-event timing and location information, the evasive bots successfully mimic human behaviors, posing a significant challenge for existing bot detection systems.

3. Threat Model

In this paper, we specifically focus on bots committing impression fraud [3]. Web publishers who seek to artificially inflate the engagement on their websites indulge in this type of fraud. Inflating engagement allows these publishers to monetize and make profits on their websites through ads, even when they cannot guarantee visits to their website from legitimate users. Advertisers pay publishers for impressions of their ad (views, clicks etc) on the publisher’s website. However, only impressions recorded from legitimate users are useful to advertisers. Publishers who don’t receive traffic from legitimate users could employ bots to record these impressions to get paid by advertisers without delivering any useful impressions to them. We focus on bots indulging in impression fraud over other types of fraud (such as credential stuffing, account takeover etc), since these bots don’t have a need to perform

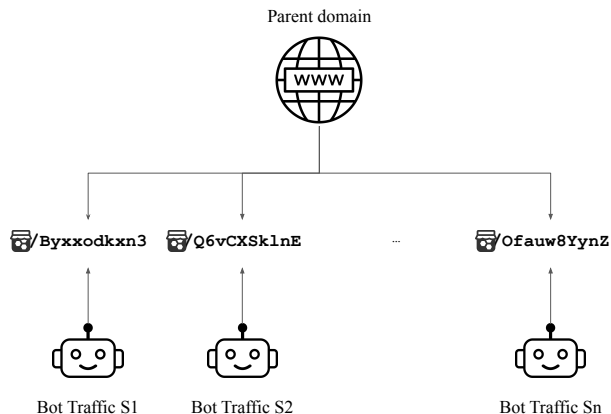


Figure 1. To collect requests from different bot services, we create multiple instances of the same honey site on the same domain. These instances differ in terms of random strings in their URL. We then drive traffic from different bot services to different instances of the honey site.

specific actions to reach their goal, thereby making it more challenging to detect them.

In our threat model, we consider publishers who incorporate anti-bot services on their websites to provide assurance of requests emerging from legitimate users, while employing evasive bots to evade detection.

4. Measurement infrastructure

In this section, we describe our measurement infrastructure including the design of our novel honey site architecture. We design our measurement infrastructure to satisfy three requirements that enable us to reliably characterize evasive bots: first, we need reliable-ground truth that we only record requests from evasive bots of interest and no other entities (real users or other bots). Second, we need decisions from bot detection services on each request to identify isolate requests that evade detection. Third, we need to collect browser attributes that constitute browser fingerprints in these requests to analyze attributes that help with evasion.

4.1. Honey site architecture

The approach of using obscure domain names for honey sites [19] cannot guarantee that the honey sites only receive requests from evasive bots. Bots that automatically send requests to such domains are typically indexing bots that visit new websites added to domain registries and other sources of DNS records. Examples of such bots includes search engine bots that do not have a need to conceal their identities. In fact, Google’s bots announce their identity through their User-Agent [28]. While evasive bots may also send requests such domains, the absence of a mechanism to isolate those requests makes it challenging to analyze them. Evasive bots indulging in impression fraud do not have a need

to perform any specific actions to reach their goal of recording views or impressions. Hence, such bots cannot be detected based on their actions/behavior.

To overcome the challenge of only recording requests from evasive bots, we deploy multiple instances of the same honey site under the same domain. These versions only differ in terms of the presence of arbitrarily chosen strings in their URL but are identical in all other aspects. We do not record requests that do not contain one of these strings in the URL. This ensures that we do not record requests from real users or generic bots that discover our domain. We also share URLs with different arbitrary strings with different bot services. Thus, these URL strings also allow us to isolate requests received from different bot services. As a concrete example, if *example.com* is the domain of our honey site, *example.com/XXXXX*, *example.com/YYYYY* and *example.com/ZZZZZ* would constitute different instances of the honey site. We then purchase traffic from 3 different bot services to each send requests to one of these URLs. Real users and other generic bots who may stumble upon our site, will not know these strings and hence cannot send requests with these exact strings. Thus, by discarding requests that do not contain a valid URL string, we can ensure that we only record requests from bots we purchased. Figure 1 shows an overview of the honey site setup we use in our data collection.

4.2. Anti-bot services

We integrated two popular commercial anti-bot services on our honey site: DataDome [29] and BotD [30]. Both DataDome and BotD provide real-time decisions on requests received on a website. DataDome advertises real-time decision for a request in under 2 milliseconds with an overall accuracy of 99% and a false positive rate of 0.01%. BotD is based on the popular open-source fingerprinting library FingerprintJS [31]. BotD claims using “the most advanced device fingerprinting technology”, and reports a detection accuracy of 99.5%.

We integrate JavaScript libraries of both these services on our honey site¹. These libraries collect information about the visiting user on the website and relay this information to their own servers. The servers respond with the final decision of whether a real human or a bot originated the request.

These services are black-boxed and do not provide information on the browser attributes they use as features to decide if a request originates from a bot. To determine this information, we crawl our honey site using OpenWPM [32]. OpenWPM is an open source tool which can be used to track the behavior and interaction of different web elements, including scripts, on a webpage.

1. As required by DataDome, for each request, we also make an API call from our server to get their decision



Figure 2. Screenshot from a seller on SEOClerks making claims about sending organic traffic to drive engagement on websites. The claims likely suggest that the seller employs bots that employ evasive fingerprints to fool real users.

Table 5 in Appendix A highlights the different browser APIs used by DataDome and BotD. We find that both these services make use of a number of popular fingerprinting APIs such as `HTMLCanvasElement.getContext` (allows drawing on the browser canvas), `window.navigator.userAgent` (returns the browser user agent), `window.navigator.plugins` (returns the plugins supported by the browser) and more. There are a few APIs which are only used by DataDome, such as `window.navigator.serviceWorker` (provides information about whether the browser supports service workers), `window.navigator.maxTouchPoints` (maximum number of simultaneous touch points supported by the device), and `window.navigator.hardwareConcurrency` (number of logical processors available on the device).

On the other hand, there are only two APIs which are accessed by BotD and not by DataDome: `window.navigator.productSub` (returns the build number of the browser), and `window.navigator.appVersion` (returns version information for the browser). Overall, we find that DataDome collects more attributes from each request as compared to BotD. In later sections, we see that DataDome has higher accuracy in detecting bots over BotD. The additional attributes collected by DataDome potentially help better detection.

4.3. Bot services

We made purchases from multiple online bot services to send traffic to different versions of our honey site. We make most of our purchases from the SEOClerks [12], an underground marketplace for web traffic where bot services advertise their traffic as being real, organic and adsense safe to boost website engagement. Their claims of being able to send real and organic traffic indicate that they are likely using evasive bots that

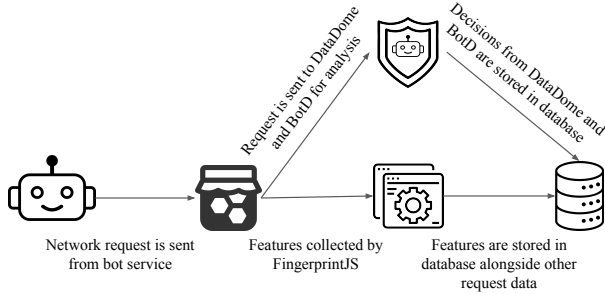


Figure 3. Overview of our data collection pipeline

alter their fingerprints to look like real users. Figure 2 captures a screenshot from a bot service on SEOClerks making such claims about their traffic. In addition to purchases from SEOClerks, we also purchase traffic from Babylon Traffic [11] and Spark Traffic [13]. While making these purchases we share URLs with different version strings with different bot services to identify the bot services of each request on our honey site.

4.4. Data Collected

To characterize the differences in the browser fingerprints of evasive bots, we extract information from different browser APIs and properties upon loading our honey site in the browser. We send this information to our server in an http request. We use FingerprintJS [31], a widely deployed browser fingerprinting library to capture this information. FingerprintJS captures over 30 different browser attributes including the list of fonts installed on the browser, the number of CPU cores on the device running the browser, the amount of memory on the device running the browser, the languages supported by the browser. While we predominantly focus on the attributes captured by FingerprintJS in our measurement analysis, we also capture features computed by CreepJS [33] along with keyboard and mouse interactions of the user.

5. Measurement analysis

In this section, we analyze the requests obtained on our honey site. Over a period of 3 months, we received a total of 507,080 requests from 20 different bot services. We first report the detection rate of the anti-bot services and then compare browser attributes of bots that evade detection against those that were detected. This analysis helps understand the attributes used by bots to evade detection and ways to overcome them.

Table 1 shows the statistics of the requests obtained from each bot service along with the evasion rate against the two anti-bot services on our honey site (DataDome and BotD). Among the 507,080 requests we received, 55.44% of requests were detected by DataDome and 47.07% of requests were detected by BotD. These results show that a significant proportion of bots are able to look like real users and evade

TABLE 1. OVERVIEW OF DIFFERENT BOT SERVICES SENDING REQUESTS TO OUR HONEY SITE INCLUDING THEIR EVASION RATE AGAINST DATADOME AND BOTD.

Bot Service	Num. Requests	DataDome Evasion Rate	BotD Evasion Rate
S1	121500	44.01%	71.58%
S2	63708	42.99%	72.29%
S3	54746	74.91%	10.26%
S4	47278	38.65%	73.85%
S5	40087	23.86%	72.65%
S6	32447	71.81%	5.45%
S7	28940	2.56%	39.99%
S8	26335	80.43%	28.9%
S9	23412	78.29%	19.33%
S10	18967	15.77%	59.23%
S11	17996	6.55%	59.36%
S12	7010	5.05%	51.44%
S13	5119	6.95%	50.52%
S14	4920	83.74%	90.08%
S15	4291	11.14%	100%
S16	4174	4.48%	0.02%
S17	2999	74.66%	7.9%
S18	1430	20.7%	100%
S19	1411	9.92%	100%
S20	382	97.12%	97.12%

anti-bot services.

Takeaway 1: Our measurement shows concrete evidence of evasive bots that are not detected by commercial anti-bot services. This shows that any characterization of differences in fingerprints between bots and real users based on the decisions of bot detection is unreliable since there exist bots that are able to present themselves as real users.

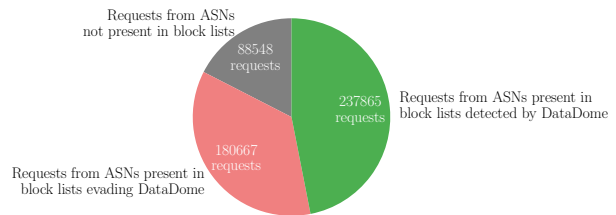


Figure 4. Pie chart showing the proportion of requests originating from IP addresses with ASNs that are not present in block lists, ASNs that are present in block lists but evading and detected by DataDome.

5.1. IP addresses for evasion

Among the requests received on our honey site, we observed requests from IP addresses with Autonomous System Numbers (ASNs) mapping to cloud services such as Amazon Web Services (AWS), DigitalOcean etc. Since such ASNs are likely flagged as those used by bots [34, 35], we check the ASNs of the requests we received against public ASN block lists [36, 37]. Figure 4 and Figure 5 show that 82.54% of requests

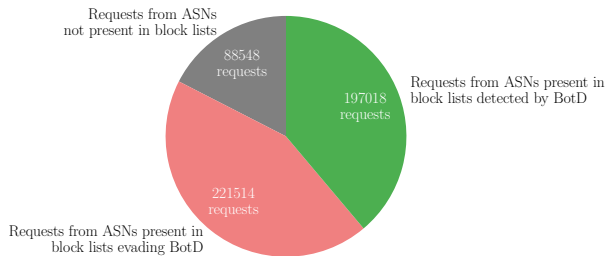


Figure 5. Pie chart showing the proportion of requests originating from IP addresses with ASNs that are not present in block lists, ASNs that are present in block lists but evading and detected by BotD.

originated from flagged ASNs. Among these, 52.93% of requests evade BotD and 43.17% of requests evade BotD. These results show that evasive bots are able to evade detection even when they send requests from flagged ASNs.

We suspect that anti-bot services may not rely on ASN block lists to reduce false positives since real users and bots can share the same ASNs but can send requests from different IP addresses. Accordingly, we ran similar analysis with blocked IP addresses using MaxMind’s minFraud API [38]. Similar to findings in prior research [19], we find that IP block lists offer limited coverage (15.86%). However, among the IP addresses that were covered, requests from 48.1% were able to evade DataDome and 68.85% were able to evade BotD. We present detailed analysis in the Appendix D.

In conclusion, we see that a significant number of bots that sent requests from blocked IP addresses and ASNs were able to evade both DataDome and BotD. This indicates that evasive bots change request attributes and don’t merely send requests from IP requests not captured by block lists to evade detection.

Takeaway 2: Evasive bots change request attributes and don’t merely rely on sending requests from IP addresses that are not captured by block lists to evade detection.

5.2. Browser attributes for evasion

Since evasive bots don’t merely rely on IP addresses, we systematically analyze the values of browser attributes to identify those used by evasive bots for evasion. Concretely, we train models to distinguish between the requests that were detected by and evaded DataDome and BotD respectively. We then use techniques from explainability of machine learning to identify browser attribute values that help with evasion. We then explore the values of these attributes on requests from bot services that were most successful with evasion to verify that they enable evasion.

5.2.1. Identifying browser attributes. We train two random forest classifiers using XGBoost [39] to distinguish between the requests that were detected and evaded DataDome and BotD respectively. Each classifier takes feature vectors representing browser attributes in each request (discussed in Section 4.4) as input and provides a binary decision on whether that request would be detected by the respective anti-bot service.

We performed a 90-10 split on the requests we received to train the classifiers. The classifier for BotD attained an accuracy 97.8% on the training set and 97.71% on the test set while the classifier for DataDome attained an accuracy of 82.09% on the training set and 81.66% on the test set. These high values for accuracy indicate that the browser attributes of requests that evade the two anti-bot services are considerably different from those of requests detected by them.

TABLE 2. TOP 5 MOST IMPORTANT BROWSER ATTRIBUTES THAT HELP EVADE DATADOME AND BOTD

DataDome	BotD
Vendor Flavors	Vendor Flavors
Plugins	Plugins
Screen Frame	Touch Support
Hardware Concurrency	Vendor
Forced Colors	Contrast

We use SHapley Additive exPlanations or SHAP [40] to analyze the decisions made by these classifiers to identify browser attributes that result in evasion. Table 2 lists the top 5 features that help evade DataDome and BotD respectively.

5.3. Browser attributes among evasive bots

We now inspect the attribute values of requests from bot services that have high evasion rates to see if they exploit the previously identified attributes for evasion. Concretely, we compare attribute values across bot services that have high evasion rate against those that have low evasion rates against the anti-bot services.

5.3.1. Bots evading BotD. We inspected requests from the top 3 bot services with highest evasion rates against BotD (S15, S18 and S19 in Table 1) and the top 3 bot services with lowest evasion rates against BotD (S6, S16 and S17 in 1). We record 7,132 requests from the top 3 bot services evading BotD and report 100% evasion among them. We record 39,620 requests from the top 3 bot services that are detected by BotD and report an evasion rate of 5.11% among them.

We did not observe significant differences between the values of vendor flavors, vendor and touch support attributes among requests from these bot services. 99.91% of requests from services evading BotD supported the Chrome PDF Viewer plugin, while 100% of requests detected by BotD did not support

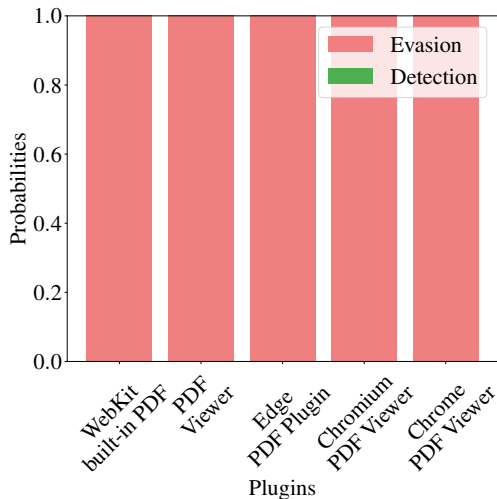


Figure 6. Bar plot showing the probability of PDF plugins that have the highest probability of evasion against BotD. This plot shows a weakness of BotD where the presence of any plugin helps evade BotD

any plugins. Motivated by these stark differences, we further investigate the impact of plugins on evading BotD. Concretely, from all requests received on our honey site, we compute the probability of evading BotD when supporting any one of 5 commonly used PDF plugins. Figure 6 shows that the presence of any PDF plugin nearly guarantees evasion against BotD.

Takeaway 3: Plugins are a potential blind spot for BotD. Evasive bots are able to evade BotD by showing support for at least one standard PDF plugin.

5.3.2. Bots evading DataDome. We similarly inspect requests from the top 3 bot services with highest evasion rates against DataDome. We record 52,746 requests from the top 3 bot services evading DataDome (S8, S9 and S17 in Table 1) and report 79.15% evasion among them. We record 51,110 requests from the top 3 bot services that are detected by DataDome (S7, S11 and S16 in Table 1) and report an evasion rate of 4.12%.

100% of requests from the top 3 bot services having the highest evasion rate against DataDome did not support any plugins. However, not using plugins does not ensure evasion against DataDome since 56.45% of requests from the 3 bot services with the lowest detection rate against DataDome did not support any plugins either. Analyzing screen frame and forced colors attributes across these bot services that evade and are detected by DataDome revealed certain values that always result in detection. However, we did not observe values for these attributes that help with evasion.

Figure 7 compares cumulative probability distribution functions (CDFs) of the values for the number of cores (captured by `hardwareConcurrency`)

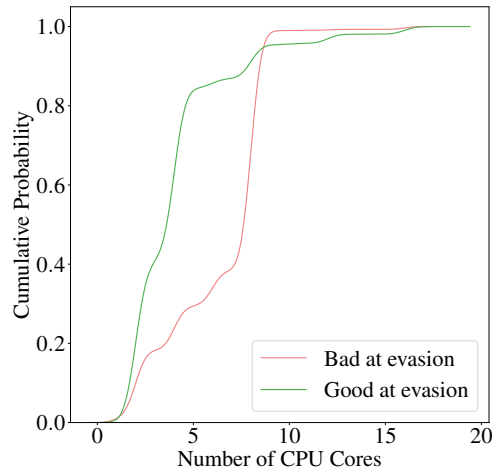


Figure 7. Cumulative probability distribution function (CDF) plots of the number of CPU cores recorded on requests from bot services that had the highest evasion rate over DataDome against those that had the lowest evasion rate over DataDome.

on requests from bot services with high evasion rates over DataDome against the values on requests from bot services with low evasion rates over DataDome. These results indicate that low values for `hardwareConcurrency` help evade DataDome. Concretely, we see that 84.7% of requests from bot services with high evasion rate against DataDome used devices having fewer than 8 cores. In contrast, 38.16% of requests from bot services detected by DataDome used devices with fewer than 8 cores. We can further assess the impact of `hardwareConcurrency` by disregarding requests that contain values for screen frame and forced colors attributes that always lead to evasion. With this refinement, we see that 84.7% of requests from bot services with high evasion rate against DataDome employ devices with fewer than 8 cores while only 19.05% of requests from bot services with low evasion rate against DataDome employ devices with fewer than 8 cores.

Thus, we observe that evasive bots evading DataDome ensure certain values being presents for combinations of attributes. This is different from evasive bots evading BotD that ensured certain values for one set of features (plugins). We investigate more combinations of attributes that help evade DataDome in Appendix E.

Takeaway 4: While `hardwareConcurrency` is a potential blind spot for DataDome, merely ensuring low values for `hardwareConcurrency` is not sufficient for evasion. Evasive bots are able to evade DataDome by ensuring low values for `hardwareConcurrency` and making sure that other attributes don't lead to detection.

5.3.3. Bots evading DataDome and BotD. Among the requests received on our honey site, the requests from two different bot services have over 80% evasion rate against both DataDome and BotD (S14 and S20 in Table 1). We receive a total of 5,302 requests from these two bot services which have 84.7% evasion rate against DataDome and 90.59% evasion against BotD.

We observe that 83.77% of these requests have fewer than 8 CPU cores indicating that they exploit hardware concurrency to evade DataDome. Interestingly, 93.02% of these requests do not have any plugins, indicating that they do not exploit BotD’s blind spot towards plugins for evasion. These requests exploit `touchSupport`, a different blind spot of BotD for evasion. Concretely, 78.36% of requests from the bot services evading both DataDome and BotD support touch events, while only 3.95% of requests from the top 3 bot services having the lowest evasion rate against BotD support touch events. In contrast, only 0.07% of requests from the top 3 bot services that only evaded BotD (Section 5.3.1) showed support for touch events and 8.61% of requests from the top 3 bot services that only evaded DataDome (Section 5.3.2) showed support for touch events.

Takeaway 5: `touchSupport` is another blind spot for BotD. Some evasive bots indicate support for touch events to evade BotD instead of supporting plugins.

6. Inconsistency analysis

Based on the different takeaways in Section 5.2, we see that presenting certain values to different browser attributes helps evasive bots with evasion against anti-bot services. One way in which evasive bots could accomplish this would be to send requests from devices that would present the desired values for attributes. For example, evasive bots could send requests from a device containing 4 CPU cores to present a value of 4 for the `hardwareConcurrency` attribute. Alternatively, evasive bots could alter browser APIs and properties of their devices to present the desired values for different browser attributes. In this case, an evasive bot could alter the `hardwareConcurrency` attribute of the `navigator` browser object to present a desired value for the attribute, even though the device may have a different value for the number of CPU cores.

In this section, we describe various inconsistencies observed in the values of different browser attributes among the requests received on our honey site. These inconsistencies provide evidence of bots manipulating browser APIs since such inconsistencies are extremely unlikely to occur when using real devices. We explore inconsistencies along a spatial and a temporal axis. Spatial inconsistencies constitute inconsistencies among browser attributes in a given request. Temporal inconsis-

tencies constitute inconsistencies in browser attributes across requests from the same device. We use insights obtained from these inconsistencies to develop FP-Inconsistent, our semi-automated technique to generate inconsistency rules to detect evasive bots (described in Section 7).

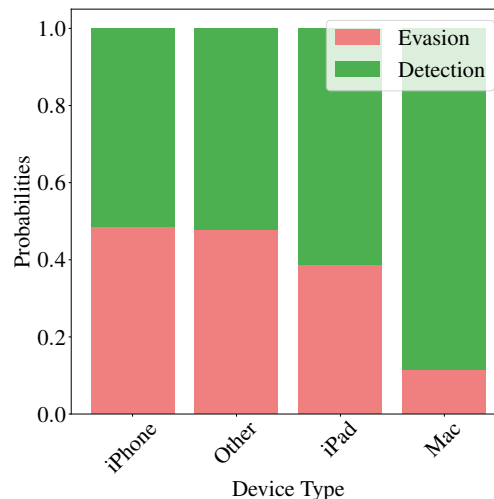


Figure 8. Bar plot showing the top 4 device types (inferred from the User-Agent) that have the highest probability of evasion against DataDome.

6.1. Spatial inconsistencies across browser attributes

Figure 8 shows the top 4 device types (inferred using the User-Agent property of the browser’s `navigator` object) that have the highest probability of evading DataDome based on the requests recorded on our honey site. From the figure, we see that iPhones have the highest probability of evasion (around 50%). We now look at the values of other browser attributes to answer if evasive bots sent requests from real iPhones or if they manipulated the `navigator` object on their browser to have their devices appear as iPhones. If bots are manipulating browser APIs and properties, we hypothesize that it would be difficult for them to ensure that all browser attributes convey consistent information. Thus, inconsistency across browser attributes indicates tampering of browser attributes which can be leveraged to improve bot detection since the browsers from real users are not likely to provide inconsistent values for attributes.

To validate our hypothesis, we look into other attributes of requests have iPhones as their device type based on the User-Agent. Since we know that iPhones have a fixed set of screen resolutions (12 resolutions [41]), we inspect the spread of screen resolutions

captured on requests from iPhones. Upon inspection, we find a total of 83 unique configurations from iPhones in the requests we received on our honey site, out of which 42 different resolutions were present among those requests from iPhones that evaded DataDome. This provides strong evidence to back our hypothesis that all bots that claim to use iPhones in their User-Agent do not originate from iPhones, since only 12 different resolutions are possible for iPhones in the real world.

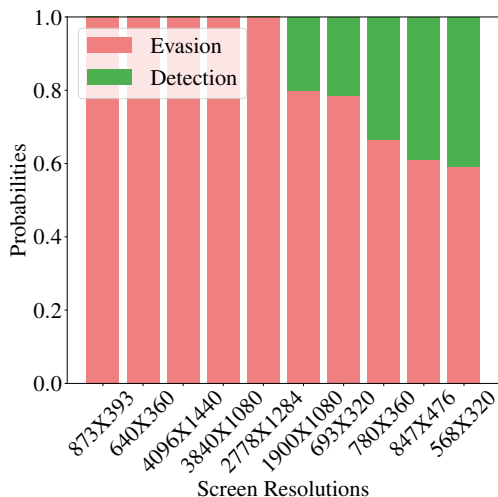


Figure 9. Bar plot showing the top 10 screen resolutions among requests received from iPhones (when inferred using the User-Agent) that have the highest probability of evasion against DataDome. 9 out of these 10 resolutions do not exist in the real world indicating an inconsistency that can be leveraged to detect bots.

Figure 9 shows bar plots of the top 10 screen resolutions on iPhones that have the highest probability of evasion in the requests we received on our honey site. iPhones in the real world do not support 9 out of 10 of these screen resolutions, showing that the evasive bots that evaded DataDome had attributes in their browser configurations that were inconsistent with iPhones. In Section 7 we discuss our systematic, data-driven, semi-automatic approach to discover such inconsistencies to improve bot detection.

Takeaway 6: While bots manipulate browser attributes to evade detection, it is difficult for them to ensure that all browser attributes are consistent with their manipulation. This provides opportunities to improve bot detection via inconsistencies. One particular value for a given attribute mapping to a large number of values for another attribute is a potential avenue to discover inconsistencies.

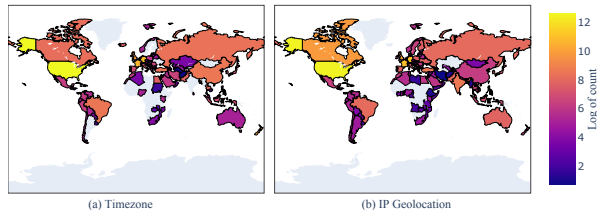


Figure 10. Plots showing a heatmap of the geographical location of requests inferred using the timezone attribute of the navigator object and the IP address. Different regions lighting up in the two heatmaps indicate that while bots alter the navigator object or IP address or both to change their geographical location, they do not ensure that the location inferred using both is consistent.

6.2. Spatial inconsistencies across browser attributes and IP addresses

Some bot services advertised sending traffic from specific geographic regions (USA, Mexico, France etc). Having this ability to send requests from specific regions suggests that the bot services are likely manipulating attributes that capture the geographical location of their devices. This manipulation introduces potential inconsistencies if the bot services did not ensure that all attributes point to the same region.

Concretely, we analyzed requests sent from 4 different bot services who claimed to send requests from the United States, Canada, Europe and France respectively. We first used MaxMind’s GeoLite 2 database [42] to extract the geolocation from the IP address of the requests obtained from these services. We took a conservative approach when matching locations where we considered locations at the same UTC offset to be a match. For example, when analyzing requests from the vendor who advertised sending requests from France, we considered all requests whose geolocations mapped to any valid UTC offset that could overlap with France (such as Europe/Berlin) to also originate from France. With this approach, we observe that over 90% of requests from each of the 4 bot services originated from the advertised geographical location.

However, we observed significant differences when repeating the same analysis using the browser’s timezone API [43] to infer location. We still used the same conservative approach of matching UTC offsets and merely replaced the geolocation inferred from the IP address with the timezone. We observed that only 76.52% of requests mapped to UTC offsets in Canada among the requests from the bot service that advertised traffic from Canada. More alarmingly, we observed that only 56% of requests mapped to UTC offsets in Europe among the requests from the bot service that advertised traffic from Europe. In contrast, we observed 92.44% of requests to originate from Canada and 99.83% of requests to originate from Europe from the corresponding bot services when inferring the geolocation from the IP address. Motivated by

these results, we computed the geographical spread of requests based on both approaches and visualize them in Figure 10. The figure reveals a number of inconsistencies in geographical locations which also constitute spatial inconsistencies that can be leveraged to improve bot detection.

Takeaway 7: Bots deliver on promises of sending traffic from specific locations by altering their IP addresses or browser attributes or both. Any inconsistencies among the locations inferred using these avenues can help improve bot detection.

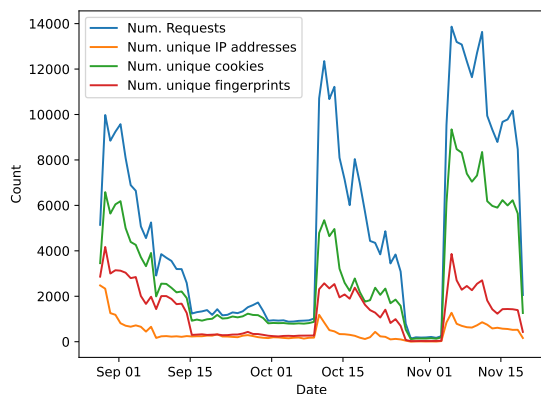


Figure 11. Temporal distribution of requests received on our honey site

6.3. Temporal inconsistencies across requests from the same device

Figure 11 shows the temporal spread of requests received on our honey site over time. The plot shows the number of requests, the number of unique IP addresses, number of unique values for cookies set by our honey site and the number of unique FingerprintJS fingerprints seen per day.

From the figure we see that even after 2 months, we receive requests with previously unseen fingerprints and IP addresses. More interestingly, the spikes in the plot correspond to days when we renewed our purchases. These spikes indicate that the bot services have access to a large number of devices with different device configurations that result in different browser attributes, and thus, different fingerprints. However, we suspect that bots have a fixed set of devices but manipulate browser attributes to create the illusion of sending requests from a large number of devices.

To provide evidence that bots manipulate their browser attributes, we inspect the value of the navigator object’s platform attribute on all requests bearing the most commonly seen Cookie. Whenever a device sends a request to our honey site, we

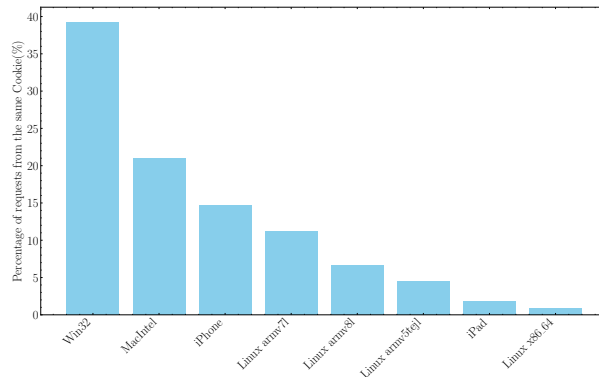


Figure 12. Percentage of requests seen across different navigator platforms for the same Cookie. The diverse spread in this figure provides strong evidence of spoofing browser attributes such as the navigator platform. Unless the attribute was spoofed, all requests would have the same navigator platform.

store a large random number in a first-party Cookie if it has not been set. Thus, requests bearing the same value for this Cookie should originate from the same device. Since the platform property of the navigator object captures information about the type of processor on a given device, we expect to always extract the same value for that device unless the entity controlling the device has intentionally altered its value. In Figure 12, we see a wide distribution for the navigator’s platform property for the device identified as sending us the largest number of requests with the same Cookie. Differing values for browser attributes that cannot change for a given device constitutes a temporal inconsistency that can be used to improve bot detection.

Takeaway 8: Bots change their browser attributes to create an illusion of sending requests from a large number of devices. However, recording differing values for browser attributes that cannot change for a given device constitutes temporal inconsistencies that provide an avenue to detect bots.

7. FP-Inconsistent

Our measurements in Section 6 reveal that there exist inconsistencies in different browser attributes for a given request as well as multiple requests from the same device over a period of time. In this section we present our approach to use these inconsistencies to enhance bot detection. We define inconsistencies as feature values that are either incompatible (unable to occur simultaneously with other values) with other features within the same request or contradictory to the same feature across multiple requests. We categorize inconsistencies into two types: spatial and temporal.

Spatial inconsistencies refer to feature values within a request that conflict or are incompatible with other feature values in that same request. Examples

include differing locations inferred from an IP address and time zone, or implausible combinations, such as an iPhone without touch input support. Our takeaways in Section 6.1 and Section 6.2 show that evasive bots incur significant spatial inconsistencies across information provided by browser attributes and IP address.

Temporal inconsistencies are feature values that are incompatible across different requests from the same user or users with the same IP address. Examples include significantly different time zones for requests from the same IP address and inconsistent device memory values for the same user. Our takeaway from Section 6.3 shows that evasive bots give rise to significant temporal inconsistencies in an attempt to evade detection by changing their attributes.

7.1. Identifying spatial inconsistencies

Our methodology for detecting spatial inconsistencies relies on the understanding that real devices can only possess a limited number of hardware and software configurations. In contrast, bots, in their attempts to mimic real devices and evade detection, as described in Section 6.3, often modify these configurations. However, these alterations typically do not account for every possible source of device information (such as JavaScript APIs, User-Agent, etc.), leading to a proliferation of device configurations in our dataset. This is especially noticeable in devices such as iPhones or iPads that are commonly owned by real users and have the highest success rate in evading detection by bot services (as shown in Section 6.1). Consequently, the increased number of bots pretending to be popular devices results in a greater variety of configurations in our historical dataset.

However, identifying such inconsistencies is challenging because analyzing all possible feature combinations is infeasible. To facilitate the analysis, we first categorize features into different groups based on the type of information each feature provides. For instance, features like Color Depth, Screen Resolution, and Touch Support are grouped because they all convey information about the device’s screen. Table 7 in Appendix C shows the various groups used in our analysis, demonstrating how we categorize features to streamline the detection of inconsistencies.

Next, we analyze pairs of features within each category to identify spatial inconsistencies. For each pair, we rank the features based on the number of unique instances recorded in our dataset. For instance, in the pair UA Device and Maximum Touch Points, we sort UA Device in descending order by the number of unique Max Touch Points values associated with it. A genuine iPhone can only five simultaneous touch points. However, when bots imitate iPhones but report a different number of touch points, our dataset reveals an implausible number of unique combinations between UA Device and Maximum Touch Points.

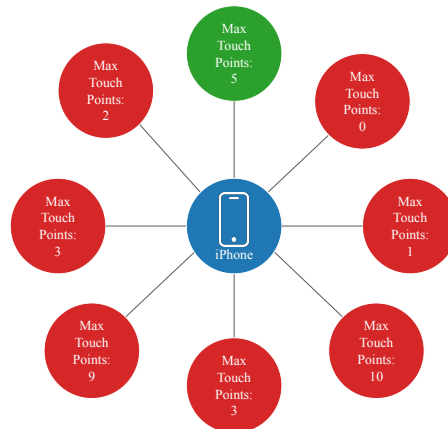


Figure 13. An example of excessive configurations of a device (iPhone) with the feature representing maximum touch points.

We start with the UA Device instance that has the highest number of unique combinations and identify cases where the combination of these two features is impossible. After identifying the inconsistent pair of feature values, we repeat the process with lower ranked unique combinations and other feature pairs. Algorithm 1 describes the process we use to identify spatial inconsistencies. This algorithm helps us identify the most frequently altered features and the spatial inconsistencies they produce. Table 6 in Appendix B provides examples of such inconsistencies in our dataset.

Algorithm 1 Algorithm to Detect Spatial Inconsistencies

- 1: **Input:** Feature categories F , Dataset containing requests D , Labels for requests L (*true* if the request is from a bot, *false* for human)
 - 2: **for all** $f \in F$ **do**
 - 3: **for all** feature pairs $\{f_a, f_b\} \subseteq f$ **do**
 - 4: Filter D where L is *false*, creating D'
 - 5: Create tuples (v_{f_a}, nv_{f_b}) , where v_{f_a} is the value of f_a and nv_{f_b} is the number of unique values of f_b found in the same row as v_{f_a} in D'
 - 6: Sort the tuples in increasing order of nv_{f_b}
 - 7: **for all** (v_{f_a}, nv_{f_b}) in the sorted order **do**
 - 8: **if** the combination is inconsistent **then**
 - 9: Label all rows in D containing (v_{f_a}, v_{f_b}) as *true*
 - 10: **end if**
 - 11: **end for**
 - 12: **end for**
 - 13: **end for**
-

7.2. Identifying temporal inconsistencies

Building upon our findings in Section 6.3, we utilize both the user identifier, set by our honey sites

in each visiting user’s browser storage and IP address to identify temporal inconsistencies. First, we use the user identifier to measure variance in immutable device features (e.g., number of CPU cores, device memory) across requests containing the same user identifier. If an incoming request increases the number of unique feature values associated with existing identifiers, we consider that request to be temporally inconsistent. For instance, if all previous requests from a user have a `HardwareConcurrency` value of 4 and a new request contains a value of 6, we label that request as temporally inconsistent.

We also use a user’s IP address to identify temporal inconsistencies related to time zones and location. If an incoming request increases the number of unique time zones (measured as an offset from UTC) associated with that IP, we classify that request as temporally inconsistent.” Similarly, we also identify temporal inconsistencies in location information provided through the IP address and `navigator.geolocation`.

7.3. Accuracy improvement through inconsistency analysis

In this subsection, we describe our methodology to use temporal and spatial inconsistencies for enhancing the detection of bots that evade DataDome and BotD. To measure the improvement in accuracy from spatial inconsistencies, we translate the inconsistencies identified in Table 6 into filter rules. These filter rules are then matched with each request that evaded detection by DataDome or BotD. For temporal inconsistencies, we use the timestamp of each request to determine the order in which requests were made, applying filter rules to identify inconsistencies created by requests arriving later.

The results in Table 3 show that using rules generated through spatial and temporal inconsistency analysis can decrease the evasion of bots against BotD by 44.95% and against DataDome by 48.11%.

TABLE 3. COMPARISON OF IMPROVEMENT TO BOTD AND DATADOME ACCURACY WITH INCONSISTENCY ANALYSIS

	BotD	Datadome
None	47.07%	55.44%
Spatial	70.33%	76.04%
Temporal	48.09%	56.53%
Combined	70.86%	76.88%

Our results on the requests received on our honey site show that using a filter list to counter commonly found inconsistencies is an effective method to detect and block evasive bots. Filter lists are commonplace in anti-tracking community, where they provide a good trade off between performance and accuracy in detecting advertising and tracking services. Currently, no such alternative exist to detect bots that show inconsistent

fingerprints. Our methodology, described in Algorithm 1, is a first step towards creating such filter list to enhance online bot detection.

8. Discussion

8.1. Improving FP-Inconsistent

8.1.1. Capturing more attributes. Even if we assume that bots have the ability to alter all browser attributes, inconsistencies provide a promising avenue for detection as long as there exist at least one pair of attributes that cannot exist in the real world. Accordingly, increasing the number of captured attributes introduces more avenues for inconsistencies among those attributes which can be leveraged for detection. In this paper, we confined FP-Inconsistent to only look for inconsistencies among HTTP headers and the attributes captured by FingerprintJS. Incorporating other browser attributes such as those captured by CreepJS can further improve FP-Inconsistent’s detection accuracy. Incorporating behavioral characteristics of users can also bolster bot detection. However, capturing such characteristics to improve bot detection comes at the cost of privacy since these attributes enable tracking when captured from real users. Privacy researchers seek to limit the amount of information exfiltrated by browsers to protect privacy.

8.1.2. Capturing attributes from real users. In this paper, we used the requests sent by bots on our honey site to devise rules for inconsistencies. Thus, these rules can be further refined by incorporating information about browser attributes captured from requests from real users. However, our honey site architecture can only guarantee reliable ground-truth that requests originate from bots and cannot be extended to guarantee requests originating from real users. Ensuring reliable ground-truth that requests originate from real users is difficult without a public deployment that naturally attracts diverse users to the site. Such a deployment still risks attracting bots thereby making it harder to guarantee ground-truth.

8.1.3. Capturing unmodifiable attributes.

Researchers have proposed side-channels to capture fundamental physical device characteristics to uniquely identify devices even among those that have identical hardware and software configurations [44, 45, 46, 47]. Such techniques can significantly empower temporal inconsistencies to detect bots. In our inconsistency analysis, we used Cookies to identify requests that originated from the same device. Bots will be able to overcome our temporal inconsistencies by merely deleting their cookies. Bots would not be able to drop unique identifiers that originate from the physical properties of hardware that cannot be modified. Such persistent identifiers, however, pose threats to privacy.

TABLE 4. IMPROVEMENT IN DATADOME AND BOTD’S DETECTION RATE ON REQUESTS FROM EACH BOT SERVICE WHEN INCORPORATING FP-INCONSISTENT

Bot Service	Num. Requests	DataDome Detection Rate	DataDome + FP-Inconsistent Detection Rate	BotD Detection Rate	BotD + FP-Inconsistent Detection Rate
S1	121500	55.99%	83.41%	28.42%	60.26%
S2	63708	57.01%	82.61%	27.71%	55.83%
S3	54746	25.09%	46.31%	89.74%	94.17%
S4	47278	61.35%	82.35%	26.15%	52.09%
S5	40087	76.14%	88.19%	27.35%	50.46%
S6	32447	28.19%	43.7%	94.55%	97.05%
S7	28940	97.44%	99.35%	360.01%	83.91%
S8	26335	19.57%	47.84%	71.1%	86.06%
S9	23412	27.71%	65.69%	80.67%	94.07%
S10	18967	84.23%	94.7%	40.64%	70.43%
S11	17996	93.45%	98.63%	59.36%	80.16%
S12	7010	94.95%	98.36%	48.56%	78.21%
S13	5119	93.04%	99.1%	49.48%	87.04%
S14	4920	16.26%	66.27%	9.92%	67.29%
S15	4291	88.86%	99.6%	0%	77.87%
S16	4174	95.52%	99.69%	99.98%	100%
S17	2999	25.34%	43.88%	92.1%	95.1%
S18	1430	79.3%	99.86%	0%	83.57%
S19	1411	90.08%	99.5%	0%	59.76%
S20	382	2.88%	7.59%	2.88%	7.07%

8.2. Deployment of filter list rules

As described in section 7.3, FP-Inconsistent can be used to generate a filter list of inconsistencies to improve bot detection. Use of filter lists to protect against trackers is a widely used approach in anti-tracking community [48, 49, 50, 51, 52, 53] These filter lists are used on the client side via an extension that matches outgoing requests and other resources with the filter lists rules to block tracking requests and other resources from executing. The filter list produced by FP-Inconsistent can be used in a similar fashion However, because the filter rules proposed by FP-Inconsistent are meant to aid in detection of evasive bots, we envision the inclusion of these rules in client-side scripts loaded by anti-bot services such as DataDome and BotD. As per our analysis in section 4.2, these services use client side scripts to collect fingerprints to aid in detection, which are then relayed to their servers for a final decision. Inclusion of filter list rules generated by FP-Inconsistent on the the client side will help these services improve detection of evasive bots.

8.3. Limitations

8.3.1. False positives from privacy-enhancing technologies. Privacy enhancing technologies [54, 55, 56] alter browser attributes to protect users from being tracked online. Thus, requests sent by users employing such technologies may present inconsistent attributes resulting in them being flagged as bots by our inconsistency analysis.

8.3.2. Evasive bots with consistent attributes. Our results show that FP-Inconsistent’s inconsistency rules

can improve the detection of evasive bots that are currently evading detection. Evasive bots will be able to overcome FP-Inconsistent if they evolve to ensure that they can alter attributes without introducing any inconsistencies. Incorporating unmodifiable attributes can help provide a fundamental solution to detect bots, but doing so comes at the cost of privacy.

8.4. Need for privacy-preserving bot detection

Our discussion in this section reveal a forceful trade-off between improving bot detection and being respectful of user privacy. Orthogonal to the scope of this paper, future research focusing on privacy-preserving bot detection such as identifying intent behind trackers to not block those interested in bot detection or an in-browser detection mechanism can bridge the gap to potentially address concerns of privacy protection as well as bot detection.

9. Conclusion

We find evidence that bots alter browser fingerprint attributes to evade detection. However, we find evidence that such evasive bots end up introducing inconsistencies among the fingerprint attributes that can be used for more reliable bot detection. We propose FP-Inconsistent, a data-driven, semi-automatic approach to discover inconsistencies in browser fingerprint attributes for detecting evasive bots in the wild that are able to evade detection by anti-bot services. As the arms race between evasive bots and anti-bot services evolves, it remains to be seen whether bots can alter their browser fingerprint attributes while avoiding inconsistency. We

believe that it would be challenging for bots to do so because a browser fingerprint is a high dimensional feature set with numerous – often subtle – correlations between attributes that are difficult to anticipate and account for when altering fingerprints. Put simply, it is challenging to tell a complex lie while keeping the story always straight. While FP-Inconsistent rule generation approach may need to be evolved to generate rules for other types of consistencies for future generation of bots, we believe the basic principle will stand over time.

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Appendix A. Comparison of APIs used by BotD and DataDome

Table 5 shows the different APIs accessed by BotD and DataDome scripts on our honey site.

TABLE 5. COMPARISON OF BROWSER APIS READ BY DATADOME AND BOTD

Browser API	DataDome	BotD
Display		
window.screen.colorDepth	✓	✗
HTMLCanvasElement.getContext	✓	✓
Navigator		
window.navigator.webdriver	✓	✓
window.navigator.vendor	✓	✓
window.navigator.userAgent	✓	✓
window.navigator.serviceWorker	✓	✗
window.navigator.productSub	✗	✓
window.navigator.plugins	✓	✓
window.navigator.platform	✓	✗
window.navigator.permissions	✓	✓
window.navigator.oscpu	✓	✗
window.navigator.mimeTypes	✓	✓
window.navigator.mediaDevices	✓	✗
window.navigator.maxTouchPoints	✓	✗
window.navigator.languages	✓	✓
window.navigator.language	✓	✓
window.navigator.hardwareConcurrency	✓	✗
window.navigator.buildID	✓	✗
window.navigator.appVersion	✗	✓
window.navigator.__proto__	✓	✗
Storage		
window.sessionStorage	✓	✗
window.localStorage	✓	✗
window.document.cookie	✓	✗
Mouse Movements		
MouseEvent.type	✓	✗
MouseEvent.timeStamp	✓	✗
MouseEvent.clientY	✓	✗
MouseEvent.clientX	✓	✗
addEventListener: mouseup	✓	✗
addEventListener: mousemove	✓	✗
addEventListener: mousedown	✓	✗
Miscellaneous		
addEventListener: asyncChallengeFinished	✓	✗
addEventListener: pagehide	✓	✗
Performance.now	✓	✗

Appendix B. Inconsistencies Identified

Table 6 lists some examples of the inconsistencies that we identified for each feature group in Table 7.

TABLE 6. INCONSISTENCIES IDENTIFIED

Feature Group	Features	Examples
Screen	(UA Device, Screen Resolution)	(iPhone, 1920x1080) (iPhone, 847x476) (iPad, 900x1600) (Samsung SM-S906N, 1920x1080) (M2006C3MG, 800x360) (Mac, 656x1364)
	(UA Device, Touch Support)	(iPhone, None) (Mac, touchEvent/touchStart) (Samsung SM-A127F, None) (M2004J19C, None) (Infinix X652B, None)
	(UA Device, Max Touch Points)	(iPhone, 1) (iPhone, 0) (iPad, 1) (iPad, 7) (Mac, 10) (Samsung SM-A515F, 0) (Pixel 7 Pro, 0)
	(UA Device, Color Depth)	(iPhone, 16) (iPad, 16)
	(UA Device, Color Gamut)	(Samsung Galaxy Tab S7, (p3, rec2020)) (SAM Galaxy S10 Smartphone, (p3, rec2020))
Device	(UA Device, Device Memory)	(XiaoMi Mi Pad4 LTE, 8) (Samsung SM-T387W, 4) (MiPad 3, 8) (Samsung SM-A515F, 1) (XiaoMi Redmi Go, 8)
	(UA Device, Hardware Concurrency)	(iPhone, 3) (iPhone, 32) (Mac, 48) (iPad, 32) (XiaoMi Mi Pad5 Wi-Fi, 1) (Pixel 2, 32)
Browser	(UA Browser, UA OS)	(Safari, Linux) (Samsung Internet, Linux) (MiuiBrowser, Linux) (Safari, Windows)
	(UA Browser, Vendor)	(Mobile Safari, Google Inc.) (Chrome Mobile, Apple Computer, Inc.)
	(UA Browser, Platform)	(Mobile Safari, Linux x86_64) (Chrome Mobile, Win32) (Chrome Mobile, Linux x86_64) (Chrome Mobile iOS, Win32)
Location	(IP Location, Time Zone)	(France/Hauts-de-France, America/Los Angeles) (Germany/Sachsen, America/Los Angeles) (Singapore/Singapore, America/Los Angeles) (United States of America/California, Asia/Shanghai) (United States of America/Virginia, Pacific/Auckland)
Browser	(Platform, Vendor)	(Linux armv5tejl, Apple Computer, Inc) (Linux aarch64, Apple Computer, Inc.) (Linux armv6l, Apple Computer, Inc.) (Win32, Apple Computer, Inc.) (Linux armv8l, Apple Computer, Inc.)
	(Platform, UA OS)	(Mobile Safari, Linux x86_64) (Linux armv8l, Mac OS X) (iPad, Android) (Chrome Mobile iOS, Win32) (Linux i686, Mac OS X)

TABLE 7. FEATURE CATEGORIES

Category	Features
Screen	UA Device, Color Depth, Screen Resolution, Touch Support, Max Touch Points, HDR, Contrast, Reduced Motion
Device	UA Device, Device Memory, Hardware Concurrency, UA OS
Browser	UA Browser, Plugins, Platform, UA OS, UA Vendor, Vendor, Vendor Flavors
Location	IP Location, Timezone, Languages

Appendix C. Feature Categories for Inconsistency analysis

Table 7 list different categories of features used for inconsistency analysis.

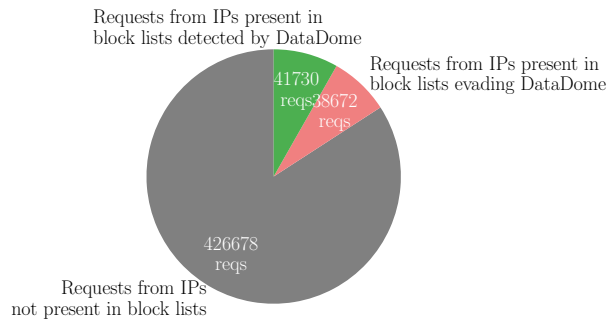


Figure 14. Pie chart showing the proportion of requests originating from IP addresses that are not present in block lists, that are present in block lists but evading and detected by DataDome.

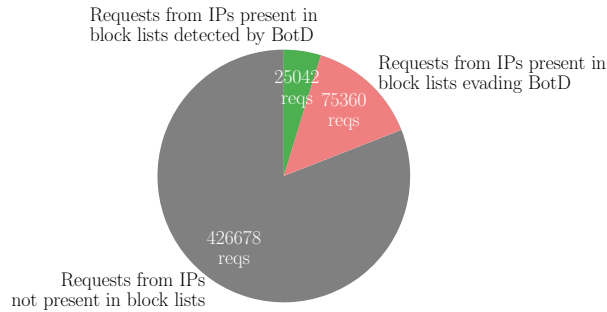


Figure 15. Pie chart showing the proportion of requests originating from IP addresses that are not present in block lists, that are present in block lists but evading and detected by BotD.

Appendix D. IP block lists

Since ASNs are coarser than IP addresses, we directly check if evasive bots send requests from blocked IP addresses. Concretely, we queried the IP addresses of the requests received on our honey site against MaxMind’s minFraud API [38]. Figure shows that 15.86% of requests originated from IP addresses that

were blocked by MaxMind. Among the requests that originated from blocked IP addresses, 48.1% of requests were not detected by DataDome and 68.85% requests were not detected by BotD. Requests originating from blocked IP addresses being able to evade detection indicates that evasive bots don’t merely rely on IP addresses for evasion.

Appendix E. Combination of browser attributes to evade DataDome

We visualized the XGBoost decision tree for DataDome described in Section 5.2. The tree with a depth of 5 indicated that all 44,168 requests having a Screen Frame value less than 20 that do not support the Chrome PDF Viewer plugin, having memory over 256 MB with less than 14 CPU cores having the width of Monospace font used in FingerprintJS larger than 131.5 were able to evade detection.