Abstract

We measure how effective Privacy Enhancing Technologies (PETs) are at protecting users from website fingerprinting. Our measurements use both experimental and observational methods. Experimental methods allow control, precision, and use on new PETs that currently lack a user base. Observational methods enable scale and drawing from the browsers currently in real-world use. By applying experimentally created models of a PET’s behavior to an observational data set, our novel hybrid method offers the best of both worlds. We find the Tor Browser Bundle to be the most effective PET amongst the set we tested. We find that some PETs have inconsistent behaviors, which can do more harm than good.

1 Introduction

Online data aggregators track consumer activities on the Internet to build behavioral profiles. Traditional forms of tracking use stateful mechanisms, where the tracker (e.g., Google’s DoubleClick) places an identifier (e.g., an HTTP cookie) with a unique value on the consumer’s browser or computer. When the consumer visits webpages where the same tracker has a presence, their browser automatically sends the identifier value to the tracker. This allows the tracker to link these visits to the same consumer. Two properties make an identifier good for tracking purposes: uniqueness and predictability. Uniqueness requires that the identifier values are sufficiently unique among consumers, whereas predictability requires the identifier values are predictable for a consumer across webpage visits.

Increased awareness about stateful tracking mechanisms has led consumers to take precautions against them (e.g., by blocking or clearing cookies). This has spurred the growth of stateless tracking mechanisms, also known as browser fingerprinting. A stateless tracker extracts fingerprints from consumers as a collection of several attributes of the browser, operating system, and hardware, typically accessed through Javascript APIs. Fingerprints collected on websites like panopticlick.eff.org and amiunique.org/fp demonstrate that they are sufficiently unique and predictable for tracking purposes [18, 39]. The list of attributes that can be used in fingerprints is rapidly increasing [44, 4, 3, 24, 21, 12, 58]. Studies have also uncovered fingerprinting code on popular webpages [4, 3, 21].

Anti-Fingerprinting Privacy Enhancing Technologies (AFPETs) aim to protect consumers against fingerprinting by masking, or spoofing, the values of attributes. For each attribute, they can either (1) standardize it, so that all of the AFPET’s users share the same or one of a small set of attribute values, thereby decreasing the uniqueness of fingerprints, or (2) vary it, so that the fingerprints of all the AFPET’s users vary across webpage visits, thereby decreasing the predictability of fingerprints.

Our goal is to find attributes that AFPETs are not masking (with either standardization or variation) and to quantify their effects on privacy. We develop a method that compares the trackability (i.e., uniqueness and predictability) of AFPET-modified fingerprints with those of the original fingerprints. Depending on the goals, AFPET evaluation could depend on the context in which the AFPET is used,
accounting for features of other users and non-users, or be a more theoretical assessment of the AFPET’s potential, untied to the vagaries of today. For example, if the goal of evaluation is to determine which AFPET to use today, one would want to know how many other users of the AFPET there are since they will form the anonymity set – the group of other users one will blend in with. If instead the goal is to determine which AFPET to fund for further development, the user numbers of today may matter less than the technical or theoretical capabilities of the AFPET. Given that no one AFPET evaluation can match all goals, we will explore points in the space of possible evaluations while focusing more on prospective evaluations.

1.1 Methods

First, we consider a more theoretical, experimental analysis that directly looks at an AFPET’s ability to mask attributes. This method runs browsers with and without an AFPET installed to determine which attributes the AFPET masks, either by standardizing or varying its value. For this purpose, we develop an experimental framework, PETInspector, which has three components: the fingerprinting server (FPServer), which collects fingerprints from visitors, the client simulator (ClientSim), which simulates consumers and drives them to FPServer with and without AFPETs, and the analysis engine (æ), which compares fingerprints across clients to produce a mask model characterizing AFPET behaviors. This tool can be applied to new AFPETs that currently lack a user base. This experimental method does not require access to the source code of AFPETs. However, it does not tell us which attributes are the most important to mask.

Next, we consider a highly context-dependent, observational method. Websites like panopticlick.org, eff.org, and amiunique.org.fp obtain large sets of real-world fingerprints, revealing which are the most trackable (i.e., unique and predictable). In principle, these datasets can be studied to evaluate an AFPET by selecting the fingerprints generated by users of that AFPET and, for each such fingerprint, checking how trackable they are compared to other fingerprints in the dataset. We have implemented the core task of measuring trackability as a tool, FPInspector, which simulates a simple tracker and computes statistics quantifying anonymity, such as entropy. In practice, however, such observational datasets may contain too few users of an AFPET, especially for new ones, for FPInspector evaluate it. Furthermore, in some cases, it may be difficult to determine which fingerprints correspond to which AFPETs. Thus, utilizing such a dataset requires a more nuanced approach.

Then, we develop a novel hybrid method combining observational and experimental data to enable the evaluation of AFPETs with low or no usage within the context of the browsers used today but without access to the AFPET source code. Our hybrid method combines FPInspector with PETInspector as outlined in Figure [1]. It contextualizes the mask model produced by PETInspector by applying it to an observational dataset of real-world fingerprints to produce a counterfactual dataset representing what the browsers would look like to trackers had everyone used the AFPET. By comparing the trackabilities on the two datasets, we can evaluate the effectiveness of the AFPET. By parametrically leveraging data from ongoing, large-scale measurement studies, our results may be updated for the ever changing landscape of browsers with little additional work.

Finally, we adjust the hybrid method to take into account the number of users an AFPET has. This shifts the analysis even further in the direction of examining the PET’s current abilities over its theoretical possibilities.

1.2 Results

Using PETInspector, we resolved with high confidence whether 15 AFPETs explicitly claiming to protect against fingerprinting mask 20 attributes of Firefox and 18 attributes of Chrome. We also looked at 11 other popular blacklisting PETs (BLPETs), which operate by blacklisting domains known to engage in tracking. While they do not make a claim of protecting against fingerprinting, they should not make matters worse by giving browsers a more unique fingerprint, a property we check them for.

We found that all but the Tor Browser Bundle masked 9 or fewer of the resolved attributes, at least in their default configurations. In particular, we found that Tor left a single attribute, platform, unmasked while all others left at least 12 attributes unmasked. PETInspector also uncovered undocumented behaviors and inconsistencies in how some PETs modify various attributes:

- Brave Browser spoofs the User-Agent to appear like Chrome. However, it modifies the Accept-Language header, language and plugins differently than baseline Chrome. To
Figure 1: Hybrid method for AFPET evaluation

Figure 2: FPServer collects 49 attributes, of which 29 remain unexercised by ClientSim. Amiunique dataset has 28 unique attributes, of which 8 aren’t collected by FPServer and 8 are collected but remain unexercised by ClientSim. The red dotted rectangle represents the intersection of attributes exercised by ClientSim and present in the amiunique dataset and used for our hybrid evaluation.

We found 6 AFPETs which masked 4 attributes, but they did not all mask the same set of attributes. To break such ties, we used the hybrid method. We used a pre-existing dataset of over 25,000 real-world fingerprints collected on the website amiunique.org. Of the 18–20 attributes resolved for each AFPET, only 12 appear in the amiunique.org dataset.

Our hybrid method finds that even with just 12
attributes, 13 of the 15 AFPETs do not provide much protection over using no PET at all, decreasing the entropy revealed from about 13 bits without any PET to 11 bits with the AFPET. It finds the Tor Browser Bundle (Tor BB) to be most effective, revealing under 3 bits of entropy.

Recognizing that automation has its limitations, we manually analyzed some of the more interesting findings. We found that some AFPETs performed better when switched out of their default configuration. While we find that some do mask attributes labeled as inconclusive by PETInspector, we did not find any falsely labeled as masked or as unmasked.

A source of entropy for Tor BB fingerprints is the revealed screen resolution, which is only partly masked. Tor BB reveals partial information about the screen resolution of its users using a spoofing strategy which depends on the true resolution for usability reasons. We explore a space of alternate spoofing strategies and find some to be just as effective according to our metrics despite being more usable, by utilizing more pixels on average for browsing than Tor.

1.3 Interpretation

BLPETs do not claim to protect against fingerprinting and AFPETs do not claim to protect against all forms of fingerprint. Thus, our results should not necessarily be interpreted as finding flaws in PETs. An AFPET that masks the one and only one attribute that it claims to mask behaves as advertised.

Nevertheless, our tool can be useful for AFPET developers. It can test whether they masked the attributes they intended to do so and help ensure that their documentation is correct. Indeed, we found that AFPET Trace and Tor did not mask all of the attributes that their documentation claimed that they did (Table 3).

BLPETs do not claim to protect against fingerprinting, but even they should avoid making browsers more fingerprintable than they already are. For example, we found that Privacy Badger made fingerprinting easier by modifying an attribute in a particular and undocumented way. Despite not making any anti-fingerprinting claims, its developers took this result seriously and updated Privacy Badger since it was an unintended side effect of their approach to privacy.

For consumers and their advocates attempting to select a PET, our results are also useful beyond the pre-existing, and sometimes flawed, documentation. In addition to double checking documentation, such consumers may be less concerned with whether PETs meet their specifications than their overall effectiveness. Our hybrid method allows us to rank the PETs in overall terms of how well they prevent fingerprinting (Table 4). This fine-grained information is not offered by the documentation of any PET.

Our results are best understood as providing a lower bound on how much room for improvement remains for AFPETs. Since AFPETs might mask attributes that we do not test, we cannot claim to have captured all the work that went into developing an AFPET. Our lower bound on remaining work is sound in that when PETInspector claims that an AFPET leaves an attribute unmasked, it really is not masking it, is not varying the attribute often enough to be effective, or is not masking enough values of the attribute to protect our test browser platforms. All three possibilities are concerning.

Our bound is only a lower bound since, by resolving only the status of 18–20 attributes of each browsing platform, we might label some attributes in need of masking as inconclusive. More attributes can be added to our tools, but the set of possible attributes is open ended and finding platforms that differ in all attributes can be difficult. In fact, we are already aware of 30 attributes that we can measure but could not make a high-confidence masking determination for due to having insufficient diversity in their values across our experimental browsing platforms. However, given the long list of issues with the attributes we did test, we may have already found enough to keep AFPET developers busy.

As for our quantification of the importance of attributes, it is based on the AmIUnique observational data, which is not perfectly representative. Given better data, our tool, without modifications, can produce more accurate measurements, and any inaccuracy in our quantification will not affect the qualitative result that an attribute is left unmasked.

1.4 Contributions

We make the following main contributions:

- We develop an experimental framework (PETInspector) to verify how 15 AFPETs (and 11 BLPETs) mask 18–20 different attributes each. By obtaining a more complete picture of PETs’ behaviors, we uncover some inconsistencies and peculiarities (Section 4).
Prior work finds that various attributes are trackable by measuring the uniqueness and predictability of fingerprints collected from real-world browsing platforms. However, few studies evaluate the effectiveness of AFPETs against fingerprinting.

Many prior studies have focused on BLPETs, which use blacklists to block known tracking domains and scripts. Since BLPETs try to prevent the consumer’s browser from interacting with trackers, metrics suggest the success of interactions (e.g., third-party requests sent, cookies placed, etc.) are good indicators of BLPET effectiveness. Studies have evaluated BLPETs by comparing empirical data with and without the BLPET when visiting popular websites. FP-Guard takes a blacklisting strategy to protect against fingerprinting: it uses heuristics to identify fingerprinting domains and blocks them. Gulyás et al. study the tradeoff between a BLPET suppressing some trackers but also leading to the browser having a more unique fingerprint by being a rare browser extension.

Most AFPETs protect against fingerprinting by spoofing browser, operating system, and hardware characteristics, without blocking specific domains and scripts. For example, PETs like the Tor Browser standardize various attribute values, whereas others like PriVaricator, FP-Block, Blink, and FPRandom vary them. Metrics used for evaluating BLPETs would not be able to meaningfully evaluate these AFPETs. Some studies have evaluated attribute varying AFPETs by observing variations in fingerprints when using these AFPETs. Vastel et al. look at how AFPETs can introduce inconsistencies between attributes leading to a more unique fingerprint. Our work differs from these by using a combination of experimental and observational data to more thoroughly evaluate AFPETs.

3 Trackers and PETs

When a user visits a webpage, trackers can have the user’s browser execute code that requests information about the user’s browsing platform, including their hardware, operating system, and the browser itself. The leftmost column of Table 3 provides a list of 49 attributes known to be good candidates for fingerprinting. The tracker can combine multiple attributes $a_1, \ldots, a_n$ to compute a fingerprint $id(b) = (a_1(b), \ldots, a_n(b))$ of the browsing platform $b$ where $a_i(b)$ represents the value of attribute $a_i$ for the platform $b$. A tracker can use fingerprints to identify browsing platforms visiting two websites as being the same one. The more unique the fingerprint is for each user, the fewer false matches the tracker will produce in linking two different users. The more predictable (ideally, changing) the fingerprint is as a user goes from website to website, the fewer matches the tracker will miss.

To protect themselves from fingerprinting, consumers can install AFPETs on their browsing platform, which can decrease the uniqueness or predictability of the platform’s fingerprints. Upon installing a PET $p$, the consumer’s browsing platform $b$ is modified to $p(b)$. As a result, the tracker now interacts with $p(b)$ and extracts the fingerprint $id(p(b))$. In this study, we look at three types of PETs:

I. Attribute standardizing. These AFPETs reveal one (full standardization) or one of a small set of possible values (partial standardization) for an attribute. Full standardization makes all AFPET users appear identical, whereas partial standardization makes them appear to be from a small number of groups, with respect to that attribute. An AFPET may choose partial over full standardization if spoofing the attribute value has usability implications.

II. Attribute varying. These AFPETs vary the value of an attribute so that the values of each
user varies across browsing activities. Such variations may affect both the predictability and the uniqueness of the revealed attribute. Laperdrix et al. [37] show that variation AFPETs can vary attributes in a manner that reduces their usability impact.

III. Interaction blocking. These BLPETs block some or all interactions between the browsing platform and trackers. They rely on a blacklist (e.g., EasyPrivacy) to block interactions matching known tracking patterns. Trackers interacting with browsing platforms with these PETs receive an error message instead of the true fingerprints.

We are primarily interested in evaluating and comparing AFPETs that modify the attribute values either by standardizing [1] or varying [II] their values. In some places, we comment on BLPETs that block interactions with known trackers [III]. We do so even for BLPETs not claiming to be AFPETs since they are popular, have been the subject of past evaluation studies, have the potential to unintentionally make fingerprints more unique (as we find with Privacy Badger), and can be used as AFPETs. (None of BLPETs that we test suggests using it as an AFPET. The BLPET FPGuard did [23], but we could not find it publicly available for testing.) However, we do not directly compare them to the AFPETs since they do not purport to modify any attributes explicitly, and their quality depends upon the quality of their blacklists, necessitating a different form of evaluation.

We leave out of scope PETs that protect against fingerprinting by blocking scripts (e.g., No-Script [32] and ScriptSafe [8]) since they have considerable impact on usability [31]. We also leave out PETs like Noisy (noiszy.com), Internet Noise (makeinternetnoise.com), and AdNauseum (adnauseam.io) that do not attempt to prevent tracking but rather to make it pointless by injecting noise into the user’s history with fake clicks and website visits.

In this paper, we consider a total of 26 PETs. We assign each PET a unique abbreviation, which we use in some tables. When the distinction is needed, we add either a “c” for Chrome or an “f” for Firefox to the name or abbreviation of PETs with versions for both browsers. We present the full list of PETs, their abbreviations, baseline browser, and strategy in Table 1. 23 of the 26 PETs are extensions for Chrome and Firefox (the two most popular desktop browsers at the time of writing), two are full browsers, and one is a browser configuration. Among browser extensions, 11 are for Chrome, and 12 are for Firefox. 12 of the 23 extensions are pairs of 6 extensions available for both Chrome and Firefox. 15 of the 26 PETs are AFPETs and purport to either standardize or vary attribute values, while 11 others are popular BLPETs. Some PETs assume mixed strategies. For example, Brave, HideMyFootprint, and Trace modify some attributes in addition to blocking some types of interactions. The distribution of the strategies adopted by these 26 PETs are presented in Figure 3.

We went over the documentation of the PETs to uncover how they purport to modify attributes. For all PETs that explicitly document masking an attribute, we place a □ in the corresponding cell in Table 3. This approach is similar to how Torres et al. produce their comparison table [63, Table 1]. However, the documentation is not always clear about which attributes are masked. One can obtain additional clarity from the programs themselves for open-sourced PETs, but source-code analyses cannot be applied to proprietary PETs. As a result, the □s in Table 3 may not reflect the full picture of how PETs mask attributes. Next, we demonstrate how we use our experimental method to obtain a more complete picture of the masking behavior.
Table 1: List of PETs we study, their abbreviation, and strategy to protection. Most PETs are browser extensions, * indicates full browsers, and ** indicates browser configurations.

| PET                        | Abbr. | Strategy | AFPET claim? |
|----------------------------|-------|----------|--------------|
| CanvasFingerprintBlock      | CFB   | I        | ✓            |
| Privacy Extension           | PE    | I        | ✓            |
| Brave                      | BR*   | I+III    | ✓            |
| Canvas Defender             | CDC   | II       | ✓            |
| Glove                      | GL    | II       | ✓            |
| HideMyFootprint            | HMF   | II+III   | ✓            |
| Trace                      | TR    | II+III   | ✓            |
| Adblock Plus               | APC   | III      | ✓            |
| Disconnect                 | DC    | III      | ✓            |
| Ghostery                   | GH    | III      | ✓            |
| Privacy Badger             | PBC   | III      | ✓            |
| uBlock Origin              | UOC   | III      | ✓            |

Firefox PETs

| PET                        | Abbr. | Strategy | AFPET claim? |
|----------------------------|-------|----------|--------------|
| Blend In                   | BI    | I        | ✓            |
| Blender                    | BL    | I        | ✓            |
| No Enum. Extensions        | NE    | I        | ✓            |
| Stop Fingerprinting        | SF    | I        | ✓            |
| Tor Browser Bundle         | Tor*  | I        | ✓            |
| TotalSpoof                 | TO    | I        | ✓            |
| Canvas Defender            | CDF   | II       | ✓            |
| CanvasBlocker              | CB    | II       | ✓            |
| Adblock Plus               | APF   | III      | ✓            |
| Disconnect                 | DF    | III      | ✓            |
| Ghostery                   | GH    | III      | ✓            |
| Privacy Badger             | PBF   | III      | ✓            |
| Tracking Protection        | TP**  | III      | ✓            |
| uBlock Origin              | UOF   | III      | ✓            |

4 Experimental Evaluation of AFPETs

We now consider an experimental, or test-based, approach to AFPET evaluation conducted with artificial users. These artificial users browse on platforms differing in whether they have an AFPET installed. By comparing fingerprints generated by these artificial users, we infer which attributes the AFPET is masking. We use the degree of masking by each AFPET as an evaluation metric.

Below, we discuss this method and our experimental framework, PETInspector, implementing it. We then describe an experiment we ran using PETInspector and the results. The results show that while one could instead look to an AFPET’s documentation for information on which attributes it masks, the documentation sometimes provides an incomplete picture of an AFPET’s behavior. We end with a discussion of this method’s limitations.

4.1 Method

Our experimental framework, PETInspector, is composed of three parts. The client simulator, ClientSim, creates and drives experimental browsing platforms, with and without various AFPETs installed, to visit a server. The fingerprinting server, FPServer, collects fingerprints when the browsing platforms, driven by ClientSim, visit it. The analysis engine, æ, compares fingerprints across clients to detect whether an AFPET varies, standardizes, or does not mask the value of an attribute. To observe these behaviors, æ compares the value of the attribute on the browsing platform without any AFPET (i.e., on the baseline browser) with the value when an AFPET is installed.

FPServer plays the role of an online tracker with the browsers and FPServer interacting to simulate fingerprinting in the wild. The components surrounding this simulation produce a view of AFPETs’ effects on fingerprints, with ClientSim telling æ which fingerprints correspond to which AFPETs.

Client Simulator ClientSim drives simulated clients using browsing platforms with different configurations to visit FPServer. For each base configuration and PET, ClientSim simulates a pair of clients only differing on whether the PET is installed, to allow the isolation of the PET’s effects.

We choose the base configurations to exercise a wide range of attribute values in hopes of triggering
an AFPET’s masking behavior even when the masking is partial. For attributes that differ across the browsing platforms, we can detect whether an AFPET was standardizing them by comparing their values across the platforms. Thus, we set up ClientSim to exercise control over as many attributes as possible. ClientSim simulates browsing platforms either locally on a computer or on pre-configured VirtualBox virtual machines [60] to exercise control over many of these attributes.

ClientSim sets up virtual machines and configures them according to stated preferences, including simulating different fonts, timezones, languages, and screen properties. ClientSim installs different fonts by adding a TrueType font file (.ttf file) to the .fonts folder. Both Firefox and Chrome allow fonts from this folder to be rendered on a webpage. To set timezones, ClientSim uses the timedatectl command available by default on Linux. ClientSim specifies the language using the locale-gen command and by changing the LANG environment variable. Moreover, ClientSim installs the corresponding Firefox language pack. Chrome does not have different installers for different languages, instead switching language based on the LANG environment variable. For screen attributes, specifically Height, Width and Depth, ClientSim uses the display server Xvfb. For native browsing platforms including Mac, Linux and Windows, we used configurations in which we found them.

Exercising control over some attributes is difficult. Some attributes require modifications to hardware (e.g., max touch points) or operating system libraries (e.g., math attributes). Screen attributes other than Height, Width and Depth cannot be simulated using Xvfb. Moreover, we restrict ClientSim to configuring attributes in the operating system while leaving browser settings intact. We do this to prevent re-configuring every browser instance after launch which may nullify the effect of the installed AFPET. As a result, ClientSim does not exercise openDB, indexedDB, two storage attributes, and six header attributes. ClientSim does not configure plugins since most plugins no longer work on Firefox [61] or Chrome [10] and they are gradually being phased out. We do not exercise the DNT enabled attribute since it conflicts with Tracking Protection. Nor do we exercise the adBlock installed (a heuristic Javascript test that attempts to insert an ad script into the page) and has lied with attributes (which checks whether the browser lied about certain attributes) since they are aimed at detecting various PET behaviors.

After setting up a simulated browsing platform, ClientSim drives browser instances on them using the Selenium Webdriver [55] to FPServer. ClientSim launches a browser in its original configuration or with a PET installed. For PETs that are browser extensions, ClientSim utilizes Selenium’s add_extension feature on the PETs’ .crx (Chrome) or .xpi (Firefox) extension files to launch a PET-enabled browser instance. For PETs that configure browsers, ClientSim launches browser instances with specific settings. For PETs that are full browsers, ClientSim uses binaries (for Brave) or specialized software (tbselenium [5, 6] for Tor BB).

The browser instances interact with FPServer in a specified pattern of reloads and idling to provide insights about the modification behavior of PETs. In hopes of triggering a PET’s ability to mask by varying attribute values, ClientSim drives its browsers across various boundaries that may cause the PET to refresh its spoofed value: reloading of a single domain, visits to different domains (we give FPServer two domain names), and browsing across sessions. We define a session to browsing separated by 45 minutes of down time, following Mozilla’s definition of a session as a continuous period of user activity in the browser, where successive events are separated by no more than 30 minutes [61].

Fingerprinting Server FPServer collects attributes known to be helpful for fingerprinting. Specifically, we set up FPServer to collect attributes collected by the open-source fingerprinting programs used by FPCentral [36] and Panopticlick [19], often by re-using their code. We list these attributes in the first column of Table 3. Similar to websites like panopticlick.eff.org and amunique.org/fp any browser visiting these domains can view their fingerprint, while a copy is stored on the server.

FPServer has minor modifications in the attributes it collects and how it collects them. For example, FPServer detects additional Noto fonts, which ship by default on Tor BB. Moreover, FPServer does not place cookies on the browsers visiting our domains, which FPCentral and Panopticlick use to identify returning visitors.

Analysis Engine To check for masking by a PET, as uses both the fingerprints collected by FPServer from the browsers driven by ClientSim and information directly from ClientSim stating which browser used
which PETs and in which configurations. Figure 4 provides an overview of $\alpha$. In short, the analysis looks for both masking by standardization and by variation. If it detects standardization or variation for an attribute, it models the attribute as masked in the mask model of the PET that it produces. It models an attributes as unmasked if it is able to thoroughly test it and find neither type of masking. The possible results of the analysis are

1. Label as inconclusive: variation testing impossible due the baseline browser varying the attribute

2. Label as masked: AFPET-induced variation detected

3. Label as masked: AFPET-induced standardization detected

4. Label as inconclusive: partial standardization cannot be ruled out due to not having browsing platforms that differ enough in the attribute

5. Label as unmasked: impactful standardization ruled out as unlikely

In more detail, $\alpha$ consumes a list of experimental results from ClientSim performed on a variety of browsing platforms. For each tested pair of an attribute and a PET, $\alpha$ first checks whether its value varied for any of browser platforms without the PETs installed as they cross the three boundaries mentioned above. If so, it cannot detect whether the PET varies that attribute since it is already varying. In this case, $\alpha$ labels the attribute as inconclusive and records the reason for this conclusion. If not, $\alpha$ goes on to check whether the attribute’s value varied for any of the browsing platforms with the addition of the PET and, if so, labels the attribute as masked for this reason.

If the attribute is not labeled under either variation check, $\alpha$ checks whether the attribute was masked by standardization. First, for each baseline browsing platform, it checks whether the value differs between the baseline platform and the platform with the PET installed. If so, $\alpha$ concludes that the PET standardized the attribute since the only difference between the two platforms is the addition of the PET and variation has already been ruled out. If not, then we can rule out full standardization with certainty but not partial standardization.

In general, ruling out partial standardization with experiments requires testing for all possible attribute values, a prohibitively expensive, if not impossible, task for many attributes. However, $\alpha$ can, in reasonable time and with reasonable confidence, rule out impactful partial standardization, that is, standardization that affects at least a fraction $f$ of the values. To do so, $\alpha$ estimates the probability of seeing at least one changed value given that at least a fraction $f$ are being standardized. If this probability is below some threshold $\alpha$, $\alpha$ rejects the idea that tool is impactfully standardizing and labels the attribute as unmasked with confidence $\alpha$. Otherwise, the result is inconclusive since not enough values of the attribute were tested. We use the geometric distribution to estimate likelihood of finding masking
given that a fraction $f$ is happening. Appendix A provides details.

4.2 Experiment

Using PETInspector, we performed an initial experiment finding no additional spoofing from AFPETs crossing sessions. Thus, to save time, our main experiment uses only a single session and does not check for the masking of attributes by variation across sessions.

We use ClientSim to simulate six browsing platforms. Three of these are virtual machines running various versions of Linux. We introduce additional changes into these virtual machines to simulate differences in the system configurations. Specifically, we install different fonts and browser versions, set up different timezones, and simulate different screen resolutions and languages. The remaining platforms run natively on a Linux desktop, Macbook Pro, and a PC laptop. We perform measurements on Firefox and Chrome browsers. More details on these configurations are in Table 2.

ClientSim drives these experimental browsing platforms to load FPServer for five reloads of each of the two domain names of FPServer. For each platform, it does these reloads a total of 28 times: one time each for 26 PETs and one time each for the two baseline browsers. All PETs are left in their default configuration.

4.3 Results

Before commenting on PETs, we make some observations about the baseline browsers. While we did not think of the choice of browsers as affecting the trackability of fingerprints, it turns out that comparing our baseline measurements for the two browsers reveals small differences in the attributes shared by them. Among the simulated platforms, Chrome sets the cpu class to unknown, the screenDepth to 24, and the buildID to Undefined, unlike Firefox which reveals different values across browsing platforms. On the other hand, Firefox does not reveal any plugins, while Chrome does. Chrome’s plugins differ across Ubuntu, Debian, and macOS. PETInspector does not find any baseline browser to vary any attributes itself (outcome (1) in Fig. 4).

Turning to PETs, PETInspector automatically produces Table 3 which displays attributes masked or not by AFPETs. We comment upon the BLPETs in text. We provide PETInspector with the masks that each tool’s documentation purports, which it uses to facilitate comparing documented behaviors with observed behaviors.

Among the 15 AFPETs, three (Trace, Privacy Extension, and No Enum. Extensions) do not lead to any detectable masking in their default configurations. The remaining 12 AFPETs mask at least one of the collected attributes.

Our experiment also detects undocumented masking of attributes by AFPETs. For example, while Canvas DefenderC, Canvas DefenderF, CanvasFingerprintBlock, Glove, and CanvasBlocker claim to spoof only the canvas fingerprint, we also find them spoofing webGL attributes. Similarly, we find undocumented modifications by Brave, Stop Fingerprinting, and TotalSpoof. We also find inconsistencies in the behavior of Brave, Privacy BadgerC, Privacy BadgerF, HideMyFootprint, and Tor BB, which we discussed in Section 1.2.

Among the 11 BLPETs, four (DisconnectF, DisconnectC, GhosteryC, and GhosteryF) do not lead to any detectable modifications of attributes, four (Adblock PlusC, Adblock PlusF, uBlock OriginC, and uBlock OriginF) modify the attribute adBlock installed, and three (Privacy BadgerC, Privacy BadgerF, and Tracking Protection) modify Do Not Track attributes. As discussed in the introduction, these BLPETs are presented as AFPETs, but their modifications can actually make their users more identifiable. Indeed, Privacy Badger was updated in response to our finding.

Given the difficulty of taking in Table 3 for the purpose of ranking AFPETs relative to one another, we provide Figure 5 considering each of these masking behaviors as equally valuable for reducing trackability. This level of abstraction in modeling AFPETs seems reasonable given our belief that trackers are foiled by any of these methods given the complexity of, for example, using a varying attribute for tracking. We produce a pre-ordering of the AFPETs where one AFPET $p_1$ is above or equal to another AFPET $p_2$ iff $p_1$ masks every attribute that $p_2$ does. Those desiring a finer gradation can look at the number of attributes masked, but must bear in mind that not all attributes are equally important to mask. The hybrid evaluation discussed in Section 5 takes into account the relative importance of different for ranking AFPETs.
Table 2: Configurations of simulated browsing platforms in our main experiment. The last three were regularly used.

| #  | Type | OS         | Addl. Fonts | Resolution | Locale & LANG | Timezone | Browser versions | Notes |
|----|------|------------|-------------|------------|---------------|----------|-----------------|-------|
| 1  | VM   | Ubuntu 16.04 | Mordred     | 450×721×24 | ru_RU.UTF-8  | GMT+6    | 56.0 63.0       |       |
| 2  | VM   | Debian 8.10  | OldLondon   | 2000×2000×16 | de_DE.UTF-8 | GMT-3    | 56.0 63.0       |       |
| 3  | VM   | Ubuntu 14.04 | (none added) | 6000×3000×24+64 | ar_SA.UTF-8 | GMT-11   | 56.0 63.0       |       |
| 4  | Local| Ubuntu 16.04 | > 40        | 1920×1080×24 | en_EN.UTF-8  | GMT-8    | 56.0 70.0       |       |
| 5  | Local| macOS 10.13  | > 145       | 1440×900×24  | en_EN.UTF-8  | GMT-8    | 56.0 70.0       |       |
| 6  | Local| Windows NT 10.0 | > 145   | 1280×720×24  | en_EN.UTF-8  | GMT-8    | 56.0 beta 69.0  | Touch screen |

Figure 5: Ranking of AFPETs by the experimental method. Arrows show the pre-order, with AFPETs at an equivalent order being grouped together. The y-axis shows the number of attributes masked.

4.4 Discussion and Limitations

As discussed in Section 1.3, the ranking above may not be suitable for some evaluation goals. For example, some AFPETs were designed to mask a single attribute and does in fact mask it (e.g., Canvas Defender\(_C\)). Our findings that such AFPETs (or BLPETs) do not mask all attributes should not be interpreted as the PET having a bug. Nevertheless, consumers and advocates seeking effective PETs may find our results useful.

As mentioned above, we may miss some masking of attributes due to not testing values that a PET standardizes away. Furthermore, we may not detect a PET varying an attribute across a boundary that we do not test. Thus, while we can be sure of masking when we find it, we cannot be sure we have found all masking.

\(\text{FPServer}\) extracts fingerprints by running first-party fingerprinting scripts on browsing platforms. Thus, we do not detect masking that happens for only third-party scripts.

To an extent, these limitations can be mitigated with more comprehensive experiments using \(\text{PETInspector}\). For example, one can modify \(\text{FPServer}\) to collect additional attributes in both first-party and third-party contexts. Moreover, one can modify \(\text{ClientSim}\) to detect variations across other boundaries and use more diverse experimental browsing platforms to be more confident about not missing standardization modifications. We will make \(\text{PETInspector}\) freely available for more extensive experimentation and further development. Our current evaluations demonstrate the benefits of an experimental evaluation method for AFPETs within the current boundaries.

Where our experiments dispute claimed masking (\(\nabla\) in Table 3), it may be due to the above limitations rather than documentation making spurious claims. PETs may mask more attributes when configured to do so, but users find it difficult to change the defaults \(\text{[40]}\), suggesting our experiments may capture typical use. Next, we perform additional man-
| Attribute            | Chrome | Firefox |
|----------------------|--------|---------|
| buildID              |        |         |
| canvas fingerprint   |        |         |
| cookies enabled      |        |         |
| cpu class            |        |         |
| h.Accept             |        |         |
| h.Accept-Encoding    |        |         |
| h.Accept-Language    |        |         |
| h.Pragma             |        |         |
| javascript fonts     |        |         |
| language             |        |         |
| local storage        |        |         |
| platform             |        |         |
| plugins              |        |         |
| screen.AvailHeight   |        |         |
| screen.AvailLeft     |        |         |
| screen.AvailTop      |        |         |
| screen.AvailWidth    |        |         |
| screen.Depth         |        |         |
| screen.Height        |        |         |
| screen.Left          |        |         |
| screen.Pixel Ratio   |        |         |
| screen.Top           |        |         |
| screen.Width         |        |         |
| session storage      |        |         |
| timezone             |        |         |
| touch.event          |        |         |
| touch.max points     |        |         |
| touch.start          |        |         |
| webGL.Data Hash      |        |         |
| webGL.Renderer       |        |         |
| webGL.Vendor         |        |         |

Table 3: AFPET masks as purported and observed by PETInspector. □ indicates AFPET’s documentation purports that the attribute is masked. The remaining symbols represent the possible outputs of PETInspector: + indicates observed masking, × indicates no masking found even when it is likely to detect it, and ⋅ indicates inconclusive results. For the results that we manually double checked, we include the outcome of that check as a superscript. Here, × denotes that the PET really does not mask the attribute, + that it does, ×/+ that it is not masked by default but can be with configuration, and ? that the manual analysis was inconclusive. Not shown are attributes that had all inconclusive results and not purported masking (nothing but ⋅): DNT enabled, IE addBehavior, adBlock installed, h.Connection, h.Dnt, h.Up.-Ins.-Req., indexedDB, math.acosh(1e300), math.asinh(05), math.atanh(05), math.cosh(10), math.exp1(1), math.log1p(10), math.sinh(1), math.tanh(1), and openDB.
ual analysis to understand the effects of configuration and why our results are in conflict with the documentation of some PETs.

4.5 Additional Manual Analysis

To address some of the limitations mentioned above, we perform manual analysis of some PETs. Specifically, we analyze AFPETs for which we found no evidence of any masking (Trace, Privacy Extension, No Enum. Extensions) and those which made a claim rejected by PETInspector (Trace, Privacy Extension, Stop Fingerprinting, Tor).

PETInspector rejects two claims of masking by Trace. We could not find the source code for Trace, but we installed the extension and manually examined it. Both the documentation and settings panel show canvas fingerprinting being masked by default, despite our studies concluding the opposite. As far as we can tell, Trace really does not mask this attribute despite claiming to. Since running our tests, Trace has been updated from version 1.0.2 to 1.8.6 and it now randomizes the canvas fingerprinting.

As for masking the user-agent, the settings panel of Trace shows that user-agent randomization is off by default, explaining our finding. (It’s under the “Advanced Features” tab, despite their webpage prominently advertising the feature.) Turning it on does randomize the user agent.

All of Privacy Extension’s masking abilities are off by default. Turning them on does result in standardizing the two attributes in question: the canvas fingerprint and the user-agent.

To analyze No Enum. Extensions, we examined both its source code and documentation. The documentation of No Enum. Extensions only claims to mask plugins and we found evidence of plugin masking in No Enum. Extensions’s source code. PETInspector was inconclusive for this attribute since it was unable to exercise the plugin list for Firefox due to Firefox making the loading of any plugins a manual process. Thus, this instance does not represent a false negative, and instead represents a failure to find a positive.

We manually tested Stop Fingerprinting and found that, like No Enum. Extensions, it masks plugins despite PETInspector’s inconclusive finding. As for the rejected claim of masking javascript fonts, Stop Fingerprinting may be doing something with the fonts, but not enough to defeat the way FPServer fingerprints them.

Examining Tor BB leads us to believe that a recent update (after Version 7.0.11), accidentally affected its masking of the platform attribute. We also find that during the same time frame, the cpuclass and h.User-Agent went from being apparently fully masked to partially masked. We have found user complaints about this change in behavior for version 8.0a10.

We also confirmed that Privacy Badger did not set the doNotTrack field of the navigator object to match the Dnt header. The code was fixed after we notified the developers of the issue.

5 Hybrid Evaluation of AFPETs

Our experimental method provides a model of how various AFPETs mask fingerprints as well a ranking of AFPETs based on the number of attributes they mask. However, it does not consider how important masking each attribute is.

We develop a hybrid method that combines the benefits of the experimental method with an observational method. We start by considering a completely observational method and then discuss how combining it with our experimental method allows us to overcome each of their limitations.

In short, the method uses mask model of each AFPET provided by the experimental method. For each attribute, we model the AFPET as masking the attribute if the mask model indicates so or if the experiment was inconclusive, thereby overestimating the AFPET’s abilities. We use this mask model to transform a set of original fingerprints collected on the amiunique website into a counterfactual AFPET-modified set, which simulates the browsing platforms in the original dataset visiting amiunique with an AFPET installed. To determine the effectiveness of the AFPET, we compare trackability in the two datasets.

5.1 Sampling

We cannot, in practice, see all the world’s browsing platforms and instead must work with a sample. The quality of the metrics computed from the sample depends upon both the nature of the metric and the sample. For example, a random sample will provide a reasonable estimation of the entropy (e.g., 50). However, estimating the proportion of users in small anonymity sets from even a random sample proves
difficult since the length of the tail of the distribution may be unclear from a random sample.

Furthermore, in practice, we must approximate truly random samples of browser platforms from available datasets since we cannot force all users to participate. We do so by using a convenience sample provided to us by the amqunique website, which collects fingerprints to understand how trackable they are. This sample comprises 25,984 real-world fingerprints collected over a period of 30 days (10/02/2017 to 11/02/2017). Each fingerprint comprises 32 different attributes.

Determining the representativeness of this sample is difficult since it can only be compared to other possibly unrepresentative samples. We compare our sample’s distributions to GlobalStat’s for desktop users [59]. We find that our sample has a higher proportion of Firefox users (42% vs. 12%) and of Linux users (19% vs. 1%). Perhaps people visiting browser fingerprinting websites have more technical knowledge and a preference for open-source technologies.

5.2 Metrics of Trackability

We haven’t yet defined what we mean by trackability. Is a tracker that can determine with 10% certainty 90% of the time that you visited a website worse than one that can determine it with 90% certainty 10% of the time? This depends upon both the tracker’s and the evaluator’s goals. With this in mind, we do not argue for a single metric, but rather consider a few.

To measure trackability of the fingerprints, we have implemented FPInspector, which consumes a dataset and characterizes how trackable its members are. One such characterization is the anonymity set. An anonymity set comprises browsing platforms with identical fingerprints that are, thus, indistinguishable from each other. Thus, the smaller and more numerous the anonymity sets, the higher the uniqueness.

FPInspector implements various proposed functions of the distribution of anonymity sets of browsing platforms for measuring uniqueness [67, 18].

The first metric which we use to measure uniqueness is entropy. For a set of browser platforms \( D = \{ b_i \}_1 \), such as those using a particular AFPET, let \( D[id(\cdot)] \) denote the multiset of fingerprints \( \{ id(b_i) \}_1 \), where \( id(\cdot) \) is the fingerprinting mechanism. The entropy of these fingerprints is given by

\[
\text{ent}(D[id(\cdot)]) = - \sum_{id_k \in D[id(\cdot)]} \Pr[id_k] \log_2(\Pr[id_k])
\]

where \( \Pr[id_k] \) is the probability of observing the fingerprint \( id_k \), which we estimate from the frequency of \( id_k \) in \( D[id(\cdot)] \). The higher the entropy, the higher the uniqueness of the fingerprints.

FPInspector also measures the proportion of users in anonymity sets of size less than or equal to 1 (prop_less1) and 10 (prop_less10). These metrics measure the proportion of browsing platforms hiding in anonymity sets of sizes at most 1 and 10. The higher prop_less1 is, the higher is the fraction of browsing platforms that can be uniquely identified. Similarly, higher prop_less10 indicates a higher fraction of browsing platforms that can be identified to a set of size at most 10. Thus, higher values of these metrics indicate higher uniqueness of the fingerprints.

FPInspector measures effectiveness of a PET \( p \) against fingerprinting mechanism \( id(\cdot) \) from the dataset of fingerprints \( D[id(\cdot)] \) in terms of a metric \( f \) in \( \{ \text{ent}, \text{prop}_\text{less1}, \text{prop}_\text{less10} \} \) as

\[
\text{eff}(p, id, D_p, D) := f(D_p[id(\cdot)]) - f(D_p[id(\cdot)])
\]

where \( D_p \) is a subset of \( D \) using the PET and \( D_p \) is the rest of \( D \).

5.3 Limitations of Observations Alone

In principle, a highly-context dependent, completely observational method could function by comparing the fingerprints produced by users of each AFPET to determine which are the least trackable. In practice, we face difficulties with obtaining a representative sample of AFPET users and determining which users run which AFPETs.

PET determination. Determining PET use from fingerprints not explicitly containing the information is difficult. This limitation can be overcome by a fingerprinting server designed to collect information about PET use. One approach is to ask visitors about their PETs, but users can be unaware of their own browser’s configurations. In some cases, PETs have a distinctive fingerprint that gives away their use, but this would only help us with a subset of PETs. Moreover, this approach would not work with AFPETs which attempt to have a common fingerprint also had by non-users of the AFPET. Alternatively, fingerprint collection websites can use automated methods to detect browser extension PETs (e.g., [58, 56]). Unfortunately, our observational data lacks this information.

PET sampling. Even with a fingerprinting server collecting PET information, getting a representative
sample of real users with AFPETs to visit the website may be difficult, since there are few AFPET users. This is especially true for new and not yet popular AFPETs. Furthermore, users of AFPETs may be systematically different from users without AFPETs, thereby introducing confounding factors influencing the trackability metrics. To remove or minimize the effect of these confounding factors, one may have to identify matched pairs of users, one using an AFPET and another not.

Due to these limitations, we cannot apply FPInspector directly to our dataset. Moreover, the PET sampling limitation may prevent application of this method directly to data collected on even fingerprinting servers designed for PET determination. Thus, we instead use FPInspector in an hybrid evaluation method that avoids the PET determination and sampling problems altogether.

5.4 Overcoming the Limitations of Observations

To overcome the difficulty of getting a sample $D_p$ of browser platforms using a PET $p$, we construct our own from a sample $D_p$ of browser platforms not using $p$. We then provide both to FPInspector, which uses $\text{eff}_f$ (see Eq. 1 above) to evaluate the PET $p$, as show in Figure 1.

This approach requires that we first get a sample of platforms not using $p$. We start with the amiunique dataset. To convert that dataset of fingerprints into one of platforms, we need a mapping of fingerprints to unique browsing platforms. We approximate this mapping using cookie IDs associated with each fingerprint. We treat fingerprints with different cookie IDs as being produced by different browsing platform. This approach is similar to Eckersley, who also uses cookies in his Panopticlick study to approximate returning visitors [18]. In the dataset, 21,395 fingerprints have a cookie associated with them, of which, 18,295 are unique.

To obtain $D_p[id(\cdot)]$, we sanitize the dataset to remove fingerprints with obvious signs of PET use, specifically those with JavaScript disabled and illegitimate screen resolutions. Additionally, we only retain fingerprints from desktop browsers (with Windows, Mac, or Linux OSes) since all the PETs we study are for desktops. These sanitizations leave 17,109 fingerprints. Finally, we separate this set into two sets of fingerprints, one from Chrome and another from Firefox browsers by looking at the User-Agent attribute in each fingerprint. This results in 9,493 Chrome and 6,516 Firefox browser fingerprints, which we use to simulate the tracker’s view of the original fingerprints for evaluating Chrome and Firefox AFPETs respectively. We find that the original fingerprints reveal 13.002 and 12.359 bits of entropy for Chrome and Firefox browsers respectively. These and other metrics are presented in Table 4 corresponding to the ‘no mask’ row.

The mask model from the experimental method provides a way to transform these original fingerprints. We apply the mask model $\hat{\rho}$ of an PET $p$ produced by PETInspector to the sample $D_p$ of platforms without a PET to generate a sample of fingerprints $D_p[id(\cdot)]$. This generated sample estimates what the original fingerprints would had looked like had the platforms used the PET $p$. We use FPInspector to calculate the trackability metrics of the modified fingerprints and unmodified fingerprints. By comparing the metrics of the original and $\hat{\rho}$-modified fingerprints, we estimate the effectiveness of the PET $p$.

Of the 49 original attributes, PETInspector provides a conclusive characterization for 18 attributes on Chrome browsers and 20 attributes on Firefox browsers. Of these, only 12 appear in the amiunique.org dataset. For a given PET, we mask these 12 attributes according to the model generated by PETInspector and fully mask the remaining 16 attributes in the amiunique.org dataset for which the experiment is inconclusive. By fully masking inconclusive attributes, we overestimate the effectiveness of PETs. Thus, we generate a set of PET-modified fingerprints (i.e., $D_p[id(\cdot)]$) from the original fingerprints and measure effectiveness of the 15 AFPETs.

5.5 Results

We present the metrics of trackability from Section 5.2 for both Chrome and Firefox AFPETs in Table 4. The original fingerprints reveal 13.002 and 12.359 bits of entropy for Chrome and Firefox browsers respectively. Applying a base mask comprising all inconclusive attributes reduces the entropies to 12.914 and 12.177 bits.

Our evaluations reveal that all AFPETs but Brave and Tor BB reveal over 11 bits of entropy and hence are marginally better than not using any AFPET at all. For these AFPETs, fewer than 20% of the fingerprints are in anonymity sets of size greater than 10. Brave does better, leaking just over 8 bits of entropy and having over 70% of fingerprints in anonymity sets of size greater than 10. Tor BB performs best since
Table 4: Trackability metrics for AFPETs.

| PET                          | ent | prop_less1 | prop_less10 |
|------------------------------|-----|------------|-------------|
| Chrome PETs                  |     |            |             |
| no mask                      | 13.002 | 0.892     | 0.983       |
| base mask, Privacy Extension, Trace | 12.914 | 0.829     | 0.982       |
| Canvas DefenderC, CFB, Glove | 12.306 | 0.641     | 0.893       |
| HideMyFootprint              | 11.77  | 0.497     | 0.825       |
| Brave                        | 8.108  | 0.072     | 0.262       |
| Firefox PETs                 |     |            |             |
| no mask                      | 12.359 | 0.875     | 0.96        |
| base mask, No Enum. Extensions | 12.177 | 0.797     | 0.949       |
| Blend In, TotalSpoof         | 12.049 | 0.747     | 0.936       |
| CanvasBlocker                | 12.002 | 0.7       | 0.941       |
| Blender                      | 11.875 | 0.678     | 0.924       |
| Stop Fingerprinting          | 11.778 | 0.726     | 0.919       |
| Canvas DefenderF             | 11.263 | 0.483     | 0.833       |
| Tor BB                       | 4.766  | 0.01      | 0.038       |

it modifies all the 12 attributes we consider.

5.6 Remaining Limitations

While this hybrid method enables us to perform a fine-grained evaluation of AFPETs with few users, it inherits some of the limitations of the methods on which it builds. For example, from a purely observational methods comes the limitations that samples can be biased and that no one metric can completely capture the quality of an AFPET. From the experimental method of Section 4, we inherit the approximate nature of the mask model, which does not account for how attributes are masked and how that affects privacy.

In particular, our analysis overestimates the effectiveness of all AFPETs, since we assume any modifications of an attribute by an AFPET renders that attribute useless to a tracker. This may not be the case. For example, Brave spoofs the User-Agent and the Accept-Language headers to different values than Chrome. While these spoofed values may continue to reveal bits of entropy, we consider the attributes to be rendered useless for tracking. Similarly, Tor BB also reveals spoofed values of screen resolution.

We can carry out a tighter evaluation by considering a tracker which can take advantage of the spoofed values. This evaluation requires knowledge of how an AFPET spoofs the attribute. For Tor BB, we performed a manual code analysis to determine how exactly Tor BB deals with screen resolution attributes. We rerun the hybrid analysis on a hand crafted mask model capturing this behavior instead of using the rough model produced by PETInspector. This provides a tighter evaluation for Tor BB that will serve as the basis for our analysis in Section 7.

Finally, the above evaluations are performed on the same set of fingerprints and applies the mask to every fingerprint in the dataset, simulating total adoption of the AFPET. This approach is appropriate evaluations with a long-term prospective, such as selecting an AFPET to fund, since a properly promoted AFPET could become nearly universal in the future. However, those looking to select a AFPET for usage today should be concerned with the number of users each AFPET has since it will affect the size of the anonymity set the AFPET produces. In the next section, we consider a modification of the above method for dealing with this issue.

We create the handcrafted mask model of Tor BB from the Firefox patch at https://gitweb.torproject.org/tor-browser.git/commit/?h=tor-browser-45.8.0esr-6.5-281d=7b3e88bd7f72d4f3feac11e74c6b506729a502b2
6 Adjusting for the Number of Users

To observe the consequences of having user bases of different sizes, we also evaluate the AFPETs taking into account their popularity. Ideally, we would do this by having the fingerprints all the users of a AFPET. However, not having access to this set of fingerprints, we instead simulate them by drawing random samples of fingerprints from the amiunique.org dataset of size equal to the number of AFPET users and estimate uniqueness metrics on the samples.

Table 5 displays the number of users of each AFPET in our list as of Dec. 2017. The popularity of extensions were obtained from the Firefox add-on library [45] and the Chrome extensions webstore [27]. Tor’s popularity was obtained from the Tor Metrics webpage [62]. For AFPETs with an undisclosed number of users, such as Braveand Tracking Protection, we are unable to perform this evaluation.

We also do not perform these evaluations for AFPETs with a user base greater than 17,109 (like Tor BB, Canvas DefenderC and CanvasBlocker), since we cannot draw a sample from our dataset of sufficient size. Attempting to draw such a sample by allowing the same fingerprint to be sampled multiple times will overestimate the effectiveness of the PET since such repeats will surely be in the same anonymity set even for PETs that do nothing.

For all other AFPETs, we compute the mean and the standard error of mean \( \text{mean} \pm \text{sem} \) of the trackability metrics from 100 random samples. Table 6 displays the entropy-based effectiveness metrics for these AFPETs, sorted according to the effectiveness. We can see that CanvasFingerprintBlock scores better than HideMyFootprint due to its high popularity, contrary to the original evaluations in Table 4. We also see that the effectiveness of tools with identical effects increases with popularity. For example, TotalSpoof and Blend In both identically modify 12 attributes, but Blend In is more effective than TotalSpoof due to its popularity. Table 6 also provides estimates of the other trackability metrics for these AFPETs.

7 Application: Informing AFPET Design

With the ability to accept handcrafted mask models, our hybrid method can help AFPET developers make
Table 6: Uniqueness metrics for different AFPETs on samples scaled according to their popularity

| PET                  | #users | ent | prop_less1 | prop_less10 |
|----------------------|--------|-----|------------|-------------|
| **Chrome PETs**      |        |     |            |             |
| HideMyFootprint      | 177.0  | 7.343 | 0.901      | 1.000       |
| Glove                | 342.0  | 8.277 | 0.886      | 1.000       |
| CanvasFingerprintBlock | 7630.0 | 11.559 | 0.313      | 0.899       |
| **Firefox PETs**     |        |     |            |             |
| TotalSpoof           | 265.0  | 7.904 | 0.889      | 1.000       |
| Blend In             | 858.0  | 9.401 | 0.777      | 0.983       |
| Stop Fingerprinting  | 1754.0 | 9.994 | 0.641      | 0.939       |
| Blender              | 1816.0 | 10.200 | 0.614     | 0.960       |
| Canvas DefenderF     | 5274.0 | 10.656 | 0.252      | 0.845       |

an informed choice while designing AFPETs. By measuring the effectiveness of hypothetical designs, AFPET developers can compare different masking strategies to tradeoff utility with trackability. We carry out such an exploration comparing alternate designs of Tor BB by applying our hybrid method on hypothetical Tor BB versions that mask attributes differently. Tor BB leaks some information about the screen resolution by only partially standardizing it. Specifically, it resizes new browser windows in quanta (step/bucket sizes) of 200×100 pixels, while capping the window size at 1000×1000 pixels, and uses the client content window size as screen dimensions [51]. As a result all Tor BB users get placed into one of 50 anonymity sets based on the revealed screen dimensions, as long as they do not change the window dimensions manually. We explore the impact of the choices of cap and quanta parameters on the effectiveness of Tor BB.

We use the number of unutilized screen pixels due to a spoofing strategy as a measure of utility loss. We measure two variants: the total number of unutilized pixels (average absolute loss), as well as the number of unutilized pixels as a percentage of the available pixels (average percentage loss). Increasing the cap parameters and decreasing the quanta parameters reduces this loss. We first measure the effectiveness of alternate strategies with strictly lower utility loss (i.e., higher cap and lower quanta parameters) than Tor BB’s. An exhaustive search of all 19,999 quanta parameters less than Tor BB’s (i.e., 1000×1000), finds no strategy achieving higher effectiveness in all metrics than Tor BB. Similarly, fixing the quanta parameters at 200×100, while increasing the cap parameters in steps of 50 pixels from 1000×1000 to 2000×2000 does not uncover any strategy with higher effectiveness either. We perform these explorations on the Firefox fingerprints in the amiunique.org dataset.

Next, we explore strategies that trade-off losses resulting from one set of parameters (e.g., quanta) with gains from another (e.g., cap) with the goal of finding a strategy that reduces the utility loss while increasing the effectiveness. We find that cap width parameter to be the most in need of improvement since less than 13% of amiunique.org fingerprints have a screen width less than 1000 pixels. We consider alternative cap widths of 1350, 1550, and 1600 since a higher percentage of fingerprints (25%, 47%, and 51% respectively) have screen widths less than these caps. We retain the cap height of 1000 pixels as more than 50% of the fingerprints remain below that cap. We exhaustively search for all 10,201 quanta in the range 200×100 to 300×200 for all three cap parameters. We set an upper bound of 300×200 as the loss may be too high for low-resolution displays for very high quanta parameters. We find 786 and 291 quanta parameters for cap widths of 1350 and 1550 respectively for which the losses are lower than Tor BB’s, but the effectiveness is higher. We display strategies with the least quanta parameters in Table 7. As we increase the cap width to 1600, none of the quanta parameters lead to a higher measure of effectiveness than Tor BB.
8 Conclusion and Discussion

We carry out an evaluation of 15 different AFPETs against fingerprinting using two different methods. We develop PETInspector and use it for experiments to determine how these PETs spoof 18–20 different attributes. In addition to uncovering inconsistencies, it provides a model of AFPETs’ behaviors. While the experimental method provides an evaluation in terms of the number of attributes that an AFPET masks, it cannot distinguish between the relative importance of masking different attributes. Our hybrid method leverages a real-world fingerprinting dataset to provide a finer grained view into the impact of modifying different attributes. We find Tor BB to be the most effective AFPET among the ones we evaluate using both methods. It standardizes the most attributes and reduces the trackability of revealed fingerprints by the highest margins among the AFPETs we evaluate. We also apply our hybrid method to find some hypothetical spoofing strategies which have a smaller utility loss than Tor, yet are just as effective.

The Tor Project is part of the team behind the FPCCentral fingerprinting repository, which spans a comprehensive collection of fingerprinting techniques. This awareness helps Tor BB developers build comprehensive defenses against fingerprinting. This however does not mean that Tor BB users are protected against all possible fingerprinting attacks. Developers must be on the lookout for new fingerprinting techniques and build in fresh defenses. While our tools cannot automatically invent new attributes, it can be extended to test them, allowing an assessment for how to deal with them.

We end with some suggestions for AFPET developers and evaluators. We recommend that developers address any attribute that PETInspector flags as unmasked. The entropy results from our hybrid method can aid in determining the order in which to address various unmasked attributes. Given our experimental results, we expect this task will keep the developers of most AFPETs busy. Next, they might want to consider any attributes that PETInspector labeled as inconclusive. After addressing these attributes, they can consider improving how an AFPET spoofs an attribute. As shown in Section 7, not all spoofing is equal. Developers should consider using Tor BB as a starting point for their development and carefully consider the default settings of their AFPET.

The set of fingerprintable attributes are open ended and will never be fully enumerated, but new attributes can be added to our tools. AFPET evaluators should keep in mind that any one-time evaluation of PETs will quickly become out of date. We encourage developers and advocates (e.g., the EFF) to use automated tools to regularly test the trackability of PETs. Our tool can fill this need.

Acknowledgements

We thank Milan Ganai for investigating how to automate the use of PETs on Windows. We thank Lay Kuan Loh and Zheng Zong for assistance in exploring the application of information flow experiments to evaluate PETs. We thank Anupam Datta for discussions about this work. We gratefully acknowledge funding support from the National Science Foundation (Grants 1514509 and 1704985). The opinions in this paper are those of the authors and do not necessarily reflect the opinions of any funding sponsor or the United States Government.

References

[1] Absolute Double. HideMyFootprint: Protect your privacy. https://hmfp.absolutedouble.co.uk. 2017. Accessed Dec. 25, 2017.
[2] Absolute Double. Trace: Browse online without leaving a trace. https://absolutedouble.co.uk/trace/ 2018. Accessed Jan. 12, 2018.

[3] Gunes Acar, Christian Eubank, Steven Englehardt, Marc Juarez, Arvind Narayanan, and Claudia Diaz. The web never forgets: Persistent tracking mechanisms in the wild. In Proceedings of the 2014 ACM SIGSAC Conference on Computer and Communications Security, pages 674–689. ACM, 2014.

[4] Gunes Acar, Marc Juarez, Nick Nikiforakis, Claudia Diaz, Seda Gürses, Frank Piessens, and Bart Preneel. Fingerprinting in the wild: dusting the web for fingerprinters. In Proceedings of the 2013 ACM SIGSAC conference on Computer & communications security, pages 1129–1140. ACM, 2013.

[5] Gunes Acar and Marc Juarez. tor-browser-selenium: A Python library to automate Tor Browser with Selenium. The webfp/tor-browser-selenium project on GitHub: https://github.com/webfp/tor-browser-selenium May 2018.

[6] Gunes Acar (gacar). tselenium: Tor Browser automation with Selenium. PyPi project: https://pypi.org/project/tselenium/ March 2018.

[7] Alexei (ghostwords). Support navigator.doNotTrack. Pull request #1861 for the EFForg/privacybadger project on GitHub: https://github.com/EFForg/privacybadger/pull/1861 July 2018.

[8] Andrew. Scriptsafe: andryou. https://www.andryou.com/ scriptsafe/ 2017. Accessed Dec. 25, 2017.

[9] Anonymous. Comment 276687 on “new release: Tor Browser 8.0a10”. Tor Blog: https://blog.torproject.org/comment/276424#comment-276424 August 2018. See responses as well.

[10] appodrome.net. CanvasFingerprint-Block: Chrome Web Store. https://chrome.google.com/webstore/detail/canvasfingerprintblock/ipmjngkmcdpmgmeibdmbfkkcecdndc?hl=en 2017. Accessed Dec. 25, 2017.

[11] Brave Browser. Fingerprint protection mode. https://github.com/brave/browser-laptop/wiki/Fingerprinting-Protection-Mode 2017. Accessed Dec. 19, 2017.

[12] Yinzhi Cao, Song Li, and Erik Wijmans. (cross-)browser fingerprinting via os and hardware level features. In 24th Annual Network and Distributed System Security SymposiumNDSS, 2017. http://www.yinzhicao.org/TrackingFree/crossbrowsertracking_NDSS17.pdf

[13] Amit Datta (tadatitam). Accept-language header has only default locale, not list of languages. Issue #429 of the Brave/Muon bug tracker on GitHub: https://github.com/brave/muon/issues/429 January 2018.

[14] Amit Datta (tadatitam). Fingerprinting: Brave’s headers, plugins different from Chrome. Issue #12479 of the Brave/Browser-laptop bug tracker on GitHub: https://github.com/brave/browser-laptop/issues/12479 January 2018.

[15] Amit Datta (tadatitam). Privacy Badger does not set the doNotTrack variable in JavaScript’s navigator object. Issue #1835 of the EFForg/PrivacyBadger bug tracker on GitHub: https://github.com/EFForg/privacybadger/issues/1835 January 2018.

[16] Chrome: Developer. NPAPI Plugins. https://developer.chrome.com/apps/npapi 2018. Accessed Jan. 12, 2018.

[17] Disconnect. Disconnect. https://disconnect.me 2017. Accessed Jan. 12, 2017.

[18] Peter Eckersley. How unique is your web browser? In Privacy Enhancing Technologies, volume 6205, pages 1–18. Springer, 2010.

[19] Electronic Frontier Foundation. Panopticlick. https://panopticlick.eff.org 2017. Accessed Dec 12, 2017.

[20] Electronic Frontier Foundation. Privacy Badger. https://www.eff.org/privacybadger 2017. Accessed Jan. 13, 2017.

[21] Steven Englehardt and Arvind Narayanan. Online tracking: A 1-million-site measurement and analysis. In Proceedings of the 2016 ACM
SIGSAC Conference on Computer and Communications Security, pages 1388–1401. ACM, 2016.

[22] eyeo GmbH. Adblock Plus: Surf the web without annoying ads! https://adblockplus.org 2017. Accessed Dec. 27, 2017.

[23] Amin FaizKhademi, Mohammad Zulkernine, and Komminist Weldemariam. Fpguard: Detection and prevention of browser fingerprinting. In IFIP Annual Conference on Data and Applications Security and Privacy, pages 293–308. Springer, 2015.

[24] David Fifield and Serge Egelman. Fingerprinting web users through font metrics. In International Conference on Financial Cryptography and Data Security, pages 107–124. Springer, 2015.

[25] fonk. TotalSpoof add-on homepage. http://fonk.wz.cz/totalspoof 2017. Accessed Dec. 25, 2017.

[26] Cliqz International GmbH. Ghostery makes the web cleaner, faster and safer! https://www.ghostery.com 2017. Accessed Dec. 27, 2017.

[27] Google. Chrome web store. https://chrome.google.com/webstore/category/extensions December 2017.

[28] Gábor György Gulyás, Dolière Francis Somé, Nataliia Bielova, and Claude Castelluccia. To extend or not to extend: On the uniqueness of browser extensions and web logins. In Proceedings of the 2018 Workshop on Privacy in the Electronic Society (WPES’18), pages 14–27, New York, NY, USA, 2018. ACM. http://doi.acm.org/10.1145/3267323.3268959 http://dx.doi.org/10.1145/3267323.3268959 doi: 10.1145/3267323.3268959.

[29] Raymond Hill. uBlock and others: Blocking ads, trackers, and malwares. https://github.com/gorhill/uBlock/wiki/uBlock-and-others%3A-Blocking-ads%2C-trackers%2C-malwares May 2015. Accessed July 5, 2017.

[30] Raymond Hill. uBlock Origin: An efficient blocker for Chromium and Firefox. https://github.com/gorhill/uBlock 2017. Accessed Dec. 27, 2017.

[31] Muhammad Ikram, Hassan Jameel Asghar, Mohamed Ali Kaafar, Anirban Mahanti, and Balachandar Krishnamurthy. Towards seamless tracking-free web: Improved detection of trackers via one-class learning. Proceedings on Privacy Enhancing Technologies, 2017(1):79–99, 2017.

[32] InformAction. NoScript: JavaScript/Java/Flash blocker for a safer Firefox experience! https://noscript.net 2017. Accessed Dec. 27, 2017.

[33] kkapsner. CanvasBlocker: A Firefox plugin to block the canvas-API. https://github.com/kkapsner/CanvasBlocker/ 2017. Accessed Dec. 25, 2017.

[34] Georgios Kontaxis and Monica Chew. Tracking protection in Firefox for privacy and performance. arXiv preprint arXiv:1506.04104, 2015.

[35] Balachandar Krishnamurthy and Craig E Wills. Generating a privacy footprint on the internet. In Proceedings of the 6th ACM SIGCOMM conference on Internet measurement, pages 65–70. ACM, 2006.

[36] Pierre Laperdrix. Fingerprint central. https://fpcentral.irisa.fr/ 2017. Accessed Oct 31, 2017.

[37] Pierre Laperdrix, Benoit Baudry, and Vikas Mishra. Fprandom: Randomizing core browser objects to break advanced device fingerprinting techniques. In 9th International Symposium on Engineering Secure Software and Systems (ES-SoS 2017), 2017.

[38] Pierre Laperdrix, Walter Rudametkin, and Benoit Baudry. Mitigating browser fingerprint tracking: multi-level reconfiguration and diversification. In Proceedings of the 10th International Symposium on Software Engineering for Adaptive and Self-Managing Systems, pages 98–108. IEEE Press, 2015.

[39] Pierre Laperdrix, Walter Rudametkin, and Benoit Baudry. Beauty and the beast: Diverting modern web browsers to build unique browser fingerprints. In Security and Privacy (SP), 2016 IEEE Symposium on, pages 878–894. IEEE, 2016.

[40] Pedro Leon, Blase Ur, Richard Shay, Yang Wang, Rebecca Balebako, and Lorrie Cranor.
Why Johnny can't opt out: a usability evaluation of tools to limit online behavioral advertising. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pages 589–598. ACM, 2012.

[41] Jonathan R Mayer and John C Mitchell. Third-party web tracking: Policy and technology. In Security and Privacy (SP), 2012 IEEE Symposium on, pages 413–427. IEEE, 2012.

[42] meh. Blender: Blend in the crowd by faking to be the most common Firefox browser version, operating system and other stuff. https://github.com/meh/blender, 2017. Accessed Dec. 25, 2017.

[43] Georg Merzdovnik, Markus Huber, Damjan Buhov, Nick Nikiforakis, Sebastian Neuner, Martin Schmiedecker, and Edgar Weippl. Block me if you can: A large-scale study of tracker-blocking tools. In Proceedings of the 2nd IEEE European Symposium on Security and Privacy (IEEE EuroS&P), 2017.

[44] Keaton Mowery and Hovav Shacham. Pixel perfect: Fingerprinting canvas in HTML5. Proceedings of W2SP, pages 1–12, 2012.

[45] Mozilla. Firefox add-ons. https://addons.mozilla.org/en-US/firefox/, December 2017.

[46] Multiloginapp. How canvas fingerprint blockers make you easily trackable. https://multiloginapp.com/how-canvas-fingerprint-blockers-make-you-easily-trackable/, 2017. Accessed Dec 19, 2017.

[47] Net-Comet. Glove: Chrome Web Store. https://chrome.google.com/webstore/detail/glove/abdgoyalbacpmknnpknqflphboefb?hl=en, 2017. Accessed Dec. 25, 2017.

[48] Nick Nikiforakis, Wouter Joosen, and Benjamin Livshits. Privaricator: Deceiving fingerprinters with little white lies. In Proceedings of the 24th International Conference on World Wide Web, pages 820–830. International World Wide Web Conferences Steering Committee, 2015.

[49] NiklasG. Stop Fingerprinting: Add-ons for Firefox. https://addons.mozilla.org/en-US/firefox/addon/stop-fingerprinting/, 2017. Accessed Dec. 25, 2017.

[50] Liam Paninski. Estimation of entropy and mutual information. Neural computation, 15(6):1191–1253, 2003.

[51] Mike Perry, Erin Clark, Steven Murdoch, and Georg Koppen. The design and implementation of the tor browser. https://www.torproject.org/projects/torbrowser/design/#privacy, Accessed Jul 21, 2017.

[52] Reşat. Blend In: Add-ons for Firefox. https://addons.mozilla.org/en-US/firefox/addon/blend-in/, 2017. Accessed Dec. 25, 2017.

[53] Franziska Roesner, Tadayoshi Kohno, and David Wetherall. Detecting and defending against third-party tracking on the web. In Proceedings of the 9th USENIX Conference on Networked Systems Design and Implementation, NSDI'12, pages 12–12, Berkeley, CA, USA, 2012. USENIX Association. http://dl.acm.org/citation.cfm?id=2228298.2228315.

[54] Samy Sadi. No Enumerable Extensions: Firefox add-on that lets you hide installed extensions and avoid being fingerprinted based on them. https://github.com/samysadi/no-enumerable-extensions, 2017. Accessed Jan. 13, 2017.

[55] Sagar Shivaji Salunke. Selenium Webdriver in Python: Learn with Examples. CreateSpace Independent Publishing Platform, USA, 1st edition, 2014.

[56] Iskander Sanchez-Rola, Igor Santos, and Davide Balzarotti. Extension breakdown: Security analysis of browsers extension resources control policies. In 26th USENIX Security Symposium (USENIX Security 17), pages 679–694, Vancouver, BC, 2017. USENIX Association. https://www.usenix.org/conference/usenixsecurity17/technical-sessions/presentation/sanchez-rola.

[57] Martin Springwald. Privacy-Extension-Chrome: Provides privacy for Chrome. https://github.com/marspr/privacy-extension-chrome, 2017. Accessed Dec. 25, 2017.

[58] Oleksii Starov and Nick Nikiforakis. Xhound: Quantifying the fingerprintability of browser extensions. In Security and Privacy (SP), 2017.
A Statistical Analysis

The statistical analysis used in this last step of the analysis engine to determine the likelihood of finding masking depends upon the number of different values for the attribute found across the base browsing platforms. As this number increases, higher-confidence (lower-valued) thresholds $\alpha$ can be achieved. Thus, inconclusive results can be avoided by using a rich set of platforms. However, this is not required for avoiding false claims of not doing impactful masking, which is controlled by $\alpha$ alone (with $f$ quantifying impactful).

In more detail, we use the geometric distribution with $f$ as the success probability. If this probability is less than $\alpha$, then $\alpha$ reports that the attribute is probably not $f$-impactfully partially standardized. We use 0.1 for $\alpha$ and 0.75 for $f$, but these are adjustable.

This approach is an estimation in two senses. First, for attributes with a finite number of values, the hypergeometric distribution would give a more accurate probability of seeing at least one standardized value, but would require knowing the number of possible values. The geometric distribution underestimates this probability, making $\alpha$ conservative in ruling out standardization, that is, this estimation does not increase the rate of false claims of not doing impactful masking.

Second, using these distributions assume that the test attributes are drawn uniformly at random. We instead craft them to be extreme values in hopes of triggering standardization away from outlying values. While this makes computing the exact probability of finding standardization impossible, it should improve the odds of doing so except for pathologically behaving PETs.