Beyond Cookie Monster Amnesia: Real World Persistent Online Tracking

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Abstract. *Browser fingerprinting* is a relatively new method of uniquely identifying browsers that can be used to track web users. In some ways it is more privacy-threatening than tracking via cookies, as users have no direct control over it. A number of authors have considered the wide variety of techniques that can be used to fingerprint browsers; however, relatively little information is available on how widespread browser fingerprinting is, and what information is collected to create these fingerprints in the real world. To help address this gap, we crawled the 10,000 most popular websites; this gave insights into the number of websites that are using the technique, which websites are collecting fingerprinting information, and exactly what information is being retrieved. We found that approximately 69% of websites are, potentially, involved in first-party or third-party browser fingerprinting. We further found that third-party browser fingerprinting, which is potentially more privacy-damaging, appears to be predominant in practice. We also describe *FingerprintAlert*, a freely available browser add-on we developed that detects and, optionally, blocks fingerprinting attempts by visited websites.

Keywords: Browser fingerprinting · Online tracking · Privacy.

1 Introduction

A number of authors have discussed the very wide variety of readily available attributes collectable by websites from a visiting browser, enabling websites to uniquely identify browsers and potentially track them; this is known as *browser fingerprinting* [1,10,25,32]. Although the range of retrievable attributes, as well as methods for retrieving them, have been widely discussed, relatively little has been published regarding the real-world prevalence of browser fingerprinting, who is deploying it, and the types of attributes collected to achieve it. This issue clearly merits further investigation, and has motivated the work described.

Browser fingerprinting is becoming an increasingly serious privacy concern despite some apparently benign applications (see Section 2.2). Its virtually permanent nature[3] is something that might be subject to future regulation, much as the use of cookies has recently received the attention of regulators in Europe. Its use is virtually invisible to users and there is no direct way of preventing it. Moreover, we found that the four browsers used by more than 88% of web users[4] (i.e. Chrome, Internet Explorer, Firefox and Edge) do almost nothing to help mitigate fingerprinting[5], alert the user to its occurrence, or even provide information about it in user help documents.

We examined the fingerprinting behaviour of the 10,000 most visited websites. We aimed to discover how many websites deploy browser fingerprinting, whether directly or through third-parties. We also examined which attributes are collected. Further, to help raise awareness of this issue, we developed a browser add-on that alerts users whenever a visited website attempts to fingerprint their browser; users can also opt to enable a fingerprinting blocking feature.

The remainder of the paper is organized as follows. Section 2 describes tracking and browser fingerprinting, and reviews relevant prior art. In Section 3 the collection of data from 10,000 websites is described; the results obtained are reported in Section 4 and analysed in Section 5. In Section 6 we discuss the relationship with the prior art. Section 7 describes the *FingerprintAlert* add-on, and the paper ends with discussion and conclusions in Section 8.

2 Background

2.1 Online tracking

Online tracking (or web tracking) is the process of monitoring a user's online activities; entities that perform tracking are known as *trackers* [23]. The methodology used in our study, like that of many other studies, cannot conclusively determine if a website is actually tracking users; we simply observe whether they collect attributes from browsers that would allow them to track via browser fingerprinting. In line with common usage, we refer to recipients of fingerprintable data (whether first- or third-party) as trackers.

In practice, the most common motive for online tracking is to enable online behavioural advertising. This describes the practice by web advertising companies of tracking users' online activities in order to display personalised and targeted advertisements [40]. Additionally, tracking is used as a tool for market research [25]. There are two main approaches to online tracking — stateful tracking involving the use of cookies[6], and stateless tracking, including the use

[3] Some browser attributes change over time (e.g. browser version) but uniquely identifying browsers is usually still possible [41], and uniquely identifying the hosting platform is also possible if a different browser is used [9].

[4] The most commonly used browser data was retrieved from `https://www.netmarketshare.com/browser-market-share.aspx` [accessed on 01/07/2018].

[5] Firefox has a limited set of options to thwart fingerprinting.

[6] A web cookie is a small amount of data sent by a website as part of an HTTP response and then stored by the browser. The browser then provides the contents of the cookie back to the same server in subsequent HTTP requests [7].

of browser fingerprinting [25] as defined in Section 2.2. In this paper, following the seminal work of Eckersley [10], we focus on the latter.

In some ways, browser fingerprinting is a more reliable method of tracking than the use of cookies [24], and it appears that browser fingerprinting is increasingly being used for this purpose. Unlike browser fingerprinting, cookies are stored on user devices and so can be controlled or deleted by users. In particular, the use of a *private browsing mode*[7] as provided by many browsers, whilst limiting the use of cookies does very little to protect users against browser fingerprinting [4]. Furthermore, while modern browsers provide a user-selectable *Do Not Track* option, this apparently does not prevent widespread tracking [2].

2.2 Browser Fingerprinting

Browser fingerprinting enables user web activity to be tracked. It relies on learning properties of a browser and its host platform, including both hardware properties and software state (cf. the term *device fingerprinting* [19]). Browser fingerprinting typically involves a web server performing some combination of: (a) collecting and analysing information contained in HTTP request headers, and (b) downloading JavaScript to the browser which collects and sends back information gathered from browser APIs. Examples of collected information include: screen resolution, CPU/GPU model, and names of installed fonts[8]. As in these examples, collectable attributes relate to both browser and host platform.

Tracking web users has long been possible by using cookies. However, the absence of a cookie (e.g. because it has been deleted by the user) means that the device can no longer be tracked [10]. By contrast, browser fingerprinting requires no files to be stored on the user's device, its effectiveness partly depends on the browser, and users have virtually no control over it [4]. It can be used for tracking web users by creating a unique ID derived by combining collected attributes [21].

Four widely discussed uses of browser fingerprinting are: targeted advertising [2,23]; social media sharing [23,34]; analytics services [2,23]; and web security [2,38]. Of course, browser fingerprinting has other uses, e.g. to act as a second layer of authentication [10] or to enhance the effectiveness of CAPTCHAs [3]. However, even in these cases the server gets the benefit, and the user is often not informed that fingerprinting is in use [43]. Determining the exact reason(s) why a website deploys browser fingerprinting is extremely difficult.

Browser fingerprinting websites perform it either as a first-party or a third-party (or both). That is, a website may download JavaScript to the browser, which can send the collected attributes back to either its own site (first-party fingerprinting) or to a third-party site (third-party fingerprinting) [35]. It is even possible that some website operators are not aware that a third-party is performing browser fingerprinting via their website [11]. This could arise because third-party fingerprinting sites typically provide client websites with the

[7] Modes of this type, which have various names, are intended to enhance the privacy properties of the browser [42].

[8] A demonstration of the wide range of information collectable from any browser is available at `https://fingerprintable.org/test`.

JavaScript which collects and sends the attributes used for fingerprinting and in return, the third-party site provides a range of services to the client website (e.g. data analytics or social plugins). As a result, some website operators may not know what data the third-party JavaScript collects from user browsers, or what it might be used for.

In the context of tracking, first-party fingerprinting gives relatively little information to a website — it merely enables multiple visits by the same browser to be linked, and gives no information about other visited websites. If the user identity is known by other means (e.g. because the user logs in) it can also indicate when this user is employing multiple devices [2]. Third-party fingerprinting, on the other hand, is much more privacy-damaging in that it enables browsers (and hence users) to be tracked across multiple websites. Later in this paper we report on the websites that perform the majority of third-party tracking.

2.3 Previous Work

Back in 2010, Eckersley [10] first described how the collection of a range of apparently trivial and readily-available browser attributes, such as time zone, screen resolution, set of installed plugins, and operating system version, could be combined to uniquely identify a browser; he gave this process the name browser fingerprinting. Since then, many other authors, including Mowery et al. [28,29], Boda et al. [8], Olejnik et al. [33], Fifield et al. [17], Takei et al. [36] and Mulazzani et al. [30], have described a range of ways of enhancing its effectiveness. In parallel, and motivated by the threat to user privacy posed by browser fingerprinting, a number of authors, e.g. Nikiforakis et al. [31], Fiore et al. [18] and FaizKhademi et al. [12] have proposed ways of limiting its effectiveness.

The BrowserLeaks website (`https://www.browserleaks.com`) and Alaca et al. [5] catalogue a wide range of types of information that could be used for browser fingerprinting. Pathilake et al. [39] have also classified some of the most widely used methods for fingerprinting. Browser fingerprinting is clearly very effective; for example, in a large-scale study, Laperdrix et al. [21] observed that an average of 86% of desktop and mobile browsers possess a unique fingerprint; other studies [10,28] have reported similar results (80–90%). It is important to note that some of the attributes that can be used for fingerprinting vary between desktop and mobile platforms; as a result the efficiency of fingerprinting also varies between platform types [21]. For example, a device model name can be retrieved from a mobile browser *user agent* but not from its desktop counterpart.

We conclude this brief review of the prior art by summarising previous work with a similar scope to that of this paper, namely examining the prevalence and nature of browser fingerprinting. In 2015, Libert [24] published the results of a study of third-party HTTP requests utilized for browser fingerprinting. Acar et al. [2] performed a large-scale study of fingerprinting focussing mainly on detection by whether a site examined the set of installed fonts. More recently, Le et al. [22] followed a similar approach, but based detection on use of the canvas API rather than the installed fonts. Englehard et al. [11] performed one of the most comprehensive studies in this area, although they focussed on tracking in general and not just on stateless (fingerprinting-based) tracking. Englehardt et al. examined the JavaScript downloaded by websites to browsers, a potentially rich source of information, using their own tool, OpenWPM. According to the authors, this tool performs better than many other similar tools such as FPDetective [2]. However, the use of automated tools to examine JavaScript has limitations, in that tools can only look for scripts they are programmed to identify, regardless of the nature of data collected by a tracker. Metwalley et al. [27] also examined the prevalence of tracking; however, they looked at a relatively limited number of websites (500) and aimed to detect all types of online tracking via passive measurements rather than looking specifically at fingerprinting.

2.4 Motivation

Despite the fact that browser fingerprinting has been extensively studied, relatively little information has appeared on its prevalence and the browser attributes that are collected in practice. To the authors' knowledge, no other study has listed all the browser fingerprinting attributes that are collected by a large set of real-world websites. This observation motivates the work described in the sequel, in which we describe a study of the fingerprinting behaviour of the 10,000 most popular websites. Unlike the work of Englehardt et al. [11] and Acar et al. [2], we chose not to examine the JavaScript itself, but instead monitor the data that is actually transferred back from the browser. While adopting a somewhat similar method, the scale of the study is more than an order of magnitude larger than the study of Metwalley et al. [27].

One important motive for understanding better the prevalence and nature of browser fingerprinting is to help in developing tools that inform the user about fingerprinting, and also enable users to exert control over the degree to which fingerprinting is possible. To this latter end, in Section 7 we describe *Fingerprint-Alert*, a browser add-on developed as part of the study, which makes users aware whenever a website is collecting information usable for browser fingerprinting. It also allows all detected fingerprinting to be blocked.

3 Data Collection Methodology

3.1 Data Gathering

The main objectives of the data collection exercise were to assess the number of websites performing browser fingerprinting, and what types of data are being collected for this purpose. To achieve our objectives, we decided to crawl a large number of well-used websites and to test their data gathering behaviour. We chose 10,000 sites, as this seemed both sufficiently many to generate representative results, and also a manageable number so we could analyse the considerable volumes of data generated. We only looked at the data transmitted, rather than analysing the downloaded JavaScript, for two main reasons: manual analysis of JavaScript on this scale was infeasible, and automated analysis, as noted above, has limitations. Moreover, the data that is sent was the key issue of concern for us, not so much how it is gathered.

We used a simple method to decide whether a web server is performing browser fingerprinting. To try to "normalize" web server behaviour, we looked only at the interactions that occur when a browser initially visits the homepage of the website, rather than other information gathering exercises that might occur (e.g. when a user tries to log in). So, a website that sends any fingerprinting browser attributes back to its, or a third-party, server at a first visit has been *deemed* to be engaged in browser fingerprinting; the precise criterion used to decide whether a site is fingerprinting is given in Section 3.3.

3.2 Experimental Set Up

In order to select which websites to crawl, we retrieved the top 10,000 websites from the freely available Majestic list of the one million most visited websites[9]. We wrote a program to crawl the homepages of these websites to discover if they employ browser fingerprinting techniques at the point when the website is first loaded (i.e. prior to any interaction). This of course means that we missed websites that employ interaction-triggered fingerprinting. The crawler was created using Selenium WebDriver[10], a Python script, the *FingerprintAlert* add-on, and the Chrome browser (details of the crawler software components and the device used can found in Appendices A.2 and A.3). The Python script instructs Selenium to visit the 10,000 websites in the list, wait for each to fully load, and then wait for a further short period before moving to the next website.

The delay is included because, in preparatory work, we manually visited 50 websites on the list and found that some only relayed information after a delay ranging from one second to several minutes following the full loading of the page. Such waits seem likely to be both to allow the various elements of the web page to be loaded and executed and to take account of dynamic content being continuously loaded (e.g. advertisements). We set the short delay to 3 seconds; this was a fairly arbitrary choice, although it was long enough to cause a number of websites to transmit data, although not sufficiently long to make the crawling process significantly more time consuming.

The add-on collects and stores all data that is relayed from the browser to one or more web servers using the GET, POST or HEAD HTTP methods[11] [16], i.e. the commonly used means by which information, including attributes used for fingerprinting, is relayed from browser to server. Whether or not the data was sent SSL/TLS-protected, i.e. using HTTPS [6], was also recorded.

[9] Majestic is a website specializing in web usage statistics, and provides a daily-updated list of the top one million websites, `https://majestic.com/reports/majestic-million` [accessed on 09/10/2017].

[10] Selenium is open-source software used to automate browsers for testing purposes — see `https://www.seleniumhq.org`.

[11] The quantity of data that can be relayed using GET or HEAD is very limited, whereas POST allows the transmission of very large volumes (megabytes) of data.

The crawling process took approximately 300 hours to complete. It took this long for several reasons, including that some websites took several minutes to fully load, and that Selenium occasionally crashed. In such cases, the crawler was restarted manually, where we re-crawled websites after a crash to ensure we did not miss any data.

3.3 Data Processing

Prior to the full crawling process we initially crawled a smaller sample (approximately 1,000 of the websites) to test the crawler. In this process we indiscriminately collected all data sent (if any) from the browser to web servers. Manual examination of the collected data revealed it included information unrelated to the visiting device or the browser (e.g. the URLs of displayed advertisements), i.e. of no interest to this study. Most importantly for our purposes, we were able identify fingerprinting attributes that had unique formats or values (e.g. screen resolution: 1920x1080) that made automatic detection possible. Using these preliminary findings, we programmed our crawler to automatically detect a set of 17 attributes (as listed in Appendix A.1). The crawler used regular expressions to examine relayed data and match them with the prepopulated attributes.

The presence of one or more of these attributes in data returned by the browser was used to determine whether or not a website was engaged in fingerprinting. This set of 17 attribute types includes many of the attributes whose use for fingerprinting is most widely discussed, so we believe that the presence or absence of an attribute of one of these types is a reasonable indicator of whether fingerprinting is being performed.

However, other attributes are much more complex, and hence are difficult to automatically identify. In subsequent manual analysis of the recorded data, we were able to identify many additional attributes because they were labelled by name in the captured data. To perform this task automatically would have been extremely difficult because some sections of the recorded data were not parsed, and the substrings of the data that were parsed varied in format (unsurprisingly given the absence of any standards for data formats for transferred attributes).

In order to manually identify fingerprinting attributes in the collected data, we first used publicly available scripts to retrieve a large set of fingerprinting attributes from the browser that was used to run the experiments (the scripts we used can be found at `https://github.com/fingerprintable`). We then attempted to match these values with the values in the collected data. Once we completed the matching, we manually inspected the matches found; this was necessary to ensure that the matches found were genuine and not coincidental similarities in strings or numbers. In most cases the match was confirmed by finding labels followed by the expected values in the collected data.

3.4 Challenges Addressed

We faced a number of challenges in both implementing crawling and processing the collected data. First, websites are unlikely to admit use of browser fingerprinting, and so we can only attempt to judge their behaviour based on the types of information retrieved from the browser, and when it was collected. As mentioned earlier, there is a wide range of attributes that, when put together, can be used to create a unique device fingerprint. Identifying and monitoring all such attributes is very challenging, especially since new attributes seem to arise frequently (given continuously evolving browser functionality). Moreover, many websites cause the browser to send a series of data strings back to the server; automatically, or even manually, identifying what these data represent is highly non-trivial. It was not always possible to parse the data sent since there is no standard for such data transmissions; indeed, some websites may deliberately obfuscate the data they send. It was therefore impossible to fully interpret all the data. Fortunately, there are certain attributes that are easily identifiable because of their special format and range of values, such as screen resolution (e.g. 1920x1080), fonts (e.g. Arial), or geolocation coordinates (e.g. 51.4167, -0.5667).

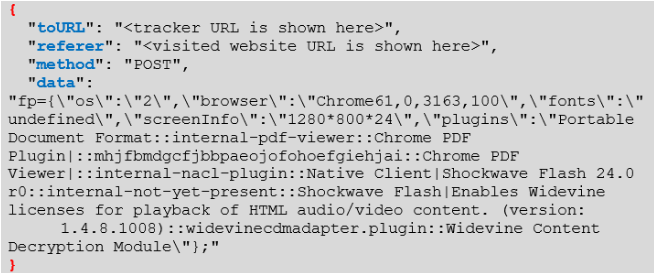
It is very difficult to determine the minimum number of attributes needed to produce a unique fingerprint. Fingerprint uniqueness depends on many factors, including the range of values of an attribute, how often it changes, and how different it is between one browser/platform and another. As a result, we made the simplifying assumption that a website is deemed a tracker if it causes a browser to send at least one of the 17 attributes given in Appendix A.1.

As our crawler was Selenium-based, it suffered from the known crashing problem [11] on certain websites, e.g. when it was unable to fully load all the elements of a website. In such cases the crawler had to be manually restarted. On average, Selenium crashed once in every 155 visited websites. Moreover, Chrome add-ons are limited to 5MB of storage and so, to ensure that the collected data did not reach that limit, we programmed the crawler to stop after every 200 visited websites, yielding an average of 3MB of collected data. However, Selenium usually crashed before reaching the 200-website limit.

The 10,000 websites took an average of 19 seconds to fully load. Our tests were performed using an Internet connection with a minimum bandwidth of 40 mbps, and so connection limitations are unlikely to be the reason for the loading delays. The time to load a website noticeably increased as we went through the list of crawled websites, i.e. the less popular websites loaded more slowly. So, in future similar experiments, we would recommend that crawlers should not timeout until at least 20 seconds have elapsed.

4 Results

The data collected in this study, as well as the tools we used for data collection and analysis, are available at `https://github.com/fingerprintable`. The dataset includes the contents of all HTTP messages sent by and to the crawled websites that attempted fingerprinting. This includes the data retrieved from the visiting device (i.e. the device used for data gathering), as well as the domain names of the sender and receiver of the data. Figure 1 shows a sample of a complete block of data from amongst those collected in our study.



```
{
  "toURL": "<tracker URL is shown here>",
  "referer": "<visited website URL is shown here>",
  "method": "POST",
  "data":
"fp={\"os\":\"2\",\"browser\":\"Chrome61,0,3163,100\",\"fonts\":\"
undefined\",\"screenInfo\":\"1280*800*24\",\"plugins\":\"Portable
Document Format::internal-pdf-viewer::Chrome PDF
Plugin|::mhjfbmdgcfjbbpaeojofohoefgiehjai::Chrome PDF
Viewer|::internal-nacl-plugin::Native Client|Shockwave Flash 24.0
r0::internal-not-yet-present::Shockwave Flash|Enables Widevine
licenses for playback of HTML audio/video content. (version:
     1.4.8.1008)::widevinecdmadapter.plugin::Widevine Content
Decryption Module\"};"
}
```

Fig. 1. Excerpt of collected data

Using a combination of automated parsing and manual inspection, we detected the transmission of 284 different attribute types. We further detected 1,914 distinct fingerprinters. 70 websites (i.e. 0.7%) timed out (e.g. because the website did not respond) during the crawling process and thus were fully, or partially, excluded from our findings. Overall, 6,876 (68.8%) of the crawled websites collected data from visiting browsers (as first- or third-parties) that could be used for browser fingerprinting. We refer to such websites as *fingerprinting websites*; of course, despite the name, the fingerprinting websites might not actually be using the collected data for fingerprinting.

Fingerprinting is most commonly performed by third-party sites; 84.5% of the 6,876 sites collecting data sent it only to third-parties. Of the rest, 2.4% were exclusively first-party fingerprinters, with the other 13.1% using both first- and third-party data collection. Over the 6,876 fingerprinting websites, data was sent to an average of 3.42 domains. The largest number of different data-collecting websites to which data was sent for a single visited website was 42.

Fingerprinting websites collected an average of 1.75KB of data. The third-party websites that collected the most data were yandex (2.9MB), optimizely (2.8MB) and casalemedia (2.1MB). Figure 2 shows the top 10 third-party websites in terms of collected data volume for a single visiting browser.

Of the attributes we can automatically detect, the three most frequently collected were: screen/browser resolution, language, and charset (i.e. character encoding). We found that fingerprinters collected, on average, 5 of the 17 pre-populated attributes. Figure 3 summarises the 10 most frequently collected attribute types. The most widely used fingerprinting third-party was google-analytics[12] (see `https://github.com/fingerprintable` for a complete list of fingerprinting third-parties); google-analytics provides web analytics as well as other web-based services to websites. DoubleClick[13] (Google's online advertising service) was the website that collected the largest volume of data overall.

As noted above, amongst the collected data we were able to identify 284 fingerprinting attributes, which we divided into six categories (see Table 1). The full list of 284 attributes can be found in Appendix B.

[12] `https://analytics.google.com`

[13] `https://www.doubleclickbygoogle.com`

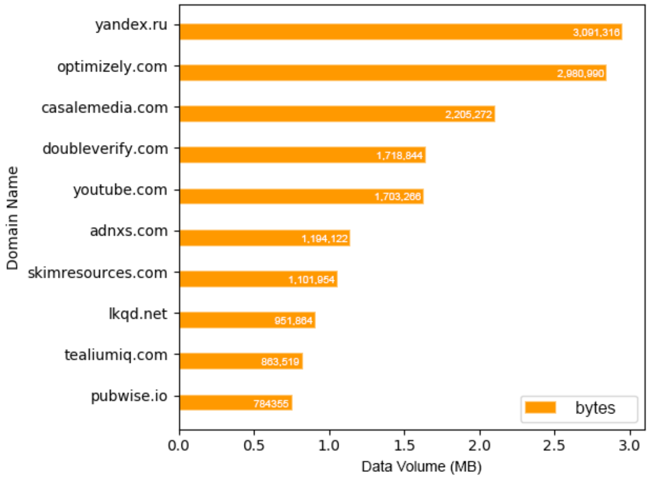


Fig. 2. Top 10 fingerprinters in terms of collected data volume per browser

Table 1. Summary of identified fingerprinting attributes

Attribute Type	**WebGL**	**Features**	**Media**	**Miscellaneous**	**Input/Output**	**Network**	**Total**
Count	114	64	41	35	20	10	**284**

5 Analysis

Processing Collected Data The crawler logged every website that relayed data if one, or more, of the 17 pre-programmed attributes were detected. We examined random samples of the collected data to identify the presence of any false positives. We found some HTTP messages that contained data that were incorrectly matched with one of the 17 attributes. We wrote a script to remove such records (e.g. if the string `1280088.jpeg` matched with the screen resolution width `1280`). This filtering reduced the number of false positives. However, in general, identifying false positives (if any) in the filtered data is non-trivial since the ability to fingerprint browsers typically depends on both the number and type of collected attributes. For example, Mowery et al. [29] have demonstrated that the canvas API alone could be enough to fingerprint a browser, and Laperdrix et al. [21] demonstrated a seemingly successful method of fingerprinting based on a specific set of just 17 attributes.

Undetected Fingerprinting As noted in Section 3.2, the crawler only visited the *homepages* of the 10,000 websites. Websites we reported as not deploying browser fingerprinting might nevertheless still be doing so on other pages. Moreover, the attribute collection reported here was unprompted (i.e. no clicking, cursor movements or typing was involved) except for loading of the web page.

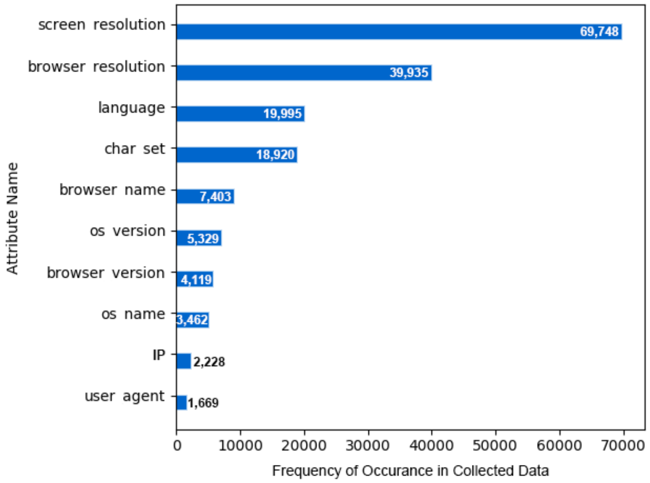


Fig. 3. Top 10 collected attributes

Through manual visits to selected websites, we found that some websites only cause the browser to send fingerprinting attributes when there are further interactions. Moreover, some websites only retrieved attributes when a user submits a form or logs in, and such cases would be too complex (if not impossible) to capture automatically. The focus of this study is fingerprinting that targets everyone, including those engaged in casual browsing.

Prevalence of Fingerprinting Our study confirms the findings of Englehardt and Narayanan [11] that fingerprinting is commonplace, at least by widely-used websites, and yet there are a relatively small number of entities actually collecting and processing attributes (mainly third-party trackers). Indeed, the top five third-party fingerprinting domains (see Figure 4) are all part of a single company, Google Inc. This finding is consistent with Libert [24], who found that 78.07% of the top one million websites send data to a Google-owned domain.

We found that 68.8% of the top 10,000 websites are potentially engaged in fingerprinting, although previous studies yielded rather different results. For example, in 2013, Nikiforakis et al. [32] found that only 0.4% of the top 10,000 websites deployed fingerprinting. A year later, Acar et al. [1] reported that 5% of the top 100,000 websites deployed browser fingerprinting using the canvas API. It thus seems likely that both the prevalence of browser fingerprinting and the number of attributes being collected for this purpose have significantly increased.

Fingerprinting Attributes We attempted to find the fingerprinting attributes reported by Alaca et al. [5] and the BrowserLeaks website in the collected data, including attributes not in the list of 17 attribute types detectable by the crawler.

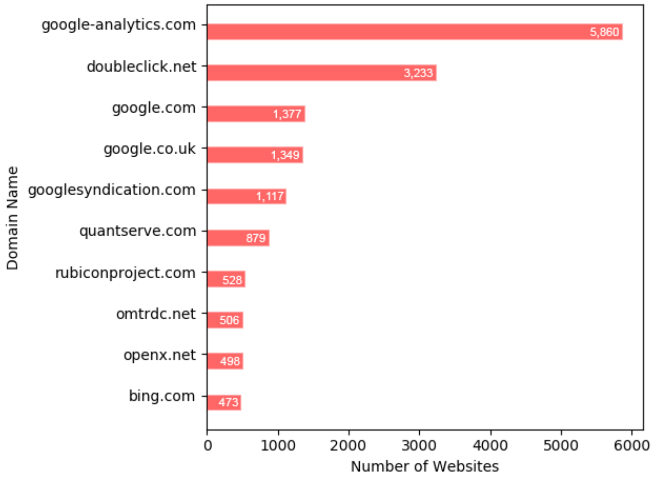


Fig. 4. Top third-party fingerprinting domains

This gave us an indication of the range of attributes that are collected in the real world, as opposed to those discussed in the literature, and also helped us improve the functioning of the add-on described in the Section 7.

As reported above, we were able to identify the collection of 284 attributes, a much larger number than those reported by previous studies. This is partly explained by the fact that previous studies have searched for a smaller number of attributes; for example Eckersley [10] and Cao et al. [9] looked for just 10 and 53 respectively. The significantly higher number we found also seems likely to be a result of the growing use of browser fingerprinting [2,32], and the fact that we monitored the HTTP messages transmitted between visited websites and potential trackers as opposed to detecting the presence of pre-identified fingerprinting scripts, as previously widely performed. Most of the attributes we were able to identify are collectable by BrowserLeaks.com. However, BrowserLeaks can also collect many attributes that we did not find any websites to be collecting, including many of the browser features collectable by *Modernizr*[14].

Deployment of HTTPS Some fingerprinting websites do not use HTTPS to send the fingerprinting attributes which are thus transmitted in plaintext; this is a potentially significant user privacy threat. Of the 1,914 distinct fingerprinters we detected, as many as 683 used only HTTP for attribute transmission, 274 mixed use of HTTP and HTTPS, and the remaining 957 used only HTTPS. That is, 50% of the fingerprinting websites used HTTP at least in some cases for transmitting what could be construed as personally identifiable information.

[14] A JavaScript library that help websites detect the availability of css and html5 features in a visitor's browser `https://modernizr.com`

Seemingly, the use of HTTP is more common in less popular websites, as Merzdovnik et al. [26] reported that as many as 60% of the top 100,000 websites performing fingerprinting used HTTP. We identified a fingerprinting website that used the WebSocket protocol[15] as well as HTTP. These results apply only to the use of HTTP/HTTPs for transmitting browser attributes, not to whether or not the visited website uses HTTPS.

Fingerprint IDs Some websites cause a browser to send a value that is explicitly labelled *fingerprint* or *fp*, along with fingerprinting attributes. These values are typically strings of alphanumerics that appear to function as platform/user identifiers. Evidently, some first- and third-party trackers share such user identifiers [13], allowing them to compile extensive profiles of users. This also means that a website or a tracker could acquire user- or platform-related information without any prior interaction with that user. Such ID-sharing practices clearly make browser fingerprinting-based tracking more privacy-threatening.

6 Relationship to the Prior Art

Our study, like that of Libert [24], examined HTTP requests; however, whereas Libert examined only third-party tracking, we also considered first-party tracking, i.e. by the visited website itself. Moreover, we focussed on browser fingerprinting and not on tracking via cookies, a topic that has been extensively examined in the prior art (e.g. Felten et al. [14], Krishnamurthy et al. [20] and Mayer et al. [25]). A further difference between the work described here and several previous studies, including that of Englehardt et al. [11], is that they examined the fingerprinting scripts while we examined the data relayed back to server via HTTP. Most significantly, and as discussed in Section 5, we detected a much higher level of browser fingerprinting than previously reported; indeed, our results suggest that fingerprinting is becoming ubiquitous.

Given that this is a rapidly changing and evolving area, it is important to repeat studies frequently, and so one contribution of our work is to reveal the current state of the art. We do not claim that the approach we have adopted is better than other approaches, but it does have the advantage of being based purely on the data itself, and not on the many and various scripts that might be used to fingerprint browsers. Our study has enabled us to give an up to date, fairly comprehensive, and large-scale list of the attributes being used in practice for browser fingerprinting.

7 Browser Add-on

Overview As part of the research described here, we developed *Fingerprint-Alert*[16], a browser add-on compatible with desktop versions of Chrome and Fire-

[15] It is a relatively new full-duplex TCP communication protocol [15].

[16] `https://chrome.google.com/webstore/detail/ielakmofegkdlpnlppfikmkbceajdofo`
`https://addons.mozilla.org/en-US/firefox/addon/fingerprintalert`

fox for both Windows and macOS. Based on the preliminary crawling described in Section 3.3, we programmed the add-on to detect the same 17 attributes. It is activated whenever a web page is loaded, and checks whether any of these pre-specified attributes are being relayed back to a web server. If the add-on detects such activity, it displays an alert that includes both the sending and receiving URLs. The add-on also provides a detailed report of detected activities, including data relayed and the corresponding destination(s). Finally, the add-on offers a user-selectable option to automatically block detected fingerprinting attempts. If selected, an HTTP message including any of the monitored attributes will be blocked from being relayed back to a remote server. Despite only detecting 17 attributes, these attributes are typically transmitted alongside other attributes which are also blocked, given that they are in the same HTTP message.

Blocking Feature Websites typically send collected data in a series of HTTP messages, and *FingerprintAlert* blocks those messages that contain at least one the 17 attributes. We found that these attributes are typically transmitted in the same HTTP message as a large number of other fingerprinting attributes, which are also blocked as a result.

As with any add-on that interferes with browser behaviour, the blocking feature of *FingerprintAlert* might cause unexpected results or even break some websites. To ensure it does not cause significant usability issues, we tested it on the 50 most visited websites from our list. We enabled the blocking feature, and spent around two minutes on each website performing actions such as signing up, logging in and clicking on links. During the tests we did not observe any unexpected behaviour or errors except for some glitches on two websites (e.g. unable to load support chat window). Nonetheless, in the unlikely event that the add-on damages a user's experience at a website, the blocking option or the notifications option can easily be disabled. The add-on will continue to record detected fingerprinting attempts even if both these options are disabled.

Challenges Detecting newer or obscure fingerprinting attributes is an obstacle that faces all privacy add-ons [11]. Moreover, websites could choose to conceal transmitted attributes, e.g. using encryption, or use fingerprinting attributes that are not publicly known. Additionally, it is difficult to automatically detect all fingerprinting attribute values, as they may be similar to other data or have no specific set of values. On the other hand, detecting and examining scripts executed on websites is likely to be hindered by changes in code, syntax and execution. For that reason, the add-on notifies the user if any HTTP message sent to a server is found to contain one or more of the selected set of 17 attributes.

Other Add-ons and Future Improvements The add-on complements, rather than replaces, other add-ons that mitigate fingerprinting, such as those that monitor and block fingerprinting scripts (e.g. Ghoesrty[17] and Privacy Badger[18]). The

[17] `https://www.ghostery.com`

[18] `https://www.eff.org/privacybadger`

main purpose of our add-on is to make users aware of fingerprinting attempts as they happen and the identity of domains collecting the fingerprinting data, and as a result increase their awareness of how widespread such practices are. The results of our study could also help in developing new tools designed to thwart fingerprinting. In the future, we aim to improve *FingerprintAlert* by increasing the number of automatically-detectable attributes. This can be achieved by further in-depth examination of the formats and values of attributes that are currently undetectable. Since the crawler is based on the add-on, any future crawls would also be made more effective by such improvements.

8 Discussion and Conclusions

Cookies are familiar to many users, especially with the introduction of regulations on their use, such as the so-called cookie law[19] covering tracking whether using cookies or any other technology. These regulations have caused many websites to announce the use of cookies. However, while users can disable local storage of cookies, cookies can be selectively deleted, and cookies expire, browser fingerprinting is virtually outside of user control and is much more permanent; it is thus significantly more threatening to user privacy.

Many authors, e.g. Nikiforakis et al. [31] and Torres et al. [37], have described means of reducing the effectiveness of fingerprinting through browser add-ons or by adjusting user-configurable browser settings. Previously described add-ons typically either hide certain attributes or fabricate their values. While such add-ons can be helpful, they also have well-known limitations; exhibiting an unrealistic set of attributes values is also fingerprintable [32] and could negatively affect the browsing experience (e.g. if screen resolution values are manipulated).

We have shown that browser fingerprinting is being conducted on a significantly larger scale than previously reported, involving the transmission of large volumes of browser and device-specific data to trackers. We also reported on the large number of fingerprinting attributes collected. As other authors have described, browser fingerprinting has significant negative implications for user privacy, and it is therefore important that the web user community is made aware of its prevalence and potential effectiveness. To this end we have developed *FingerprintAlert*, that informs users when fingerprinting is occurring and can also block it. If web user privacy is to be preserved, fingerprinting technology needs to be made user-controllable so users can limit the degree to which they are tracked. Our browser add-on contributes to this by providing users with the option to block browser fingerprinting. In the longer term it may be necessary for regulators to examine ways of limiting the degree to which users are tracked using fingerprinting, and/or for browser manufacturers to find ways of developing browsers that limit how easily one user can be distinguished from another.

Ethical Issues. Clearly any experiment involving real world websites raises potential ethical issues. However, no data relating to individuals were accessed,

[19] `http://ec.europa.eu/ipg/basics/legal/cookies/index_en.htm` [accessed on 14/04/2018]

no vulnerabilities in websites were discovered or exploited, and all websites were accessed as intended by their providers. Websites were crawled only once, except in cases of a crawler crash where an additional visit was required. All the results are publicly available, as described in Section 4.

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Appendix

A Crawling Components and Environment

A.1 Prepopulated List of Attributes

Resolution, OS, OS Version, User-Agent, Browser Name, Browser Version, WebGL Renderer, WebGL Vendor, WebGL Version, GPU, GPU Vendor, Installed Plugins, Language, Geolocation, City, IP Addresses, and Charset.

A.2 Crawler Software Components

Component	Details
Browser add-on	FingerprintAlert 1.0
Programming language	Phython 3.6.3
Automation tool	Selenium 3.8.1

A.3 Computing Environment

Component	Details
Device	MacBook Pro (10.1.1)
OS	MacOS Sierra 12.1
Browser	Chrome 62.0.3202.94

B Attributes Collected by Fingerprinters

B.1 WebGL

aliased line width range, aliased point size range, alpha bits, angle instanced arrays, antialiasing, blue bits, depth bits, experimental-webgl, ext blend min max, ext disjoint timer query, ext frag depth, ext shader texture lod, ext srgb, ext texture filter anisotropic, fragment shader high float precision, fragment shader high float precision range max, fragment shader high float precision range min, fragment shader high int precision, fragment shader high int precision range max, fragment shader high int precision range min, fragment shader low float precision, fragment shader low float precision range max, fragment shader low float precision range min, fragment shader low int precision, fragment shader low int precision range max, fragment shader low int precision range min, fragment shader medium float precision, fragment shader medium float precision range max, fragment shader medium float precision range min, fragment shader medium int precision, fragment shader medium int precision range max, fragment shader medium int precision range min, green bits, max 3d texture size, max anisotropy, max array texture layers, max color attachments, max combined fragment uniform components, max combined texture image units, max combined vertex uniform components, max cube map texture size, max draw buffers, max fragment input components, max fragment uniform blocks, max fragment uniform components, max fragment uniform vectors, max program texel offset, max render buffer size, max samples, max texture image units, max texture lodbias, max texture size, max transform feedback interleaved components, max transform feedback separate attribs, max transform feedback separate components, max uniform block size, max uniform buffer bindings, max varying components, max varying vectors, max vertex attribs, max vertex output components, max vertex texture image units, max vertex uniform blocks, max vertex uniform components, max vertex uniform vectors, max view port dims, min program texel offset, oes element index uint, oes standard derivatives, oes texture float, oes texture float linear, oes texture half float, oes texture half float linear, oes vertex array object, performance caveat, red bits, renderer, shading language version, stencil bits, unmasked renderer webgl, unmasked vendor webgl, vendor, version, vertex shader high float precision, vertex shader high float precision range max, vertex shader high float precision range min, vertex shader high int precision, vertex shader high int precision range max, vertex shader high int precision range min, vertex shader low float precision, vertex shader low float precision range max, vertex shader low float precision range min, vertex shader low int precision, vertex shader low int precision range max, vertex shader low int precision range min, vertex shader medium float precision, vertex shader medium float precision range max, vertex shader medium float precision range min, vertex shader medium int precision, vertex shader medium int precision range max, vertex shader medium int precision range min, webgl, webgl compressed texture s3tc, webgl compressed texture s3tc srgb, webgl debug renderer info, webgl debug shaders, webgl depth texture, webgl draw buffers, webgl lose context, webgl2, webkit ext texture filter anisotropic, webkit webgl compressed texture s3tc, webkit webgl depth texture, webkit webgl lose context.

B.2 Features

adblock, application cache, background size, blending, bluetooth, border image, border radius, box shadow, budget, canvas winding, credentials, css animations, css columns, css gradients, css reflections, css transforms, css transforms 3dc, css transitions, drag and drop, flex box, flex box legacy, font face, generated content, get battery, get game pads, get user media, hash change, history, hsla, img hash, inline svg, installed fonts, installed plugins, java enabled, js, media decvices, mime types, multiple bgs, opacity, permissions, post message, presentation, register protocol handler, request media key system access, request midi access, rgba, send beacon, service worker, shockwave flash, smil, svg, svg clip paths, text shadow, towebp, unregister protocol handler, usb, vibrate, web sql database, web workers, webkit get user media, webkit persistent storage, webkit temporary storage, webrtc, websockets.

B.3 Media

ac-base latency, ac-channel count, ac-channel count mode, ac-channel interpretation, ac-max channel count, ac-number of inputs, ac-number of outputs, ac-sampler ate, ac-state, an-channel count, an-channel count mode, an-channel interpretation, an-fft size, an-frequency bin count, an-max decibels, an-min decibels, an-number of inputs, an-number of outputs, an-smoothing time constant, audio ogg, avc1.42c00d, avc1.42e01e (mp4a.40.2), codecs1, dynamiccompressor, h264, hybridoscillator, mp3, mp4a.40.2, mpeg, opus, oscillator, theora, video mp4, video ogg, vorbis (ogg), vorbis (vp8), vorbis (vp9), vorbis (wav), wav, webm, wm4a.

B.4 Miscellaneous

app code name, battery level, charging, charging time, charset, collect time, cookie enabled, cpu cores, discharging time, do not track, geolocation, graphics card vendor, hardware concurrency, has timezone mismatch, incognito, indexed db, js heap size limit, languages, local storage, navigator, online, open data base, platform, product, product sub, referrer, renderer, session storage, timestamp, timezone, total js heap size, used js heap size, user agent, vendor, vendor sub.

B.5 Network

downlink, effectivetype, is proxied, is tor, is using tor exit node, local ip, onchange, public ipv4, public ipv6, rtt.