Cookie Synchronization: Everything You Always Wanted to Know But Were Afraid to Ask

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ABSTRACT

User data is the primary input of digital advertising, fueling the free Internet as we know it. As a result, web companies invest a lot in elaborate tracking mechanisms to acquire user data that can sell to data markets and advertisers. However, with same-origin policy and cookies as a primary identification mechanism on the web, each tracker knows the same user with a different ID. To mitigate this, Cookie Synchronization (CSync) came to the rescue, facilitating an information sharing channel between 3rd-parties that may or not have direct access to the website the user visits. In the background, with CSync, they merge user data they own, but also reconstruct a user’s browsing history, bypassing the same origin policy.

In this paper, we perform a first to our knowledge in-depth study of CSync in the wild, using a year-long weblog from 850 real mobile users. Through our study, we aim to understand the characteristics of the CSync protocol and the impact it has on web users’ privacy. For this, we design and implement CONRAD, a holistic mechanism to detect CSync events at real time, and the privacy loss on the user side, even when the synced IDs are obfuscated. Using CONRAD, we find that 97% of the regular web users are exposed to CSync: most of them within the first week of their browsing, and the median user ID gets leaked, on average, to 3.5 different domains. Finally, we see that CSync increases the number of domains that track the user by a factor of 6.75.

CCS CONCEPTS

• Security and privacy → Web protocol security; • Networks → Network privacy and anonymity; • Social and professional topics → Surveillance.

KEYWORDS

Cookie Synchronization, Cross-domain tracking, HTTP Cookies

1 INTRODUCTION

In the online era, where behavioural advertising fuels the majority of Internet, user privacy has become a commodity that is being bought and sold in a complex, and often ad-hoc, data ecosystem [17, 24, 35, 38]. Users’ personal data collected by IT companies constitute a valuable asset, whose quality and quantity significantly affect each company’s overall market value [40]. As a consequence, it is of no doubt that in order to gain advantage over their competitors, web companies such as advertisers and trackers participate in a user data collecting spree, aiming to retrieve as much information as possible and form user profiles. These detailed profiles contain personal data [12] such as interests, preferences, personal identifying information, geolocations, etc. [5, 31, 44], and could be sold to 3rd-parties for advertising or other purposes beyond the control of the user [30, 36, 37].

Highlighting the importance of this data collection, web companies have invested a lot in elaborate user tracking mechanisms. The most traditional one includes the use of cookies: they have been commonly used in the Web to save and maintain some kind of state on the web client’s side. This state has been used as an identifier to authenticate users across different sessions and domains. Initially, 1st-party cookies were used to track users when they repeatedly visited the same site, and later, 3rd-party cookies were invented to track users when they move from one website to another. The same-origin policy (SOP) was invented a few years later [45] to restrict the potential amount of information trackers can collect about a user and share with other 3rd-party platforms.

To overcome this restriction, and create unified identifiers for each user, the ad-industry invented the Cookie Synchronization (CSync) process [19]; a mechanism that can practically “circumvent” the same-origin policy, and allow web companies to share (synchronize) cookies, and match the different IDs they assign for the same user while they browse the web. Sadly, recent results show that most of the 3rd-parties are involved in CSync: 157 of top 200 websites (i.e. 78%) have 3rd-parties which synchronize cookies with at least one other party, and they can reconstruct 62-73% of a user’s browsing history [11]. Furthermore, 95% of pages visited contain 3rd-party requests to potential trackers and 78% attempt to transfer unsafe data [46]. Finally, a mechanism for respawning cookies has been identified, with consequences in the reconstruction of users’ browsing history, even if they delete their cookies [1].

Although past works highlight the use of CSync across the most popular sites worldwide, they avoid diving into the details and fail to thoroughly explore this increasingly popular technique. In fact, the majority of related works perform their analysis using crawled data by fetching the top Alexa websites. Consequently, little is known on how CSync works in the wild, how many of real users’ cookies are getting synced during their everyday browsing,
2 COOKIE SYNCHRONIZATION

2.1 How does Cookie Synchronization work?

Figure 1 presents a simple example to understand in practice what is CSync and how it works. Let us assume a user browsing several domains like website1.com and website2.com, in which there are 3rd-parties like tracker.com and advertiser.com, respectively. Consequently, these two 3rd-parties have the chance to set their own cookies on the user’s browser, in order to re-identify the user in the future. Hence, tracker.com knows the user with the ID user123, and advertiser.com knows the same user with the ID userABC. Now let us assume that the user lands on a website (say website3.com), which includes some JavaScript code from advertiser.com?syncID=user123&publisher=website3.com (1) GET advertiser.com?syncID=user123&publisher=website3.com Cookie: {cookie_ID=userABC}

Get a redirect to tracker.com to synchronize the information tracker.com knows about userABC with the information advertiser.com knows about user123, using a REDIRECT request (step 2), instructing the user’s browser to visit tracker.com

Figure 1: Example of advertiser.com and tracker.com synchronizing their cookieIDs. Interestingly, and without having any code in website3, advertiser.com learns that: (i) cookieIDs userABC==user123 and (ii) userABC has just visited the given website. Finally, both domains can conduct server-to-server user data merges.

tracker.com but not from advertiser.com. Thus, advertiser.com does not (and cannot) know which users visit website3.com. However, as soon as the code of tracker.com is called, a GET request is issued by the browser to tracker.com (step 1), and it responds back with a REDIRECT request (step 2), instructing the user’s browser to issue another GET request to its collaborator advertiser.com this time, using a specifically crafted URL (step 3):

GET advertiser.com?syncID=user123&publisher=website3.com Cookie: {cookie_ID=userABC}

When advertiser.com receives the above request along with the cookie ID userABC, it finds out that userABC visited website3.com. To make matters worse, advertiser.com also learns that the user whom tracker.com knows as user123, and the user userABC is basically one and the same user. Effectively, CSync enabled advertiser.com to collaborate with tracker.com, in order to: (i) find out which users visit website3.com, and (ii) synchronize (i.e., join) two different identities (cookies) of the same user on the web.

2.2 Cookie Synchronization, Personalized Advertising & Privacy Implications

Digital advertising has moved towards a more personalized model, where ad-slots are purchased programmatically (e.g., Real Time Bidding (RTB) based auctions) in auctions, based on how well the profile of the visitor matches the advertised product. Consequently, advertisers need to obtain user data (e.g., interests, behavioral patterns) to use as input in their sophisticated decision engines. The core component for this data purchasing/sharing includes CSync [16].
It allows trackers and advertisers to perform common user identification and by participating in data markets enrich their knowledge base with user information from several data sources.

There are several privacy implications for the online users who access websites planted with such sophisticated tracking technologies. Using CSync, in practice, advertiser.com learns that: (i) what it knew as userABC is also user123, and (ii) this user has just visited website3.com. This enables advertiser.com to track a user to a much larger number of websites than was initially thought. Indeed, by collaborating with several trackers, advertiser.com is able to track users across a wide spectrum of websites, even if those websites do not have any collaboration with advertiser.com.

To make matters worse, the ill effects of CSync may reach way back in the past - even up to the time before the invention of CSync. Assume, for example, that someone manages to get access to all data collected by tracker.com, and all the data collected by advertiser.com (e.g., by acquisition [30, 36], merging or hacking of companies [22]). In the absence of CSync, in those two datasets, our user has two different names: user123 and userABC. However, after one single CSync, those two different names can be joined into a single user profile, effectively merging all data in the two datasets. Nowadays, such cases of server-to-server user data merges are taking place at a massive scale [11], with the different web companies conducting mutual agreements for data exchanges or purchases, in order to enrich the quality and quantity of their user data warehouses [6, 30].

As if these threats to user privacy were not enough, CSync can rob users of the right to erase their cookies. Indeed, when coupled with other tracking technologies (i.e. evercookie [39], or user fingerprinting [9]), CSync may re-identify web users even after they delete their cookies. Specifically, when a user erases her browser state and restarts browsing, trackers usually place and sync a new set of userIDs, and eventually reconstruct a new browsing history. But if one of them manages to respawn [1] its cookie (e.g. through evercookie [39]), then through CSync, all of them can link the user’s browsing histories from before and after her state erase. Consequently: (i) users are not able to abolish their assigned userIDs even after carefully erasing their set cookies, and (ii) trackers are enabled to link user’s history across state resets.

### 3 COOKIES SYNCHRONIZATION DETECTION

In this paper, we design CONRAD, a holistic methodology to detect CSync events in real time, on the user side. CONRAD monitors the HTTP(S) traffic of the user on the browser level and detects userIDs when shared from one domain to the other. To achieve that, it uses a (i) Heuristics-based (stateful) detection mechanism (Section 3.1), where the IDs from cookies are tainted and alert is raised when they are exfiltrated to a domain other than the owner of the cookie. However, as also presented in past studies [2], more and more companies include encryption (or cryptographic hashing) in the CSync-related APIs, thus concealing the synced IDs. To deal with these cases, CONRAD uses a (ii) ML-based (stateless) detection mechanism (Section 3.2) capable of classifying with high accuracy such possible concealed synchronizations, without relying on any previously stored cookie IDs, but only using characteristics from the connections themselves. Figure 2 provides a high level overview of CONRAD’s internal components.

For each CSync detection method, CONRAD extracts its information flow: the chain of domains that share the synced ID, the domain that triggered the CSync event, the domains that (without having access to the website) used this sync request to set and sync their own userIDs (see Table 1). This way, our tool is able to measure the diffusion of anonymity loss for the given user by analysing what number of their overall userIDs budget got synced, and to how many 3rd-party domains. In addition, by using a simple pattern matching technique, CONRAD extracts possible personal information leaks tailored with the synced ID (see Section 5.5).

Although there are several existing techniques for detecting ID-sharing events even when cookies are encrypted, accurate CSync detection in real time is a hard task. The main advantages of our approach, contrary to existing detection mechanisms [1, 2, 11] are as follows: (i) It offers the ability to detect synchronizations when the userID is embedded not only in the URL’s parameter, but also in its path (either in case of request/response URL or Location URL of the referrer). (ii) By filtering-out domains of the same provider, our approach can discriminate between intentional CSync and unequivocally legitimate cases of internal ID sharing, thus avoiding false positives. (iii) It is capable of detecting Cookie Synchronization at real time, even when shared IDs are encrypted.

#### 3.1 Heuristics-based detection

Technically, as we see in Table 1, CSync is nothing more than a request from the user’s browser to a 3rd-party domain carrying (at least one) parameter that constitutes a unique ID set by the calling companies [22]). In the absence of CSync, in those two datasets, our user has two different names: user123 and userABC. However, after one single CSync, those two different names can be joined into a single user profile, effectively merging all data in the two datasets. Nowadays, such cases of server-to-server user data merges are taking place at a massive scale [11], with the different web companies conducting mutual agreements for data exchanges or purchases, in order to enrich the quality and quantity of their user data warehouses [6, 30].

![Figure 2: High-level overview of CONRAD’s internal components.](image)

| URL1 | URL2 | URL3 |
|------|------|------|
| a.com | b.com | c.com |

| Table 1: Examples of userIDs synchronized among various domains. |
|---------------------------------------------------------------|
| **URLs of Cookie Synchronization HTTP Requests** |
| 1. a.com/id/csync?1234567890abcdefg/1234567890abcdefg |
| 2. b.com?id=1234567890abcdefg/1234567890abcdefg |
| 3. c.com?id=1234567890abcdefg/1234567890abcdefg |

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domains different than the cookie setter. In particular, our Cookie Synchronization detection methodology includes the following steps, which are also illustrated in Figure 3:

1. We extract all cookies set on the user’s browser. To accomplish that, we parse all HTTP requests in our dataset and extract all Set-Cookie requests.
   a. We filter out all session cookies. These are cookies without expiration date, that get deleted after the end of a session.
   b. We parse the cookie value strings using common delimiters (i.e. “;”, “&”). By extracting potentially identifying strings (cookie IDs), we create a list with the cookie IDs that could uniquely identify the user in the future.
2. We detect possible ID-sharing events in the HTTP requests:
   a. We identify ID-looking strings that are unique per user, carried either (i) as parameters in the URL, (ii) in URL path, or (iii) in the referer field. As ID-looking strings, we define strings with specific length (> 10 characters) – false positives do not matter at this point.
   b. If this ID is seen for the first time, it is stored in a hashtable along with the URL’s domain (receiver of the ID).
   c. If this ID has already been seen, we consider it as a shared ID and the requests carrying it as ID-sharing requests.
3. To check if the above ID-sharing requests regard different domains, we use several external sources (DNS whois, blacklists etc.) to filter-out cases where the IDs are shared among domains owned by the same provider (e.g., amazon.com and amazonaws.com) [25]. This way, our approach can discriminate between intentional ID leaking and legitimate cases of internal ID-sharing, thus avoiding false positives.
4. Finally, to verify if the detected shared ID is a userID able to uniquely identify a user, we search this ID within the list of cookie IDs extracted in the first step. If there is a match, then we consider this request as CSync.

Figure 3: Heuristics-based CSync detection mechanism.

3.2 Cookie-less detection

It is apparent that in order for the above methodology to be a viable CSync detection method, cookie IDs need to be shared in plaintext. However, major web companies such as DoubleClick [19] have started encrypting the cookie ID in an attempt to protect the actual cookie from being revealed to unwanted parties that may snoop the user’s traffic (plugins or even ISPs).

While the former case is obvious why companies would want to block such snooping, the latter case may not be clear why and, thus, we discuss this case further. In particular, under the traditional, plaintext case of cookie ID syncing, the same source company can sync independently with multiple 3rd-parties for the same user cookie ID. Thus, no-one forbids these other 3rd-parties from syncing their IDs with each other, and find out that they have information about the same user, something that goes beyond what the source company intended to do (top example of Table 2). With hashing or encryption of the cookie ID, these 3rd-parties are unable to do this syncing (bottom example of Table 2). As a consequence of this encryption, CSync events can proceed undetected, if the previously used detection method is employed.

To address this scenario, in this paper, we propose a novel method for identifying CSync which is oblivious to the IDs shared. This mechanism is able to identify with high accuracy CSync events in web traffic, even when the leaked IDs are protected and cannot be matched. To build this mechanism, we employ machine learning methods, which we train on the ground truth datasets created with the previous, heuristic-based technique. In particular, we analyze various features extracted from the web traffic due to CSync, and train a machine learning classifier to automatically classify a new HTTP connection as being a CSync event or not. Here, we make the assumption that the various features used to characterize, and eventually detect, CSync with plaintext IDs, are equally used, and have the same distributions and variability as in the CSync with encrypted IDs. We believe this is a reasonable assumption, since the companies employing encrypted IDs are not expected to change the rest of their mechanism which delivers these IDs and triggers CSync with their partners; these companies only want to obfuscate the IDs to avoid further, and unwanted, CSync.

For training the classifier, we extract various relevant features from the network traces. As ground truth, we use confirmed CSync events which were detected with the heuristics-based method described earlier. Beyond these confirmed events, there are id-sharing events which were first selected by the method as potential CSync events, but eventually were rejected as non-CSync, as they did not match cookie IDs already seen by the method (step 1 in Figure 3).

The features available for these network events can be several; we constrain the learning algorithm to use only features available at run time, and during the user’s browsing to various websites:

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A known limitation of this approach is its inability of capturing a small portion of 1st-party cookies set by javascript.

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Table 2: Examples of Cookie Synchronization between 3rd-parties with plaintext and encrypted cookie IDs.

| Description | Example |
|-------------|---------|
| ID syncs beyond the 1-1 of source domain (plaintext): | Domain syncs ID Tracker1 ID1: \( \rightarrow \) ID1=ID; Domain syncs ID Tracker2 ID2: \( \rightarrow \) ID2=ID; Tracker1 syncs ID1 with Tracker2 ID2: \( \rightarrow \) ID2=ID1=ID; |
| ID syncs beyond the 1-1 of source domain (encrypted): | Domain syncs h(ID,A) with Tracker1 ID1: \( \rightarrow \) ID1=h(ID,A); Domain syncs h(ID,B) with Tracker2 ID2: \( \rightarrow \) ID2=h(ID,B); Tracker1 syncs ID1 with Tracker2 ID2: \( \rightarrow \) h(ID,A)=h(ID,B), i.e., ID1=ID2; |

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[1] A known limitation of this approach is its inability of capturing a small portion of 1st-party cookies set by javascript. [7]
Various machine learning algorithms can be applied: Random Forest, Support Vector Machines, Naive Bayes, and even more advanced methods such as Neural Networks. However, a balance must be found between training the given algorithm to reach a good accuracy, the computation cost for this training, as well as the capability of the algorithm to be used at real time on the user device.

This method aims to address two possible scenarios that can arise while IDs are being shared: First, we consider the realistic scenario that an already identified set of id-sharings are candidate CSync events (as found by the heuristics-based method), but cannot be validated as CSyncs because of the cookie ID being encrypted or unavailable, and therefore not matching the repository of IDs. Second, we consider the scenario where various HTTP connections are ingested by the method, and it needs to decide at run-time which are CSync events and which are not. This case is a more generalized version of the previous scenario, and attempts to detect CSync events, as an alternative method to the heuristic-based approach. In either of the two cases, we follow a generally accepted methodology (e.g., [34]) that separates training such a machine learning model, from applying it at real-time. The training can be performed offline, on an existing dataset (e.g., the one we collected, or from anonymous user network traffic donations), and the model trained can be distributed accordingly with the tool at hand. Then, the tool can apply the classifier on each network connection under question, for real-time classification.

Table 3: Summary of contents in our dataset.

| Description | #    | Description | #    |
|-------------|------|-------------|------|
| Total mobile users | 850 | Unique shared IDs (S) | 68215 |
| Requests captured | 179M | Unique userIDs synced (C∩S) | 22329 |
| Unique Cookies (C) | 8.97M | CSync requests | 263635 |
| ID sharing requests | 412805 | | |
5 PRIVACY ANALYSIS

By applying CONRAD in our dataset, we find several IDs passed from one domain to another. We detect 68215 such unique shared IDs. From these IDs, 22329 were actually cookie IDs from previously set cookies that were synced among different domains. In total, these cookie IDs were found in 263635 synchronization events (see Table 3 for a summary). From the CSyncs detected in our dataset, userIDs were found in 91.996% of the cases inside the URL parameters, 3.705% in the Referrer URL, and in 3.771% of the cases in the URL path. Thus, CONRAD was able to detect 3.771% more cases of CSyncs than existing detection methods [1, 29, 32].

Cookies: To have a good view of the cookie activity of users, we extract all (1st & 3rd-party) cookies set in users’ browsers across the year, and in Figure 6, we plot the distribution of number of cookies per visited website. The median user receives a fairly constant number of 12.25 cookies per visited website per month, on average.

Next, we extract the unique identifiers (i.e., cookie ID) set in these cookies. A cookie ID constitutes a unique string of characters that websites and servers associate with the browser and, thus, the user who stored the cookie. Thereby, here, we consider a cookie ID as a unique user identifier called userID. As it can be seen in Table 3, in our dataset, there are almost 9 million such unique IDs.

In Figure 7, we plot the distribution of the number of unique userIDs assigned to the users per domain. The vast majority of the users (80%) receive, on average, only 2.2 userIDs per domain, across the year. This means that users tend not to erase their cookies frequently, thus, allowing web domains to accurately identify them through time and during the users’ browsing. Only 1.13% of users erase their cookies (either manually or by browsing with Private/Incognito Browsing), receiving more than 9.5 different userIDs per domain, on average. This means that it is very rare for a domain to meet a previously known user with a different alias.

5.1 Initiation of Cookie Synchronization

First, we correlate the cookie domain (the setter), the synchronizing request’s Referrer field, and the publisher that the user visited, in order to extract the domain that triggered the CSync on the user’s browser. As seen in Table 4, there are 4 distinct cases: (i) the CSync was initiated by the publisher who syncs the userID he assigned for the user; we find 2.692% of these cases in our dataset, (ii) the synchronization was initiated from a publisher’s iframe, by the guest 3rd-party which syncs its own userID (49.668%), (iii) a 3rd-party which participated in a previous synchronization (case (i) or (ii) above) and uses the sync request to share its own userID (45.697%). Lastly, there is a rare case (iv), where a 3rd-party participating in a previous synchronization of the publisher’s userID (case (i)) initiates a new round of sync while it continues to share the publisher’s userID (0.2658%). Obviously, in case (iv), the initiating 3rd-party shares with its 3rd-party affiliates, a userID assigned by a domain (the publisher) beyond its control, and possibly awareness.2

5.2 How are users exposed to CSync?

CSync impacts users’ privacy by leaking assigned userIDs, and sharing them with 3rd-parties. In our dataset, we see that for users with regular activity on the web (> 10 requests per day), 97% were exposed to CSync at least once. This means that CSync constitutes a phenomenon affecting the totality of online users. Next, we study how long it takes for the first synchronization to happen, or in effect, how quickly a user gets exposed to CSync after she starts browsing. Recall that as mentioned in Section 4, all participating users, during bootstrapping phase, had all state from their browsers erased. This means that our proxy was able to capture the very first cookie that was set during the user’s monitoring period. Of course, the time depends on the browsing patterns of each user, however, as we see in Figure 8, a median user experiences at least one CSync within the first week of browsing. In fact, a significant 20% of users get their first userID synced in 1 day or less. It is worth noting that users tend to browse the same top websites repeatedly (e.g., facebook.com, twitter.com, cnn.com), so the set cookies are already shared and no sync is fired.

Next, we investigate if the synchronizations the users are exposed to, change over time. Hence, we extract CSyncs per user, and normalize with the user’s total number of requests. In Figure 9, we plot the average synchronizations per request across the year. As

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shown, CSync is persistent through the duration of an entire year, with the user being exposed to a steady number of synchronizations across time. Specifically, we see that the average user receives around 1 synchronization per 68 requests.

Considering the different user IDs that trackers may assign to a user, in Figure 10, we measure the number of unique user IDs that got synced per user. Evidently, a median user gets up to 6.5 user IDs synced, and 3% of users has up to 100 user IDs synced. It becomes apparent that the IDs of a user may leak to multiple 3rd-party domains through CSync. To measure the user ID leak diffusion, in Figure 11, we plot the distribution of synchronizing requests per user ID. As we see, the median user ID gets leaked, on average, to 3.5 different domains. There is also a significant 14% that gets leaked to up to 28 different 3rd-parties.

To better understand the effect of CSync on the diffusion of the overall user privacy, we measure for each user the number of domains that learned about them (i.e., learned at least one of their user ID) before and after CSyncs. From the distribution in Figure 12, the domains that learned about the median user after CSyncs grew by a factor of 6.75, and for 22% of users this factor becomes > 10. This means that before the rise of CSync, when the user visited a website, the domains that could track them were only the publisher and the included 3rd-parties, but in an independent fashion. However, with the introduction of CSync, the number of domains that can track the user drastically increased (6.75x for median user), severely decreasing their online anonymity.

### 5.3 Buy 1 - Get 4 for free: ID bundling and Universal IDs

We find 63 cases of domains which set on the users’ browsers cookies with user IDs previously set by other domains. For example, we see the popular baidu.com, the world’s eighth-largest Internet company by revenue, storing a cookie with an ID baiduuid = (idA), and more than 5 different domains after this incident setting their own cookie using the same ID baiduuid = (idA). This by-product of CSync, enables trackers to use universal IDs, thus, bluntly violating the same-origin policy and merging directly (without background matching) the data they own about particular users.

In addition, we find 131 cases of domains storing in cookies the results of their CSyncs, thus composing ID Summaries. In these summaries, we see the user IDs that other domains use for the particular user previously obtained by CSyncs. An example of such summaries in JSON is shown in Table 5. As one can see, the cookie set by adap.tv includes the user IDs and cookie expiration dates of valueclick.com, medi아mat.com, turn.com and rocketfuel.com. In our dataset, we find at least 3 such companies providing ID Summaries to other collaborating domains. This user-side info allows (i) the synchronizing domains to learn more user IDs through a single synchronization request, and (ii) adap.tv to re-spawn any deleted or expired cookies of the participating domains at any time, just by launching another CSync.

### 5.4 Spilling user IDs out of TLS

It is well-known that mixing encrypted and non encrypted sessions in TLS is a bad tactic [10]. Using TLS, everything except IPs and ports is encrypted [15] in a HTTP connection. As a result, although there are sophisticated estimation techniques [18], no observer can monitor what the user is actually browsing over TLS, or the IDs assigned to her. Given that our proxy is monitoring only HTTP traffic (see Section 4), one would expect that no information from secure TLS sessions would be captured. To our surprise, and as already found in [33], in our dataset we see user IDs that originated from TLS sessions getting leaked over plain HTTP to plain 3rd parties. As a result, any curious, in-path observer (e.g., a snooping ISP) can eavesdrop the leaked user IDs. To make matters worse, we see

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**Table 5: Example of an ID Summary stored on the user's browser. It includes user IDs and expiration dates used for the particular user by 4 different domains.**

| ID Summary stored in cookie by adap.tv |
|---------------------------------------|
| key=valueclickinc:value=708b532c-5128-4b00-a4f2-2b1fac03de81:expiresat=wed apr 01 15:03:42 pdt 2015,key=mediαmatinc:value=60e05435-9357-4b00-8135-273a46820ef2:expiresat=thu mar 19 01:09:47 pst 2015,key=turn:value=2684830505759170345:expiresat=fri mar 06 16:43:34 pst 2015,key=rocketfuelinc:value=63951114977143484:expiresat=sun mar 29 15:43:36 pst 2015" |

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[1] As soon as we verified this leak, we notified publishers and also our volunteering users who updated their signed consent.
The websites a user browses can easily leak through the referrer field, even if the user’s IP address is frequently changed. Obviously, the more 3rd parties were participating in the Cookie Synchronization, the easier it would be for the monitoring entity to capture HTTP requests loaded with these synced cookies and, thus, re-identify the user using a secure VPN.

We measured such cases in our dataset and found 44 users (5%) affected by the ID-spilling of CSync. The majority of leaked domains regard popular content providers, where an eavesdropper from the referrer field, apart from the domain, can also see sensitive information. From Figure 13, the median (90th percentile) user has 70 (226) TLS URLs leaked through CSync.

### 5.5 Sensitive information leaked with userIDs

The websites a user browses can easily leak through the referrer field during a CSync. Moving beyond this type of basic leak, in our dataset we find several cases of privacy-sensitive information passed to the syncing domain regarding the particular user with the particular synced ID. By deploying a simple string matching script, we look for keywords (e.g., gender, age, name, etc.) and find:

- 13 syncs leaking the user’s city level location
- 2 syncs leaking the user’s registered phone number
- 10 syncs leaking the user’s gender
- 9 syncs leaking the exact user’s age
- 3 syncs leaking the user’s full birth date
- 2 syncs leaking the user’s first and last name
- 16 syncs leaking the user’s email address
- 4 syncs leaking user login credentials: username/password

The above information constitutes not only a severe privacy threat for the user, but can also enables potential impersonation attacks.

### 5.6 Who are the dominant CSync players?

In order to assess the content that CSync parties provide, we extract all domains involved in CSync, and using EasyList, EasyPrivacy [14] and the blacklist of the Disconnect browser extension [8] (enriched with our additions after manual inspection), we categorize them according to the content delivered. This way, we create five categories of domains related with:

1. Advertising
2. Analytics
3. Social
4. 3rd-party content (e.g., CDNs, widgets, etc.)
5. Other

As we saw in Figure 11, the median userID gets shared with more than one domains. We find that ad-related domains participate in more than 75% of the overall CSyncs through the year. Consequently, as we can also observe in Figure 14, ad-related domains have learned as much as 90% of all userIDs that got synced, with Social and Analytics-related domains following with 24% and 20% respectively. In Figure 15, we plot the top 20 companies that learned the biggest portion of the total userIDs through CSyncs in our dataset. Interestingly, the top 3 companies (i.e., rubiconproject.com, 360yield.com and openx.net) learned more than 30% of all userIDs in our dataset each. There is also a significant number (14) of companies that learn more than 20% of userIDs.

### 6 COOKIE-LESS DETECTION

In this section, we explore two different scenarios outlined in Section 3.2 regarding the detection of CSync via ID sharing, while such IDs may be obfuscated to remove the possibility of matching them with past IDs shared between entities. First, we explore the scenario where IDs have been shared, detected by the heuristic-based approach, but have not yet been confirmed as CSync events. That is, we consider an already identified set of id-sharing, which is candidate CSync events, but cannot be validated as CSyncs because of the cookie ID being encrypted or unavailable (Section 6.1). Second, we take a step back and consider the more general case where various HTTP connections are ingested by the method, and it needs to decide at run-time which are CSync events and which are not based on given features (Section 6.2).

Towards this end, we train and test the classifier in these two experiments. We remind the reader of the assumption made earlier: the distributions of the features describing the CSync events with unencrypted IDs, have the same variability in the cases of encrypted IDs, and therefore can be used for the detection of such cases. This assumption allows us to handle the problem as an out-of-sample estimation, leaving as future work the final validation with a set of ground-truth data of encrypted IDs that we also know their unencrypted versions.

**Data and Features:** Based on the ground truth data presented earlier with the heuristic-based technique, we have 412.8k id-sharing events, from which 263.6k are confirmed CSync, and 149.2k are identified as non-CSync. The features available for these events can be various, as already explained in 3.2. The ones we use are features available at run time, and during the user’s browsing to websites.

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1. There are specific directives [21] for Referrer field hiding when referring over TLS visited domains.

2. In a dataset with both HTTP and HTTPS traffic, market shares may differ since there are companies operating over SSL only (e.g., DoubleClick)

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| Role       | Domain                                                                 |
|------------|-------------------------------------------------------------------------|
| Visited website | https://financialexpress.com                                               |
| cookie setter | https://tapad.com                                                        |
| SetCookie   | D0821FA0-8A80-4D9E-BC85-C40EAC4E4F5                                      |
| Cookie syncer | http://delivery.swid.switchadhub.com/adserver/user_sync.php?SWID=c4f3265166a9ccf5f6fd0472f12f3776f6a2ekey=PM2&swid=D0821FA0-8A80-4D9E-BC85-C40EAC4E4F5 referer: financialexpress.com                                     |
| Get-cookie  | cf43265166a9ccf5f6fd0472f12f3776f6a2ekey=PM2&swid=D0821FA0-8A80-4D9E-BC85-C40EAC4E4F5 |
| Cookie syncer | http://tags.bluekai.com/site/99967&id-D0821FA0-8A80-4D9E-BC85-C40EAC4E4F5 referer: financialexpress.com                                     |
| Get-cookie  | c4f3265166a9ccf5f6fd0472f12f3776f6a2ekey=PM2&swid=D0821FA0-8A80-4D9E-BC85-C40EAC4E4F5 |
| Cookie syncer | http://tags.bluekai.com/site/28929d1-f82e-11e7-ac1b-0424a110005/30967/id-D0821FA0-8A80-4D9E-BC85-C40EAC4E4F5 referer: financialexpress.com                                     |
| Get-cookie  | c4f3265166a9ccf5f6fd0472f12f3776f6a2ekey=PM2&swid=D0821FA0-8A80-4D9E-BC85-C40EAC4E4F5 |

Table 6: Example of ID-spill from SSL in our dataset.
The final machine learning classifier used is decision tree with balanced dataset across the three classes, and 10-cross fold validation. The last row’s results are computed given an unseen, and unbalanced test set, maintaining the original ratio of classes. 

### Table 7: Performance of decision tree model trained on different subsets of features available at runtime for classification, given already identified id-sharing entries, and 10 cross-fold validation.

| Feature subset | F | TPR | FPR | PR | RC | EM | AUC |
|----------------|---|-----|-----|----|----|----|-----|
| NoOfParams+  | 1  | 0.639 | 0.639 | 0.408 | 0.639 | 0.498 | 0.500 |
| WhereFound+  | 1  | 0.643 | 0.610 | 0.612 | 0.643 | 0.535 | 0.602 |
| StatusCode*+ | 1  | 0.648 | 0.619 | 0.723 | 0.648 | 0.523 | 0.633 |
| TypeOfYear + | 1  | 0.735 | 0.432 | 0.752 | 0.735 | 0.701 | 0.661 |
| Browser*+    | 1  | 0.700 | 0.492 | 0.710 | 0.700 | 0.651 | 0.628 |
| ParamName+   | 1  | 0.815 | 0.295 | 0.828 | 0.815 | 0.803 | 0.834 |
| EntityName*+ | 1  | 0.803 | 0.295 | 0.806 | 0.803 | 0.793 | 0.854 |
| [id-less]*  | 5  | 0.840 | 0.242 | 0.842 | 0.840 | 0.833 | 0.887 |
| [high imp.]+| 6  | 0.870 | 0.206 | 0.877 | 0.870 | 0.865 | 0.919 |
| ALL          | 9  | 0.900 | 0.144 | 0.901 | 0.900 | 0.898 | 0.946 |

### Table 8: Performance of decision tree model trained on different subsets of features available at runtime for classification, given a pre-filter for ID-looking strings. All results besides the last row are with balanced dataset across the three classes, and 10-cross fold validation. The last row’s results are computed given an unseen, and unbalanced test set, maintaining the original ratio of classes.

| Feature subset | F | TPR | FPR | PR | RC | EM | AUC |
|----------------|---|-----|-----|----|----|----|-----|
| NoOfParams+  | 1  | 0.541 | 0.314 | 0.384 | 0.541 | 0.495 | 0.706 |
| StatusCode*+ | 1  | 0.666 | 0.229 | 0.675 | 0.666 | 0.598 | 0.764 |
| TypeOfYear + | 1  | 0.760 | 0.162 | 0.724 | 0.760 | 0.695 | 0.834 |
| EntityName*+ | 1  | 0.865 | 0.075 | 0.863 | 0.865 | 0.860 | 0.962 |
| ParamName+   | 1  | 0.870 | 0.083 | 0.878 | 0.870 | 0.859 | 0.953 |
| [id-less]*  | 4  | 0.904 | 0.037 | 0.904 | 0.904 | 0.898 | 0.973 |
| [high imp.]+| 4  | 0.919 | 0.051 | 0.923 | 0.919 | 0.914 | 0.978 |
| ALL          | 5  | 0.920 | 0.051 | 0.925 | 0.920 | 0.916 | 0.978 |
| Unbalanced   | 5  | 0.981 | 0.004 | 0.989 | 0.981 | 0.984 | 0.999 |

**Algorithms:** The final machine learning classifier used is decision tree-based. Others like Random Forest, Support Vector Machines and Naive Bayes were tested, but the decision tree algorithm outperformed them, with significantly less computation and memory overhead. Indeed, more advanced methods can be used, such as Neural Networks, but since the decision tree-based algorithm works very well, we leave this exploration for the future.

**Metrics:** To evaluate the performance of the classifier on the different classes and available features (F), standard machine learning metrics were used such as Precision (PR), Recall (RC), F-measure (FM), True Positive rate (TPR), False Positive rate (FPR), and area under the receiver operating curve (AUC).

### 6.1 CSync in ID-sharing HTTP

In this experiment, we assume there is already in place an existing web activity monitoring mechanism for the HTTP traffic of the user, similar to the method outlined in Figure 3. However, there are candidate CSync events that cannot be confirmed, as the IDs cannot be matched with SET cookie IDs, either because these actions are not available to the method, or because the IDs are encrypted. In this case, a machine learning classifier can be trained to detect if an id-sharing HTTP request is a true CSync event, by matching its pattern to past verified CSync events. This is necessary when the machine learning classifier is trained to detect if an id-sharing HTTP request is a true CSync event, by matching its pattern to past verified CSync events. For this experiment, we use two classes: the CSync events and the id-sharing but non-CSync events, to train and test a decision tree classifier under different subsets of features. The training and testing was performed using 10 cross-fold validation process. The results are shown in Table 7. We observe that independently, each of the features considered have some predictive power, except for the NoOfParams feature. When the most important features (using information gain as metric) are combined, a weighted AUC of 0.919 is achieved. When we select non-ID related features, a weighted AUC=0.887 is reached, and with all features the classifier can reach a weighted AUC=0.946.
In [1], authors conduct a CSync privacy analysis by studying a small dataset of 3000 crawled sites, in conjunction with re-spawning cookies and how, together, they affect the reconstruction of user’s browsing history by trackers. In [32] they measure the advertising ecosystem cost to users. Focusing on user privacy and targeted advertising, they use CSync as a metric for anonymity loss, showing that users receive 3.4 CSyncs per ad-impression.

Papadopoulos et al. [33] present how CSync can wreck a secure browsing session. They show cases where 3rd-parties may leak a user’s cookie IDs and browsing history, thus increasing the identifiability of the user to a snooping ISP. By probing the top 12k Alexa sites they find 1 out of 13 websites exposing their users to these privacy leaks even when they use TLS and secure VPN services. In a recent census by Englehardt et al. [11], authors measure CSync and its adoption in a small subset of 100,000 crawled sites, before highlighting the need of further investigation given its increased privacy implications. Their results show that 157 of top 200 (i.e. 78%) 3rd-parties synchronize cookies with at least one other party.

In [16] they study the economics and the revenue implications of CSync from the point of view of an informed seller of advertising space, uncovering a trade-off between targeting and information leakage. Similarly, in [4], authors explore the role of data providers on the price and allocation of consumer-level information and develop a simple model of data pricing that captures the key trade-offs involved in selling information encoded in 3rd-party cookies. In [15] they investigate tracking groups that share user-specific identifiers in a dataset collected after recording the browsing history of 100 users for two weeks. In this dataset, they detect 660 ID-sharing groups and found domains with sensitive content (such as health-related) that shared IDs with domains related to ad-trackers.

In [2] they aim to enhance the transparency in ad ecosystem with regards to information sharing, developing a content-agnostic methodology to detect client- and server-side flows of information between ad exchanges by leveraging retargeted ads. By using crawled data, authors collected 35548 ad impressions and identified 4 different kinds of information sharing behaviour between ad exchanges. In [3], they study the diffusion of user tracking caused by RTB-based programmatic ad-auctions, considering CSync as the core component of such auctions and the primary factor of the diffusion of privacy leaks. Results of their study show that under specific assumptions, no less than 52 tracking companies can observe at least 91% of an average user’s browsing history.

Contrary to these works, we conduct a first of its kind, full-scale study of CSync by analysing a year-long dataset of 850 real users, thus avoiding any biases from crawling websites using artificial personas. Additionally, since nowadays mobile drives the majority of the network traffic, our work is the first to study CSync in the growing ecosystem of mobile devices.

8 SUMMARY AND DISCUSSION

One of the most popular techniques for trackers to share the IDs they assign to users today is Cookie Synchronization, with which different domains can merge their databases in the background. However, syncing userIDs of a given user increases the user identifiability while browsing, thus reducing their overall anonymity on the Web. In this paper, we build CONRAD: a holistic system to detect CSync events, either when the synced IDs are available in plaintext, or even when they are obfuscated (i.e., hashed, encrypted). Using our detection mechanism, we are the first to explore CSync in the mobile ecosystem and the first to analyze it in depth, using a year-long dataset of real mobile users. CONRAD is able to capture 3.771% more CSync cases than related work.

Results: Our analysis of 263k CSync requests, syncing 22.3k unique userIDs, led to the following findings:

- 97% of users are exposed to CSync at least once. The median user is synced at least once within the first week of browsing.
- Ad-related domains participate in more than 75% of all CSync through the year, learning as much as 90% of all synced userIDs.
- Three companies learn more than 30% of all userIDs, each.
- The median userID gets leaked to 3.5 domains, on average.
- The average user receives around 1 synchronization per 68 HTTP requests, and gets up to 6.5 of their userIDs synced.
- The number of domains that learn about the median user after CSync grows by a factor of 6.75.
- We find 63 cases, where domains set cookies on the users’ browsers with userIDs previously set by other domains. This universal identification model enables collaborating domains to share data without background database merges.
- We find 131 cases of domains storing in cookies their CSync results forming ID Summaries.
- 5% of users suffer from ID-spilling in their secure TLS traffic.
- several sensitive information (e.g., gender, birth dates) is passed to the syncing domain along with the userID.

In addition to the classic, heuristics-based method applied to collect the above findings, in this work, we proposed a novel, CSync detection mechanism able to detect at real time CSync events, even if the synced IDs are obfuscated. In particular, this online, machine learning classifier can be trained to provide insights as to what each HTTP connection is, and how likely it is to be performing CSync, without the need to match the IDs to SET cookie actions. We use the set of detected CSyncs from the heuristics-based method as ground truth, to train our machine learning, cookie-less detection algorithm. We were able to achieve high accuracy (84%-90%) and high AUC (0.89-0.97), when non-ID related features were used.

Countermeasures: Nowadays, the most popular defence mechanism of CSync is the use of the traditional ad-blockers. Indeed, since the vast majority (75%) of CSync takes place among ad-related domains (see Figure 14), it is easy to anticipate that by blocking ad-related requests, one can eliminate a large portion of the privacy leak that CSync causes. However, the all-out approach of ad-blockers causes significant harm on publishers’ content monetization models, forcing some of them to deploy anti-adblocking mechanisms [21, 27, 28] and deny serving ad-blocking users [26, 41, 43].

Mitigating mechanisms against CSync require a more targeted blocking strategy, that would not blindly harm the current ad-ecosystem. Instead, by applying detection techniques such as CONRAD, and blocking the specific traffic which has been found to facilitate CSync, we believe that the harmful privacy leakage and loss of anonymity of users due to CSync can be avoided, without the dire consequences on publishers’ business models.

Impact: User data collection and sharing activities done without users’ explicit consent can be illegal with hefty penalties imposed to
companies involved, as described in the new EU regulations for protecting user personal data and online privacy (GDPR and e-Privacy). Thus, it is important to design practical web transparency tools such as CONRAD, readily available to privacy researchers, regulators and end-users to investigate personal data leakage and anonymity on the Web, due to 3rd parties’ activities such as CSRF [20].

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