Cross-Device Tracking: Systematic Method to Detect and Measure CDT

Konstantinos Solomos  
FORTH, Greece  
solomos@ics.forth.gr

Panagiotis Iliia  
FORTH, Greece  
pilia@ics.forth.gr

Sotiris Ioannidis  
FORTH, Greece  
sotiris@ics.forth.gr

Nicolas Kourtellis  
Telefonica Research, Spain  
nicolas.kourtellis@telefonica.com

ABSTRACT

Online advertising, the backbone of the free Web, has transformed the marketing business by creating countless opportunities for advertisers to reach potential customers. The advertising ecosystem exists upon a complex infrastructure composed by intermediate entities and technologies whose main goal is to deliver personalized ads to such customers. In recent years, however, advertisers have started to develop new advanced techniques such as Cross-Device Tracking, to detect and track the user’s activity across multiple devices and target them on the all possible device. For this method to work, a variety of user data is collected, aggregated, processed and traded behind the scenes, and often times, without the user-data owner’s informed consent. Therefore, despite the enormous value of online advertising and support it offers to the Web, the prevalence and intensity of these tracking and targeting practices prompt serious concerns for the online users’ privacy.

In this paper, we propose a novel methodology for systematically investigating Cross-Device Tracking and various components affecting its targeting performance. We materialize our methodology into a platform that is able to perform small and large scale automated measurements, under different experimental scenarios, emulated users and settings. By conducting a variety of measurements with our framework, we are able to detect and measure Cross-Device Tracking with average accuracy of 78-96%, and also report significant insights about its internal mechanisms and its impact on online user’s privacy.

KEYWORDS

Online Tracking, Privacy Enhancing Technologies, Behavioral Advertising

1 INTRODUCTION

Online advertising has become a driving force of today’s economy, shaping the socio-economic and technological landscape with the provision of new services and applications. As stated in [1], digital ad spending in 2017 has reached $209 billion worldwide, and for the first time surpassed spending for TV-based advertising. The eminence of online advertising is that it can be easily tailored to the audience, to become personalized according to each user’s interests.

Until recently, ad-companies targeted users with ads relevant to the behavior shown on each specific device. However, as users possess multiple devices [2, 3], advertisers started moving towards more advanced targeting practices that are specifically designed to track and target users across their devices. These advances indicate a radical transformation of the ad-landscape from device-centric to user-centric. In this new paradigm, advertisers try to identify which devices (i.e., smartphone, tablet, laptop) belong to the same user them across all devices. Figure 1 illustrates a typical cross-device tracking (CDT) scenario, where a mobile user is targeted with relevant ads across her different devices, due to the behavior she exhibited to the ad-ecosystem from her mobile device.

According to a recent FTC Staff Report [4], CDT can be deterministic or probabilistic, and companies that engage in such practices typically use a mixture of both techniques. Deterministic tracking, which utilizes 1st-party login services that require user authentication (e.g., Facebook, Twitter, Gmail), can identify the user across multiple devices with certainty. These 1st-party services often share information (e.g., a unique identifier) to 3rd-parties, enabling them to perform a more effective CDT. Alternatively, in the case of probabilistic CDT, there are no shared identifiers between devices, and 3rd-parties try to identify which devices belong to the same user by considering network access data, common patterns in browsing history and behavior, etc. In either case, the implications for user privacy are severe: ad-companies are capable of tracking individual users across all their digital space and screens, and use such information in a non transparent way.

Several analytics/tracking companies such as Criteo [5] and Tapad [6], promote that they can track the user across multiple devices (even on smart TVs, cable boxes, etc.) with high accuracy. However, apart from some empirical evidence about the existence of CDT, there is a limited number of studies investigating it. In the most closely related work, Zimmeck et al. [7], designed an algorithm that, given logs of users’ browsing activity, correlates mobile and
desktop devices into pairs by considering devices’ browsing history and IP addresses. While this approach shows that correlation of devices is possible when such data are available, it does not provide an approach for detecting and measuring it.

To the best of our knowledge, our work is the first to propose a novel methodology for investigating probabilistic CDT in an automated and systematic way, and measuring various parameters that affect its performance on the Web. In effect, our work takes the first and crucial step in understanding the inner workings of the CDT ecosystem.

The methodology proposed in this paper is designed based on the following idea: if cross-device tracking actually exists, and if trackers that employ such techniques (i.e., CDT-trackers) manage to successfully correlate the user’s devices, it could be possible to detect it by identifying cross-device targeted behavioral ads (i.e., ads that are delivered on one device, but have been triggered because of the user’s browsing behavior on a different device). In an effort to make trackers correlate the different devices of the end-user, and serve cross-device targeted ads, we employ artificially created personas with specific interests to emulate realistic browsing activity across the user devices. Furthermore, we built CoDeT, a novel framework that materializes our methodology in order to collect, categorize and analyze all the ads delivered to the different user devices, and evaluate with simple and advanced statistical methods, the potential existence of CDT.

Through a variety of novel experiments, we are able to measure CDT with 78-96% accuracy. Specifically, in the simplest experiment, where the user exhibits significant browsing activity mainly from the mobile device, we achieve average accuracy of 78% for 10 different behavioral profiles. When the user exhibits significant browsing activity from both devices (mobile and desktop), with a matching behavioral profile, we observe CDT with an average accuracy of 83%. Finally, in the case of visiting specifically chosen websites that employ multiple known CDT-trackers, we observe an average detection accuracy of 96%. We also find that browsing in incognito can reduce the effect of CDT, but does not eliminate it, as trackers can perform device matching based only on the current browsing session of the user, and not all her browsing history.

Overall, our main contributions in this work are:

- Design a novel methodology for detecting CDT by triggering behavioral cross-device targeted ads on one user device, according to specifically-crafted emulated browsing behaviors (personas), and then detecting those ads when delivered on a different device of the same user.
- Implement CoDeT, a practical framework for CDT measurements. CoDeT has been designed to provide scalability for fast deployment of multiple parallel device instances, to support various experimental setups, and to be easily extensible.
- Conduct a set of experiments for measuring the potential existence of CDT in different types of emulated users and behaviors, with an average accuracy of 78-96%, and investigating the various factors that affect its performance under different classes of experimental setups and configurations.

2 BACKGROUND & RELATED WORK

In this section, we provide the necessary terminology to understand the technical contributions of our work, and in parallel we present various mechanisms and technologies proposed in related works.

2.1 Personalized Targeted Advertising

As the purpose of advertising is to increase market share, the advertising industry continuously develops new mechanisms to deliver more effective ads. These mechanisms involve the delivery of contextual ads, targeted behavioral ads, and also retargeted ads.

Contextual advertising refers to the delivery of ads relevant to the content of the publishing website. With regards to the effectiveness of contextual advertisement, Chun et al. [8] found that it enhances brand recognition and that users tend to have favourable attitudes towards it. In one of the first works in this area, Broder et al. [9] proposed an approach for classifying ads and web pages into a broad taxonomy of topics, and then matching web pages with semantically relevant ads. A large body of work also investigates targeted behavioral advertising with regards to different levels of personalization, based on the type of information that is used to target the user [10–12], and its effectiveness [13–16]. Interestingly, Aguirre et al. [11] found that, while highly personalized ads are more relevant to users, they increase users’ sense of vulnerability. In another study, Dolin et al. [17] measured users’ comfort regarding personalized advertisement. In a different direction of investigation, Carrascosa et al. [18] developed a methodology that employs artificially-created behavioral profiles (i.e., personas) for detecting behavioral targeted advertising at scale. Their methodology could distinguish interest-based targeting from other forms of advertising such as retargeting. An extensive review of the literature about behavioral advertising can be found in [19].

2.2 Leakage of Personal Information

In order to serve highly targeted ads, advertisers employ various, often questionable and privacy intrusive, techniques for collecting and inferring users’ personal information. They typically employ techniques for tracking users visits across different websites, which allow them to reconstruct parts of the users’ browsing history. Numerous works investigate the various approaches employed by trackers, and focus on protecting users’ privacy.

In a recent work, Papadopoulos et al. [20] developed a methodology that enables users to estimate the actual price advertisers pay for serving them ads. The range of these prices can indicate which personal information of the user is exposed to the advertiser and the sensitivity of this information. Liu et al. [21] proposed AdReveal, a tool for characterizing ads, and found that advertisers frequently target users based on their interests and browsing behavior. Lecuyer et al. [22] proposed XRay, a data tracking system that allows users to identify which data is being used for targeting, by comparing outputs from different accounts. In another work, they propose Sunlight [23], a system that employs methodologies from statistics and machine learning to detect targeting at large scale.

Bashir et al. [24] developed a methodology that detects information flows between ad-exchanges. This approach leverages retargeted ads, in order to detect when ad-exchanges share the user’s
information between them, for tracking and retargeting the user. Datta et al. [25] developed AdFisher, a tool that explores causal connections between users’ browsing activities, their ad settings and the ads they receive, and found cases of discriminatory ads. This tool uses machine learning to determine, based on the ads received, if the user belongs to a group of users that exhibit a specific browsing behavior i.e., visited specific websites that affected their behavioral profile. Castelluccia et al. [26] showed that targeted ads contain information that enable reconstruction of users’ behavioral profiles, and that user’s personal information can be revealed to any party that has access to the ads received by the user.

In order to enable ad targeting without compromising user privacy, Toubiana et al. [27] and Guha et al. [28] proposed Adnostic and Privad, respectively. These two approaches try to protect users’ privacy by keeping user profiles on the client-side and thus, hiding user activities and interests from the ad-network. Furthermore, in an attempt to provide a better alternative, Parra-Arnau et al. [29], proposes a tool that allows users to control which information can be used for the purpose of advertising.

Furthermore, many works investigate privacy leakage, specifically, in mobile devices and the different factors influencing mobile advertising [30–34]. A recent study by Papadopoulos et al. [30] compared privacy leakage when visiting mobile websites and using mobile apps. Meng et al. [34] studied the accuracy of personalized ads served by mobile applications based on the information collected by the ad-networks. Also, Razaghpanah et al. [32] developed a technique that detects third-party advertising and tracking services in the mobile ecosystem and uncovers unknown relationships between these services.

2.3 Web Tracking

As mentioned previously, various techniques are employed for tracking and correlating users’ activities across different websites. Many works investigated stateful tracking techniques [35–39], and also stateless techniques such as browser fingerprinting [40–45]. One of the first studies about tracking [46], investigated which information is collected by third parties and how users can be identified. Roesner et al. [35] measured the prevalence of trackers and different tracking behaviors in the web.

Olejnik et al. [36] investigated “cookie syncing”, a technique that enables third parties to have a more completed view on the users’ browsing history by synchronizing their cookies. Acar et al. [42] investigated the prevalence of “evercookies” and the effects of cookie respawn in combination with cookie syncing. Englehardt and Narayanan [37] conducted a large scale measurement study to quantify stateful and stateless tracking in the web, and cookie syncing, while Lerner et al. [39] conducted a longitudinal measurement study of third party tracking behaviors and found that tracking has increased in prevalence and complexity over time.

With regards to stateless tracking, Nikiforakis et al. [43] investigated various fingerprinting techniques employed by popular trackers and measured the adoption of fingerprinting in the web. Acar et al. [41] proposed a framework to detect fingerprinting by identifying and analyzing specific events such as the loading of fonts, or accessing specific browser properties. In another work, Nikiforakis et al. [44] proposed PriVaricato, a tool that employs randomization to make fingerprints non-deterministic, in order to make it harder for trackers to link user fingerprints across websites. Also, in a recent work, Cao et al. [47] proposed a fingerprinting technique that utilizes OS and hardware level features, for enabling user tracking not only within a single browser, but also across different browsers on the same machine.

2.4 Cross-Device Tracking

A few recent works investigate cross-device tracking that is implemented based on technologies such as ultrasound and Bluetooth, and measure the prevalence of these approaches [48–50]. As in this work we focus on web based cross-device tracking, our work is complementary to works that investigate such technologies.

A work by Brookman et al. [51], one of the few that investigate CDT on the web, provides some initial insights about the prevalence of trackers. This work examines 100 popular websites in order to determine which of them disclose data to trackers, identifies which websites contain trackers known to employ CDT techniques, and also investigates if users are aware of these techniques.

During the Drawbridge Cross-Device Connection competition of the ICDM 2015 conference [52], the participants were provided with a dataset [53] that contained information about some users’ devices, cookies, IP addresses and also browsing activity, and were challenged to match cookies with devices and users. This resulted in a number of short papers [54–60] that describe different machine learning approaches followed during the competition for matching devices and cookies. Some of the proposed methods achieved accuracy greater than 90%, and seen from a different point compared to our study, showed that users’ devices can be potentially correlated if enough information is available. In addition, Funkhouser et al. [61] proposed a Bayesian similarity algorithm based on device characteristics and identifiers, that correlates pairs of devices with accuracy higher than 90%.

Zimmeck et al. [7] conducted an initial small-scale exploratory study on CDT based on the observation of cross-device targeted ads in two “paired” devices (mobile and desktop) over the course of two months.

Following this exploration, they collected the browsing history of 126 users, from which 107 have provided data from both their desktop and mobile device, and designed an algorithm that estimates similarities and correlates the devices into pairs. This approach, which is based on IP addresses and browsing history, and achieves high matching rates, shows that users’ network information and browsing history can be used for pairing user devices, and thus potentially for CDT. Overall, our work builds on these early studies, as well as past studies on web tracking on different platforms. Research around CDT is still very limited; in fact, only [7, 51] initially studied some of its aspects, but without proving its actual existence or providing a methodology for detecting it. Consequently, to fill-in this gap, we propose the first of its kind methodology, and implement a novel framework, that enables systematic investigation and measurement of probabilistic CDT.

3 OVERVIEW OF METHODOLOGY

The main objective of this work is to provide a methodology for investigating CDT and its mechanics, as employed by the ad-ecosystem
entities. Therefore, our methodology emulates realistic browsing activity of end-users across different devices, and collects and categorizes all ads delivered to these devices based on the intensity of the targeting. Finally, it compares these ads with baseline browsing activity to establish if CDT is present or not, at what level, and for which types of user interests.

The design objectives of this methodology are the following:

• Ability to statistically distinguish and detect probabilistic CDT in a systematic and repeatable fashion.
• Scalability, for fast, multi-location deployment of multiple parallel device instances, which allows extensive experimentation.
• Support the investigation of cross-device tracking in both directions, i.e., mobile → desktop, and desktop → mobile.
• Support short and long-term experiments, for data collection in ad-hoc fashion or historically through time.
• Extensibility through modular design, so that new methods available in the future can be easily deployed and tested.

3.1 Design Principle

In general, we consider the CDT performed by the ad-ecosystem a very complex process, with multiple parties involved, and a non-trivial task to dissect, study and understand. To that end, it is inherently difficult to identify the privacy leakage due to CDT. To infer its internal mechanics we rely on probing the ecosystem with consistent and repeatable inputs \((I)\), under specific experimental settings \((V)\), allow the ad-ecosystem to process and use this input via transformations and modeling \((F)\), and produce outputs that we can measure on the receiving end \((Y)\):

\[(I, V) \xrightarrow{F} Y\]

In this expression, the unknown \(F\) is the probabilistic modeling performed by CDT ad-entities, allowing them to track users across their devices, regardless if users consented to this tracking or not. Following this design principle, our methodology allows to push realistic input signals to the ad-ecosystem via website visits, and measure the ecosystem’s output through the delivered ads, to demonstrate if \(F\) enabled the ecosystem to perform probabilistic CDT. Moreover, the methodology allows repetitive experimentation under the same setup, enabling systematic and repeatable measurements.

3.2 Challenges & Considerations

Based on this guiding design principle, an overview of our methodology is illustrated in Figure 2. Next, we summarize its basic assumptions and design considerations.

No 1st-party logins. Many users utilize popular online services that leak users’ identifiers to 3rd-parties, making it easier to track them across different devices (since they can be identified with certainty). In our methodology, we assume that the emulated user does not visit or log into any 1st-party service that employs deterministic CDT and thus, there is no common identifier (e.g., email address, OSN UID) shared between the user’s devices.

Devices, IP addresses and Browsing. The approach we follow is based on triggering and identifying behavioral cross-device targeted ads, and specifically ads that appear on one of the user’s devices, but have been triggered by the user’s activity on a different device. For this trigger to be facilitated, the ad-ecosystem must be provided with hints that these two devices belong to the same user. Zimmeck et al. [7] suggest that in many cases, the devices’ IP address is adequate for matching devices that belong to the same user. Relevant industrial teams [62, 63] claim that more signals can be used, such as location of devices, browsing, etc. In fact, CDT-entities typically utilize such network-level information [64] to boost the accuracy of their methods.

Following these observations, our methodology requires a minimum of three different devices (as shown in Figure 2): one mobile...
device and two desktop computers, with two different IP addresses. We assume that two devices (i.e., the mobile and one desktop) belong to the same user, and are connected to the same network. That is, these devices have the same public IP address, are active in the same geolocation as in a typical home network, and will be considered by the ad-ecosystem as producing traffic from the same user. The second desktop (i.e., baseline PC), which has a different IP address, is used for receiving a different flow of ads while replicating the browsing of the user’s desktop (i.e., paired PC). This control instance is used for establishing a baseline set of ads to compare with the ads received by the paired PC.

CDT Direction: Mobile to Desktop. In principle, the design allows the investigation of both directions of CDT. That is, users may first browse on the mobile device, and then move to their desktop, and vice versa. However, according to a recent article [65], consumers typically use mobile devices to search for products, but make purchases on larger-screen computers. Also, ad-targeting companies such as AdBrain [66] and Criteo [67] support that the direction from mobile to desktop is more suitable for cross-device retargeting.

Even though the proposed methodology allows studying both directions of CDT, in this work we focus on the mobile to desktop direction (Mob \(\rightarrow\) PC). In essence, the mobile device performs a specifically instructed web browsing session, i.e., training phase; then, the two desktop computers also perform some web browsing, i.e., testing phase, where they visit a set of pages and collect the delivered ads. The browsing performed by the two desktop devices is synchronized by means of visiting the same pages in the same order, and performing the exact same clicks.

Emulating user behavior with personas: Training Phase. To trigger CDT, we first need to demonstrate to the ad-ecosystem some activity from a user’s browsing behavior (\(I\)). In order to make the methodology systematic and repeatable, but also produce realistic browsing traffic from scripted browsers, we visit specific websites to emulate a user’s behavior according to some predefined, carefully-crafted personas. We leverage an approach similar to Carrascosa et al. [18] to emulate browsing behavior according to specific user interests (i.e., travel and vacations, sports, shopping), and create multiple personas of different granularities, spanning from generic to more narrow categories. For each persona, our approach identifies a set of websites (dubbed as persona pages) that have at the given time active ad-campaigns. This training activity aims to drive CDT-trackers into possible device-pairing between the two user’s devices with a high degree of confidence.

Control pages: Testing Phase. The browsing based on a given persona can be considered as the input to the ad-ecosystem (\(I\)), and the ads delivered to the involved devices as the output of the ad-ecosystem (\(Y\)). To reduce any bias from possible behavioral ads delivered to specific type of websites, and following past works on this topic [18, 24], the desktops collect ads by visiting neutral websites that typically serve ads not related to their content. We refer to these neutral websites as control pages.

CDT Detection: Comparing Signals. Various statistical methods can be used to associate the input signal \(I\) of persona browsing in the mobile device, with the output signal \(Y\) of ads delivered to the potentially paired-desktop. For example, methods that perform similarity computation between the two signals in a given dimensionality (e.g., Jaccard, Cosine) can be of use. These methods, as well as typical statistical techniques (e.g., permutation tests) capture only one dimension of each input/output signal and thus, might not be suitable for measuring with confidence the high complexity of the CDT signal. In this case, more advanced methods can be employed, such as Machine Learning techniques (ML) for classification of the signals as similar enough to match, or not, based on features from the experimental setup (\(\mathcal{V}\)), and the input/output features. In our analysis, we mainly focus on ML to compute the likelihood of the two signals being the product of CDT, as it takes into consideration this multidimensionality in the feature space.

3.3 Possible Experimentations & Extensions

This methodology allows a researcher to experiment in different ways while investigating cross-device tracking. Both persona and control pages can be used as input in either of the two types of devices (mobile or desktop). For example, the personas mechanism can be used to provide input webpages for visiting only from the mobile device, and control pages only from the desktop devices. In this case, the browsing signal for the specific persona is inputted to the ad-ecosystem from the mobile device, and the desktop devices are the recipients of the output signal. This setup, which purposely does not establish a behavioral profile on all the user’s devices, aims to reveal cases of device pairing based solely on the IP address of the devices. By using two devices with the same IP address (a mobile and a desktop), and establishing a behavioral profile only on one of them (e.g., the mobile device), we can demonstrate the effect of pairing by detecting cross-device targeted ads on the device that has not gone under behavioral training (i.e., the desktop). This setup can be considered as providing a clearer input signal to the ad-ecosystem from the two paired devices.

Alternatively, the method can perform behavioral training on all devices, and measure the difference in signal recorded between the mobile-desktop and the mobile-baseline desktop pairs. This experimental setup aims to ease device pairing, as the devices exhibit similar browsing activity. In effect, this setup blurs the input signal put into the ad-ecosystem, by having all devices providing similar input \(I\). To be able to identify cross-device tracking under this setup, such an experimentation needs to be executed for a longer period of time, to collect adequate samples for the signal comparison. Consequently, the method would compare the cumulative outcome of the user’s desktop (that has the same IP address with the mobile device) with the baseline desktop PC. The former accounts for both ad retargeting (due to the desktop’s browsing) and cross-device ad targeting (due to the paired mobile), while the latter only for ad retargeting (due to the baseline desktop’s browsing).

Finally, the selection of browsing pages to be visited by the mobile and/or desktop devices (persona and control pages) can be either generic, or focused on specific pages that include an abundance of trackers and other third party entities specializing in CDT. Our methodology could also support the use of some specifically crafted pages under our control, similarly to [68], or apply smart filtering techniques on existing webpages, in order to isolate the effect of individual trackers and study their behavior with regards to CDT. Such functionalities can enable privacy researchers and
policy makers to investigate potential violations of users’ privacy, by tracking and targeting sensitive user categories such as health, religion, sex orientation, etc. In essence, this methodological design allows for extensibility with new methods invented in the future, for better input signal generation (e.g., for persona building), device emulation with more realistic browsing behavior, more precise webpage parsing for ads extraction, extension of features used in the machine learning process, better machine learning algorithms, etc. The next section details how the proposed methodology can be implemented into a real functioning system.

4 CODET: A SYSTEM TO MEASURE CDT

A high level overview of our methodology, and its materialization by our framework CoDeT, is presented in Figure 2 and described in §3. In the following, we provide more details about its building blocks, and argue for various design decisions taken while implementing this methodology into the fully-fledged automated system.

First, in §4.1, we describe the process followed for selecting the webpages to be visited by the devices as input to the ad-ecosystem. Second, in §4.2, we explain the functionality of the experimental setup selector and how mobile and desktop devices are emulated. Third, in §4.3, we detail the methods used for parsing the pages visited to extract ads and associate categories to their landing pages, and finally, in §4.4, we present the machine learning modeler for detecting CDT within our experimental setups.

4.1 Input Signal: Personas & Control Pages

Persona Pages. A critical part of our methodology is the design and automatic building of realistic user personas. Each persona has a unique collection of visiting links, that form the set of persona pages. Since we do not know in advance which e-commerce sites are conducting cross-device ad-campaigns, we design a process to dynamically detect active persona pages of given interest categories. Our approach for persona generation is shown in Figure 3.

We use the persona categorization of Carrascosa et al. [18], for their top 50 personas, and iterate through the Google Product Taxonomy list [69], to obtain the related keywords. We do not search deeper than Level 4 of this list and we store two to three keywords as a label for each persona, as we want to capture the user interests in a more general and descriptive categorization.

For capturing active ad-campaigns we use Google Search, as it reveals campaigns associated with products currently being advertised. That is, if a user searches for specific keywords (e.g., “men watches”), Google will display a set of results, including a list of sponsored links from e-commerce sites and services conducting campaigns for the terms searched. In this way, we use the keywords set for each persona, as extracted above, and transform them to search queries by appending common string patterns such as “buy, sell, offers” to create queries in a neutral fashion. This procedure is repeated until at least five (and a maximum of ten) unique domains per persona are collected. If the procedure fails to capture more than five unique domains, no persona is formed.

In general, our method can generate a large number of different personas, corresponding to various interests and online behaviors: from generic to specific categories. However, as the effectiveness of a persona depends on the active ad-campaigns, and also due to the computation overhead involved in creating each persona, in our experiments we only deploy the 10 personas shown in Table 1.

Control Pages. For retrieving the display ads from the devices, we employ a set of webpages that contain: (i) easily identifiable ad-elements and (ii) a sufficient number of ads that remains consistent through time. These pages have neutral context and, therefore, do not affect the behavioral profile of the device during the visit. For most of the experiments in §5 we use a set of five popular weather websites2 as control pages, similarly to [18]. We also empirically confirmed the neutrality of ads served on this set of pages, and the lack of contextual ads. When visiting the set of control pages, our method extracts, analyzes and categorizes all the ads received, in order to identify those that have been served to the user’s desktop because of the browsing on the mobile device.

4.2 Experimental System Setup

The experimental setup contains different types of units, connected together for replicating browsing activity on multiple devices. Typically, CDT is applied on two or more devices that belong to the same user, such as a desktop and a mobile device. Therefore, the system contains emulated instances of both types, controlled by a number of experimental parameters.

---

2www.accuweather.com, www.wunderground.com, www.weather.com, www.weather-forecast.com, www.meteocheck.com
Experimental Setup Selector. As shortly described in § 3, we need two phases (training and testing) of browsing to different types of webpages, in order to successfully measure CDT. For that reason, we set the two browsing phases in the following way: During the training phase, the selected device visits the set of Persona Pages for a specific duration, referred as training time ($t_{train}$). The test phase is the set of visits to control pages for the purpose of collecting ads. During this phase, we control the duration of browsing, and we call it testing time ($t_{test}$). In fact, the process of training and testing is repeated several times, in order for the ad-ecosystem to be exposed repeatedly to the given signal. The experimental setup selector controls various parameters and the values selected: which device and what type will be trained, tested, the times $t_{train}$ and $t_{test}$, the sequence of time slots for training and testing from the selected device, number of repetitions of this procedure, etc.

Desktop Device. The desktop devices are built on top of the web measurement framework OpenWPM [37]. This platform enables launching instances of the Firefox browser, with any set of extensions, and collects a wide range of measurements in every browsing session. It is also capable of storing the browser’s specific data (cookies, local cache, temporary files) and export a browser profile after the end of a browsing session, which can be then loaded in a future session. With these options, we can perform stateful experiments, as a typical user’s web browser that stores all the data through time, or stateless experiments to emulate browsing in incognito mode.

Mobile Device. For the mobile device, we use the official Android Emulator [70]) that allows us to create and control emulated Android devices of different vendors, OS versions etc. For the automation of browsing, we use Appium UI Automator [71], and built the mobile browsing module on top of those components to automate the visits to pages via the Browser Application. Our mobile browsing module provides attributes that can drive to a more realistic interaction with a website, e.g., scrolling rate, click rate, and sleep time. Similarly to the desktop device, the mobile Browser App can run in a stateful or stateless mode.

4.3 Page Parser, Ad Extractor & Ad Categories

Page Parser. To collect the display ads, we first need to identify specific DOM elements inside the visited webpages. This task is challenging due to the dynamic Javascript execution and the complex DOM structures generated in most webpages. For the reliable extraction of ad elements and identification of the landing pages we follow similar methodology with Liu et. [21]. As landing pages, we refer to the destination websites that a user would be redirected to when clicking on the ads.

The functionality of the Page Parser is to parse the rendered HTML webpage and extract the attributes of the display ads, which also contain the landing page. In most modern websites, the displayed ads are embedded in iframe tags that create deep nesting layers, containing numerous and different types of elements. However, since the ads served by the control pages are found directly inside the iframes, the Ad Extractor described next does not have to handle such behavior.

Ad Extractor. This module is activated when the visited page is fully loaded and no further changes occur on the page’s content, or up to a time threshold of 60 seconds for content, and a hard timeout of 120 seconds for network responses. At first, as outlined in Algorithm 1, the module identifies all the active iframe elements and filters out the invalid ones that have either empty content or zero dimensions. Then, it retrieves the href attributes of image and flash ads and parses the URLs, while searching for specific string patterns such as adurl=, redirect=, etc. These patterns are typically used by the ad-networks for encoding URLs in webpages. Finally, the module forms the list of candidate landing pages, which are then processed and analyzed to create the set of true landing pages. The Ad Extractor module is fully compatible with the crawlers, and does not need to perform any clicks on the ads (e.g., ad banners), since it extracts only the previously described data (i.e., URLs) directly from the rendered webpage. Also, the click on the ads would contribute to the known problem of ad-fraud, and impact the budget of advertisers.

Algorithm 1: Functionality of Ad Extractor.

**Input:** Webpage // the rendered HTML webpage  
**Output:** LandingPages // list of candidate landing pages  

LandingPages←∅  
AlliFrames←Collect_All_Iframes(Webpage)  
for iframe in AlliFrames do  
  if iframe is not empty and visible then  
    References = Collect_All_References(iframe)  
    for ref in References do  
      if ref contains landingpage then  
        LandingPages ← Add_Reference(ref)  
    return LandingPages

Ad Filter. This module processes the list of candidate landing pages in order to finally obtain the true landing pages. At this phase, the platform stores only the active ad-domains, after filtering the list of landing pages with the EasyList [72] filter provided by AdBlockPlus. Similarly to previous works [24, 37], we decided to use EasyList as it is regularly updated. Other filter lists, or a combination of them could also be used to enrich the Ad Filter and increase its accuracy.

Ad Categories. To associate landing pages or browsing URLs with web categories, we employ the McAfee TrustedSources database [73], which provides URLs organized into categories. This system categorized 96% of the true landing pages of our collection into a total of 76 unique categories, by providing up to four semantic categories for each page. The remaining unclassified domains are manually classified into the categories above. The final output of the Page Parser contains the landing pages of ads for every test phase, along with their categories. This module also stores metadata from the crawls such as: time and date of execution, the number of identified ads, the number of categories, the type and phase of crawl, etc.

4.4 CDT Machine Learning Modeler

Probabilistic CDT is a kind of task generally suitable for investigation through ML, after some necessary preprocessing of the data at hand. Previous work by Zimmack et al. [7], as well as industry directions [62, 63] claim that probabilistic device-pairing is based on specific, well-defined signals: IP address, geolocation, type and frequency of browsing activity. In our methodology, since we control
these parameters, by definition, we construct the ground truth with our experimental setups. That is, we control (i) the devices used, which are potentially paired under a given IP address, geolocation and browsing patterns, (ii) the control instance of baseline desktop device, and (iii) the browsing performed with the personas.

Before applying any ML method, every instance of the input data has to be transformed into a vector of values; each position in this vector corresponds to a variable (feature). Features are different properties of the collected data: browsing activity of a user during training time, experimental setup used with the devices (persona, etc.), time-related details of the experiment, as well as information about the collected ads, which is the output signal received from the given browsing activity. These sets of features can be studied systematically to identify statistical association between the input and output signals, given an experimental setup. In effect, our feature space is comprised of a union of these vectors, since all features are either controlled, or measurable by us. The only unknown is whether the ad-ecosystem has successfully associated the devices or not, and if it has exhibited this in the output signal via ads.

For more advanced ML methods to be applied here, we transform the problem of identifying if such vectors are similar enough, into a typical binary classification problem, where the predicted class describes the existence of pairing or not, that may have occurred between the mobile device and one of the two desktop devices. As a paired combination, we consider the desktop device that exists under the same public IP address with the mobile device. The “not paired” combination is the mobile device and the control/baseline instance of desktop with no IP address, or other relation to the mobile device. In general, these ML methods are similar (or just a lower bound of complexity) to the ones used by advertising companies. In the next section, we experiment with different algorithms on the produced datasets, to obtain the best model that can decide if there has been CDT or not by the ad-ecosystem.

5 MEASURING CDT WITH CODET

This section describes in detail the design and execution of various experiments that explore different operational settings of the framework, while measuring the appearance of CDT and its effect on the ad-ecosystem. First, in § 5.1, we provide details of the experimental setups, including type of devices used, browsing parameters, machine learning algorithms tested, and performance metrics used. In § 5.2, we present preliminary experiments as a first validation of our platform; in § 5.3, we introduce the first class of experiments designed to emulate real users’ short-lived browsing behavior through different personas, and measure the existence of CDT. In § 5.4, we introduce the second experimental class, designed to emulate users’ long-lived browsing behavior, where the behavioral browsing happens in multiple devices. We also study setups that focus on browsing pages infused with CDT entities, in an attempt to input a stronger signal to the ad-ecosystem, and measure the improvements in CDT detection. Finally, in § 5.5, we study how functionalities available to users to avoid tracking (e.g., incognito browsing) affect CDT, across several types of personas.

5.1 Experimental Setup

Timeline of phases. Each class of experiments is executed multiple times (or runs), through parallel instantiations of the user devices within the framework (as shown in Figure 2). Each experimental run is executed following a timeline of phases as illustrated in Figure 4. This timeline contains $N$ sessions with three primary stages in each: Before, Mobile, and After. The Before ($B_i$) stage is when the two desktop devices perform a test browsing in parallel, before the mobile device is used, to establish the state of ads before the mobile device injects signal into the ad-ecosystem. The Mobile ($M_i$) stage is when the mobile device performs a train and a test browsing. This phase injects the signal from the mobile during training with a persona, but also performs a subsequent test with control pages to establish the state of ads after the training. Finally, the After ($A_i$) stage is when the two desktops perform the final test browsing to establish the state of ads after the mobile training.

After extensive experimentation, we found that a minimum training time $t_{train}=15$ minutes and testing time $t_{test}=20$ minutes are sufficient for injecting a clear signal over noise, from the trained device to the ad-ecosystem. There is also a waiting time ($t_{wait}=10$ minutes) and resting time ($t_{rest}=5$ minutes) between the stages of each session, to allow alignment of instantiations of devices running in parallel during each session. In total, each session lasts 1.5 hours and is repeated $N=15$ times during a run. Through the experimental setup selector, we define the values of such variables ($t_{train}, t_{test}, t_{wait}, t_{rest}, N$, type of device), offering the researcher flexibility to measure and detect different cases of CDT.

Experimental Classes. For each of the classes of experiments, we construct different datasets using the framework at hand and the methodology detailed in § 4.4, and summarized in Table 2. We vary the training and testing time, the number of personas used and how their data are combined, as well as browsing functionalities such as keeping or not the state of the emulated user.

Statistical Analysis of Device Signals. In order to analyze the similarity of signals (ads from a given category delivered in each device), we apply two analyses. First, to measure the similarity of distribution of ads delivered, we categorize them based on the tools described in § 4.3 and create appropriate frequency vectors, populated through time: one time vector for each device and each semantic category. We compare the signals using a two-tailed permutation test and reject the null hypothesis that the frequency of ads delivered (for a given category) come from the same distribution, if the t-test statistic leads to a p-value smaller than a significance level $\alpha < 0.05$. Given that such a uni-dimensional test
5.2 Platform Validation for Ad Measurements

A first set of preliminary experiments is introduced here, to demonstrate that our platform can (i) successfully identify and collect the ads delivered to our multiple devices (mobile and desktops), (ii) inject browsing signal from a device, thus biasing it to have a realistic persona and (iii) lead to matching/pairing of devices, which could be due to same behavioral ads, retargeting ads or CDT.

First, we use a simple experimental setup: we connect three instances of desktop device and one mobile device under the same IP address. We create one persona (as in § 4.1), with an interest in "Online Shopping-Fashion, Beauty", and following the given timeline of phases, we run this experiment for two days. Then, we perform one-dimensional statistical analysis, as introduced in § 5.1, and find that there is no similarity between the mobile with any of desktop devices (null hypothesis rejected with highest p-value=0.030), while all desktop distributions are similar to each other (null hypothesis accepted with lowest p-value=0.33). These statistical results indicate that there is no clear device-pairing (at the level of ad distribution for the given persona), and that we should consider controlling for more factors to instigate it.

Consequently, we expand this experiment by also training one of the desktop devices using the same persona as with mobile. By repeating the same statistical tests, we find that the mobile and desktop with the same browsing behavior receive ads coming from the same distribution (null hypothesis accepted with lowest p-value=0.84), while the other devices show no similarity with each other or the mobile (null hypothesis rejected with highest p-value=0.003). This result indicates that browsing behavior under a shared IP address can boost the signal towards advertisers, which they can use to apply advanced targeting, either as CDT, or retargeting on each device or a mixture of both techniques.

Finally, these preliminary experiments and statistical tests provide evidence for the effectiveness of our framework to inject enough browsing signal from different devices under selected personas, and to collect ads delivered that can be analyzed and linked back to those personas, and importantly, to potential CDT between the devices involved. Next, we present more elaborate experiments with our framework, in order to study CDT in action.

5.3 Detecting CDT in Short-lived Browsing

Independent Personas: Setup 1a. This experimental setup emulates the behavior of a user that browses frequently about some

Table 2: Characteristics of the datasets used in each setup (S) of experiments. S={1,2,3} are the setups of experiments in § 5.3, § 5.4 and § 5.5, respectively; I_total: the total duration of experiment; I_train: the training duration; I_test: the testing duration; I: independent personas; C: data combined from personas; STF: stateful browser; STL: stateless browser; B: boosted CDT browsing.

| S | Personas | Runs | I_train | I_test | I_total | Samples | Features |
|---|----------|------|---------|--------|---------|---------|----------|
| 1a | 10 (L, STF) | 4 | 15min | 20min | 37 days | 240 | 1100 |
| 1b | 10 (C, STF) | - | - | - | - | 2400 | 2201 |
| 2a | 2 (L, STF) | 4 | 480min | 30min | 6 days | 192 | 600 |
| 2b | 2 (C, STF) | - | - | - | - | 384 | 750 |
| 2c | 2 (L, STF, B) | 4 | 480min | 30min | 6 days | 192 | 500 |
| 2d | 2 (C, STF, B) | - | - | - | - | 384 | 576 |
| 3a | 5 (L, STL) | 2 | 15min | 20min | 9 days | 120 | 450 |
| 3b | 5 (C, STL) | - | - | - | - | 600 | 880 |

Table 3: Performance evaluation for Random Forest in setups 1a and 1b. Left value in each column is the score for Class 0 (C0=not paired desktop); right value for Class 1 (C1=paired desktop).

| Persona (setup) | Precision C0 | Precision C1 | Recall C0 | Recall C1 | F1-Score C0 | F1-Score C1 | AUC |
|-----------------|--------------|--------------|-----------|-----------|-------------|-------------|-----|
| 1 (1a)          | 0.89         | 0.60         | 0.57      | 0.90      | 0.70        | 0.72        | 0.73 |
| 2 (1a)          | 0.84         | 0.78         | 0.81      | 0.82      | 0.82        | 0.80        | 0.82 |
| 3 (1a)          | 0.81         | 0.73         | 0.78      | 0.76      | 0.79        | 0.74        | 0.76 |
| 4 (1a)          | 0.87         | 0.78         | 0.87      | 0.78      | 0.87        | 0.78        | 0.82 |
| 5 (1a)          | 0.94         | 0.65         | 0.68      | 0.93      | 0.79        | 0.76        | 0.80 |
| 6 (1a)          | 0.57         | 0.67         | 0.81      | 0.38      | 0.67        | 0.46        | 0.59 |
| 7 (1a)          | 0.81         | 0.87         | 0.89      | 0.76      | 0.85        | 0.81        | 0.81 |
| 8 (1a)          | 0.86         | 0.85         | 0.89      | 0.81      | 0.87        | 0.83        | 0.84 |
| 9 (1a)          | 0.74         | 0.90         | 0.91      | 0.73      | 0.82        | 0.81        | 0.81 |
| 10 (1a)         | 0.77         | 0.85         | 0.81      | 0.81      | 0.79        | 0.83        | 0.81 |
| combined (1b)   | 0.77         | 0.84         | 0.81      | 0.84      | 0.82        | 0.84        | 0.89 |
topics, but in short-lived sessions in her devices. Given that most users do not frequently delete their local browsing state, this setup assumes that the users’ browser keeps all state, i.e., cookies, cache, browsing history. This enables trackers to identify users more easily across their devices, as they have historical information about them. In this setup, every experimental run starts with a clean browser profile, and cookies and temporary browser files are stored for the whole duration of the experimental run. We use all personas of Table 1, and the data collection for each persona lasts ~4 days.

We perform the same statistical analysis as in §5.2, and find that in 4/10 personas, the mobile and paired desktop ads are similar (null hypothesis accepted with lowest p-value=0.13), while the mobile and baseline desktop ad distributions are different (null hypothesis is rejected with highest p-value=0.009). This inconsistency is reasonable since the statistical analysis is based only on one dimension, the frequency count of types of ads appearing in the devices, which may not be enough for fully capturing the existence of device-pairing. Also, the IP address might not be enough of a factor for the ad-ecosystem to lead to CDT. For these reasons, we choose to use more advanced, multidimensional ML methods which take into account the various variables available, to effectively compare the potential CDT signals received by the two devices.

The classification results of the Random Forest algorithm are reported in Table 3. This algorithm was the best performing one compared to the other two. We use AUC score as the main metric score in our analysis, since the ad-industry seems to prefer higher Precision scores over Recall, as the False Positives have a greater impact on the effectiveness of ad-campaigns. As shown in Table 3, the model achieves high AUC score for most of the personas, with a maximum value of 0.84. Specifically, the personas 2, 4 and 8 scored highest in AUC, and also in Precision and Recall, whereas persona 6 has poor performance compared to the others. These results indicate that for high scoring personas, we successfully captured the active CDT campaigns, but for the personas with lower scores, there may not be active campaigns for the period of the experiments.

In order to retrieve the variables that affect the discovery and measurement of CDT, we applied the feature importance method on the dataset of each persona, and selected the top-10 highest scoring features. For the majority of the personas (7 out of 10) the most important features were the number of ads (distinct or not) and the number of keywords in desktop. In some cases, there were also landing pages that had high scoring, but this was not consistent across all personas.

**Combined Personas: Setup 1b.** Here, we use all the datasets collected individually, for each persona in the previous experiment (setup 1a), and combine them into one unified dataset. This setup emulates the real scenario of a user exhibiting multiple and diverse web interests, that give extra information to the ad-ecosystem about their browsing behavior. Of course, in this combined dataset there is an increase in the possible feature space to accommodate all the domains and keywords from all personas. In fact, it contains 2021 features as it stores the vectors of landing pages and keywords, for all the different types of personas. In total, there were 890 distinct ad-domains described by keywords in 76 distinct categories.

The ads delivered in all three devices during these sessions are shown in Figure 5 (left). For most sessions (~90%), the mobile device was exposed to fewer than five ads, since the mobile version of websites typically delivers a smaller number of ads, designed for smaller screens and devices. On the contrary, the desktop devices had a higher exposure to ads compared to the mobile device. Also, the two desktops receive a similar number of ads (on average 2 to 4 ads on every visit to the control pages). Similar observations can be made for the keywords categories of ads (Figure 5 (right)).

Additionally, Figure 6 reports the occurrence of the top-10 key words of the mobile and their frequency of occurrence in the other devices. The most frequent term in the mobile keywords is ”Online Shopping”, since many of the personas were related to interests that involved shopping. The two desktops appear to have similar distribution for the top keywords of the mobile, and appear to be fairly different than the mobile. However, in some cases like online shopping and travel, the paired desktop appears to be closer to the mobile. Interestingly, even though the two desktops appear to have similar distribution for the top keywords of the mobile, and are different than the mobile, the paired desktop appears to have some keywords which are closer to the paired mobile, hinting to the effect of cross-device tracking.

In this dataset, we apply feature selection with the Extra-Trees classifier to select the most relevant features and create a more accurate predictive model. This method reduces the feature space to
984 useful features out of 2201. Next, we use the three classification algorithms and a range of hyper-parameters for each one. Also, we apply a 10-fold nested cross-validation method for selecting the best model (in terms of scoring performance) that can give us an accurate, non overly-optimistic estimation [75]. Again, the best selected model was Random Forest, with 200 estimators (trees) and 200 depth of each tree, with AUC=0.89 (all results in Table 3). The model’s performance is high in all the mentioned scores, which indicates that the more diverse data the advertisers collect, the easier it is to identify the different user’s devices. This result is in line with Zimmer et al. [7], who attempted a threshold-based approach for probabilistic CDT detection on real users’ data, lending credence to our proposed platform’s performance.

We also measure the feature importance, shown in Figure 7, for the top-30 features. One third of the top features are related to crawl specific metadata, whereas about half of the top features are keyword-related. Interestingly, features such as the day and time of the experiment, and the number of received ads are important for the algorithm to make the classification of the devices. Furthermore, time-related features are indeed expected to be important as they give hints on when the browsing signal was injected to the ad-ecosystem. These results also give credence to our initial decision to experiment in a continuous fashion with regular sessions injecting browsing signal, while at the same time measuring the output signal via delivered ads. In addition, keyword-based features are important for the classification, revealing that since ads of similar categories get delivered in paired devices instead of non-paired, the keywords help our classifier to identify the cross-device pairing.

Data Validation. We validate the representativeness of the data collected from these experiments by examining the trackers that appear in the pages visited by the personas, as well as the landing pages for each device. We use the Ghostery plugin⁴ to detect them and measure their frequency of inclusion. From the trackers detected in the persona and control pages, and using the list provided by [7], 27% were found to be CDT-related, including both deterministic and probabilistic. In fact, the top-10 trackers, which may perform both types of CDT, include Google, Google Syndication, Google Analytics, Doubleclick, Facebook, YouTube, Criteo, Trivago, Advertising.com and Krux, which are in line with the top CDT trackers found in [7, 51]. Also, 14.2% of these trackers are explicitly focused on CDT, including Criteo, BlueKai, AdRoll, Cardlytics, Drawbridge, again in line with the results in [7].

Going a step further, in Figure 8 we analyze the trackers appearing in the top-10 most frequent landing pages (ads) for each device. The most frequent ones are Google and Facebook, while Criteo, a well-established CDT-tracker is found with a higher frequency on the paired desktop, hinting the existence of CDT in our dataset. The high appearance of Google, Facebook, and Doubleclick trackers, and the well known collaboration between them (sharing data, cookie syncing, etc.), entails that if the user accessed such webpages and leaked any identifier, the cross-device tracking will be very effective. Also, these collaborations, accompanied by the variety of third parties, reveal the complexity and plurality of the ad-ecosystem, making the process of distinguishing the effectiveness of each individual CDT tracker a non trivial task. This could be supported by an extension of our framework, as we discussed in 3.3.

5.4 Detecting CDT in Long-lived Browsing

Independent Personas: Setup 2a. In this set of experiments, we allow the devices to train for a longer period of time, to emulate the scenario where a user is focused on a particular interest, and produces heavy browsing behavior around the specific category. This long-lived browsing injects a significantly higher input signal to the ad-ecosystem than the previous setup, which should make it easier to perform CDT. In order to increase the setup’s complexity, and make it more difficult to track the user, we allow all devices (i.e., 1 mobile, 2 desktops) to train in the same way under the same persona. In effect, this setup also tests a basic countermeasure from the user’s point of view, who tries to blur her browsing by injecting traffic of the same persona from all devices to the ad-ecosystem.

In this setup, while all devices are trained with the same behavioral profile, we examine if the statistical tests and ML modeler can still detect and distinguish the CDT. This experiment contains three different phases during each run. The mobile phase, where the mobile performs train crawls for $t_{train}=480$ mins, and a testing crawl for $t_{test}=30$ mins. In parallel with the mobile training, the

---

⁴https://www.ghostery.com/
two desktops perform test crawls for $t_{test} = 30$ mins. After mobile training and testing, both desktops start continuous train and test crawls alternately for 8 hours ($t_{train} = t_{test} = 30$ min).

Due to the long time needed for executing this experiment, we focus on two personas constructed in the following way. We use the methodology for persona creation as described in § 4.1, and focus on active ad-campaigns, resulting to two personas in the interest of "Online Shopping-Accessories", and "Online Shopping-Health & Fitness" (loosely matching the personas 1 and 4 from Table 1). Then, we performed 4 runs of 16 hours duration each, for each persona. In this setup, since all devices are uniformly trained, we did not include the keyword vector of the persona pages into the datasets, to not introduce any bias in the classifiers from repetitive features.

The statistical analysis for this experiment reveals potential CDT, since we accept the null hypothesis for the distribution of ads delivered in the paired desktop and mobile (lowest $p$-value $= 0.052$), and reject it in the baseline desktop and mobile (highest $p$-value $= 0.006$). This consistency is interesting, since for this setup all three devices are uniformly trained with the same persona, and thus all of them collect similar ads due to retargeting. However, there is no similarity between the distributions of ads in the devices that do not share the same IP address. To clarify this finding, we applied the mentioned ML algorithms, and the classification results are shown in Table 4. To the point, the algorithms again detect CDT between the mobile and the paired desktop, even though all devices were exposed to similar training with the same persona. In fact, Logistic Regression performed the best across both personas, with AUC $\approx 0.81$, and $F_1$-score $\approx 0.80$ for both classes.

When computing the importance of features, the desktop number of ads and keywords and the desktop time slot are in the top-10 features overall. Based on these observations, we believe that the longer training time allowed the ad-ecosystem to establish an accurate user profile, and perform retargeting on the paired desktop, based on the mobile’s activity. The CDT was possible, even though there was a competing baseline desktop attempting to "scramble" the input signal to the ad-ecosystem.

**Combined Personas: Setup 2b.** We follow a similar approach with before (§ 5.3) and combine all data collected from the setup 2a into a unified dataset. Under this scenario, in which we mix data from both personas, the classifier again performs well, with AUC $= 0.89$. Important features in this case are the number of ads and keywords delivered to the desktops, the time of the experiment, and number of keywords for the desktop.

**Boosted Browsing with CDT trackers and Independent Personas:** In the next set of experiments, we investigate the role of CDT trackers in the discovery and measurement of CDT. In particular, we attempt to boost the CDT signal, by visiting webpages with higher portion of CDT-type trackers. Therefore, the experimental setup and the preprocessing method remain the same as in the previous setup 2a, but we select webpages to be visited that have active ad-campaigns and their landing pages embed the most-known CDT trackers: Criteo, Tapad, Demdex, Drawbridge. We also change the set of our control pages, so that each one contains at least one CDT-tracker. News sites have a plurality of 3rd-parties compared to other types of sites [37]. Thus, for boosted browsing, we chose the set of control pages for this experiment to contain 3 weather pages and 2 news websites. Since the neutrality may not be applied to all such sites, we manually verified that the selected pages do not serve contextual ads.

Performing the same analysis as earlier, we find that mobile and paired desktop have ads coming from the same distribution (lowest $p$-value $= 0.10$), and that there is no similarity between the ads delivered in the mobile and baseline desktop (highest $p$-value $= 0.007$). For a clearer investigation of the importance of the CDT-trackers, we also evaluate the findings with the ML models. The evaluation results of this experiment are presented in Table 4.

For persona 1, Logistic Regression and Random Forest models perform near-optimally, with high precision of Class 1, high recall for Class 0, average $F_1$-Score $= 0.93$ for both classes, and AUC $= 0.93$. For persona 4, the scores are even higher, outperforming the other setups and experiments, as all metrics for Logistic Regression scored higher than 0.98. Overall, these results indicate that we successfully biased the CDT detection, by tricking the trackers to identify the emulated user in both devices, and providing enough output signal (ads delivered) for the statistical algorithms to detect the CDT.

**Boosted Browsing with CDT trackers and Combined Personas:** In the next set of experiments, we investigate how to boost the CDT signal, by visiting webpages with higher portion of CDT-type trackers. Therefore, the experimental setup and the preprocessing method remain the same as in the previous setup 2a, but we select webpages to be visited that have active ad-campaigns and their landing pages embed the most-known CDT trackers: Criteo, Tapad, Demdex, Drawbridge. We also change the set of our control pages, so that each one contains at least one CDT-tracker. News sites have a plurality of 3rd-parties compared to other types of sites [37]. Thus, for boosted browsing, we chose the set of control pages for this experiment to contain 3 weather pages and 2 news websites. Since the neutrality may not be applied to all such sites, we manually verified that the selected pages do not serve contextual ads.

Performing the same analysis as earlier, we find that mobile and paired desktop have ads coming from the same distribution (lowest $p$-value $= 0.10$), and that there is no similarity between the ads delivered in the mobile and baseline desktop (highest $p$-value $= 0.007$). For a clearer investigation of the importance of the CDT-trackers, we also evaluate the findings with the ML models. The evaluation results of this experiment are presented in Table 4.

For persona 1, Logistic Regression and Random Forest models perform near-optimally, with high precision of Class 1, high recall for Class 0, average $F_1$-Score $= 0.93$ for both classes, and AUC $= 0.93$. For persona 4, the scores are even higher, outperforming the other setups and experiments, as all metrics for Logistic Regression scored higher than 0.98. Overall, these results indicate that we successfully biased the CDT detection, by tricking the trackers to identify the emulated user in both devices, and providing enough output signal (ads delivered) for the statistical algorithms to detect the CDT.

**Combined Personas:** We follow a similar approach with before (§ 5.3) and combine all data collected from the setup 2c into a unified dataset. Under this scenario, the classifier (Logistic Regression) again performs very well, with AUC $= 0.93$. Important features in this case are the number of ads delivered to the desktops, the time of the experiment, and number of keywords for the desktop.

**Boosted Browsing with CDT trackers and Combined Personas:** In the next set of experiments, we investigate how to boost the CDT signal, by visiting webpages with higher portion of CDT-type trackers. Therefore, the experimental setup and the preprocessing method remain the same as in the previous setup 2a, but we select webpages to be visited that have active ad-campaigns and their landing pages embed the most-known CDT trackers: Criteo, Tapad, Demdex, Drawbridge. We also change the set of our control pages, so that each one contains at least one CDT-tracker. News sites have a plurality of 3rd-parties compared to other types of sites [37]. Thus, for boosted browsing, we chose the set of control pages for this experiment to contain 3 weather pages and 2 news websites. Since the neutrality may not be applied to all such sites, we manually verified that the selected pages do not serve contextual ads.

Performing the same analysis as earlier, we find that mobile and paired desktop have ads coming from the same distribution (lowest $p$-value $= 0.10$), and that there is no similarity between the ads delivered in the mobile and baseline desktop (highest $p$-value $= 0.007$). For a clearer investigation of the importance of the CDT-trackers, we also evaluate the findings with the ML models. The evaluation results of this experiment are presented in Table 4.

For persona 1, Logistic Regression and Random Forest models perform near-optimally, with high precision of Class 1, high recall for Class 0, average $F_1$-Score $= 0.93$ for both classes, and AUC $= 0.93$. For persona 4, the scores are even higher, outperforming the other setups and experiments, as all metrics for Logistic Regression scored higher than 0.98. Overall, these results indicate that we successfully biased the CDT detection, by tricking the trackers to identify the emulated user in both devices, and providing enough output signal (ads delivered) for the statistical algorithms to detect the CDT.

**Boosted Browsing with CDT trackers and Combined Personas:** In the next set of experiments, we investigate how to boost the CDT signal, by visiting webpages with higher portion of CDT-type trackers. Therefore, the experimental setup and the preprocessing method remain the same as in the previous setup 2a, but we select webpages to be visited that have active ad-campaigns and their landing pages embed the most-known CDT trackers: Criteo, Tapad, Demdex, Drawbridge. We also change the set of our control pages, so that each one contains at least one CDT-tracker. News sites have a plurality of 3rd-parties compared to other types of sites [37]. Thus, for boosted browsing, we chose the set of control pages for this experiment to contain 3 weather pages and 2 news websites. Since the neutrality may not be applied to all such sites, we manually verified that the selected pages do not serve contextual ads.
of interest. Every desktop executed browsing in a stateless mode, while the mobile device in a stateful mode. For each of the five personas we collected data for two runs, following the timeline of phases as in setup 1a.

The distributions between mobile vs. paired desktop, as well as mobile vs. baseline desktop, were found to be different (highest p-value=0.034). Also, none of the ML classifiers performed higher than 70% (in all metrics), and thus we could not clearly extract any significant result. Specifically, the highest AUC score for personas 1 and 2 was 0.70 with the use of the Random Forest classifier, and for personas 3 and 4 was 0.73 using the Logistic Regression classifier. The worst scoring, independent of algorithm, was recorded for persona 5, with AUC=0.57, and Precision/Recall scores under 0.50.

**Combined Personas: Setup 3b.** When the data from all five personas are combined, the classifier performing best was Logistic Regression, with AUC=0.79. Overall, these results point to the semi-effectiveness of the incognito browsing to limit CDT. That is, by removing the browsing state of a user on a given device, the signal provided to the CDT entities is reduced, but not fully removed. In fact, when the data from various personas are combined, the CDT is still somewhat effective, since the devices have the same IP address.

## 6 DISCUSSION & CONCLUSION

Through extensive experiments with CoDeT, we were able to trigger CDT trackers into potential pairing of the emulated users’ devices, which allowed us to statistically verify that CDT is indeed happening, and measure its effectiveness on different user interests and browsing behaviors, independently and in combination. In fact, CDT was very prominent when user devices were trained to browse pages of similar interests, reinforcing the behavioral signal sent to CDT entities, and specifically when browsing activity is related with online shopping, since those types of users seem to be more targeted by advertisers. The CDT effect was further amplified when the visited persona and control pages had embedded CDT-trackers, pushing the accuracy of detection up to 99%. As a basic countermeasure we tested the effect of incognito browsing to CDT performance. Browsing in a stateless mode showed a reduced, but not completely removed CDT effect, as incognito browsing obfuscates somewhat the signal sent to the ad-ecosystem, but not the network access information. Further, when combining data from different personas, CDT was still prominent even in incognito browsing.

Indeed, our data collection was performed across relatively short time periods, in comparison to the wealth of browsing data that advertising networks have at their disposal. In fact, we anticipate that CDT companies collect data about users and devices for months or years, and even buy data from data brokers, to have the capacity of targeting users with even higher rates. To that end, we believe that high accuracies self-reported by CDT companies (e.g., Lotame: >90% [76], Drawbridge: 97.3% [77]), are indeed possible.

**Impact:** Undoubtedly, CDT has a strong impact on user privacy, but the actual extent of this tracking paradigm and its consequences to users, the community, and even to the ad-ecosystem itself, are still unknown. In fact, since CDT is heavily depended on user’s browsing activity, and the ad-ecosystem employs such collected data for targeting purposes, one major line of future work is the study of targeting sensitive user categories (e.g., gender, sexual orientation, etc.) via CDT. This is especially relevant nowadays with the enforcement of recent EU privacy regulations such as GDPR and ePrivacy. This is where CoDeT comes in play, as it provides a concrete, scalable and extensible methodology for experimenting with different CDT scenarios, understanding its mechanics and measuring its impact. In fact, the modular and extensible design of our methodology allows the community to investigate CDT in depth and propose new extensions to study the CDT ecosystem: new plugins, personas and ML techniques. To that end, our design constitutes CoDeT into an enhanced transparency tool that reveals potentially illegal biases or discrimination from the ad-ecosystem.

**Future work:** To have a more exhaustive investigation of CDT, ideally we should have deployed: more paired devices running in parallel in the same setups, for longer periods of time, with different device characteristics, across multiple locations around the world, using more personas, etc. However, each of these experiments entails high computation and time overhead to setup and monitor, making it difficult to run possibly hundreds of new such experiments in the context of this work. Thus, our initial effort focused on defining, executing and analyzing basic experimental setups that provide conclusive and statistically significant evidence that CoDeT works well in detecting CDT, leaving further investigation, including comparing with real users’ browsing, as future work.

## REFERENCES

1. Peter Kalka and Rani Molla. Recode - 2017 was the year digital ad spending finally beat TV. https://www.recode.net/2017/12/4/17334601/2017-digital-ad-spend-advertising-beat-tv, 2017.
2. Pew Research Center - Mobile Fact Sheet. http://www.pewinternet.org/fact-sheet/mobile/, 2018.
3. The expert’s guide to cross-device conversion & attribution. https://www.tapad.com/use-the-experts-guide-to-cross-device-conversion-attribution, 2018.
4. Cross-device tracking. Technical report, Federal Trade Commission, 2017.
5. Criteo. The top attribution methodologies for cross-channel roi. https://www.criteo.com/insights/top-attribution-methodologies-for-cross-channel-roi, 2018.
6. Tapad. Tapad device graph - creating a unified view of the consumer. https://www.tapad.com/device-graph/, 2018.
7. Sebastian Zimmereck, Jir S. Li, Hyangtae Kim, Steven M. Bellovin, and Tony Jehara. A privacy analysis of cross-device tracking. In 26th USENIX Security Symposium, USENIX Security 17, pages 1391–1408. USENIX Association, 2017.
8. Kwang Yeun Chun, Ji Hee Song, Candice R. Hollenbeck, and Jong-Ho Lee. Are contextual advertisements effective? International Journal of Advertising, 33(2):351–371, 2014. doi: 10.2501/IJA-33-2-351-371.
9. Andrea Broder, Marcus Fontoura, Vanja Josifovski, and Lance Riedel. A semantic approach to contextual advertising. In Proceedings of the 30th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, SIGIR ’07.
10. Alexander Bleier and Maik Eisenbeiss. Personalized online advertising effectiveness: The interplay of what, when, and where. Marketing Science.
11. Elizabeth Aguilera, Dominik Mazur, Dhruv Grewal, Ko de Buyer, and Martin Wetzel. Unraveling the personalization paradox: The effect of information collection and trust-building strategies on online advertisement effectiveness.
12. Catherine E Tucker. Social networks, personalized advertising, and privacy controls. Journal of Marketing Research, 51(5):546–562, 2014.
13. Jun Yan, Ning Liu, Gang Wang, Wen Zhang, Yun Jiang, and Zheng Chen. How much can behavioral targeting help online advertising? In Proceedings of the 18th International Conference on World Wide Web, WWW ’09.
14. Ayman Farahat and Michael C. Bailey. How effective is targeted advertising? In Proceedings of the 21st International Conference on World Wide Web, WWW ’12.
15. Randall A. Lewis, Justin M. Rao, and David H. Reiley. Here, there, and everywhere: Correlated online behaviors can lead to overestimates of the effects of advertising. WWW ’11.
16. Spy? Tadoted versus Invasive Ads and Consumers Perceptions of Personalized Advertising. Electronic Commerce Research and Applications, 29, 2018.
17. Claire Dolin, Ben Weinsheil, Shawn Shan, Chang Min Hahn, Euirim Choi, Michelle L Mazurek, and Blase Ur. Unpacking perceptions of data-driven inferences underlying online targeting and personalization. In Proceedings of the 2018
[69] https://www.google.com/basepages/producttype/taxonomy-en-US.txt, 2015.

[70] Run apps on the Android Emulator. https://developer.android.com/studio/run/emulator/, 2018.

[71] Automation for Apps. http://appium.io/, 2018.

[72] https://easylist.to/, 2018.

[73] Customer URL Ticketing System. https://www.trustedsource.org/, 2018.

[74] Measuring Cross-Device, The Methodology. 2016.

[75] Gavin C Cawley and Nicola LC Talbot. On over-fitting in model selection and subsequent selection bias in performance evaluation. *Journal of Machine Learning Research*. 2016.

[76] Lotame. Cross-Device ID Graph Accuracy: Methodology. https://www.lotame.com/cross-device-id-graph-accuracy-methodology/, 2016.

[77] Drawbridge. Drawbridge Cross-Device Connected Consumer Graph Is 97.3% Accurate. https://drawbridge.com/news/p/drawbridge-cross-device-connected-consumer-graph-is-973-accurate, 2015.