Data Analytics for Cybercrime and Undesirable Online Behaviors

Cross-Device Tracking

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Abstract

In this study, we address the complexities of cross-device tracking in the evolving digital ecosystem, focusing on the challenges posed by user behaviour and privacy considerations. We use python scripts to analyse large datasets from HTTP archives. Our methodology involves setting up a database to streamline analysis via SQL queries, targeting third-party domain requests, sensitive data transfer and cookie proliferation. We perform comparative analysis of cross-device behaviours and website categories to identify patterns in tracking activity. Our findings reveal intricate tracking mechanisms across devices and indicate varying levels of tracking intensity across different website categories. The study underscores the balance between effective tracking and privacy, and highlights the need for advanced solutions in CDT.

Contents

1 Introduction

1.1 Overview

Increasingly, internet users are utilizing multiple devices to assist with their daily tasks. According to a study by Criteo[1], 31% of purchases involve the use of multiple devices. Users tend to review a product several times from different devices before making a purchase decision. Consequently, company owners, website and app developers have become interested in cross-device tracking to enhance conversion rates and gain deeper insights into consumer behavior. In our research, we aim to explain what cross-device tracking is, its purpose, the potential risks it poses to website users, and demonstrate its usage through practical examples. Additionally, we will compare two categories of websites to identify signs of cross-device tracking implementation.

1.1.1 Definition

Cross-device tracking is the process of monitoring user behavior across various devices, such as PCs, smartphones, and tablets, to create the most comprehensive user profile possible by gathering as much information about the user as possible. There are different types of cross-device tracking, which will be described in more detail in Chapter 1.3.

It should be noted that in the modern world, the scope of cross-device tracking is expanding, for instance, with the use of smart homes, as the number of devices increases over time, allowing this technology to be integrated into all areas of a user's life. Additionally, with the development of artificial intelligence, this technology is becoming increasingly precise in recognizing information about users.

1.1.2 Purpose

One of the primary reasons companies are exploring cross-device tracking is to improve their marketing strategies and make their advertising more targeted. By understanding their customers better through a more complete profile, which includes their activities across multiple devices, companies can more accurately predict both immediate and future buying habits. This not only allows for better-customized advertising that resonates with specific user groups but also helps companies save money by not wasting resources on ineffective ads. While this technology is not universally used yet, its adoption is growing among many companies[2].

Adobe's Cross-Device Analytics, a feature of Adobe Analytics, is a great example of using and implementing this technology. It offers a user-centric view, linking a user's activities across multiple devices like smartphones, tablets, and computers. Key features include Field-Based Stitching, which connects user activities on different devices based on deterministic methods, and Device Graph, which analyzes connections between devices. This helps in attributing user actions accurately, such as linking an ad click on one device to a purchase on another, offering valuable insights for marketing strategies while considering user privacy[3].

However, sales are not the only area where cross-device tracking can be useful. It's also an excellent resource for political parties or media outlets to find their audience, tailoring the right messages or news to specific target groups. The principle is the same: the more information you

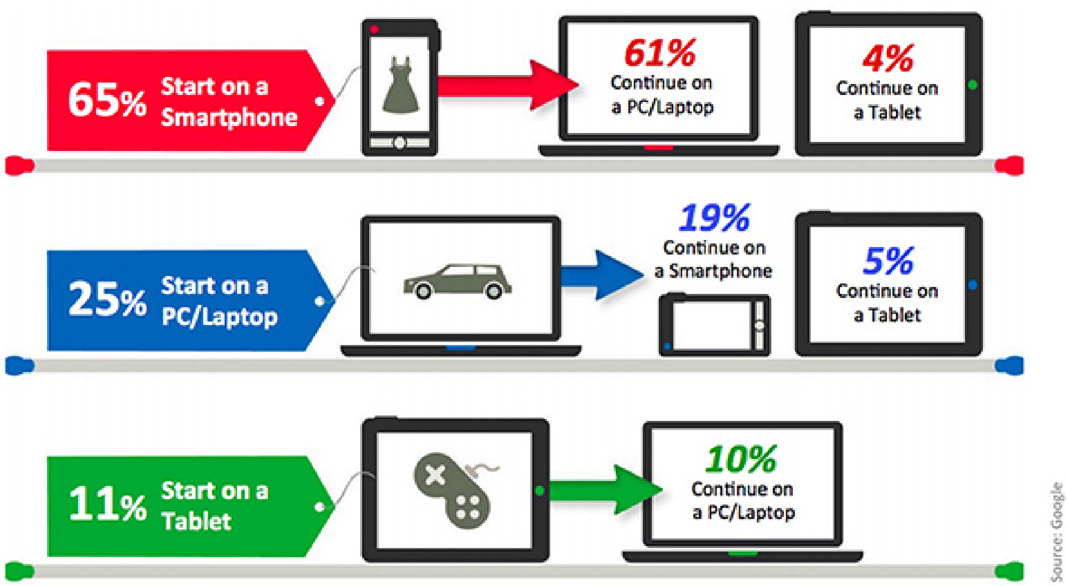
[1] https://www.criteo.com/de/blog/die-chancen-von-cross-device-optimal-nutzen/
[2] https://cdt.org/wp-content/uploads/2015/10/10.16.15-CDT-Cross-Device-Comments.pdf
[3] https://experienceleague.adobe.com/docs/analytics/components/cda/overview.html?lang=en

have about a user, the easier it is to tailor your approach to them. The more sources of information (i.e., devices), the more you can track the behavior and interests of the user.

1.2 Importance in Modern Digital Exosystem

1.2.1 Evolution of User Behavior

The digital landscape has seen a major evolution in user behavior, particularly in the way people interact with technology. In the early stages of the internet, user behavior was device-specific, primarily bounded to desktop computers. This era was characterized by more predictable online activities, with users typically accessing the internet from fixed locations and a small amount of different devices, which made user tracking relatively easy.



The invention of mobile technologies, especially smartphones changed online activities significantly and lead to a transformation in user behavior. Users began interacting with digital content across multiple platforms and often seamlessly switching between devices. For reference, Google published an interesting statistic, that shows more than 80 percent of all users switching their device during the user journey. Multi-platform interaction introduced a new level of complexity in understanding user behavior as users were no longer restricted to a single device.

Moreover, the rise of smart devices and the Internet of Things in the last years are the reason for even more complex interactions between devices. Today, a wide network of connected devices are creating a diverse and complex digital footprint.

1.2.2 Challenges in User Tracking

Parallel to the evolution of users online behavior, the task of tracking users across multiple devices has become increasingly challenging. As there exists no universal login system or consistent identifiers across different websites, establishing a meaningful user profile from disparate device usage is really complex.

Privacy considerations make cross-device tracking even more complicated. With increasing sensitivity to data privacy and the introduction of strong regulations like the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), tracking users across devices must navigate the line between effective data collection and respect for user privacy and consent.

The diversity of devices and platforms results in fragmented data sources, requiring advanced technological solutions for data integration and analysis. The need for algorithms and technologies is necessary to not only gather but also accurately interpret the large amount of data generated by multi-device usage.

Looking ahead, these challenges will even intensify with the continuous evolution of technology. The integration of artificial intelligence and machine learning will potentially lead to advancements in user tracking, but also brings additional complexities regarding privacy regulations. The task of user tracking demands innovative solutions that are adaptable, take privacy into account and are able of decoding increasingly complex device interactions.

1.3 Techniques Employed in CDT

1.3.1 Deterministic Tracking

1.3.2 Probabilistic Tracking

1.3.3 Browser Fingerprinting

1.3.4 Cookies and Tracking Pixels

1.3.5 Location Data

2 Study

2.1 Methodology

2.1.1 Data Collection

In the beginning our idea was to automate the data collection by using OpenWPM, a tool that automates the tasks of controlling a browser and collecting data. However, after some time it turned out that the general effort to set up such automation is not proportionate to the data we ultimately need. The only advantage would have been to replicate the user journey one-to-one and then possibly have more consistent data available. Nevertheless, we are now continuing with the manual data collection approach.

To analyze the cross-device tracking capabilities of various news websites, we conducted a systematic data collection using HTTP Archive (HAR) files. This process involved capturing network traffic data from both desktop and mobile devices. We selected our set of 20 websites by first categorizing them into news websites and shopping websites. These websites were chosen based on their popularity and the diversity of their content and geographical origin.

Prior to data collection, we created a test account on each of the selected websites. This was essential to ensure consistency in the user experience and to capture potential deterministic cross device tracking data across different sessions and devices.

To standardize the browsing environment and eliminate the most external variables, the data collection was executed using a virtual machine. This enables us to attribute any differences observed in the tracking mechanisms to the device type rather than other environmental factors.

Google Chrome was used as the web browser for this exercise as its developer tools with many functionalities allowed us to generate the HAR files.

The first part of the data collection involved accessing each news website from a desktop device. The user journey for all websites of both categories started with logging in using the previously created test account. For news websites the second part was navigating to a prominent news topic and try to imitate common user behavior. For shopping websites the second part included adding one or more items to the shopping cart and then proceed to checkout, but stop just before the actual payment.

The same procedure was replicated on mobile devices, to be more precise on an iPhone, in order capture the mobile user experience on the same websites. The HAR files of the mobile user journey was captured using Safari Developer Tools while connecting the iPhone to the MacBook via cable.

The resulting data set comprised 40 HAR files - 10 from desktop devices and 10 from mobile devices, corresponding to the same set of news websites and shopping websites. This data set will be the starting point for our subsequent analysis of cross-device tracking practices.

2.1.2 Data Analysis

cookieLog	
id	INT
domain	TEXT
host	TEXT
device_type	TEXT
website_type	TEXT

(a) cookieLog

emailHashes	
id	INT
host	TEXT
hash_type	TEXT
domain	TEXT
device_type	TEXT
website_type	TEXT

(b) emailHashes

thirdPartyLog	
id	INT
domain	TEXT
host	TEXT
device_type	TEXT
website_type	TEXT

(c) thirdPartyLog

Since our data is relatively large (50-100MB per HTTP archive), we performed most of the analysis using Jupyter Notebooks and the Python library haralyzer. In the initial stages of our data analysis, we began with a traditional approach, using print statements to inspect and debug the data. This method, while straightforward, quickly proved to be inadequate for handling larger datasets. As the volume and complexity of the data increased, it became apparent that a more robust and scalable solution was necessary. We then started to set up a database that includes three tables in the following way, so we can perform the major part of our analysis with a small delay using simple SQL statements in combination with python scripts. The query results were then visualized using diagrams.

Our approach was then to determine which parts of the HTTP requests are relevant for us to make statements about cross-device tracking activities.

The first and perhaps most important part of our analysis consisted of filtering out HTTP requests that were sent to third-party domains. We are particularly interested in which domain the request was sent to and how often requests to such domains were recorded. We also wanted to compare the websites with each other in terms of the number of requests to third-party providers. We used the thirdPartyLog table in our database to filter and visualize the respective requests.

It is also interesting to see whether any sensitive data was sent to third-party providers. This means that we examine all HTTP requests and responses to see whether a simple, hashed or encrypted version of our email address can be found. We looked for plain and base64 encoded versions of our mail address as well as SHA1, SHA256, SHA224 and SHA512. In order filter and visualize our results, we used the emailHashes table of our database.

To get a general overview of the cookies set, we also wanted to determine the specific domains that have set the most cookies and possibly establish a correlation with the third-party domains that were requested the most. We focused on the quantity of cookies set by each domain, offering insight into the role these entities play in the broader context of online tracking, particularly in cross-device scenarios. We used the cookieLog table for this part.

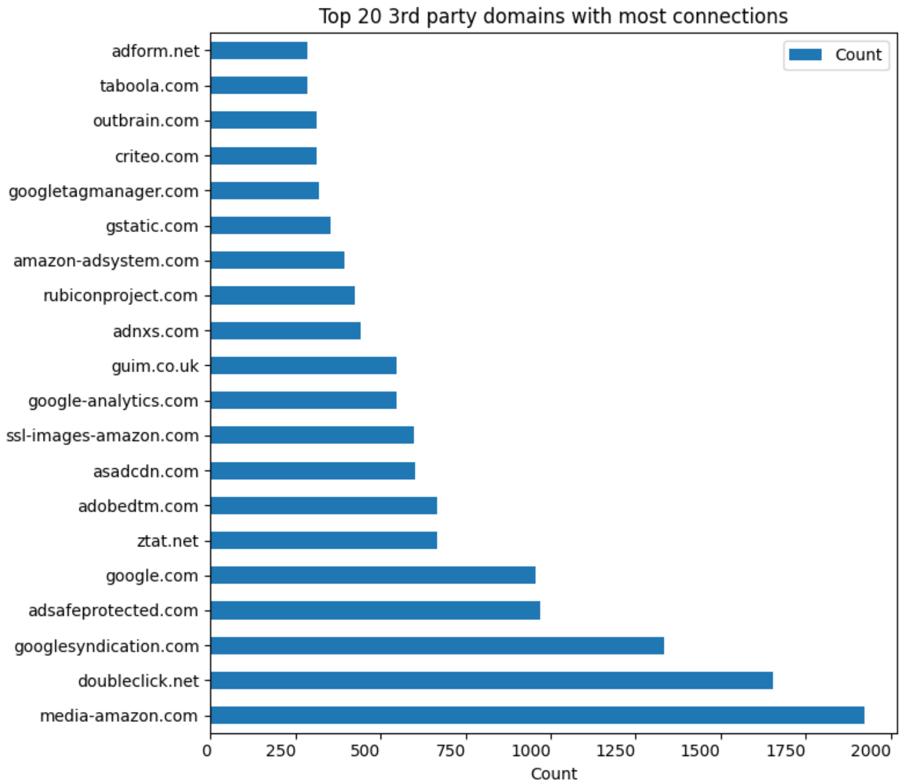
In order to also qualitatively analyze the cookies that were set, we looked at each website to see if there were identical cookies that were set for the same website on the desktop and the mobile device. To be even more specific, we checked which cookies could be identifiers that are used to uniquely identify a user across multiple devices so that, for example, customized advertising can be placed. This part is done manually as we have to look at possible identifiers by ourselves, because it is difficult to automatically filter out identifiers.

In the last part of our analysis, we wanted to carry out a comparative analysis. In fact, we have two variables that seem interesting for comparison. First, the device type, to show differences in behavior between mobile and desktop devices, and second, the website category by which we divided our websites in the initial step.

Our plan was to conduct the previous analysis again, but this time to differentiate and look at the relevant category. In the best case scenario, we can see interesting results that give an indication of which categories are more affected by cross device tracking activities.

2.2 Results

2.2.1 Requests to third party domains

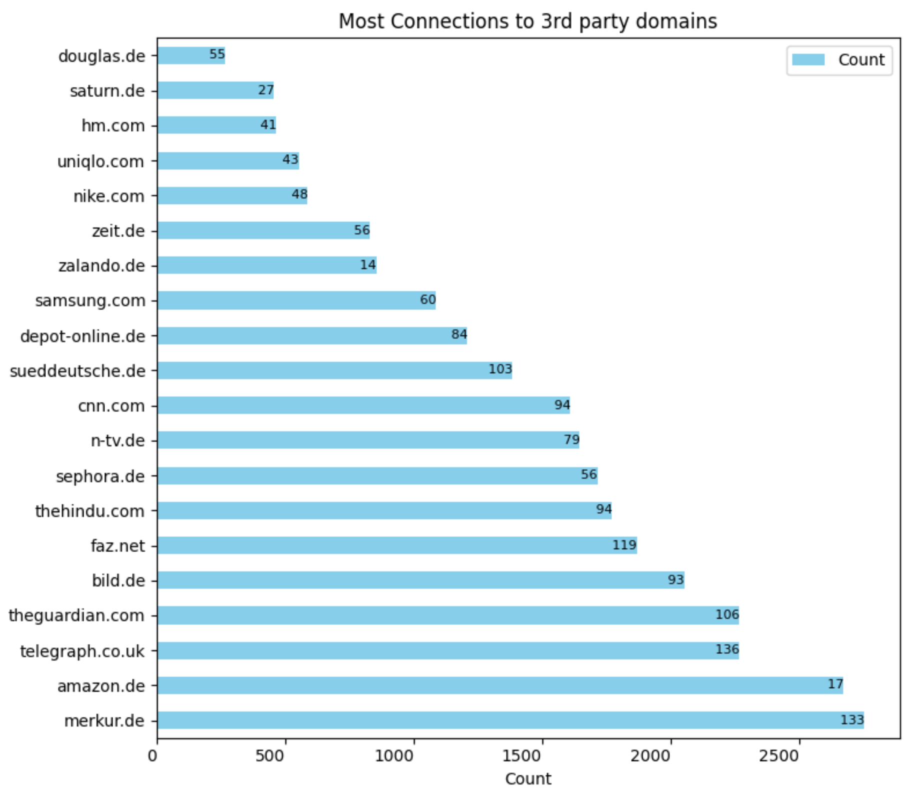


In our test runs on news and shopping sites, we were able to identify links to a total of 537 different third-party domains. Some of the domains were operated by the website that we observed. For example theguardian.com connected to guardianapps.co.uk which is obviously operated by the same company and is no third party. We tried to filter out the majority of all domains that belong to the same company as the website we were observing, but it is possible, that we missed some. Additionally, it was noticeable that most of the domains we found were connected to or part of Google and Amazon (see table). But we were also able to collect queries to other major tech companies such as Microsoft, Facebook and even TikTok.

This shows once again how big a role these companies play in the context of online user tracking. Of course, this doesn't prove cross-device tracking, but it does give us an indication of how much data is being shared with third parties, and the likelihood that this data is being used to create accurate user profiles.

Amazon	**Google**
media-amazon.com	doubleclick.net
ssl-images-amazon.com	googlesyndication.com
amazon-adsystem.com	google.com
amazon.com	google-analytics.com
cloudfront.net	gstatic.com
amazonaws.com	googletagmanager.com
	googletagservices.com
	google.de
	googleapis.com
	googleadservices.com
	recaptcha.net
	youtube.com
	ytimg.com

Table 1: third-party domains related to Amazon and Google



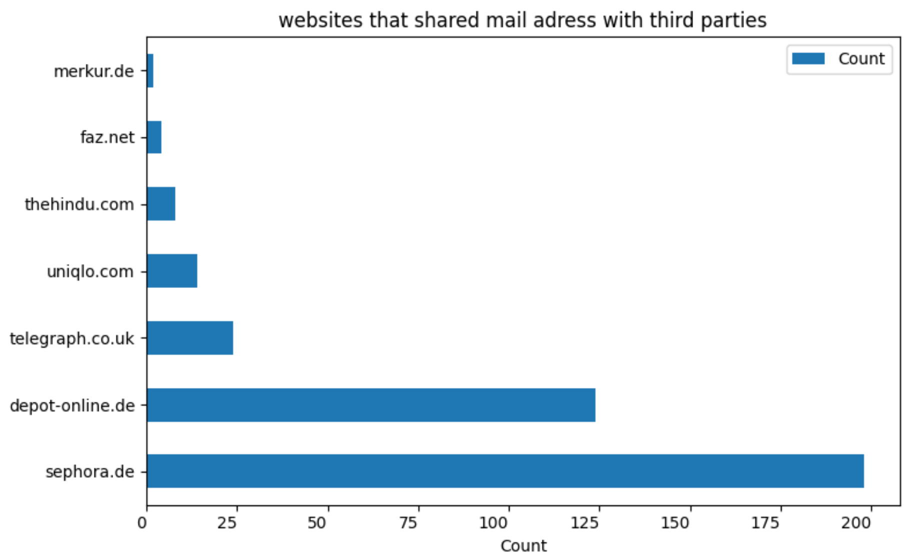
We observed that more than half of all websites have made more than 1000 requests to third party domains. Four websites even made more than 2000 requests.

The bar chart illustrates the diversity of third-party domain connections by showing the number of unique domains to which each site communicated. On average, a website made 1,416 requests to approximately 72 different third-party domains. This is typical of the complex network of third party services that modern sites rely on.

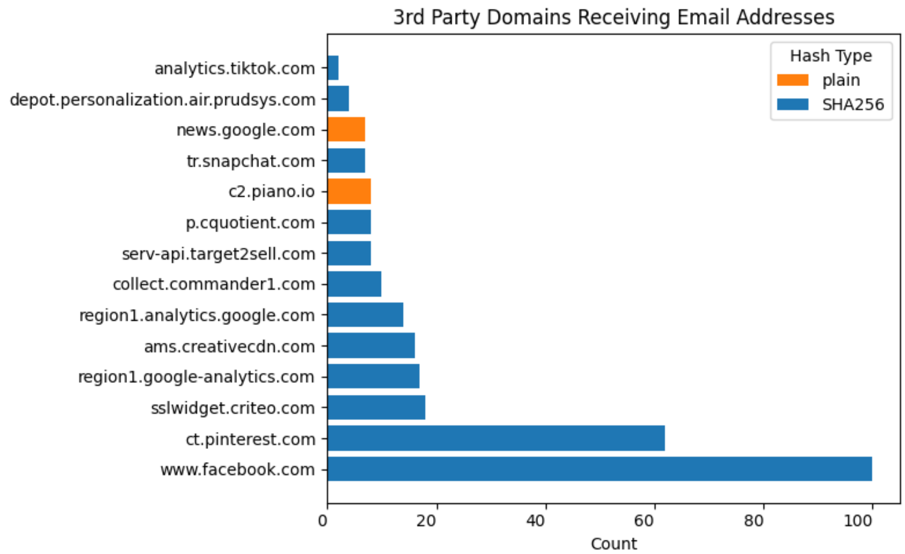
A notable exception case is Amazon, which had the second highest total number of requests but interacted with only 17 unique domains. This anomaly could indicate a reliance on a select set of services, possibly indicating Amazons strategy of using proprietary systems for cross-device tracking and other functions, thereby limiting interactions with external third parties. Such a strategy could reflect enhanced data control measures and a consolidated approach to digital tracking.

2.2.2 Sensitive Information to third party providers

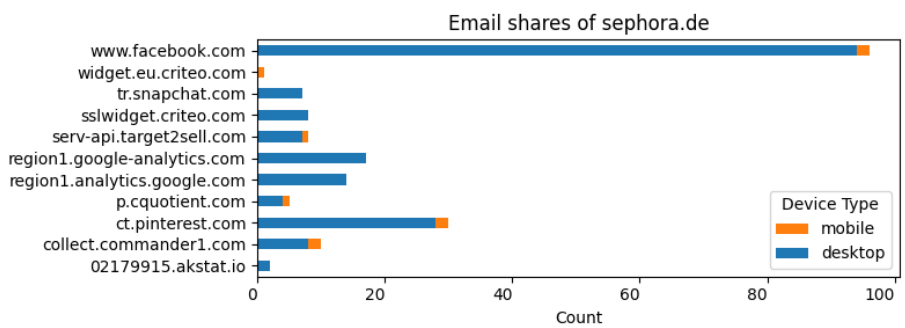
In the study of sensitive information sharing with third parties, particularly focusing on email data, both hashed and plain, significant insights were revealed. The analysis centered on tracking the flow of email addresses to various third-party websites. The findings indicate a diverse range of websites receiving this sensitive data, with notable variations in the frequency and method of information sharing.



Moreover, when analyzing the encryption methods used, a predominant reliance on SHA256 hashing is observed. This pattern suggests a general preference for SHA256 as a security measure in the transfer of email data. However, instances of plain text email sharing are not absent, as evidenced by c2.piano.io and news.google.com, which shared email addresses 8 and 7 times, respectively, without encryption.



We filtered out any subdomains of our test websites for this visualization in advance including domains that are obviously relating to one of them (e.g zalando.com, nikecloud.com, user.id depot.com). Notably, spehora.de stood out for initiating nearly half of all email address transfers, often sharing data with major tech companies, including Facebook, Google, and even platforms like Snapchat and TikTok. This demonstrates the depth and breadth of data sharing practices and underscores the potential risks to user privacy, especially when it involves sharing sensitive information like email addresses. We considered this particular case as very interesting and thus conducted a follow up analysis of the sensitive data sharing activity of sephora.de.



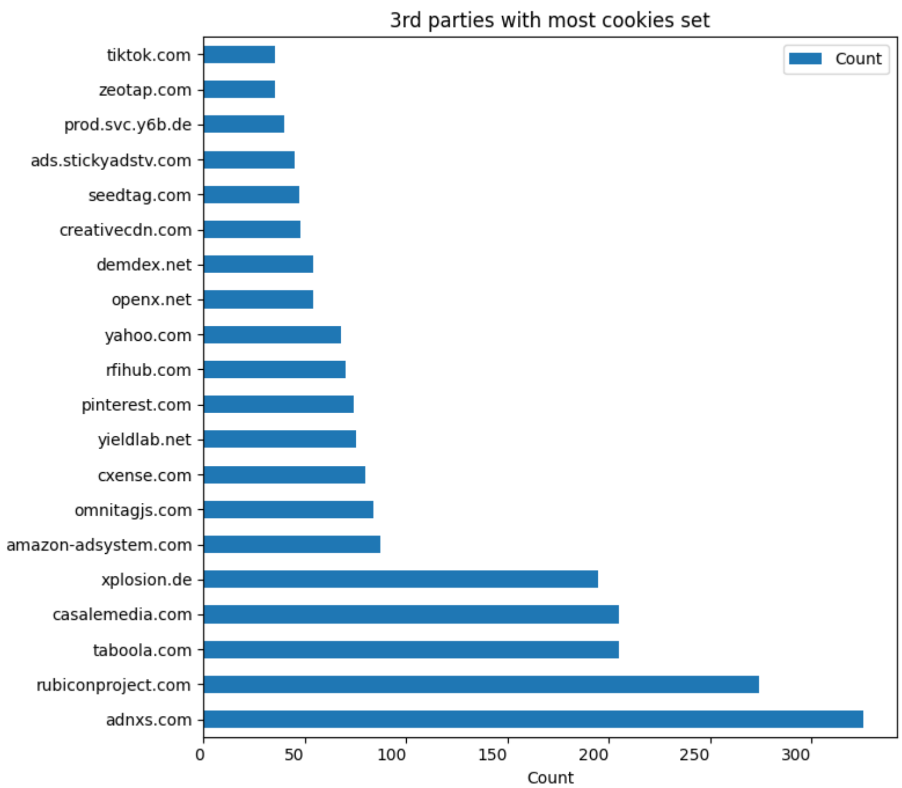
Approximately 70% of our total recorded email forwards go to 78% of the total recorded third-party recipients originating from sephora.de. Almost every domain receiving the sensitive data is associated with tracking user activity and potentially uses the mail adress to create user graphs. Especially Google Analytics is increasingly recognized for its crucial role in cross-device tracking, which is becoming an essential aspect of understanding user behavior across different platforms and devices[4]. Furthermore, the small share of mobile to desktop devices sharing sensitive data is also interesting, but we will investigate this mor ein detail in Part 3 of this paper.

In conclusion, the explained findings raise critical discussions about the privacy and security

[4]https://www.optimizesmart.com/cross-device-reports-in-google-analytics-via-google-signals/

measures in place for the transfer of sensitive data like email addresses. The varied use of encryption methods, along with the sheer number of third parties involved, highlights the complexity and potential vulnerabilities in the current digital landscape regarding data privacy.

2.2.3 Cookie Analysis



Certain domains, such as adnxs.com (AppNexus), taboola.com and rubiconproject.com showed a high frequency in cookies set and amount of connections from our test websites and were leading in terms of the number of requests, which indicates their comprehensive role in tracking and advertising across multiple platforms.

This underscores their significant role in the digital advertising ecosystem, especially in cross-device tracking. Amazon, through domains like amazon-adsystem.com and Google through domains like youtube.com, emerged as prominent trackers as well, but surprisingly despite having registered a high number of connections from our test websites, were much less dominant in cookie setting in comparison to the previously mentioned competing providers.

This finding suggests, that the big players are more likely to use alternative tracking mechanisms beyond traditional cookies, possibly including fingerprinting or pixel tracking.This finding aligns with its vast online presence and interest in user data for both e-commerce and advertising purposes.

The high volume of cookies set by these entities in genereal suggests an extensive network of data collection, crucial for building comprehensive user profiles across different devices.

2.2.4 Duplicate identifiers across mibile and desktop devices

As we have logged in in the beginning of all our test runs, it is likely that the websites have cross device tracked the test user via deterministic cross device tracking. Our analysis revealed several cookies with equal values across devices, indicating their potential use as cross-device identifiers. The relevant output can be found in appendix 1 and include:

1. DSID and User IDs: Various user ID cookies, were consistently found across devices. For instance, userId in faz.net and authId in sueddeutsche.de, with their unique alphanumeric strings, suggest a potential for user-specific identification across different browsing sessions and devices.

2. Encoded and Hashed Values: Cookies with base64 encoded strings (e.g., u in cnn.com) or hash values (e.g., hasheduseremail in sephora.de) were identified as consistent across devices. These formats are typically used to encode identifiable information in a non-readable format, enhancing security while still allowing for user tracking.

3. Unique Device or Session Identifiers: Cookies like UUID in merkur.de, with values that seem to be unique to each user, appeared consistently across different devices. This uniqueness is a strong indicator of their role in cross-device identification.

The presence of equal identifiers across devices underscores the sophisticated nature of current online tracking methodologies. These identifiers enable a seamless tracking experience, allowing advertisers and websites to create comprehensive user profiles by linking activities across multiple devices. This capability has significant implications for targeted advertising and personalized content delivery.

The results suggest that once websites have established a user's identity using deterministic methods, as indicated by cookies such as userId and authId, the next step is often cookie synchronisation. This process involves passing unique identifiers to third parties who can then use them to match the user's profile in their own databases. For example, the consistent appearance of UUID cookies across devices provides a solid foundation for synchronisation processes. The transfer of such cookies to different domains, as evidenced by the breadth of cookie syncing in our data, implies a sophisticated network where user information is exchanged to allocate a user to one or more devices.

The implications of cookie syncing are magnified when considered in the context of graph sharing. By piecing together data points from multiple sources, companies create comprehensive graphs that map a user's digital footprint across multiple devices. These graphs are not static; they are dynamic, evolving with each user interaction and feeding into algorithms that refine the understanding of user behaviour.

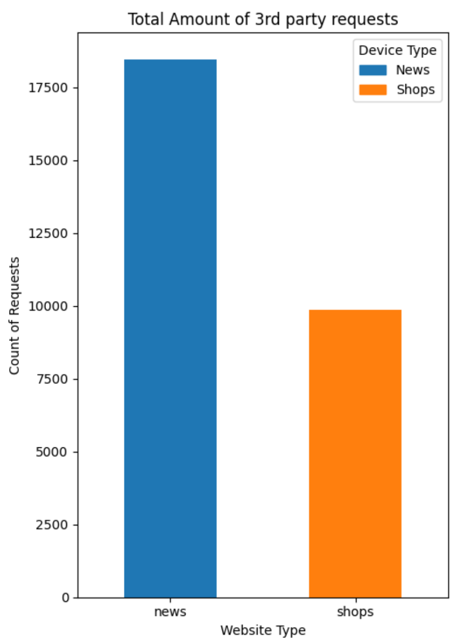
Given that identifiers such as DSID and hashed values such as hasheduseremail are consistent across devices, the likelihood of these being used to create cross-device graphs is high. The entities that receive these synchronised cookie values, such as third party advertising technology domains, are willing to construct or contribute to the construction of these graphs.

3 Comparative Analysis

3.1 Ecommerce websites vs news websites

In our research, a crucial element was the comparison of two types of websites. This comparison enabled us, firstly, to hypothesize about the potential uses of cross-device tracking and, secondly, to understand when user data is more susceptible to being shared with third parties. We compared online shopping sites and news websites. This choice of categories was driven by the common use of cross-device tracking, which is typically needed either for advertising purposes, beneficial to sales-focused companies, or for targeting specific audiences, a tactic often employed by political entities. At the beginning of our study, we assumed that cross-device tracking would be more prevalent in online stores. However, the data we gathered did not confirm our assumptions. Instead, we were able to draw interesting conclusions about how these two types of sites collect and use sensitive user data, and what potential risks there might be for the users.

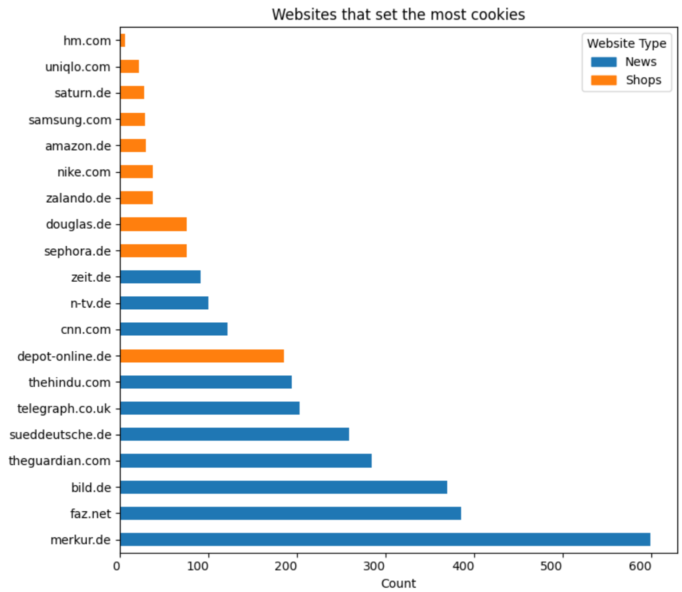
3.1.1 Comparing Third-party requests

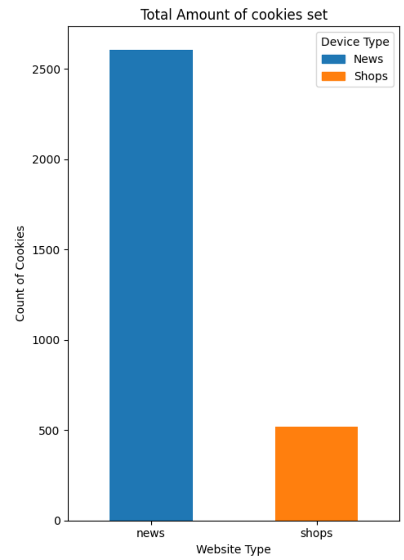


One of the key aspects for comparison are third-party requests, as they are a primary indicator that sensitive data might be shared with third parties to create a more accurate user profile. We decided to find out which type of website makes more third-party requests. The chart demonstrates that in our dataset, news websites sent almost twice as many requests as online stores. This could be due to the fact that news websites almost always have more advertising, trackers for analytics, or social media widgets, which require reaching out to third-party servers. This makes such sites an ideal environment for cross-device tracking, and thus for collecting the maximum amount of user data.

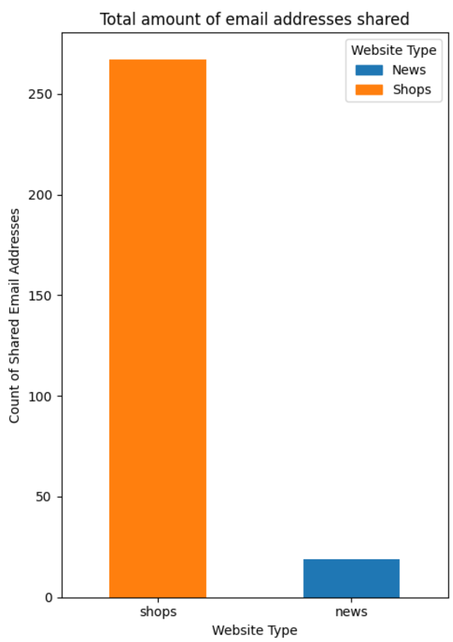
3.1.2 Comparing cookies set

Cookies are a very important step in linking a user's activity on one device with their activity on another. Cookies also store information about the pages viewed, the time of site visits, and even the user's interaction scenario with the site, which are crucial for cross-device tracking.





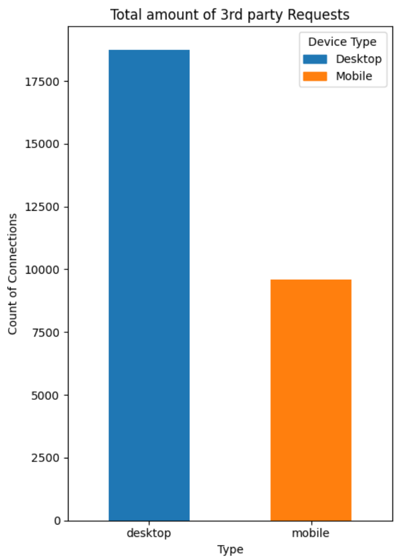
3.1.3 Shared email addresses

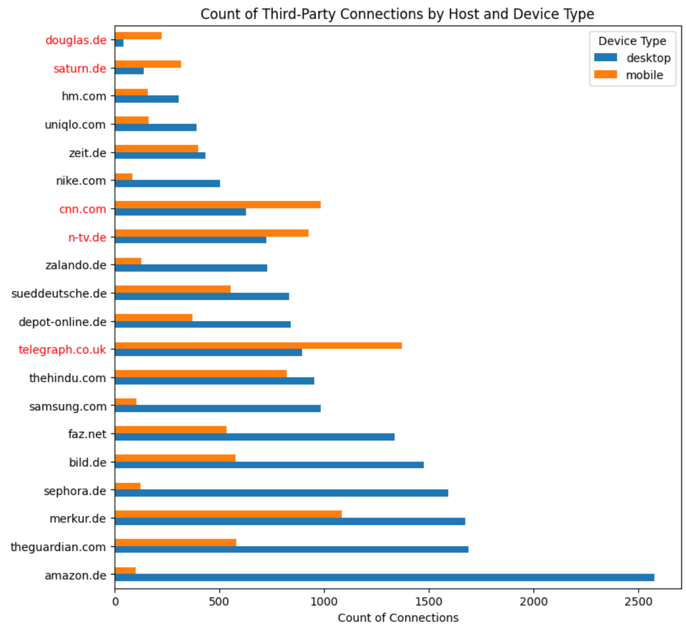


One of the most interesting findings of our research is the fact that online stores distributed email addresses more than ten times as often as news websites. The email address is a key identifier for linking a user's various devices. Therefore, it can be concluded that online stores also use cross-device tracking to create a unified customer profile, but apparently employ methods different from those used by news platforms. As noted earlier, the company Sephora initiated a significant portion of the email address transfers, raising concerns about the privacy of data used by this company. In any case, such research results could be due to the fact that sales-oriented websites are more interested in retaining customers by offering personalized discounts and deals via email, while for news sites, individual user interaction is not as crucial as content and advertising targeting.

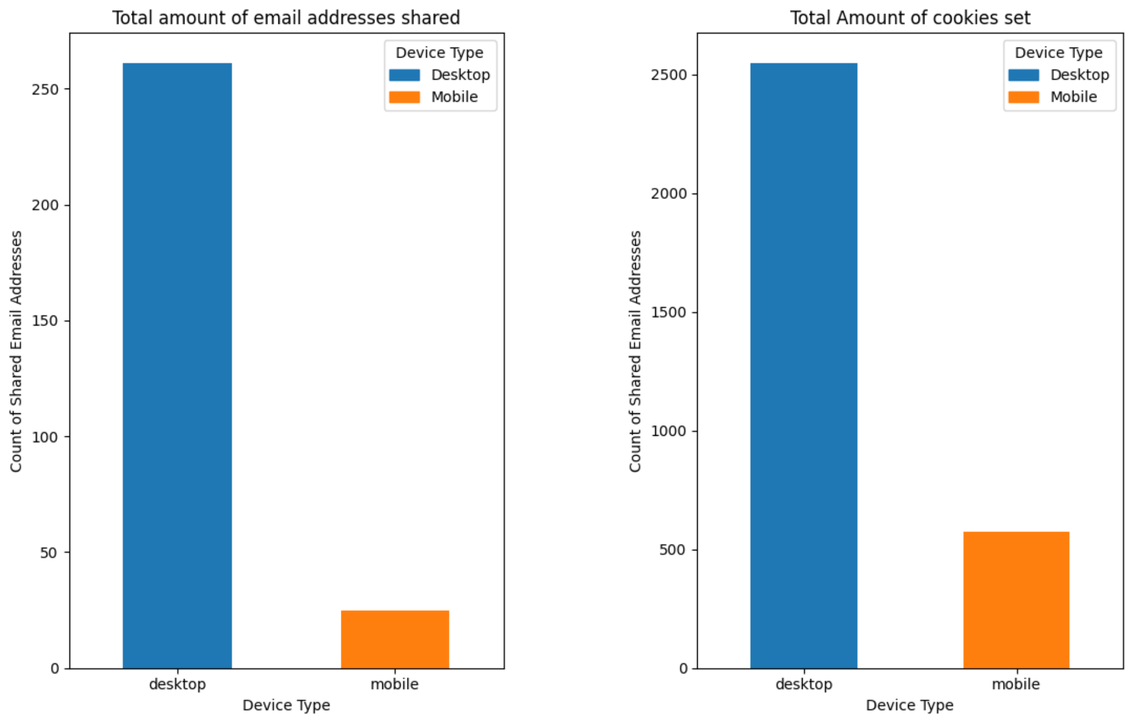
3.2 Mobile vs desktop

We compared mobile and desktop devices in terms of the total amounts of each analysis category and noticed that data collection varied across different devices.





For example, desktop devices showed more involvement from third parties. 15 out of 20 sites used more third-party connections on desktop devices than on mobile devices. The reason might be that desktop versions of websites are usually more extensive, incorporating more advertising networks, which initiates more communication with external servers. Additionally, users are likely to prefer desktop devices for more involved interactions with a website (such as making purchases, payments, registering on a site, or generally using the site for an extended period), so it is very beneficial for companies to implement cross-device tracking in the desktop versions of their websites.



A similar trend is observed in the setting of cookie files and the transfer of email addresses. It appears that website owners prefer to use traditional PCs as the primary target for long-term user data tracking, while mobile devices serve as an additional source after creating a unified user profile through cross-device tracking. This strategy uses the strengths of each device type. Desktops are used for detailed data collection and in-depth user interactions, while mobile devices supplement this information, providing insights into on-the-go behaviors and preferences. This combination ensures a more complete picture of the user's online interaction.

4 Limitations and difficulties

One of the main methodological limitations we encountered in this study was the fact that we could not use Android devices to collect survey data, so our data collection was limited to iPhones only. This limitation has a significant impact on the generalizability of our results, as Android has a significant share of the global smartphone market. The exclusion of Android devices may lead to a skewed understanding of cross-device tracking behaviors and patterns, potentially overlooking findings relevant to the Android ecosystem. Furthermore, we were not able to intercept HTTP requests from within an application, which would also have been interesting additional data to investigate

In terms of technical and operational challenges, the main challenge we faced was that a significant amount of cross-device tracking activity takes place on the server side, beyond the reach of traditional data collection tools. This server-side operation was a big challenge for us, as it limits insight into the mechanisms and decision-making processes that drive cross-device tracking. Server-side tracking involves data processing and linking that is not directly observable, making it difficult to assess the full scope and effectiveness of advertisers' and platforms' cross-device tracking strategies.

Our study primarily focused on deterministic cross-device tracking methods that link devices based on identifiable information, such as login credentials. While deterministic tracking is a reliable means of establishing connections between devices, it is only one part of the cross-device tracking landscape. Probabilistic tracking methods, which infer device connections based on behavioral patterns and device characteristics, remain largely unexplored in our research due to their complexity and the impossibility of proving them. This focus on deterministic methods limits our understanding of the cross-device identification and tracking techniques described in Part 1.

In conclusion, while this study contributes valuable insights into cross-device tracking practices, it is also limited by various factors. Future research should aim to address these limitations by incorporating a broader array of devices, exploring probabilistic tracking methods, and developing techniques to shed light on server-side tracking operations.

5 Appendix

5.1 Duplicate Identifiers Output

```
Host: zeit.de
_pcus = eyJ1c2VyU2VnbWVudHMiOm51bGx9

Host: cnn.com
u = aHR0cHM6Ly9lZGl0aW9uLmNubi5jb20vYnVzaW5lc3M%3D
_cnn_uid = OTQxNTVhNTUtMGVjZC00ZGEzLWFmNzMtNTJjZjM1ZWQzN2M5

Host: faz.net
loginName = eWFubmlja25hc3RqYQ
userId = 3e53cfbaa80389a22720b68db84f527d
srvid = bb395a13b39656152115c1c3cdba904e

Host: merkur.de
_gali = id-subLvl1136460
UUID = eWFubmljay5uYXN0amFAZ21haWwuY29t
id_userid_pid = cd2499b88adfe913d527d757233bb865b447981e1bea34d74947547314c4279c

Host: sueddeutsche.de
_pprv = eyJjb25zZW50Ijp7IjAiOnsibW9kZSI6Im9wdC1vdXQifSwiMSI6eyJtb2RlIjoib3B0LW91dC...
_pcus = eyJ1c2VyU2VnbWVudHMiOm51bGx9
pa_user = %7B%22id%22%3A%22adb3877d-fcbc-4ec2-894f-6648ae74c4fe%22%7D
_pprv = eyJjb25zZW50Ijp7IjAiOnsibW9kZSI6Im9wdC1pbiJ9LCIxIjp7Im1vZGUiOiJvcHQtaW4ifS...
consentUUID = bbc5ad70-5a64-4521-8eb7-065208a1809a_26
authId = adb3877d-fcbc-4ec2-894f-6648ae74c4fe

Host: telegraph.co.uk
_pcus = eyJ1c2VyU2VnbWVudHMiOnsiQ09NUE9TRVIxWCI6eyJzZWdtZW50cyI6WyJMVHJldHVybjowZT...
_pcus = eyJ1c2VyU2VnbWVudHMiOnsiQ09NUE9TRVIxWCI6eyJzZWdtZW50cyI6WyJMVHJldHVybjowZT...
_pctx = %7Bu%7DN4IgrgzgpgThIC5QAUByBJAZgWwCbLwgFYA3MANhMVAAcYpMBLADORGYHsAvEAGhAAu...
consentUUID = e928ace6-ec18-4159-9597-1287a271b8d7_26
permutive-id = ae117a9a-37e0-4632-b69f-d912abc2843a
tmg_pid = PNIfmdPmds5vu6v

Host: thehindu.com
pubmatic-unifiedid_cst = zix7LPQsHA%3D%3D
AWSELB = D54D83371CA73269B30D9CD8F7A2329AB776287862C53884B438BAF2EA6E18262E3A59471...
AWSELBCORS = D54D83371CA73269B30D9CD8F7A2329AB776287862C53884B438BAF2EA6E18262E3A5...
_pctx = %7Bu%7DN4IgrgzgpgThIC4B2YA2qA05owMoBcBDfSREQpAeyRCwgEt8oBJAEzIEYOAmATgFYA7...

Host: zeit.de
_sp_v1_ss = 1:H4sIAAAAAAAAAItWqo5RKimOUbKKRmbkgRgGtbE6MUqpIGZeaU4OkF0CVlBdi1tCKRYA...
_pcus = eyJ1c2VyU2VnbWVudHMiOm51bGx9
```

```
_pctx = %7Bu%7DN4IgrgzgpgThIC5gF8A05owMoBcCGOkiIeAdgPakjoQCWOUAkgCbEDMAbAAwAsnAnDz...

Host: depot-online.de
__rtbh.uid = %7B%22eventType%22%3A%22uid%22%2C%22id%22%3A%2269638e8bc82beb01fbd95a...

Host: samsung.com
flpe = oaXGAjtvEtJfjmrX/h3xO/JAPowfwxiyWjDOZrRU11WabSV+iFR1bnPh3EHe+SG5+YsFSmlophN...

Host: sephora.de
hasheduseremail = 69638e8bc82beb01fbd95ae63968c186965aa5e18a4fd0b343639857d05be7c9
encrypteduserid = 4rS/rSHIyoF1mZh+BZr8PQ==
dwcustomer_5e55f69a7ebb6b69a6e78799321b1dea = acleQkaf6v8VEVIxhGRPj4qltU
__rtbh.uid = %7B%22eventType%22%3A%22uid%22%2C%22id%22%3A%224rS%2FrSHIyoF1mZh%2BBZ...
cquid = O0cMxg9O42I9Xo/AHRDIBN7BOlV6rfiTNnGAnGrpApU=|69638e8bc82beb01fbd95ae63968c...
cookie_user_id = 4rS%2FrSHIyoF1mZh%2BBZr8PQ%3D%3D
email = yannick.nastja@gmail.com

Host: uniqlo.com
bounceClientVisit6178v = N4IgNgDiBcIBYBcEQM4FIDMBBNAmAYnvgO6kBOArgHYCWAjmAPZkDGjAt...
cquid = KFIMXY84g33OmCmbNc+6BivPb/wMpR6zwdUJWHKdE/4=|69638e8bc82beb01fbd95ae63968c...


theguardian.com, amazon.de, douglas.de, hm.com, zalando.de, n-tv.de, saturn.de,
nike.com
- no duplicate identifiers found
```

5.2 Github Repository

6 References