Targeted Ads Analysis: What are The most Targeted Personas?

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***Abstract*—In recent years, the handling of personal information in web advertisements have been regulated and updated frequently. The algorithms for targeted advertisements delivered based on users' browsing history and search results is opaque, and hence there is a concern of invasion of privacy. Therefore, we have four research questions as a survey of targeted advertisements by cookie information. Which personas are most likely to be targeted? Which websites are most frequently targeted? How long are they displayed? Is automatic observation possible? To answer these questions, we developed a system that obtains automatically transitions websites and targeted advertisement URLs for each persona using Selenium, a portable framework. We report the development of the system and the results of our experiment.**

***Index Terms*—privacy, targeted ad**

I. Introduction

Online targeted advertising aims to deliver personalized and relevant ads to individual users based on their interests, demographics, locations and browsing history. It is extremely common in the online ecosystem. The widespread adoption of data analytics, tracking technologies and algorithms enables advertisers to segment audiences and deliver ads that are more likely to resonate with users. Personalized advertising campaigns are reported to be much more effective as compared to their non-personalized ads.

Privacy issues are key concerns in online targeted advertising. 1) *Data collection without consent.* Online advertising often involves the tacking and collection of user data, including browsing history, search queries and demographic informations. Users may not be aware of the data being collected. Because people are worried about their privacy, more and more folks are using anti-tracking and ad-blocking tools [13]–[15]. 2) *No transparency.* Personal data collected for online advertising is frequently shared with third-party entities, such as advertisers, ad networks and data brokers. Most of data sharing were performed among ad networks, where users are not able to have access. The lack of transparency makes individuals feel privacy violation. 3) *Ad Fraud and Malvertising.* Online advertising ecosystems are vulnerable to fraudulent activities including click fraud and the distribution of malicious ads. This risks not only for users but also for business entities who provide advertisements. Regulations, such as the EU's General Data Protection Regulations (GDPR) [10], the California Consumer Privacy Act (CCPA) [11], and Japanese Act on the Protection of Personal Information [12], require businesses to be more transparent and accountable in their data collections.

Observing the inside of online targeted advertising is not trivial. There are several technical challenges: First, *Complex algorithms.* Online targeted advertising operates through complex and secret algorithms to determine the winner of auction of web visitors. However, Ad network platforms typically do not disclose the algorithm. The specific targeting criteria and user profiles are mostly hidden. Second, *Dynamic and real-time nature.* Online auction is performed in real-time. The ad impressions and the advertisement are decided within milliseconds. The decision depends on a time of day with varying the population of active web visitors. For example, repeating access to a particular website results sequence of different advertisements even though almost identical environment are used. These uncertain environment makes it challenging to capture the features of targeted ads accurately. Third, *Many involved factors.* To determine targeted ads, there are many involving factors including *user profile* (browsing history, search queries, demographic information and interests), *website contextual relevance* (travel, foods, gaming and so on), and *browser tracking* (cookies, location, device identities, and device fingerprinting).

Many studies for online targeted advertising have been made so far. Engeehardt and Narayanan [1] conducted a comprehensive study of online tracking practices across a vast number of websites. Tracking technologies, including cookies, fingerprinting and third-party requests were investigated. Estada-Jimenez et al. [2] find the third party connections triggered thought the most popular Ecuadorian website and measured the impact of online tracking. They disclose the statistics of web tracking and ad-related tracking in Ecuador. Cook et al. [3] leverage the new ad auction, called Header Bidding, to infer the relationship between trackers and advertisers. In comparison with the conventional real-time auction, header bidding allows to have access the winning price of auction because the most processes are done in client side. However, this approach is limited to the websites where header bidding is implemented. Unfortunately, the header bidding is not main stream yet for online advertising.

To address the challenges for observing online target advertising, we propose a simple platform utilizing Selenium, a web automation tool, to simulate user interactions with online tagged adverting while employing multiple user profiles. Each user profile represent a distinct set of characteristics, interests, and behaviors, allowing a diverse range of users. Our platform allows monitoring the ads displayed to each user profile called *persona* with attributes age, gender, interests and browsing histories. By comparing the observed targeted ads across the user profile for short-term and long-term observations, we aim to infer the algorithm used to determine ads and trend in the targeting criteria.

With the observed features in online targeted ads, we attempt to answer the the following research questions:

- What are the most targeted personas in online targeted advertising?
- Which websites received the highest levels of targeting in online advertising?
- What is the average duration of visitor targeting in online advertising?

In this work, we make several contributions to the field of online targeted advertising.

- We propose a novel way to observe the online targeted advertising. By employing this approach, we are able to gain valuable insights int the mechanism within the targeted advertising.
- Our experiment show the prime factors for targeted advertising. Through our experiment for some major websites with multiple user profiles, we find the key elements that advertisers consider when providing ads to specific audience.
- We find that the duration of targeting user since the user visits the advertisement. We gain insights into how long users are subjected to targeted ads. It helps to gain user control to avoid the visiting and clicking ads.
- Our study improves the transparency of online targeted advertising. By uncovering the underlying factors, duration of user targeting, we provide valuable insights that promote understanding how targeted adverting operates.

II. Ad Network

A. Overview

The online advertising ecosystem consists of several key components that work to facilitate the buying, selling and delivery of online advertisements.

Fig. 1 illustrates the online advertising ecosystem, where *advertisers* A_1, A_2, A_3 are organizations that wish to distribute advertisements and aim to promote their commercial products or services to targeted audience. Advertisers fund *Ad networks* M_1, M_2, M_3. They aggregate ad inventory from multiple publisher and offer it to advertiser.

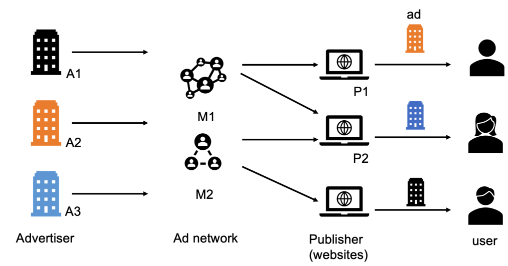

Fig. 1. Ad Network

Digital marketplaces called Ad Exchanges where publisher can auction their ad inventory and advertiser bid for ad placements in real-time. *Publishers* AD_1, AD_2, AD_3 are website owners who provide space of displaying advertisements. They host ads and generate revenue through ad impressions or clicks. *Users* generate data such as browsing behavior, search queries, and interaction with ads. This data is collected by ad networks and used to analyze user preferences, interests and demographics.

III. Proposed Measurement

In this section, we present our proposed methodology for observing online targeted advertising using multiple user profiles. We outline the steps involved in defining personas, identifying targeted ads, and constructing the architecture using Selenium. Our approach aims to address our research questions effectively and provide valuable insights into the dynamics of online targeted advertising.

A. Challenges

1) Delay of targeted ads delivery: Due to the real-time auctions involving multiple bidders, targeted ads may take some time to be displayed, causing a delay in their appearance relative to the other web content. Furthermore, these ads are often embedded within `iframe` tags, making them inaccessible to conventional crawler, which adds an additional obstacle to capturing and analyzing targeted ads effectively.

2) Distinguish targeted ads: Differentiating targeted ads from non-targeted ads can be challenging. Even when accessing a website using a new browser without any history, ads are often displayed based on the website's content. Deterring whether ads are targeted and personalized for individual users becomes difficult.

B. Persona

A *persona* refers to a user profile of a specific segment of users who share common characteristics, interests, and behaviors.

For each persona, we establish a fresh Chrome account as a user profile. Within each profile, we employ a web search engine to conduct targeted queries that help characterize their specific interests. For instance, if the person represents an elderly individual interested in finding good

TABLE I
List of personas

No	persona	query words
1	childcare	'baby goods', 'baby stuff'
2	education	'exam', 'preparatory school', 'tutoring school'
3	gourmet	'home-delivery', 'co-op'
4	fashion	'coordinator', 'pump'
5	elderly	'nursing home', 'supplement'
6	residence	'rent', 'home'
7	electronics	'iphone', 'mac'
8	dieting	'diet medicine', 'diet method'
9	gaming	'game', 'software', 'app'
10	control	N/A

nursing homes and food for their health, we simulate their preferences by conducting searches using relevant keywords and visiting relevant websites. Table I shows the list of personas with search queries in this study. We model nine typical persona and one control persona who has no interests, used for comparison.

C. Definition of targeted ads

Targeted ads rely on user data when they visit a website. While the exact algorithms used by AdTech companies are confidential, it's commonly understood that they consider user demographic details like gender, age, and website browsing history. To distinguish between targeted and non-targeted ads, several algorithms have been studied so far. For example, Carrascosa et al. [7] proposed a simple heuristic method. Other approaches utilize machine learning for this task.

In our work, we suggest a more straightforward approach to identify targeted ads. We propose identifying targeted websites by creating artificial personas. For instance, for a "childcare" persona, we conduct searches using specific keywords like 'baby goods' or 'baby stuff' in Table I multiple times with a prepared Google account. We designate the top five websites from these searches as *targeted* for the "childcare" persona. Even if other childcare-related ads are displayed, if they appear bellow the top five search results, we consider them as *non-targeted*. This definition simplifies the process of identifying targeted ads. We arrived at setting the threshold of the top five websites through various trials involving different personas and analyzing the displayed ads' outcomes.

Let X and Y be the number of targeted and the whole (targted plus non-targeted) ads in a website. We define *targeting rate* R of the website as

$$R = X/Y$$

The targeting rate varies over the website and the personas, representing a quantification of the demand for web content in the context of targeted advertising.

D. Measurement system

Our proposed system for measuring online advertising works in the following processes.

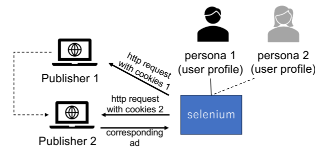

Fig. 2. System Architecture

1) Login to the Chrome profile associated with the persona, utilizing the Selenium `add_argument` method to specify the profile.
2) Navigate through various websites to simulate browsing behavior.
3) Capture the URLs used for delivering ads by utilizing Selenium's `switch_to_frame` method and `find_element_by_id` method.
4) Repeat the browsing process across the defined set of personas and websites.

Fig. 2 illustrates the system architecture and how it works for retrieving online targeted ads. Table II shows the sample of the output log of observing webpages. The index is of the advertisement frame.

Table III shows the list of websites. We collect the typical websites that seem to display frequently targeted ads rather than non-targeted ads. In this experiment, we choose website in Japan for simplification but investigate arbitrary site similarly.

E. Results

1) Targeting rate: The experiment was conducted from July 28, 2022 through August 31, 2022, utilizing a residential network located in Japan.

Table IV shows the targeting rates for nine personas, as well as the control persona, across different websites. The table shows the average targeting rate for each persona and the average rate for the websites themselves.

Among the personas, gourmet exhibited the highest targeting rate, indicating a significant level of interest (53%) in targeted advertising for this particular category. As for the targeting publishers, the highest website is Q&A, which has 60% of ads are targeted. The least one was blog (18%).

2) Duration of targeting: What is the duration of targeting activation?

Targeted ads have a limited duration and do not persist indefinitely. After a few days, they cease to appear. We conducted observations to determine when targeted ads stopped displaying on the browsers of various personas. Table V shows the last day on which we identified targeted ads for each site and persona. The longest duration of advertising was observed for the elderly persona, spanning 32 days. Notably, the website featuring sweet contents exhibited the longest duration of 31 days.

3) Distribution of targeting ads: The intensity of targeted ads is influenced by the time elapsed since a user's initial visit to a website. As time progresses, the number

TABLE II
Example of system output (ad URL)

date	index	URL
2022-10-24 14:26:58.295321	1	https://store.google.com/jp/product/pixel_7/
2022-10-24 14:26:58.295321	2	https://www.bellemaison.jp/shop/
2022-10-24 14:26:58.295321	3	https://cat.jp2.as.criteo.com/delivery/
2022-10-25 12:44:02.751080	1	https://www.uniqlo.com/jp
2022-10-25 12:44:02.751080	2	https://jp.shein.com/
2022-10-25 12:44:02.751080	3	https://pets-kojima.com/

TABLE III
List of 10 web sites to be investigated

site	URL	abbreviation
Q&A	http://ja.uwenku.com/question/p-nrfjwnhr-nn.html	ExcelJS and Node.js for editing xlsx files
Web design	http://www.htmq.com/csskihon/	fundamental CSS
IT	https://ichi.pro/	Web scraping with Node.js and Puppeteer
affiliate	https://sukiaraba-game.jp/?p=41542	comparison games
Anime	https://yuuublogkakutou.com/donfinish	stories of Anime
game cheating	https://www.oi-mori.com/	walk-through Doubutu-No-Mori
sweet treat	https://myrecommend.jp/gifts-of-sweets-129/	summary of sweet treat for gift
sightseeing	https://yochi-orange.com/canada-eastside-trip/	sightseeing courses in Canada
interior-supple	http://simplemodern-interior.jp	42 Scandinavian styles
blog	https://www.marorika.com/entry/bootstrap-beginner	Bootstrap beginner

TABLE IV
Targeted ads rate (number of targeted ads/total number of ads)

site / persona	**Q&A**	Web-design	IT	affiliate	Anime	game	sweet	sightseeing	interior	blog	mean[%]
childcare	2/3	1/3	1/4	1/3	1/4	1/2	1/6	0/7	1/5	0/5	27
education	2/3	1/3	3/4	1/3	1/4	1/2	1/6	2/7	0/5	2/5	37
gourmet	2/3	2/3	3/4	2/3	0/4	1/2	4/6	4/7	2/5	2/5	**53**
fashion	2/3	2/3	2/4	1/3	3/4	1/2	2/6	3/7	1/5	1/5	46
elderly	2/3	1/3	3/4	2/3	3/4	1/2	3/6	5/7	0/5	1/5	51
residence	2/3	1/3	1/4	0/3	0/4	1/2	3/6	0/7	1/5	0/5	25
electronics	2/3	1/3	3/4	2/3	3/4	1/2	3/6	5/7	0/5	1/5	51
dieting	1/3	1/3	3/4	2/3	2/4	1/2	2/6	3/7	1/5	0/5	40
gaming	1/3	1/3	2/4	1/3	2/4	1/2	2/6	3/7	1/5	1/5	37
mean [%]	**60**	40	58	43	43	50	38	40	16	18	

of targeted ad decreases, indicating that a decrease in the number of winning bids by advertisers Initially, a significant number of bidders complete for ad placements, but as time goes on, the number of ads displayed gradually decreases.

To examine the temporal distribution of targeted ad demands, we conducted a four-day experiment starting from November 26, 2022, utilizing the childcare persona for browsing. We observed the number of targeted ads every five minutes over a 24-hour period.

Fig. 3 shows the distribution of the mean number of targeted ads per hour. Across all websites, there were consistently more than 20 ads displayed initially, but the count gradually declined over time. By the 10-hour mark, some sites had no targeted ads appearing.

Based on our findings, we conclude that the demand for targeted ads decreases as time progresses after the user's initial visit to a website.

4) Long-term Trends: The targeted personas and web content preferences can undergo changes over time and across different regions. In this evaluation, we analyze the

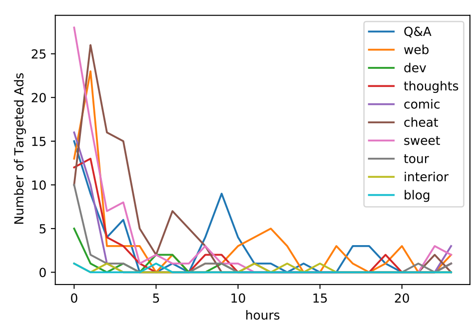

Fig. 3. Number of targeted ads per hour

changes in targeted rates between the years 2021 and 2022. Table VI and VII show the top nine personas and the top two publishers (websites) in terms of targeted rates.

Although the exact rankings of the top personas may differ between the two years, the elderly and gourmet personas consistently rank in the top two for both years. Notably, the gaming persona experienced a substantial

TABLE V
(Experiment 1) Date the targeted ad was last observed

persona \ site	Q&A	Web-design	IT	affiliate	Anime	game	sweet	sightseeing	interior	blog	mean[%]	
childcare	8/25	8/17	8/16	8/25	8/26	8/22	8/27	8/15	8/7	N/A	8/20	24
education	8/31	8/31	8/25	8/26	8/10	8/31	8/23	8/29	8/27	8/27	8/26	30
gourmet	8/31	8/9	8/20	8/24	N/A	8/26	8/26	8/29	8/25	8/17	8/23	27
fashion	8/21	8/18	8/20	8/24	8/26	8/24	8/24	8/17	8/19	8/9	8/20	24
elderly	8/26	8/31	8/31	8/30	8/26	8/31	8/31	8/29	8/22	8/21	**8/28**	**32**
residence	8/26	8/14	8/14	8/25	8/3	8/26	8/26	8/23	8/9	8/9	8/18	22
electronics	8/28	8/26	8/21	8/16	8/11	8/30	8/30	8/30	8/8	8/24	8/22	26
diet	8/26	8/26	8/17	8/26	8/26	8/21	8/26	8/26	8/27	8/7	8/23	27
gaming	8/15	8/26	8/22	8/26	8/26	8/26	8/26	8/26	8/26	8/16	8/24	28
mean	8/25	8/22	8/21	8/25	8/19	8/26	**8/27**	8/25	8/18	8/18		
duration [day]	29	26	25	29	23	30	**31**	29	22	22		

TABLE VI
Comparison of targeted ad rates for persona

rank	2021	2022
1	elderly 79 %	gourmet 53 %
2	gourmet 72 %	elderly 51
3	fashion 71	electronics 51
4	childcare 63	fashion 46
5	residence 62	diet 40
6	diet 53	**gaming 37**
7	education 46	education 37
8	electronics 40	childcare 27
9	**gaming 10**	residence 25

TABLE VII
Comparison of targeted ad rates (Web site)

	highest	least
2021	Q&A 56	interior 25
2022	Q&A 60	interior 16

Fig. 4. Site “Development“ (left: manual, right: automatic)

change, rising from the 9th rank in 2021 to the 6th rank in 2022. This significant shift can be attributed to the release of a popular game in 2022, which resulted in a notable 44% increase in sales. This example highlights how targeted personas can vary based on social events.

Predicting trends in targeted personas becomes challenging due to their dynamic nature. Consequently, alerting users about these targeting trends becomes equally difficult. The ever-changing landscape of targeted advertising makes it challenging to anticipate shifts and patterns accurately.

IV. Discussion

A. Accuracy

The accuracy of our proposed method in observing targeted ads is a crucial aspect to assess. However, it is important to acknowledge that certain factors, such as unforeseen design changes or technical limitations, may affect the reliability of ad capture. To evaluate the effectiveness of our automated system utilizing Selenium, we conducted a comparative analysis against a manual evaluation of nine selected websites.

Table VIII shows the absolute and relative error observed during this evaluation. We examined the difference in the counts of targeted ads between the automated system and the manual investigation. On average, there were 0.3 differences out of 4.2 ads in the targeted rate, resulting in a relative error of 7.1%. Note that the highest errors were observed in websites associated with affiliate marketing and anime.

Figure 4 gives the example of website where inconsistencies in targeted ads are observed between automated and manual observations. The targeted ads are highlighted with red rectangles in the figure. Note that, even with identical environments, the resulting targeted ads may vary, which is an inevitable occurrence. Table IX shows the elapsed time required for observing targeted ads. Our proposed system demonstrates a mean time of 16.6 seconds, which is significantly lower compared to the almost double time taken for manual investigation. Despite a 7% accuracy loss, our system offers substantial time savings for conducting investigations.

To enhance the accuracy of our system, we plan to conduct further investigations and make improvements. Addressing the identified errors will be a key focus to ensure the reliability and precision of our automated method in observing targeted ads.

TABLE VIII
ABSOLUTE ERROR OF AUTOMATIC OBSERVATION SYSTEM

site	Q&A	Web-design	IT	affiliate	Anime	game	sweet	sightseeing	interior	blog	mean[%]
error counts	0.3/3.0	0.0/3.0	0.5/4.0	0.4/3.0	0.0/4.0	0.0/2.0	0.7/6.0	0.8/7.0	0.3/5.0	0.0/5.0	0.3/4.2
relative error [%]	10	0	13	13	0	0	11	11	7	0	7.1

TABLE IX
OBSERVATION TIME FOR ADS ON ONE WEBSITE

	our system [s]	manual [s]
mean	16.6	37.7
standard deviation	3.3	3.2

B. Implications of findings

Our investigation revealed variations in the targeting rate across different personas, with those expressing an interest in gourmet topics exhibiting the highest targeted rate.

Several factors may contribute to this observation. Firstly, industries related to gourmet interests might allocate more funds to advertising compared to sectors like childcare, education, and residence, fostering increased competition in bid advertisements and subsequently elevating the bids for the gourmet persona. Secondly, companies associated with gourmet themes may possess greater financial resources for advertising. We plan to determine the average revenue of industries within gourmet-related categories to substantiate this hypothesis. Lastly, the size of the persona's population influences the targeting rate, where gourmet personas, spanning a broader age range compared to childcare personas, attract a larger user base, consequently contributing to an augmented targeted rate.

C. Considerations on User with Multiple Personas

What if a user shares multiple personas?

The scenario wherein a user shares multiple personas is a common occurrence and raises intriguing questions. We note that our observations deliberately circumvented the impact of compounding multiple interests by deliberately selecting a solitary topic of interest while excluding other influencing factors. Consequently, our observation delineates an ideal setting for the examination of a unique category.

In situations where users possess multiple interests, the proportion of targeted ads may see an increase. However, it is essential to underscore that we define a targeted rate for each distinct persona. Thus, when multiple personas are amalgamated, we need to revise a comprehensive definition of the targeted rate. This particular aspect is earmarked for investigation in future studies, representing a compelling avenue for further exploration.

V. RELATED WORKS

Prior work related to our study can be categorized into the following types. (1) Selenium-based collection, (2) Crowdsourcing Detection, and (3) Header Bidding Observation. Our study is classified into (1), but its personas are designed simpler than the prior work.

A. Selenium-based Collection

Bertmar et al. [9] introduced a Selenium-based data collection tool designed to assess the impact of various factors on ad personalization, particularly in relation to user profiles that were manually crafted. Their research focused on investigating how personalization evolves over time for users with diverse personas, encompassing factors such as interests, occupation, age, and gender. Their longitudinal study spanned a duration of 21 days and involved the operation of 51 virtual machines. The outcomes of their experiment demonstrated that personalized ads exhibited variations contingent on the user's persona and geographic location. Moreover, they highlighted the significant influence of whether users were logged into a Google account or not on the nature of targeted advertising.

B. Crowdsourcing Detection

Lordanous et al. [6] introduced a real-time ad detection tool deployed on real devices to gather statistics concerning the ads users encounter during online browsing. Their methodology involves the utilization of a tailored protocol for statistics collection, which does not need the creation of artificial profiles with demographic information. Additionally, they put forth a straightforward count-based heuristic for the detection of targeted ads, leveraging statistics generated from interactions across multiple domains. To safeguard user privacy, they have developed a system named *eyeWnder*, which got feedbacks from approximately 1000 users over a span of one year.

C. Header Bidding Observation

Cook et al. [3] utilized header bidding (HB) to observe the actual bids made by advertisers for a specific user profile. In contrast to traditional real-time bidding (RTB), HB provides visibility into all bids directed at a target user, exposing the bidding behavior of all advertisers. By leveraging HB, they gained access to all bids and conducted an analysis of how advertisers' bidding preferences varied across different personas. The study involved controlled experiments featuring 16 personas and the crawling of Alexa's top 50 sites utilizing the OpenWPM configuration. Their findings highlighted that, on average, bidders paid a 2.0 USD CPM (Cost Per Mille) across all personas for intent users, which was 5 times higher compared to non-intent users.

VI. Conclusion

This paper focuses on investigating privacy concerns in online targeted advertising and proposes an automated system to unveil the targeted user profiles and the web publishers involved. Through experiments conducted with prominent websites and representative user profiles (personas), we monitored targeted ads over an extended period. Our findings indicate that the profile most frequently targeted was the one demonstrating an interest in gourmet topics, while the publisher most commonly engaged in targeting was a Q&A-related site. Furthermore, our study reveals that the targeting effect remains active for approximately 22 days. We believe that these insights into online targeted advertising trends can be valuable for users seeking to manage their online behavior effectively.

As a future avenue of research, we plan to investigate the dynamics of advertising expenditure by advertisers and explore strategies to safeguard user privacy against behavioral tracking.

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