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# ATOM: Ad-network Tomography

**Abstract:** Data sharing between online trackers and advertisers is a key component in online behavioral advertising. This sharing can be facilitated through a variety of processes, including those not observable to the user’s browser. The unobservability of these processes limits the ability of researchers and auditors seeking to verify compliance with recent regulations (e.g., CCPA and CDPA) which require complete disclosure of data sharing partners. Unfortunately, the applicability of existing techniques to make inferences about unobservable data sharing relationships is limited due to their dependence on protocol- or case-specific artifacts of the online behavioral advertising ecosystem (e.g., they work only when client-side header bidding is used for ad delivery or when advertisers perform ad retargeting). As behavioral advertising technologies continue to evolve rapidly, the availability of these artifacts and the effectiveness of transparency solutions dependent on them remain ephemeral.

In this paper, we propose a generalizable technique, called ATOM, to infer data sharing relationships between online trackers and advertisers. ATOM is different from prior approaches in that it is universally applicable — i.e., independent of ad delivery protocols or availability of artifacts. ATOM leverages the insight that by the very nature of behavioral advertising, ad creatives themselves can be used to infer data sharing between trackers and advertisers — after all, the topics and brands showcased in an ad are dependent on the data available to the advertiser. Therefore, by selectively blocking trackers and monitoring changes in the characteristics of ad creatives delivered by advertisers, ATOM is able to identify data sharing relationships between trackers and advertisers. The relationships discovered by our implementation of ATOM include those not found using prior approaches and are validated by external sources.

**Keywords:** data sharing, tracking, advertising, privacy measurement, regulatory compliance, tomography

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## 1 Introduction

**Investment in online behavioral advertising is growing rapidly.** Over the past decade, the advertising industry has demonstrated a clear preference for online behavioral advertising — i.e., displaying individually targeted ads based on what is known about the users’ online habits and behaviors. In fact, recent reports by eMarketer [31] and the Interactive Advertising Bureau (IAB) [20] have estimated the 2021 programmatic digital ad spend in the United States alone to be between \$160-211B and in excess of \$315B by 2025. This represents a 10-18% year-over-year growth and over two-thirds of the ad spend across all media (including television, print, and radio) [17].

**Online behavioral advertising has led to the commodification of data.** In online behavioral advertising, brands place bids for ad slots made available by online publishers when a user loads their service. The logistics of the associated bidding process are often fully outsourced to programmatic advertising organizations called Demand Side Platforms (DSPs or *advertisers*). These advertisers allow bids to be made and their associated dollar values to be computed in real time. In simple terms, bid values are dependent on the ad slot (e.g., the location and size of the slot) and the likelihood of the attracting the engagement of the specific user (estimated by known user characteristics such as their interests, location, purchase habits, etc.). Bearing in mind our simplified overview ignores many complexities of the advertising ecosystem.

For brands and advertisers, such targeting has been shown to be significantly more cost-effective than traditional (i.e., contextual) advertising [11] when presented with high quality user data. Today, the online advertising landscape contains an entire data ecosystem focused on harvesting and trading user data. This online data ecosystem satisfies advertisers’ need for high quality user data and publishers’ dependence on advertising revenue. Unfortunately, this commodification of user

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data has resulted in the development of privacy-invasive user tracking practices (e.g., stateless tracking methods such as browser fingerprinting [52, 58]) and the emergence of data sharing relationships between online entities that are unknown to the user (e.g., through cookie syncing [34, 65], server-side sharing [10, 23, 32], or third-party data brokers [16, 30]).

**Emerging regulations around data sharing will be hard to enforce.** In recent years, regulators have taken notice of the increasing concerns surrounding the lack of online privacy controls [8, 15], the opacity of online user data harvesting and sharing [9], and the failure of the advertising ecosystem’s self-regulation efforts [47, 49, 51]. This has resulted in the passage of numerous privacy-focused regulations that explicitly limit how user data might be gathered, handled, and shared. Most relevant to our work are the EU’s GDPR [26], California’s CCPA [25] and CPRA [33], and Virginia’s CDPA [21]. Each of these regulations attempt to improve transparency in the online data ecosystem by requiring organizations to disclose the sale or sharing of non-public consumer data to third-parties. Unfortunately, despite a few successes in reining in the online data ecosystem’s data gathering practices [27, 28], these regulations are hard to enforce for two key reasons. First, the absence of private right of action [50] creates bottlenecks at the enforcement agencies. Second, many aspects of the regulations are not amenable to large-scale auditing systems that can verify regulatory compliance [67]. For example, the enforcement of regulations surrounding data sharing will be largely ineffective due to the absence of general techniques to identify evidence of incorrectness or incompleteness of disclosed data sharing relationships.

**Identifying data sharing relationships is difficult.** Broadly, data sharing in the online advertising ecosystem occurs between online trackers (who gather user data) and online advertisers (who obtain this data for the purposes of targeted advertising). This sharing can be facilitated either by real time direct communication between the two entities (i.e., server-side data sharing), by real time re-directed communication facilitated through the user’s browser (i.e., client-side sharing), or indirectly through data brokers and other middlemen (i.e., indirect sharing). We describe each of these data sharing mechanisms in more detail in §2. The main challenge facing researchers seeking to measure these relationships is the absence of a suitable vantage point from which to observe or infer sharing. More specifically, measurements of the advertising ecosystem are typically only afforded a view of interactions passing through

the user’s browser. Consequently, only client-side sharing can be observed and recorded. Unfortunately, current data sharing mechanisms are increasingly migrating towards server-side sharing or indirect sharing due to recent browser policies that block third-party cookies. Therefore, the relationships facilitated through server-side remain opaque to researchers and auditors.

**The applicability of current approaches to measure server-side and indirect data sharing are limited.** Interactions that facilitate data sharing between trackers and advertisers that do not involve the user’s browser are generally invisible to researchers and auditors. Therefore, any mechanism to infer unobservable data sharing must exclusively rely on client-observable side channels. Current approaches have leveraged the side channels associated with specific artifacts of advertising and ad delivery protocols. Unfortunately, these artifacts are not widespread and limit the capabilities of the approaches that depend on them. For example, Cook et al. [44] used client-observable advertiser bids as a side channel through which data sharing relationships could be inferred. However, advertiser bids are only visible when publishers enable ad delivery through client-side Header Bidding — an increasingly uncommon situation given the ad industry’s recent move towards server-side Header Bidding [12, 14, 22]. Working towards the same goal, Bashir et al. [38] used retargeted ads (i.e., ads which showcase a product previously visited by a user) to infer when server-side data sharing must have occurred. Once again, the scope of this approach is limited to the identification of data sharing relationships for retargeting. We highlight these prior approaches in detail in §5. *What is lacking is a generalizable (i.e., artifact- and mechanism-independent) approach to infer data sharing relationships between trackers and advertisers.*

**We develop a generalizable technique to infer data sharing.** At a high-level, our work is based on the insight that: *by their very nature, personalized ads present an always-observable side channel that can be used to infer data sharing relationships between advertisers and trackers.* We arrive at this insight as follows:

- Data sharing in the online advertising ecosystem occurs primarily to facilitate online behavioral advertising — i.e., to present personalized ads. Therefore, by the very nature of online behavioral advertising, the characteristics of the ad creatives (e.g., topic, brands, etc.) displayed to a user must *always* be in-

fluenced by the data available to an advertiser. This presents an always-observable side channel.

- As a consequence of the data-dependence of ad creatives, the creatives presented by an advertiser having no data about a user will be significantly different than the creatives presented by an advertiser having rich data about a user’s interests and browsing habits. For example, an advertiser that is aware of a user’s interests in soccer will present different creatives and brands to the user than an advertiser with no knowledge of their interests.
- The flow of information about a user’s interests originates at online tracking organizations that harvest information about a user’s online activities. This means that by blocking a tracking organization’s ability to observe a user we also disrupt all information flows between that tracking organization and its data sharing partners. Therefore, when the creatives presented by an advertiser are found to be statistically dependent on (un)blocking of a tracking organization, we have evidence of a data sharing relationship between the tracker and advertiser.

In this paper, we validate and operationalize this insight by testing the following hypotheses.

*H1. Characteristics of ad creatives are dependent on user interests (§3).* To test this hypothesis, we first create a number of online user personas associated with specific interest groups (e.g., sports, arts, etc.). Next, we use computer vision to extract the characteristics of the ad creatives delivered to each of these personas when they visit a predefined set of websites. Finally, we conduct statistical testing to identify if these extracted characteristics are dependent on the persona interest group they were derived from. A positive finding of dependence would demonstrate that browsing history does impact the extracted characteristics of delivered ad creatives — thus satisfying a necessary condition for using ad creatives to infer data sharing relationships.

*H2. Characteristics of ad creatives can be used to infer tracker-advertiser data sharing relationships (§4).* We test this hypothesis by creating online user personas and gathering ad creatives while systematically blocking popular tracking organizations from observing the persona. Next, we use statistical modeling to quantify the impact of blocking each of the ten largest tracking organizations on the creatives delivered by each advertiser. We then use this measured impact to identify trackers that, when present, significantly impact the delivered creatives of each advertiser. We infer the presence of a

data sharing relationship between these trackers and the corresponding advertiser. Finally, we validate the correctness of our inferences using known client-side sharing relationships and public disclosures made available through CCPA’s data broker registry [29].

## 2 Background: Mechanisms of online behavioral advertising

Online behavioral advertising relies on two key processes working together in unison: ad bidding and user data harvesting/dissemination. In this section, we provide a high-level overview of these processes.

### 2.1 Ad bidding mechanisms

Online advertising seeks to provide users with ads tailored to their individual interests. This requires coordination between publishers (who have the attention of users) and brands (who seek to capture the attention of ‘profitable’ users) to occur in real time. Two programmatic mechanisms help achieve this coordination: real-time bidding and header bidding.

**Real-Time Bidding (RTB).** RTB is currently the most popular mechanism for trading ad inventory in real time [46] and has been heavily promoted by the Interactive Advertising Bureau since 2010 [5]. In RTB, entities participate in the *supply side* or *demand side*.

*The supply side.* When a user visits the website of a publisher, the browser is directed to contact the publisher’s ad-server to facilitate the process of obtaining ads to display to the user. The publisher’s request is then forwarded, via a browser re-direct, to a *supply-side platform* (SSP) along with information known to the publisher, as a first-party, about the user (e.g., user demographics, location, etc.) and the *floor price* for the impression. The floor price represents the minimum value that the advertiser is willing to accept for the ad slot. The SSP then augments this information with its own data about the user. This is possible since the browser redirect includes the SSP’s own cookie. This allows the SSP to create a more complete picture of the advertising opportunity (*impression*). A summary of this impression opportunity is then sent to an *ad exchange*.

*The demand side.* Ad exchanges facilitate bidding on impression opportunities. When an SSP shares an impression opportunity summary with an ad exchange, the

summary is shared with all clients of the ad exchange and the bidding process is started. Clients of the ad exchange are typically *demand-side platforms* (DSPs). These DSPs make programmatic bids on impression opportunities on behalf of brands. In order to select an impression and a bid value for their clients, DSPs leverage data obtained from the supply side, third-party data brokers, and their own history with the user (made possible through *cookie syncing* described in §2.2). If the winning bid exceeds the floor price set by the publisher, the ad exchange forwards the ad creative supplied by the winning DSP to the SSP, charges the DSP a commission for the successful bid, and pays the bid value to the SSP. The SSP forwards the ad creative to the publisher, charges the publisher a commission for the successful impression, and pays the bid value to the publisher.

*When the publisher's floor price is not met.* In the event that the publisher's SSP is unable to provide it with a bid that exceeds the floor price set by the publisher, the publisher must repeat the entire RTB bidding process with their next preferred SSP. This is repeated until the impression is sold to a DSP. There are two major consequences of this 'waterfall' approach used in RTB: (1) publishers may not be able to sell their impression inventory without extensive delays, (2) the impression may not be sold for its true market value (since not all bidders get to bid simultaneously).

**Header Bidding (HB).** Header Bidding is an emerging alternative to RTB. Promoted by AppNexus, HB aims to provide more value for publishers and advertisers by: (1) removing middlemen (i.e., SSPs and ad exchanges) from the bidding process and (2) flattening the waterfall approach of RTB [13]. HB achieves this by: (1) allowing direct relationships between publishers and any entity interested in the inventory of the publisher and (2) soliciting bids from all interested parties simultaneously. Notably, HB has been described as an 'existential threat' by Google (the largest beneficiary of RTB) and is at the center of an ongoing anti-trust suit brought against Google [19]. Technically, the process may occur either through 'client-side' or 'server-side' HB.

*Client-side HB.* When a user visits the website of a publisher, the browser executes a script referred to as a HB wrapper. The HB wrapper solicits bids for each ad slot from *all* the publisher's HB partners. These may be DSPs, SSPs, or ad exchanges. This is done by having the browser initiate connections with the HB servers of each partner. The requests sent to the HB partners over these connections include information about the page and ad slot. Since the connections are initiated by

the user's browser, they also include any cookies already set by the HB partner. Each partner may then respond to these requests with their bids for the impression (including their ad creative and bid value). Similar to the process for RTB, these bids are informed by any user data available to the HB partners — either their own or from third-party sources. The wrapper then forwards all bids that are received within a pre-determined timeout period to the publisher's ad server. Finally, the ad-server charges the winning bidder and forwards the winning ad creative to the user's browser. Unique to client-side HB is the browser's access to all bids, including their values and associated creatives, received for each ad slot.

*Server-side HB.* Client-side HB requires the user's browser to solicit and forward bids from each of the publisher's HB partners. This poses a strain on the website's performance, user's browser, and network resources. Server-side HB provides a more efficient alternative in which the bids are solicited directly by the publisher's (or publisher-subscribed third-party) servers — i.e., the HB wrapper logic is moved away from the user's browser. While this provides notable performance improvements, it poses a new challenge: since bids are solicited from outside the user's browser, they no longer contain the cookies set by the HB partner. This reduces the data available to HB partners when determining the creatives and values for their bids. To compensate for this loss of data, several server-side HB vendors are now providing cookie syncing mechanisms so bidders may still access their cookies prior to bidding [6].

It is also to be noted that an entity can play the role of an SSP, DSP, Ad exchange, third-party tracker or any combination of the four e.g., Criteo is a notable tracker and also provides DSP services.

## 2.2 Data harvesting and dissemination

As is clear from the online advertising mechanisms described in §2.1, user data plays a key role in determining advertisers' bids for ad slots. With high quality data about the user, their bids will more accurately reflect the 'true value' of the impression for their clients. This has spurred an entire industry that is focused on harvesting and disseminating user data so that they may be sold to advertisers seeking to optimize their bids. In this section, we provide an overview of the key methods by which user data is harvested and disseminated.

**Data harvesting: Stateful and stateless tracking.** Technologies to track the online activities of users are

widespread across online services and platforms. Organizations that provide these technologies facilitate the monetization of online services and, in return, obtain the ability to track users across a variety of services and platforms. Tracking technologies may be stateful or stateless. Stateful tracking technologies rely on assigning unique identifiers to each user they encounter. These unique identifiers are stored in the user’s browser in the form of a cookie. Therefore, when a user visits a service in which the tracking organization is integrated, this cookie notifies the organization of the visit. While stateful tracking presents a deterministic way of identifying users across the web, they can be cleared by the user (making tracking impossible). In order to address the limitations of cookies, stateless tracking mechanisms are used. Stateless tracking does not rely on state saved on the user’s device. Instead, they work on the premise that each device is unique and relying on real-time measurements of user’s device is sufficient to identify individual user’s across services. On the Web, these measurements seek to find unique characteristics of the user’s browser using the JavaScript API provided by the browser. These characteristics include the browser’s user agent, default languages and encoding, installed plugins, and canvas fingerprints amongst many others [58]. Unlike stateful techniques, these are not deterministic — i.e., there is no guarantee that two users cannot share the exact same characteristics. However, they are difficult to differentiate from non-tracking uses of the browser’s API — making them harder to block. Typically, online trackers use a combination of stateless and stateful approaches to track users.

**Client-side data sharing: Cookie syncing.** In order to learn of a user’s visit to a website, a tracker needs to be integrated into the website by the publisher. Cookie syncing allows collaboration between trackers so that they can learn of the user’s visit as long as any one of them is integrated — essentially allowing them to share data about the user’s online activities. This is achieved by having one partner redirect the user’s browser to the other partner by requesting for resources from it (e.g., pixel images). For example, if `tracker-1.com` and `tracker-2.com` are partners, `tracker-1.com` will invoke a request to `tracker-2.com` causing the browser to also send `tracker-2.com`’s cookie in this request. Cookie syncing can also be used to help data sharing partners coordinate their databases. For example, `tracker-1.com` may also provide its own unique identifier for the user (as a parameter in the URL) in the resource request sent by

the browser to `tracker-2.com`. When this request is received by `tracker-2.com`, it builds an association with `tracker-1.com`’s unique identifier and its own cookie. This allows `tracker-2.com` to integrate any out-of-band data received from `tracker-1.com` into its own database [65]. Cookie syncing is heavily used in RTB and HB to allow DSPs, who may not be integrated on the publisher site, to make informed assessments of the impression opportunities. Amongst the popular data sharing mechanisms in the online advertising ecosystem, only cookie syncing is visible to the user’s browser.

**Out-of-band data sharing.** Cookie syncing presents two main drawbacks: (1) they reduce the performance of webpage loads by forcing a large number of browser redirects and (2) they are impacted by the current restrictions on third-party cookies implemented by popular web browsers [18]. To circumvent these challenges, data sharing between entities in the advertising ecosystem is increasingly being facilitated through mechanisms that do not involve the user’s browser — making them invisible to users, auditors, and researchers.

*Universal ID.* Universal ID based approaches are a solution to the recent browser restrictions on setting and accessing third-party cookies [23, 24]. The idea behind them is to leverage user identifiers such as email addresses or user ids that are supplied to publishers as a way to uniquely identify users across the entire advertising pipeline. This erases the need for matching cookies in order to sync databases. At a high-level, the process works as follows: (1) a user visits `website.com` in which `tracker-1.com` is included, (2) `website.com` passes the user identifier known to it (e.g., email address used during sign up) in the request sent to `tracker-1.com`, (3) `tracker-1.com` records the user identifiers presence on `website.com`. When `tracker-1.com` and `tracker-2.com` wish to collaborate, they can simply perform a join operation on their databases to augment their records of each user. The most popular implementation of universal ID is UnifiedID 2.0 by TradeDesk (endorsed by the IAB) [23].

*Data brokering.* Data brokers are aggregators of user data from many sources including online trackers, credit card companies, state and federal authorities, etc. Comprehensive information about users meeting specific characteristics (e.g., living in a specific zip code and of a specific age with a recent purchase of a specific product) are often purchased by advertisers and synced with their own datasets to facilitate more accurate bids in the behavioral advertising ecosystem [70].

In this paper, we propose and validate a technique to identify tracker-advertiser data sharing relationships that: (1) is agnostic to ad bidding and delivery mechanism (§2.1) and (2) is independent of the methods used by trackers and advertisers to share their data (§2.2).

### 3 Ad creatives and user interests

In this section, we focus on testing the following hypothesis: *H1. Characteristics of ad creatives are dependent on user interests.* If valid, this will: (1) demonstrate that displayed ads are dependent on user behavior, (2) show that our methods for analyzing ad creatives are able to capture these dependencies, and (3) satisfy a necessary condition for our attempt to use characteristics of displayed ads to infer data sharing relationships. We provide a description of our methodology in §3.1 and our results in §3.2.

#### 3.1 Methodology

**Overview.** Our goal is to understand if the characteristics of ad creatives are dependent on user interests. At a high-level, we achieve this by: (§3.1.1) creating ‘interest groups’ (e.g., arts and sports) and curating a list of websites associated with each of these interests; (§3.1.2) constructing a set online personas that crawl websites in order to signal specific interests to the advertising ecosystem; (§3.1.3) gathering and extracting characteristics from the ad creatives displayed to each of these personas when they visit a set of websites; and (§3.1.4) conducting statistical testing to analyze the dependence of the extracted characteristics of ad creatives on the interest categories of their personas.

##### 3.1.1 Creating interest groups

We aim to communicate an ‘interest’ to the advertising ecosystem solely by simulating browsing activity. This decision is motivated by similar previous work by Cook et al. [44]. We start by creating 16 ‘interest groups’ based on the persona categories from [44] (Adult, Art, Business, Computers, Games, Health, Home, Kids, News, Recreation, Reference, Regional, Science, Shopping, Society, Sports). To assign websites to each group, we obtain a set of popular (US Top 100) websites belonging to each of our interest groups from

Similar Web [7] and Alexa Top Sites [1]. Next, to establish the uniqueness of each ‘interest group’, we filter out groups that have significant (50%) inter overlap. We further filter out websites with ‘cookie banners’ (in accordance with GDPR [26]), as instrumenting opt-in/out was out of the scope of this work. We then manually curate the remaining six ‘interest groups’ (adult, games, health, news, sports, and travel) and their lists, to ensure the website’s fit with the corresponding interest group. Following the best practices highlighted in [69], our set of websites in each category were gathered in Oct-2021.

Next, we used OpenWPM [48] to crawl each remaining site to verify that they were functional and contained trackers on them. Verifying tracker presence is crucial since having no trackers on a website prevents our persona’s ‘interest’ signal from being communicated to advertisers. Tracker presence was measured by counting the number of unique matches between web requests generated from the page load and the EasyPrivacy tracker list [3]. Finally, we selected 50 sites for each interest group. These were the 50 sites with the largest number of trackers present on them. The top 5 sites amongst these were used for ad collection in §3.1.3 while the remaining 45 were used to construct personas. One site from each group was also manually selected to communicate ‘intent’ — i.e., perform an action to signify high interest in the topic (e.g., adding an interest-related product to a shopping cart or performing a search about an interest-related topic).

##### 3.1.2 Constructing online personas to signal interests

In order to signal interests to entities in the advertising ecosystem, we constructed a total of 5400 personas — 900 for each of our six interest groups. Of these, half were selected to communicate intent on the ‘intent site’ for their associated interest group. Each persona was associated with a unique browser running on an isolated virtual machine with a unique IP address. This was done to ensure that tracking entities would not misconstrue the uniqueness of each persona. The browser of each persona was automated using OpenWPM and crawled the curated set of websites associated with their interest groups. Following the best practices for crawling studies [36], [55], [45], our OpenWPM configuration enabled bot mitigation and disabled tracking protection.

### 3.1.3 Gathering ads and extracting characteristics

*Gathering ads.* After a persona finished crawling the list of sites in its interest group, it waited for an hour before visiting a set of ad collection sites from which all ads were gathered. The pause was to ensure that any signals measured by trackers were eventually delivered to advertisers. The set of ad collection sites included five websites for each interest group as mentioned in §3.1.1. In addition, we also gathered ads shown to a *control persona* with no previous browsing history (i.e., using a fresh browser and IP address). We assigned one website from each interest groups ad collection websites to the control group. We did this to remove any bias towards a single interest group. The ads gathered by this persona serve as our *control group* for comparisons. In order to gather ads, we extracted all response URLs containing images and matched them with the set of filters from EasyList. The matching URLs denote known advertising domains that sent an image. The images associated with each of these domains were then filtered to remove any images smaller than 20KB (to remove icons or pixel images). The remaining images were the ad creatives delivered to each of our personas. Manual validation was performed on a random subset of 300 unique images to verify that the remaining images were ad creatives. In total, our personas gathered 5.3M ads of which 31.5K were unique. Importantly, *our approach gathers all ad creatives regardless of whether they were associated with RTB or HB.*

*Crawl synchronization.* We executed our crawls in nine serial *runs* spanning over a 45 day period. Each run consisted of the execution of 100 instances of each persona. Our crawls were executed to ensure that the start of each of our nine runs were synchronized across the six interest groups — i.e., the  $n^{\text{th}}$  run of all interest groups began simultaneously. Each run was executed only after completion of the prior run. This precaution was taken as a best-effort attempt to mitigate the effect of any latent temporal confounders that might impact our subsequent data collection.

*Extracting ad characteristics.* To extract characteristics of each ad, we relied on Google Cloud Platform’s (GCP) Vision API [2]. Specifically, for each recorded ad creative, we used it to obtain the following characteristics: (1) all written text from the image and (2) textual descriptions of identified landmarks and logos in the image. Taken all together, these extracted characteristics present a textual description of the supplied ad creative.

### 3.1.4 Analyzing ad dependence on interest groups

*Converting ad descriptions to count vectors.* The extracted characteristics of each ad creative effectively act as its semantic textual description, allowing us to use standard text analysis techniques to measure semantic similarity between ad creatives. We aggregated the descriptions of ads into nine ‘documents’ for each interest group (and control group). Each document consisted of the descriptions of ads shown to the 100 personas belonging to one run and one interest group. This aggregation was necessary to deal with sparsity of keywords and facilitate significance testing. We then created a global corpus consisting of all words occurring in all documents. Finally, each document  $d$  was converted into a count vector  $X^d$  where  $x_i^d$  denoted the frequency of the  $i^{\text{th}}$  word (from the global corpus) in document  $d$ . At the end of this step, we were left with nine count vectors for each interest and control group.

*Measuring dependence on interest group.* We computed the cosine similarity between the count vectors of each pair of documents. This presented us with: (1) a distribution of within-group similarities — i.e., a distribution representing the measure of similarity of ads shown to the same interest group across different periods of time and (2) a distribution of across-group similarities for each pair of interest groups — i.e., a distribution representing the measure of similarity of ads shown to the two interest groups. Finally, to validate our hypothesis about the dependence of ads on interest groups, we analyzed the mean values of each of these similarity distributions and tested their differences for statistical significance using a two-sample  $t$ -test ( $p < .05$ ). Put another way, for any pair of interest groups ( $g_1, g_2$ ), we compare  $D_{sim}(g_1, g_2)$  and  $D_{sim}(g_1, g_1)$  using a two-sample  $t$ -test. Here,  $D_{sim}(g_i, g_j)$  denotes the distribution of cosine similarities between the count vectors of  $g_i$  and  $g_j$ . We conclude that our hypothesis is valid if our findings indicate: (1) high within-group similarities — i.e., semantics of ads shown to an interest group are similar over time, (2) low across-group similarities — i.e., semantics of ads shown to two unrelated interest groups are not similar, and (3) statistical significance between the differences in within- and across-group similarities.

## 3.2 Methodology validation and results

We now present the results of our experiments to validate our methodological decisions and our hypothe-

sis. Specifically, we: (§3.2.1) test the impact of number of interest-related sites crawled by a persona on the number of ads received; (§3.2.2) validate our decision to use unique VMs and IP addresses for each persona; (§3.2.3) validate the quality of ad descriptions returned by the GCP Vision API; (§3.2.4) demonstrate the dependence of ad creatives shown to our personas on the personas’ interest group; and (§3.2.5) examine the impact of demonstrating ‘intent’ during crawling.

### 3.2.1 Validation: Number of sites in an interest group

Advertisers are likely to make stronger bids (higher than the floor value of the slot) on users for whom they have strong signals of a specific interest. Consequently, one expects this to result in more targeted ads and less unfilled ad slots — crucial to the success of our study. However, it is unclear *how many websites to include in each interest group for our personas to signal a strong and specific interest*. Although we expect that more websites related to one interest will always be better, the scale of our measurements require us to find a workable trade-off between practicality and signal strength. To address this question, we conducted a pilot experiment in which the number of websites in each interest group was varied and the number of ads and unique ads gathered from our ad gathering sites were measured. In this experiment, we altered the number of websites in each interest group from 5 to 50 (in increments of five) using the same website selection process outlined in §3.1.1. Then, we created 40 personas for each of these interest groups using the same approach outlined in §3.1.2. Finally, we measured the total and unique number of ads displayed to each of these personas on our set of ad gathering sites. We found a steady increase in the median number of unique ads presented to each persona until the size of our interest groups reached 40 websites. Increasing the number of websites in the interest groups beyond 40 websites resulted in marginal and strongly diminishing gains. These results informed our final decision to use 45 websites in each of our interest groups.

### 3.2.2 Validation: Unique IPs and VMs

Allocating personas to their own VM and IP address for a large-scale study such as ours is monetarily expensive and challenging to automate. To decide whether this effort was necessary, we conducted a pilot experiment to determine whether such ‘sandboxing’ of personas im-

Interest Group	Ads unique to interest group	
	Isolated	Non-isolated
Adult	51%	43%
Sports	42%	48%
Travel	72%	49%

**Table 1.** Impact of using isolated VMs and IP addresses on the fraction of ads that are unique to each persona (*cf.* §3.2.2).

pacted the uniqueness of ads received by them. In this experiment, we selected three interest groups (adult, sports, and travel) containing 45 websites and allocated 100 personas to each. We allocated unique VMs and IP addresses to 50 of the personas of each interest group. The remaining set of 150 personas (50 from each interest group) used the same VM and IP address. For each setting (isolated and non-isolated), we: (1) extracted all the unique ads shown to each interest group (i.e., we do not count the same ad shown twice to a persona) and (2) measured the fraction of these ads that never occurred on any of the other interest groups (e.g., the fraction of unique ads shown only to our sports personas). Observing a difference between these fractions measured from each setting would suggest that isolating a persona influences the uniqueness of the ads received by it. Our results are shown in Table 1. We see a notable difference in the fraction of ads unique to each interest group — particularly in the travel interest group. To verify the significance of these differences, we used a  $\chi^2$ -test to test the dependence of number of ads unique to each interest group on the isolation setting used. We found a statistically significant relationship between these variables ( $p < .05$ ). There have been numerous research efforts to highlight the importance of crawl configuration decisions on inferred results [36, 55]. Our work uses the best practices highlighted in these studies and also contributes to them. One insight from this pilot experiment is the need to create ‘sandboxed’ personas during measurements of personalized ads. This result informed our decision to isolate each of the personas used in our study.

### 3.2.3 Validation: Quality of ad descriptions

The Google Vision API provides us with the capabilities to extract features such as logos, text, faces, landmarks, objects, and web entities present in an image. We conducted a pilot experiment to determine which of these features would facilitate meaningful text descriptions that captured the semantics of the ad. We

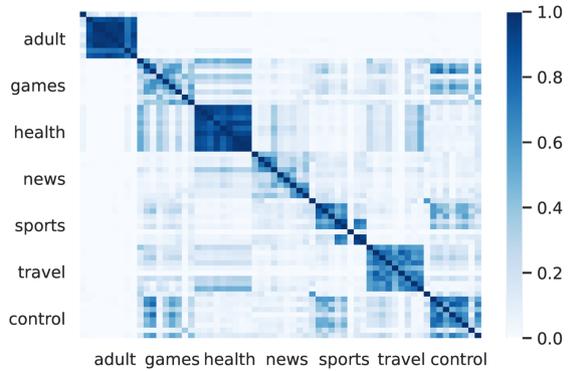
randomly sampled 263 unique ads obtained from our prior experiment (§3.2.2) and manually analyzed their images and the corresponding data extracted by the Vision API. The API identified text in 86%, logos in 28%, and faces in 16% of all images. Upon manual inspection, we found the text extracted from these images to be 100% accurate. Perfect accuracy was also found for logos extracted from these images when the API returned a confidence score greater than 80%. Other extracted features were found to be limited in their confidence scores and accuracy. Based on these results, we exclusively relied on the text and high-confidence brand/logo description features extracted from each image.

### 3.2.4 Dependence of ad creatives on interests

Using the methodology outlined in §3.1, we analyzed the dependence of our features extracted from ad creatives on the interest groups they were served to. If our hypothesis is valid and our method for extracting features from ad creatives is accurate, we expect to find that: (1) there are high similarities in the ads shown to personas belonging to the same interest groups; (2) there are low similarities in the ads shown to personas belonging to different interest groups; and (3) these differences in similarities are statistically significant.

*Within- and across-run similarities.* Figure 1 visualizes the similarities of features extracted from ad creatives within and across each run and each interest group. Each interest group contains nine runs and each cell in the heat map represents the cosine similarity between the count vectors obtained from the corresponding runs of the associated interest groups. We notice a pattern of higher similarity scores along the diagonal. This indicates that ads shown to the same interest group are in fact more similar than ads shown to different interest groups. Importantly, for every run, we find that the mean within-group similarities are significantly higher than the mean across-group similarities — providing evidence that ads are influenced by our interest groups and personas’ browsing histories. This difference is particularly high in the adult and health interest groups which suggests that these interest groups are the subject of significantly different ad targeting.

*Significance testing of differences in within- and across-interest group similarity distributions.* Following the procedure outlined in §3.1.4, for each pair of interest groups  $(g_1, g_2)$ , we verified the statistical significance of differences in the within- and across-group similar-



**Fig. 1.** Heatmap depicting the inter- and intra-group cosine similarities across the nine runs and interest and groups.

ity distributions (i.e.,  $D_{sim}(g_1, g_1)$  and  $D_{sim}(g_1, g_2)$ , respectively). We found that all pairs of interest groups where  $g_1 \neq g_2$  had statistically significant differences (two-sample  $t$ -test with  $p < .05$ ). Table 2 shows the means of each of these distributions — i.e.,  $D_{sim}(g_i, g_j)$ . These results *validate our hypothesis that the characteristics of ad creatives are dependent on user interests and our methods to extract these characteristics.*

### 3.2.5 Influence of communicating intent

Previous work has shown that communicating intent impacts the behavior of online advertisers. Specifically, Cook et al. [44] showed that communicating intent caused advertisers to increase the value of their bids. We verified whether this also caused a change in the ads displayed to users. To measure the impact of intent, we compared the within- and across-group similarity distributions for the ‘intent’ and ‘no-intent’ personas — i.e., for all pairs  $(g_1, g_2)$ , we compare  $D_{sim}(g_1^{\text{intent}}, g_2^{\text{intent}})$  with  $D_{sim}(g_1^{\text{no intent}}, g_2^{\text{no intent}})$  using a two-sample  $t$ -test ( $p < .05$ ). Our results are illustrated in Table 2. Here,  $\downarrow$  and  $\uparrow$  denote as statistically significant decrease and increase, respectively, in the mean of the corresponding  $D_{sim}(g_1, g_2)$  distribution when switching from intent personas to no intent personas.

*Within-group similarities.* When  $g_1 = g_2$ , a statistically significant decrease ( $\downarrow$ ) suggests that ads displayed to a personas in  $g_1$  become more diverse when intent is communicated during crawling. This case occurred only for personas in our health interest group. No significant increases were found when  $g_1 = g_2$ .

	Adult	Games	Health	News	Sports	Travel	Control
Adult	0.71	0.00	0.01	0.00	0.00	0.00	0.00
Games	0.00	0.42	0.19	0.07 ↑	0.13	0.13	0.29
Health	0.01	0.19	0.87 ↓	0.13	0.04	0.18	0.07
News	0.00	0.07 ↓	0.13	0.36	0.09	0.05	0.07
Sports	0.00	0.13	0.03	0.09	0.34	0.05 ↑	0.22
Travel	0.00	0.13	0.18	0.05	0.05 ↑	0.62	0.10
Control	0.00	0.29	0.08	0.08	0.22	0.10	0.41

**Table 2.** Mean of the distribution of ad similarities between each pair of interest groups. Each cell associated with the interest groups  $g_1$  and  $g_2$  denotes the mean of the distribution of similarities of ads shown to personas from  $g_1$  and  $g_2$ . Higher values indicate higher similarity between the ads for the corresponding interest profiles. In all cases where  $g_1 \neq g_2$ , the differences in the distributions of within- and across-group similarities was statistically significant (cf. §3.2.4). ↑ and ↓ indicate a statistically significant increase or decrease in this similarity when no ‘intent’ action was communicated (cf. §3.2.5).

*Across-group similarities.* When  $g_1 \neq g_2$ , a statistically significant decrease (↓) suggests that the ads displayed to  $g_1$  and  $g_2$  became more similar when intent was communicated. This case occurred for the (news, games) interest group pair. A statistically significant increase (↑) indicates that the ads displayed to  $g_1$  and  $g_2$  became less similar when intent was communicated. This case occurred for the (sports, travel) interest group pair. In general, our results *do not suggest a widespread influence of intent on ad creatives delivered to personas.*

### 3.2.6 Takeaways

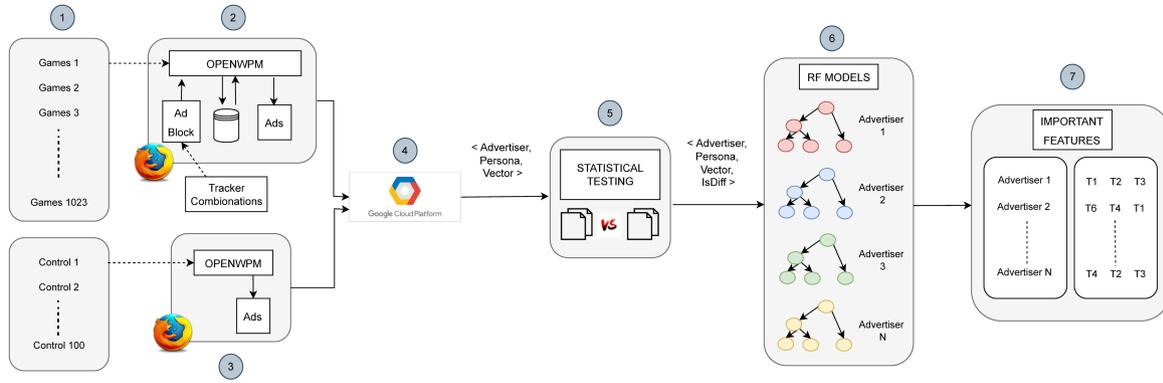
Taken all together, our analysis allows us to conclude that *characteristics of ad creatives are dependent on user interests* and that *our methods for communicating user interests and characteristics of ad creatives are effective*. Further, we also find that: a browsing history of about 40 sites related to a specific interest is sufficient for measuring personalized ads related to that interest (§3.2.1); isolating unique personas so that they possess their own unique browser, VM, and IP address has a significant influence on their measured personalized ads (§3.2.2); extracting text and logo descriptions are sufficient to obtain an effective text representation of ad creatives (§3.2.3); and communicating ‘intent’ during a crawl does not have a widespread influence on the nature of personalized ads received when interests are already communicated by long and interest-specific browsing histories (§3.2.5). Additional configuration details, websites used for personas, and ads gathered can be found at <https://vitalstatistix.cs.uiowa.edu:2443/maaz/atom-archive>.

## 4 Inferring data sharing

Our previous results effectively show that it is possible to use features extracted from ads to measure the relationship between interest groups and personalized ads. We now use the insight that *specific trackers are responsible for communicating these interest groups to the advertisers of these personalized ads*. Therefore, by systematically blocking specific trackers, we can use these ad features to understand which advertisers are no longer able to deliver ads similar to those typically associated with the interest group — signifying the presence of a data sharing relationship between the set of blocked trackers and the advertiser. We operationalize this insight to build ATOM. ATOM is a generalizable framework to identify evidence of tracker-advertiser data sharing relationships. By providing validation of ATOM’s inferred data sharing relationships, we also validate the hypothesis *H2. Characteristics of ad creatives can be used to infer tracker-advertiser data sharing relationships*. We provide a description of the methods used to construct and empirically evaluate ATOM in §4.1 and highlight the results from a test deployment in §4.2. Figure 2 gives a high-level overview of ATOM’s architecture.

### 4.1 Methodology

**Overview.** Our goal is to use the features of personalized ads to infer-tracker advertiser relationships. We achieve this in two distinct phases: a data collection phase in which online personas are used to gather ads while selectively blocking trackers of interest and a relationship inference phase in which the influence of spe-



**Fig. 2.** Overview of ATOM. ① We curate websites associated with interest-related and control personas. ② Using OpenWPM, we train and log ads shown to each interest-related persona while blocking some combination of tracking organizations. ③ Simultaneously, we collect ads observed by each control persona. ④ We extract labels from gathered ads. ⑤ We measure significance of differences in labels extracted from ads shown by individual advertiser to our control and interest-related personas. ⑥ We use Random Forest models to fit the targeting behavior of each advertiser. ⑦ We extract trackers found to have a high influence on the accuracy of the Random forest model associated with each advertiser.

cific trackers are measured on the ads delivered by each advertiser. In our data collection phase, (§4.1.1) we configure ATOM to conduct crawls while selectively communicating interests to a specific set of trackers; and (§4.1.2) then we gather, label, and identify the advertiser associated with the ads observed after ATOM’s crawls are complete. Once our data collection is complete, (§4.1.3) we use a statistical approach to determine which blocking conditions caused which advertisers to change their behavior; and (§4.1.4) account for the probabilistic nature of data sharing and multi-tracker data sharing relationships to finally produce inferences about the trackers responsible for enabling the personalization capabilities of observed advertisers.

**4.1.1 Data collection: Crawling to signal interests**

Our goal in this stage is to conduct crawls that signal an interest to a specific set of trackers. We use lessons from our previous analyses to inform our crawling methods.

*Selecting an interest group.* We create *one* interest group with 45 manually curated websites (cf. §3.2.1). It is important that: (1) the trackers whose data sharing relationships are being studied are highly present in the websites associated with the selected interest group and (2) a large number of advertisers are seeking to deliver personalized ads to personas in this interest group.

*Constructing online personas and controlling interest leakage.* Next, we configure ATOM to create online personas that selectively hide their interests from a specific set of trackers. Given a set of trackers, ATOM creates

one persona for which all communication to that set of trackers is blocked by the browser. No other tracker from any organization is blocked in this step. This is done by matching the browser’s outgoing requests with the set of filter rules associated with the supplied set of trackers. Each of these created personas then begin to crawl the websites in their associated interest group. Based on our results in §3.2.2, ATOM associates a unique VM instance and IP address to each created persona.

**4.1.2 Data collection: Collecting and processing ads**

Once all the ‘interest signaling’ crawls are complete, ATOM pauses for a period of two hours. This is to ensure that any interest signals gathered by trackers are disseminated through the advertising ecosystem. The duration of our wait period was influenced by prior work by Cook et al. [44]. Next, each persona visits a predetermined set of websites to gather and extract features from all displayed ads using the same process described in §3.1.3. During this phase of data gathering, all trackers are unblocked for all personas to prevent accidental blocking of any ad delivery mechanisms.

*Identifying advertisers associated with displayed ads.* Unlike our experiments in §3, it is now necessary to identify the advertiser (typically, the DSP) associated with each ad. This is done by identifying the response (sent to the browser) that is responsible for delivering the ad creative. The domain of the source of this response is extracted and its parent organization is identified from a supplied list of domain-organization mappings. This

parent organization is labeled as the advertiser associated with this ad creative.

*Collating data.* Finally, ATOM combines (by summing together) all the count vectors associated with ads delivered by each advertiser to each persona (represented as the set of trackers blocked in its configuration). This produces a count vector record for each advertiser-persona pair. These *vector records* are saved as: [advertiser, persona, <combined count vector>].

#### 4.1.3 Analysis: Finding changes in advertiser behavior

Once data collection is complete, ATOM possesses multiple sets of (advertiser, persona) vector records — each associated with one data collection run. Next, it uses these records to identify all the (advertiser, persona) pairs that demonstrated a change in the advertiser’s behavior. This is done by using the (advertiser, control) vector records as a reference for the advertiser’s typical behavior when no blocking is performed. A  $\chi^2$ -test is used to identify the (in)dependence between the observed count vectors and their sources (control or persona). If a dependence is found ( $p < .05$ ), the advertiser is identified to have sent statistically different ads to the control and the persona (which is associated with a specific blocking condition). This indicates a change in behavior caused by the blocking of the specific trackers. Following this step, each vector record is augmented with its significance status with reference to the control and are of the form [advertiser, persona, <combined count vector>, is\_different\_from\_control].

#### 4.1.4 Analysis: Inferring data sharing relationships

*Why relationship inferences cannot be deterministically ‘solved’.* In a noise free and deterministic scenario, the vector records from the prior step would be sufficient to ‘solve for’ all tracker-advertiser data sharing relationships — one would only need to find the minimal set of tracker blocking configurations under which an advertiser demonstrated a statistical difference from the control. Unfortunately, this is not likely because online advertising is an inherently probabilistic process in which advertisers may simultaneously lose one ad auction and win another with identical bid values, users, and user data. This can be for reasons including minor network delays that prevent a bid response from reach-

ing the auction on time, a change in strategy by other bidders, or even restrictions on the rate at which ad inventory can be used. The presence of this noise also impacts our data — e.g., it may create cases where a tracker-advertiser relationship is present but not shown in our records because the corresponding advertiser did not win enough auctions for us to extract meaningful features from their creatives. Further complicating analysis are the facts that: (1) it is practically impossible to guarantee that all trackers belonging to a specific organization are blocked and (2) many advertisers may have relationships with several tracking organizations — therefore, it is possible that even when  $n - 1$  of these organizations are accounted for and blocked the  $n^{\text{th}}$  tracker organization is able to observe and communicate persona interests with the advertiser.

*Inferring relationships with interpretable statistical models.* To account for such noise, similar to prior work [44], ATOM uses an interpretable random forest model to learn the correlations between the presence/absence of a tracker and the changes in advertiser behavior. For each advertiser, this is done as follows:

- *Segmenting vector records.* ATOM splits the multiple vector records *for each* (advertiser, persona) pair into a cross-validation set and a holdout set. For example, if there are ten (advertiser<sub>*i*</sub>, persona<sub>*j*</sub>) records — one from each of ten data collection runs, a sample of eight may be placed in a cross-validation set and the remaining two may be placed in a holdout set.
- *Model building and cross-validation.* The vector records in the cross-validation dataset are split into a predetermined number of *folds* such that each fold contains the same number of records associated with each persona. We then construct a random forest model that uses the tracker blocking configuration (obtained from the persona id) as a feature and seeks to predict whether is\_different\_from\_control is True or False. Models are built using a grid search over a set of random forest configuration parameters and the model with the highest average accuracy over all the cross-validation folds is returned.
- *Model testing.* The best performing cross-validated model is then presented with the features from the holdout set and its accuracy is measured.
- *Relationship inference.* If a model demonstrates reasonably high accuracy (determined by a supplied threshold) over the holdout set, it has effectively

learned of correlations between tracker presence and the advertiser’s behavior. When this occurs, ATOM extracts the information gain associated with each feature (i.e., tracker presence) from the model. This is a measure of the feature’s importance in aiding the model’s accuracy. ATOM makes an inference of a data sharing relationship between an advertiser and a tracker if the information gain associated with the tracker is more than one standard deviation higher than the mean information gain for all features. Note that this is a conservative approach to reduce the likelihood of false-positives.

The decision to use a random forest model was due to its interpretability and lower susceptibility to overfitting. The decision to use a holdout set for testing was to ensure that overfitting did not occur.

#### 4.1.5 Configuration for ATOM’s test deployment

*Data collection configuration.* Based on the data obtained from our analysis in §3.2, we selected the ‘games’ interest group in our test deployment of ATOM. To select trackers to analyze, we used the following process:

- *Obtaining a list of trackers present in the interest group.* We used EasyList to identify all tracking domains observed in the ‘games’ interest group using our crawl data from §3.
- *Identifying the parent organizations of identified trackers.* We used external data sources including WHOIS records, TLS certificates, and WebXray [61] to identify the parent organizations of each identified tracker. Organization names in WHOIS records and TLS certificates have been used and validated in prior work seeking to identify common owners of domains and network infrastructure [37, 43, 62, 66, 67]. This same process was also used to identify the parent organizations of advertisers.
- *Selecting trackers to analyze.* Using the organization names obtained from this process, we grouped all our tracking domains by their parent organization. We selected the ten organizations with the largest number of trackers as the subject of our test deployment. These organizations were: Alphabet, Rubicon, Adobe, GumGum, OpenX, Pubmatic, Index Exchange, Facebook, 33Across, and Oracle.

Each persona was then associated with one unique combination of blocked tracking organizations. This resulted

in a total of 1,024 (i.e.,  $2^{10}$ ) personas. An additional 100 *control personas* that performed *no tracker blocking* were also created. Finally, each persona began their data collection as described in §4.1.1-§4.1.2. The process was repeated ten times over the period of two months.

*Analysis configuration.* Our test deployment split the ten sets of vector records such that eight sets were used for cross-validation and two sets were used for holdout testing. A 60% threshold was used for relationship inference — i.e., we only report inferences from models that had higher than 60% accuracy on the holdout data.

## 4.2 Results

We now present the results of our test deployment of ATOM. Specifically, we: (§4.2.1) present relationship inferences made by ATOM using the configuration outlined in §4.1.5 and then (§4.2.2) validate these inferences using existing techniques to identify tracker-advertising data sharing relationships.

### 4.2.1 Relationships inferred by ATOM

*Advertiser model accuracy.* In total, the models developed by ATOM for nine advertisers were found to have an accuracy higher than our 60% threshold. A summary of our results for these models is provided in Table 3. We find that the accuracy of models built to understand OpenX, EAI, and The Trade Desk was 100%. Further analysis shows that this occurs when a very large fraction of tracker blocking configurations (i.e., personas) result in statistically different ads than the control — suggesting that these organizations have relationships with nearly all of the ten largest tracking organizations. This is confirmed by the presence of a nearly uniform distribution of information gain across all trackers and low standard deviation of information gain. In general, we find that our models outperform previous work using bid values as a side channel.

*Relationships inferred from model interpretation.* ATOM was able to identify 11 tracker-advertiser relationships for nine advertisers. We note that our decision to only return the relationships with a information gain of one standard deviation higher than the mean results in very conservative inferences about the existence of data sharing relationships. This was specifically chosen to reduce the rate of false-positives from our deployment. Of the nine advertisers, Alphabet appears

Advertiser	Accuracy	Inferred relationships
OpenX	100%	Oracle <sup>1</sup> (.12), Alphabet <sup>2</sup> (.12)
Exp.Ad.Intel	100%	OpenX <sup>2</sup> (.27)
Trade Desk	100%	GumGum <sup>2</sup> (.15)
Adform	99%	Alphabet <sup>2</sup> (.20)
Pubmatic	97%	Alphabet <sup>2,3</sup> (.15)
Media Math	96%	OpenX <sup>2</sup> (.17), Facebook (.15)
Amazon	88%	Alphabet <sup>2</sup> (.66)
Flashtalking	86%	Alphabet (.67)
Criteo	60%	Alphabet (.90)

**Table 3.** Summary of advertiser model performances and inferred relationships. ‘Accuracy’ denotes the constructed model’s performance over the holdout set. ‘Inferred relationships’ denotes the trackers identified by ATOM to have highest influence on the corresponding advertiser’s performance and their corresponding information gains. <sup>1</sup>, <sup>2</sup>, and <sup>3</sup> denote that the relationship was verified using CCPA disclosure documents, analysis of client-side cookie syncing, and by analyzing header bidding bids, respectively.

as one of the most influential data suppliers to six. This is not surprising since: (1) Alphabet trackers are the most widespread and (2) their dominance in the RTB bidding ecosystem (as an SSP, adexchange, and DSP) is well known. Interestingly, from the information gain associated with Alphabet trackers, we find that several large advertisers including Amazon, Flashtalking, and Criteo appear to have nearly exclusive relationships with Alphabet amongst the ten largest tracking organizations. OpenX was the second most connected tracker with relationships to Exponential Advertising Intelligence and Media Math.

#### 4.2.2 Validation of inferred relationships

To validate our results we use prior work (analyzing bid values and cookie syncing) and external sources of data (CCPA public data sharing disclosures) to identify data sharing relationships. We were able to validate nine of our 11 inferred data sharing relationships.

*Validation via CCPA disclosures.* In accordance with the CCPA, all data brokers must disclose their data sharing partnerships. These can be identified through analysis of their privacy policies. Unfortunately, the CCPA’s limited definition of a data broker does not include the trading of de-identified user data obtained by typical online trackers. Therefore, of all the tracking organizations in our test deployment, only Oracle is currently registered as a data broker. We were able

to verify the relationship between Oracle and OpenX through their disclosure.

*Validation via KASHF [44].* KASHF identifies data sharing relationships by analyzing changes in an advertiser’s bid values for a persona. This bidding behavior is visible for the specific case where publishers facilitate client-side header bidding using prebid.js. During our experiment with ATOM, all header bidding bids were recorded during the data collection. We used KASHF on this dataset of bids. We were able to validate the relationship between Alphabet and Pubmatic. No other relationships could be identified or validated.

*Validation via client-side cookie syncing.* Finally, we validate each of our inferred data sharing partners by analyzing our data for cookie syncing relationships between them. Cookie syncing is identified by finding any redirect chains that contain a cookie. We use the framework developed by Iqbal et al. [54] to identify cookie syncing from our logs of HTTP requests and responses. In total, we identified 7 advertisers engaging in cookie syncing relationships. Of these, 4 were performing cookie syncing with an Alphabet-owned tracker.

#### 4.2.3 Takeaways

Taken all together, we conclude that the *characteristics of ad creatives can be used to infer tracker-advertiser data sharing relationships*. We prove this hypothesis by building and deploying ATOM. By only leveraging features from personalized ads, ATOM is able to build high quality models of several advertisers and infer their data sharing relationships with trackers (§4.2.1) while maintaining a low false-positive rate (§4.2.2).

## 5 Related work

**Measurements of data gathering practices.** Significant work has been done to catalog the data gathering practices of online advertisers and trackers. Krishnamurthy et al. performed longitudinal measurements, using automated browser extensions, to quantify prevalence of trackers [56, 57]. They showed a 30% increase in tracker presence on popular websites. Following work by Roesner et al. [68] measured more complicated aspects of tracking such as cookie syncing. Analyzing a wider range of tracking mechanisms allowed them to show that 20% of a users browsing history is gathered by trackers.

Whereas, works by Cahn et al. [41] and Papadopoulos et al. [65] on characteristics of web cookies and cookie syncing, established high prevalence of cross site tracking using cookies. Most recently, Iqbal et al. [52, 53] used machine learning approaches to identify a variety of stateful and stateless tracking approaches used by online trackers. Other work has focused on the interplay between the data gathering and online targeting ecosystems. Specifically, Olejnik et al. [63, 64] measured how mechanisms of the online advertising ecosystem (such as Real Time Bidding) could be exploited to facilitate user data gathering. Bashir et al. [39] further highlighted this by empirically demonstrating that mechanisms such as Real Time Bidding were exploited by many online tracking entities to provide them with access to up to 92% of a user’s browsing history. Research contributions have also included the development of platforms and methodologies for measuring online data gathering practices. For example, researchers have built tools such as XRay [60], FPDetective [35], OpenWPM [48], and AdGraph [53] to enable reliable and scalable measurements of online tracking behaviors.

**Measurements of data sharing practices.** Data gathering has been studied extensively due to its visibility in the browser. However, it becomes extremely difficult to observe data after it exits the browser. Furthermore, as highlighted in §2.2, advertisers and trackers have a natural incentive to share data to maximize their performance and revenue. This makes it crucial to understand these data flows. To our knowledge only two works in the past attempt to address this issue. Bashir et al. [38] trained personas and gathered retargeted ads to uncover data flows between trackers and online retargeting advertisers. The key idea being that: If an advertiser  $A$ , serves a retargeted ad to a persona without observing it directly, this behavior can be indicative of server-side data sharing between  $A$  and the trackers that observed the persona. This technique sets a lower bound on identifying server side relationships as it only considers a specific case of personalized advertising — i.e., retargeting. Furthermore, manually identifying retargeted ads faces serious scalability challenges. *In contrast with this work, ATOM programmatically includes all categories of possible personalized ads — not just retargeted ads.* Cook et al. [44] introduced KASHF, a programmatic framework to train personas and identify server side relationships. Leveraging exposure to bid values from client side Header Bidding, KASHF measures correlation between presence of a tracker and bid values. If blocking a tracker during persona train-

ing alters bidding patterns of an advertiser, they conclude there exists a relationship between said tracker and advertiser. KASHF uncovers several tracker advertiser relationships which were previously unknown. The sustainability of KASHF takes a hit as publishers migrate towards server side Header Bidding, eliminating the crucial vantage point KASHF requires. Our work ATOM, builds upon KASHF, as an ad-delivery / artifact-availability agnostic framework. *ATOM uses ad creatives instead of bid values to infer relationships between trackers and advertisers, awarding it immunity against changes in publisher or advertiser practices.* Common to both these prior approaches and our own is the concept of ‘network tomography’ [4] as the fundamental measurement approach. Essentially, these studies make inferences about the internals of the ad ecosystem by predictably modifying its input and monitoring the effects of these modifications on the observable outputs. These pairs of inputs and outputs are then used to make inferences about the unobservable internals of the ecosystem. The idea has been used widely in the context of Internet measurement. For example, Bu et al. [40] leveraged the principles of network tomography to infer a network’s internal link-level performance by analyzing end-to-end multicast measurements from a collection of trees. Similarly Castro et al. [42] provided an overview of using network tomography to measure link and router level performances in large scale communication networks whereas, Lawrence et al. [59] catalogs developments surrounding network tomography with a focus on active network tomography.

## 6 Discussion

### Evolution of the online advertising ecosystem.

In recent years, users’ privacy-awareness has significantly increased. This has spurred many changes in the technologies and regulations surrounding user data. Notably, regulators and developers of popular browsers have sought to limit privacy-invasive behaviors by forcing transparency of data handling practices and providing the user with more control over their data. Unfortunately, this has resulted in the rapid development of technologies to circumvent these protections. One such example is the development of server-side cookie syncing solutions such as UnifiedID as a response to browser limitations on tracking via third-party cookies. Given the current push towards server-side solutions for advertising and tracking, it is predictable that measurement of

the online data ecosystem will become more challenging. ATOM aims to address this push towards server-side tracking and sharing technologies by developing a framework for identifying data sharing relationships even when they are not visible to the client. By leveraging the output of the advertising ecosystem rather than a specific artifact within it, ATOM is expected to remain useful despite the rapid churn in technology.

#### **Frameworks to improve regulatory enforcement.**

As user data and advertising continue to remain the primary monetization model for the Internet, users can expect limited transparency and consent in to how their data is being used. Recent regulatory efforts such as the GDPR, CCPA, and CDPA have sought to remedy these harms. However, a major impediment to their effectiveness is the inability to measure their violations and the limited resources available to the bodies that are tasked with enforcing them. It is crucial for researchers and governing bodies to invest in the development of auditing frameworks to address these challenges. ATOM contributes to this need by providing a general framework for gathering statistically grounded evidence for potential violations of data sharing disclosure regulations.

**Limitations.** Fundamentally, ATOM is a best-effort attempt to develop an artifact- and mechanism-independent method to identify data sharing relationships in the online behavioral advertising ecosystem. It faces several limitations that impact its capabilities.

*Scalability.* In our test deployment of ATOM, we face many challenges related to scalability. Most notably, in order to account for the possibility of one advertiser having sharing relationships with multiple trackers, we need to consider all possible combinations of tracker blocking configurations — a challenge that resulted in the need to synchronize crawls for 1024 personas. However, given the current oligopoly in the tracking ecosystem, we plan to address this challenge with scale, by re-configuring ATOM to focus on a smaller set of trackers and increasing our focus on ads from a larger number of advertisers.

*Completeness of ad corpus.* ATOM captures and identifies ‘ad images’ only and depends on filter lists to identify these ads. We acknowledge that due to the absence of an exhaustive and programmatic ad identifying mechanism, our ad corpus is incomplete. We also plan to integrate other forms of media (video, gif, multilayered ads) to ATOM in the future. However, our current results demonstrate that we can infer server side relationships by only using ad images with high significance.

*Contract ads.* Since it is impossible to differentiate between programmatic and contract ads, we collect both. Programmatic ads are delivered via HB or RTB and facilitate personalized ads, whereas contract ads are fixed for a website irrespective of users. However, since contract ads are website specific, their presence in each persona would assign them low significance in our analysis.

*Simplistic ad features.* We rely on very simple, yet seemingly effective features, extracted from ad creatives by the Google Vision API. This decision was made based on the manual validation from our pilot experiment concerning the quality of other extracted features. It remains unclear if more advanced image processing tools might improve the performance of ATOM.

*Probabilistic results.* As described in §4.1.4, this research effort is complicated by the inherently probabilistic nature of online advertising. This restricts our ability to make claims of definite relationships between trackers and advertisers. Instead, we can only provide statistically sound evidence of these relationships. We address this limitation by configuring ATOM to conservatively infer errors.

*Lack of validation mechanisms.* Given the inability to validate the correctness of all our inferences, we limit our use of ATOM as a tool to inform stakeholders of *potential violations* of disclosure regulations and motivate deeper investigations.

**Conclusions.** In this paper, we presented ATOM — an artifact- and protocol-independent mechanism for identifying data sharing relationships in the online advertising ecosystem. ATOM is built on the insight that personalized ads themselves contain information about an advertiser’s knowledge of a user’s activities. We demonstrate the validity of this insight (§3) and then operationalize it (§4) to uncover data sharing relationships, including those not visible to a user’s browser and those not discovered by any existing methods.

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