Analyzing Facebook Political Advertisers' Targeting

Avijit Ghosh* Giridhari Venkatadri† Alan Mislove†
*IIT Kharagpur †Northeastern University

***Abstract*—Online advertising—now with aggregate revenues in the hundreds of billions of dollars each year—is strongly driven by targeting, or the ability for an advertising platform to help an advertiser select exactly which users should see their ad. To enable such targeting, advertising platforms routinely collect detailed data on users, a practice which has led to a raucous debate over privacy. Unfortunately, regulators and the public at large often have little visibility into these advertising platforms, as the providers are often resistant to transparency. Recent events, however, have caused platforms to start offering limited transparency for political ads.**

In this paper, we focus on Facebook and collect data from Facebook's Political Ad Archive on *all* political ads corresponding to a large list of political advertisers. We then cross-reference this data set with the crowdsourced ProPublica Political Ad Database (which contains information about ads' targeting parameters), allowing us to have ground truth data on advertising campaigns' impressions, money spent, and targeting parameters. Analyzing the resulting data set, we find that well-funded advertisers tend to use privacy-sensitive targeting features more frequently and that less-well-funded advertisers tend to more narrowly target their audiences geographically. We will make the resulting data sets available to the community to enable further study.

I. Introduction

Advertising now funds most of the popular web sites and internet services: companies including Facebook, Twitter, and Google all provide their services for free, in exchange for collecting data from their users as they interact with the service. In fact, these services now have aggregate advertising revenues in the hundreds of billions of dollars each year. The user data that they collect is filtered, aggregated, processed, and mined, and then used to offer enhanced targeting features to advertisers (allowing advertisers to specify who should see their ads in ever more complex ways).

Unfortunately researchers, regulators, and the public at large have little visibility into the resulting advertising ecosystem, with almost no understanding of how different advertisers use the targeting features. Some services have built "transparency" tools for end users that claim to show users the data about them and how it is used, but these tools have been shown to present only a sanitized version of the data platforms have collected [2], [24]. What we do know about these platforms is often collected from end user contributions of ads [1], [2], which typically suffer from a small, potentially biased, sample size. Moreover, most platforms do not reveal much to end users about how they were targeted, nor do they reveal information about the total impressions or monetary cost of ads. The result is that as these advertising platforms are affecting our society to an even greater degree, we still have very little understanding of how they are being (mis)used.

Recent events, however, have opened up new opportunities. The fallout from malicious ads during the 2016 U.S. election [18], compounded with the privacy issues brought up by the Cambridge Analytica scandal [23], has lead to advertising platforms being under pressure from regulators and the public to reveal information on how their platforms are being used during political campaigns. In particular, Google [14], Twitter [4], and Facebook [11] have all released tools that provide information about ads that are being run, including aggregate impressions and monetary cost.

In this paper, we focus on Facebook's tool and use this new data source to examine the behavior of advertisers. We aim to better understand how advertisers are using targeting features at a platform-wide scale, and to better understand how this behavior is correlated with advertiser spend. For example, which advertisers are using more privacy-sensitive targeting features? How prevalent is the use of these features overall?

To perform our analysis, we collect data on all advertisements that have been made available from Facebook's Ad Archive [11] for 10,691 advertisers, covering 640,517 ads and over 15B impressions. The above large list of political advertisers is derived from a large set of crowdsourced political ads, obtained from ProPublica's Facebook Ad Database [20]. While Facebook's Ad Archive includes impression statistics and monetary cost, it does not provide information on targeting. To obtain information about how these ads were targeted, we cross-reference this data set with ProPublica's Ad Database, finding matches for 193,778 of these ads. We then use the resulting cross-referenced data set to examine the targeting strategies used by advertisers.

Overall, this paper makes the following contributions:

- We reverse-engineer Facebook's Ad Archive, and download statistics on all ads (for a large list of 10,691 political advertisers) up through December 12, 2018. We will make this data set available to the community.
- We develop techniques to cross-reference this data set with the targeting information from ProPublica's Ad Database, making the resulting cross-referenced data set available to the community as well.
- We find that well-funded advertisers use privacy-sensitive targeting mechanisms more frequently, with over 40% of ads run by the most well-funded advertisers targeted using contact lists (e.g., users' personally-identifiable information) and almost 20% using look-alike targeting.
- We find that less well-funded advertisers tend to advertise to more focused geographic areas and use more general user demographic targeting, possibly due to less sophistication and a more geographically-focused customer base.

II. Background and Related Work

We begin by providing context about Facebook's advertising platform, and about the relevant transparency services used, before discussing related work.

A. Facebook's advertising platform

Facebook leverages detailed user data to provide a feature-rich advertising platform [8] for advertisers to target ads to Facebook users. An ad on Facebook's ad platform must always have a Facebook page associated with it (which we refer to as a *Page ID*, as there is a unique identifier for each page), and typically consists of the name and thumbnail of the page, some text content, some image or video content, and a landing webpage that is reached by clicking on the ad.

The advertising platform supports several types of targeting [12]; we briefly describe the salient types.

Attribute-based targeting In addition to age, gender and location, advertisers can target users based on a wide range of various other attributes, which are typically grouped into one of three types: demographics, behaviors, and interests [2]. Advertisers can also target users using combinations of these attributes (combining attributes via or, and, or negation operations). Facebook then creates an *audience* of matching users, which the advertiser can then target ads to.

Activity-based targeting Advertisers can target users who performed a specific activity (e.g. visited the advertiser's website, performed a specific action on the advertiser's website, used the advertiser's app etc.)

PII-based targeting Advertisers can target specific users (e.g. their past customers), as Facebook's platform allows advertisers to upload a list of personally identifying information (PII) [5] corresponding to those users. Facebook then internally matches the uploaded data to Facebook users. Facebook refers to both audiences created using PII-based targeting, and those created using activity-based targeting as *custom audiences* [27].

Lookalike targeting To help advertisers reach users who are similar to their past customers, Facebook's platform allows advertisers to create audiences of users who are "similar to" [13] a custom audience that the advertiser has created.

In addition to specifying the targeting for a given ad, advertisers can choose to have the delivery of their ad optimized according to different objectives (such as delivery to the maximum number of people), can use different strategies to bid on these optimization events, and can set budgets (such as a daily or lifetime budget) for their ads.

B. Facebook political Ad Archive

To address regulatory concerns about political ads following the Cambridge Analytica scandal [23], Facebook launched an Ad Archive [11] on May 24, 2018. The repository obstensibly contains all of the advertisements that Facebook deems to be political in nature [11]:

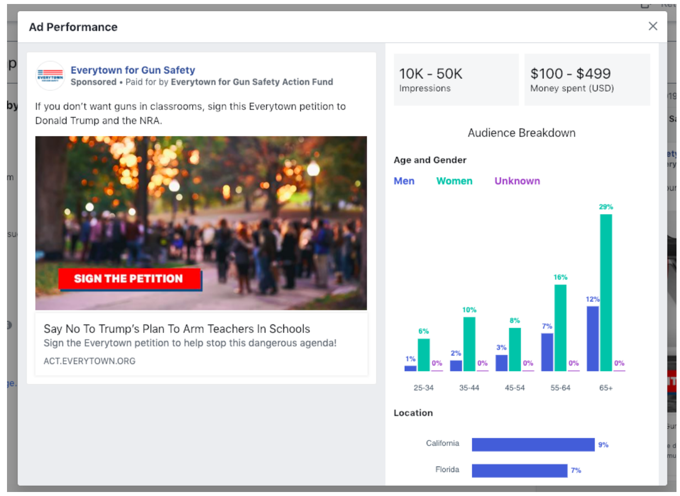


Fig. 1: Example data from Facebook's Ad Archive, showing impression and monetary statistics for a given ad campaign.

> The Ad Archive contains ads about elected officials, candidates for public office and issues of national importance, such as education or immigration.

Facebook's Ad Archive does not directly provide a list of all political ads; instead, it is searchable via free text queries over the ad content and advertiser's Page ID. Results can further be filtered to only cover certain Facebook pages, certain countries (currently Brazil, the U.K, and the U.S. are supported), particular ad types (where ads are classified into either political and issue-based ads, or news ads), and whether the ad is currently active.

Figure 1 presents a snapshot of a typical result from the Ad Archive. For each ad, the Archive contains the (a) Page ID that ran the ad, (b) content of the ad, (c) lifetime, (d) source of funding, (e) total number of ad impressions corresponding to the ad, (f) the total amount of money spent on the ad, (g) breakdown of impressions jointly across age and gender, and (h) breakdown of impressions across location (typically states for U.S. based ads). Importantly, the archive *does not* contain any information about the targeting mechanisms used; it only provides information on how it was ultimately delivered.

C. ProPublica political Ad Database

With the aim of increasing the transparency around political advertising, ProPublica (a non-profit newsroom focusing on investigative journalism) developed a browser extension [21] to collect political ads on Facebook in a crowdsourced manner. The extension collects ads seen by users as they browse Facebook, along with the explanations provided by Facebook for why the users are seeing these ads (containing limited information [2] about how the ad was targeted). In fact, Facebook recently moved to block ProPublica's browser extension [17], further underscoring the importance of increasing transparency of how ad platforms are used.

Similar to Facebook's Ad Archive, ProPublica's Ad Database also focuses on political ads and uses a pre-trained, continuously-updated machine learning algorithm to identify which ads are political [16]; these are then released as a database that is updated daily and can be downloaded as a whole [20] or searched via an interface [10]. As of January 29, 2019, the ProPublica extension has 9,832 users on Google Chrome and 3,828 users on Firefox (as revealed by the respective web stores). The extension is used in several countries, including Germany, Italy, Australia, Austria and the U.S. [9].

D. Related work

We now briefly review work related to the present study.

Online advertising platforms A number of recent studies investigated the major advertising platforms (including those of Facebook and Google) and found a number of privacy issues including privacy leaks [7], [15], [26] and discriminatory advertising [6], [22], [25]. Facebook's *Why am I seeing this ad?* mechanism, which aims to explain why a user was targeted with a particular ad, was studied in detail in [2]. This work demonstrated via controlled experiments that these explanations were often incomplete; for example, at most one out of multiple targeting attributes specified by the advertiser was revealed, with attributes sourced from external data brokers *never* being revealed. However, this limited mechanism is the only source of data on ad targeting available to end users.

Advertiser behavior A recent study [1] used a browser extension to collect ads and their accompanying explanations (similar to ProPublica) from over 600 users and thus study the Facebook advertising ecosystem. However, this study has the drawback that it does not have a global view of the system, including information about advertisers' ad inventories, about the total money spent on each ad, etc.

Another ongoing project [19] is actively collecting and archiving political advertising data from the political ad archives of multiple sites, including Facebook. Their project is complementary to ours: they focus on collecting and analyzing data from multiple ad platforms' transparency services, while we focus on cross-referencing the ads with targeting information from crowdsourced data sources.

III. Dataset collection

In this section, we describe our dataset and the methodology we used to collect it.

A. Obtaining a set of political ads

Recall that the only way to view data in Facebook's Ad Archive is by searching for free-text terms or for the advertiser's Page ID. Thus, one way to "crawl" the Ad Archive is by issuing a number of different queries with differing search terms; however doing so may be subject to bias due to the choice of search terms. Instead, we first identify a set of Page IDs, and then collect *all* of their ads. We start with the set of advertisements in the ProPublica Ad Database (described in Section II-C), as it represents a large database of political advertisements seen on Facebook by U.S.-based users.

We downloaded the ProPublica Ad Database on December 12, 2018; we found that it contained 82,120 ads seen between May 7, 2018 and December 12, 2018. These 82,120 ads represented 46,939 ads with distinct content[1] from 10,691 unique advertisers. Unfortunately, ProPublica's data set does not contain the Page ID of the advertiser, but does contain a link to the advertiser's Facebook page; to obtain their Page ID, we visited each Facebook page and obtained the Page ID from inside the HTML.

B. Collecting the political ad inventory

Using our browser's inspect feature, we reverse-engineered the Facebook Ad Archive search functionality and found the underlying API call (parameterized by either search keywords or the Page ID) that browsers make when searching for ads. For each of the 10,691 pages, we queried the above API with the Facebook Page ID, and obtained the list of the ads run by the advertiser that were in the Ad Archive.[2,3]

For each ad, we then obtained the information about the ad's performance (impressions, money spent, etc) via a second API call that we reverse-engineered in a similar manner in to the first one. The information about ad performance returned by this API call is coarse-grained: the total money spent is only reported as a range of values (e.g., <$100, $100-$499, $500-$999, ... >$1M). Similarly the total number of impressions is reported in ranges (e.g., <1K, 1K-5K, 5K-10K, ..., >1M), and the distribution of demographics is only reported in terms of overall percentages that are rounded to integers. For our analysis, we consider the total money spent on—and the total number of impressions received by—a particular ad as the mid-point of the range reported for that ad.

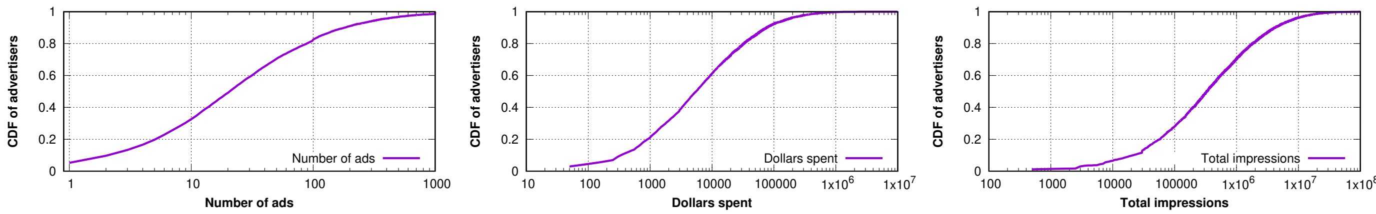
All together, we collected data on 640,517 U.S.-based ads from the Facebook Ad Archive, corresponding to 8,414 Page IDs.[4] Just as with the ProPublica Ad Database, we found that ads with the same content could be surfaced as multiple independent results by Facebook's political ad inventory: only 175,564 (27.4%) of these ads had unique content and Page ID. Multiple results with the same ad content typically differed in terms of the distribution of users reached, or the total amount spent, or the range of dates over which the ad ran, suggesting that they could correspond to different runs of the same ad (varying the targeting parameters or at different points in time).

[1] We observed that when two ads in the database had the same advertiser and text, they differed in terms of their targeting information.

[2] The query requires us to specify a limit on the number of resulting ads. For each advertiser, we set this limit to be 1,000 to be sufficiently large. 10,448 out of the 10,691 advertisers had fewer than 1,000 ads; we might miss some ads for the remaining 243 advertisers.

[3] In our original crawl on December 12, 2018, we observed that 1,284 pages (12.0%) had *exactly* 100 ads returned by Facebook's API. We suspected an error, so on January 29, 2019 we re-crawled all 1,725 pages where Facebook returned 100 or more ads; to make this data comparable with the remainder, we then discarded all ads that started after December 12, 2018 and kept the performance of the ads active on December 12, 2018 from the original crawl. As expected, the "spike" of pages with exactly 100 ads went down dramatically, confirming a likely data collection error.

[4] There were 2,277 Page IDs for which the Facebook Ad Archive returned 0 ads. This is likely an artifact of the difference in political ad detection methodology between Facebook and ProPublica.



(a) (b) (c)

Fig. 2: Aggregate statistics about advertisers. The figures show the distribution of the number of ads run, the total money spent, and the total impressions achieved by ads from different advertisers, respectively.

C. Associating targeting information

Since Facebook's Ad Archive only contains information about the impressions (i.e., the demographics of users who were ultimately shown the ad), we supplement this with information from ProPublica's Ad Database concerning how each ad was targeted by the advertiser. Unfortunately, associating individual ads from Facebook's Ad Archive with ads from ProPublica's Ad Database is non-trivial as ProPublica does not include the individual Ad ID. Thus, we associate ads between Facebook and ProPublica based on matching (a) the name of the page running the ad, (b) the title of the ad, and (c) the text of the ad itself; only if all three match do we associate the two ads.[5]

Out of the 175,564 unique ads (ad content and Page ID) that we collected from Facebook's Ad Archive, we found at least one match in ProPublica's Ad Databases for 20,918 (11.91%), and multiple matches for 6,626 (3.77%).[6] These 27,544 unique ads correspond to 193,778 total ads in the Facebook Ad Archive (recall that ads appear multiple times if the advertiser runs the same ad with different targeting parameters). The relatively low rate of matching is likely due to the crowdsourced nature of the ProPublica data set—with fewer than 15,000 users having the ProPublica browser extension, it is unsurprising that many of the ads on Facebook were not seen by these users.

We then obtained the targeting information for the ads in the ProPublica Ad Archive by parsing the raw "ad explanation" HTML scraped by ProPublica. We then matched it against a set of patterns derived from prior work [2], mapping each of the explanations into one of the following categories: *PII-based Targeting*, *Data Brokers*, *Lookalike Audience*, *Interests*, *Data from Mobile*, *Biographical Data*, *Behavioral/Demographics*, *Social Neighborhood*, *Responded to Event*, *Age/Gender/Location*, and *Liked Advertiser's Page*.

[5]We do not match by the ad image as we found that these were compressed differently in the two archives.

[6]Each ad in the Facebook Ad Archive was unique, as identified by the unique Ad ID. However, the ads shown on Propublica could not be ascertained to have come from unique ads, since Facebook allows an ad to have multiple targeting parameters and the explanation text changes depends on which user receives it [2]. Therefore, for all the matches found in the ProPublica Ad Database for a particular ad in Facebook's Ad Archive, we assume that *all* those targeting types were used for the particular ad in the merged dataset.

D. Limitations

Before proceeding with our analysis, there are a few important limitations of our dataset that are worth calling attention to. First, our analysis is limited *only* to political ads, and may not be representative of other advertising domains. This limitation is a function of data availability; both Facebook's and ProPublica's databases only contain ads determined to be political in nature. Were other data sources available, we could easily extend our analysis to incorporate those ads. Second, as discussed above, both Facebook and ProPublica have different methodologies for determining what ads are political. Thus there may be discrepancies between the two, causing ads to be collected by one data set but not the other.

IV. Analysis

We now analyze the dataset collected in the previous section, focusing on the overall characteristics of the advertisers, how they target users, and how that varies with advertiser funding. Throughout this section, our analysis of targeting information is limited to the 193,778 ads that we were able to cross-reference with ProPublica's Ad Database; all other analyses are over our entire dataset of 640,517 ads.

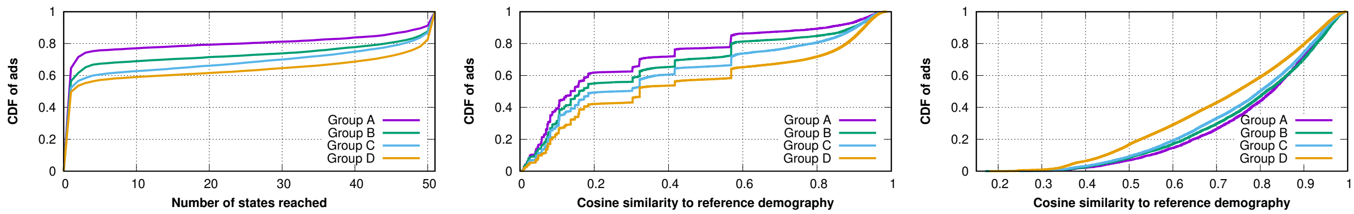
A. Analysis of money spent

We begin by plotting the cumulative distribution of the total number of ads (Figure 2a), the total amount spent Figure 2b, and the total impressions Figure 2c, for each page ID (advertiser). We can immediately observe a wide range of amounts spent, ranging from a few tens of dollars to millions of dollars, with the median advertiser spending a total of $5,500.

In order to understand how the targeting behavior of advertisers with different budgets varies, we divided the advertisers into four equal-sized quantiles based on their total amount spent. *Group A* contains one quarter of the pages, consisting of those spending between $0 and $1,299. Similarly, *Group*

Group	Pages	Ads	Total Spent	$/Ad
A	2,122	13,557	$1,177,700	$86.87
B	2,075	48,421	$6,299,450	$130.09
C	2,115	114,042	$25,079,750	$219.91
D	2,102	464,497	$270,310,750	$581.94

TABLE I: Aggregate advertising activity across groups of advertisers with different ranges of budgets



(a) (b) (c)

Fig. 3: Comparison of advertiser impression distributions for different Groups. (a) shows the number of states targeted by different advertisers. (b) and (c) present the cumulative distribution of cosine similarity between the impression distribution and the overall Facebook population for location (for (b)) and age/gender (for (c)).

B contains those spending between $1,300 and $5,500; *Group C* contains those spending between $5,500 and $22,900, and *Group D* contains those spending over $22,900.

To further characterize advertisers within each group above, we present their aggregate advertising activity in Table I. We see unsurprisingly that the advertisers who spend the most run the most ads, and represent the vast majority of the overall ad revenue (over 89%). However, we also observe that when we control for the number of ads run, the advertisers in Group D also spend substantially more *per ad*, suggesting that they run their campaigns differently from advertisers who spend less.

B. Variation in targeting behavior

Next, to examine how these advertisers target their ads, we present the distribution of targeting strategies used for ads run by the groups of advertisers in Table II. We see that as advertisers' budgets grow, they make more frequent use of PII-based targeting and Lookalike Audiences: for example, Lookalike Audiences increases over four-fold in frequency from Group A to Group D ads. Using these two targeting features brings up privacy concerns, as they are based on either advertisers uploading users' personal information or by users' activity on third-party websites and apps. Moreover, these two targeting features also suggest increased advertiser sophistication, as advertisers themselves have to bring data to Facebook to use these (as opposed to, say, Interests, which is generated entirely by Facebook). In parallel, we observe that generic targeting features (e.g., Age/Gender/Location) are much more common for advertisers with lower budgets.

	% Ads for each Group			
Type of targeting (%)	**A**	**B**	**C**	**D**
Age/Gender/Location	25.53	14.31	9.01	6.01
Behavioral/Demographics	11.64	13.84	13.16	11.14
Biographical Data	0.47	0.53	0.44	0.58
Data Brokers	0.14	0.25	0.26	0.23
Data from Mobile	5.55	3.44	0.63	0.54
Interests	21.77	20.87	17.63	16.21
Liked Advertiser's Page	7.34	3.84	3.87	2.17
Lookalike Audience	4.27	7.36	17.85	17.05
PII-based Targeting	17.28	31.13	33.11	43.17
Social Neighborhood	2.86	1.16	0.67	0.26

TABLE II: Distribution of targeting strategies. Some ads lack targeting explanations, hence not all columns sum to 100%.

C. Variation in specificity of outcome

Finally, we examine the result of this different targeting by examining the distribution of impressions reported by Facebook. To do so, we compare each ad's impression distribution to the entire Facebook population using a reference distribution provided by Facebook's ad interface [3]. In other words, for each dimension (age/gender and location), we compute a vector of *all* Facebook users; we compute a similar vector for each ad's impressions. We then compare these two vectors using cosine similarity (which is 1 if they are identical, and 0 if they are completely divergent).

We plot the distributions of the cosine similarity of location (U.S. states) in Figure 3b and of age/gender in Figure 3c; we also plot the distribution of number of states reached in Figure 3a. We can see in Figure 3b that the Group A ads are more divergent from the overall Facebook user geographic distribution across U.S. states (the spikes occur when advertisers primarily target a single state). This is reinforced by Figure 3a, where we see that advertisers with lower budgets more frequently target a specific set of locations: while almost 65% of ads from Group A target a single state, only 50% of ads from Group D do so. However, in Figure 3c we observe that Group D is more divergent from the overall Facebook population in terms of age and gender.

These results are somewhat counter-intuitive, given that Group D uses sophisticated targeting techniques (such as PII-based targeting) more often. While we do not know the underlying reason for sure, we hypothesize that since the Group A advertisers use Facebook's basic targeting features more frequently, they are more likely to narrow their targeting based on location (as they are, by definition, more niche advertisers) but less likely to target in ways that would segregate based on age and gender. We leave a full exploration to future work.

V. Conclusion

The increasing influence of targeted advertising necessitates a better understanding of advertisers' targeting behavior. In this paper, we cross-referenced two advertising data sets to measure such behavior. We hope this paper serves as a starting point to analyze the databases now being provided by ad platforms.

REFERENCES

[1] A. Andreou, M. Silva, F. Benevenuto, O. Goga, P. Loiseau, and A. Mislove. Measuring the Facebook Advertising Ecosystem. *NDSS*, 2019.

[2] A. Andreou, G. Venkatadri, O. Goga, K. P. Gummadi, P. Loiseau, and A. Mislove. Investigating Ad Transparency Mechanisms in Social Media: A Case Study of Facebook's Explanations. *NDSS*, 2018.

[3] About Potential Reach. https://www.facebook.com/business/help/1665333080167380?helpref=faq_content.

[4] Twitter Ads Transparency Center. https://ads.twitter.com/transparency.

[5] Custom Audiences from your Customer List. https://www.facebook.com/business/help/606443329504150.

[6] A. Datta, M. C. Tschantz, and A. Datta. Automated Experiments on Ad Privacy Settings: A Tale of Opacity, Choice, and Discrimination. *PETS*, 2015.

[7] I. Faizullabhoy and A. Korolova. Facebook's Advertising Platform: New Attack Vectors and the Need for Interventions. *CoRR*, https://arxiv.org/abs/1803.10099, Workshop on Technology and Consumer Protection (ConPro), 2018.

[8] Facebook Ad Platform. https://www.facebook.com/business.

[9] Facebook Political Ad Collector. https://projects.propublica.org/facebook-ads/.

[10] Facebook Political Ad Collector Searchable Interface. https://projects.propublica.org/facebook-ads/.

[11] Facebook Political Ads Archive. https://www.facebook.com/ads/archive/.

[12] Facebook ad targeting options. https://www.facebook.com/business/ads/ad-targeting.

[13] Facebook: About Lookalike Audiences. https://www.facebook.com/business/help/164749007013531.

[14] Google Ad Transparency Report. https://transparencyreport.google.com/political-ads/library.

[15] A. Korolova. Privacy Violations Using Microtargeted Ads: A Case Study. *Journal of Privacy and Confidentiality*, 3(1), 2011.

[16] J. Larson, J. Angwin, and J. Valentino-DeVries. How We Are Monitoring Political Ads on Facebook. https://www.propublica.org/article/how-we-are-monitoring-political-ads-on-facebook.

[17] J. B. Merrill and A. Tobin. Facebook Moves to Block Ad Transparency Tools—Including Ours. https://www.propublica.org/article/facebook-blocks-ad-transparency-tools.

[18] H. P. N, G. Bharath, L. Dimitra, K. John, and F. Camille. The IRA, Social Media and Political Polarization in the United States, 2012-2018. *Oxford Computational Propaganda Research Project*, 2018.

[19] Online Political Ads Transparency Project. https://engineering.nyu.edu/online-political-ads-transparency-project.

[20] Political Advertisements from Facebook. https://www.propublica.org/datastore/dataset/political-advertisements-from-facebook/.

[21] Propublica Political Ad Collector. https://projects.propublica.org/political-ad-collector/.

[22] L. Sweeney. Discrimination in Online Ad Delivery. *SSRN*, 2013.

[23] M. Schroepfer. An Update on Our Plans to Restrict Data Access on Facebook. 2018. https://newsroom.fb.com/news/2018/04/restricting-data-access/.

[24] N. Singer. Acxiom Lets Consumers See Data It Collects. https://www.nytimes.com/2013/09/05/technology/acxiom-lets-consumers-see-data-it-collects.html.

[25] T. Speicher, M. Ali, G. Venkatadri, F. N. Ribeiro, G. Arvanitakis, F. Benevenuto, K. P. Gummadi, P. Loiseau, and A. Mislove. On the Potential for Discrimination in Online Targeted Advertising. *FAT**, 2018.

[26] G. Venkatadri, Y. Liu, A. Andreou, O. Goga, P. Loiseau, A. Mislove, and K. P. Gummadi. Privacy Risks with Facebook's PII-based Targeting: Auditing a Data Broker's Advertising Interface. *IEEE S&P*, 2018.

[27] What's a Custom Audience from a Customer List? https://www.facebook.com/business/help/341425252616329/.