Measuring Personalization of Web Search

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Web search is an integral part of our daily lives. Recently, there has been a trend of personalization in Web search, where different users receive different results for the same search query. The increasing level of personalization is leading to concerns about Filter Bubble effects, where certain users are simply unable to access information that the search engines’ algorithm decides is irrelevant. Despite these concerns, there has been little quantification of the extent of personalization in Web search today, or the user attributes that cause it.

In light of this situation, we make three contributions. First, we develop a methodology for measuring personalization in Web search results. While conceptually simple, there are numerous details that our methodology must handle in order to accurately attribute differences in search results to personalization. Second, we apply our methodology to 200 users on Google Web Search and 100 users on Bing. We find that, on average, 11.7% of results show differences due to personalization on Google, while 15.8% of results are personalized on Bing, but that this varies widely by search query and by result ranking. Third, we investigate the user features used to personalize on Google Web Search and Bing. Surprisingly, we only find measurable personalization as a result of searching with a logged in account and the IP address of the searching user. Our results are a first step towards understanding the extent and effects of personalization on Web search engines today.

General Terms: Design, Measurement

Additional Key Words and Phrases: Internet Filter Bubble, Personalization

1 INTRODUCTION

Web search services like Bing and Google Web Search (Google Search) are an integral part of our daily lives; Google Search alone receives 17 billion queries per month from U.S. users [8]. People use Web search for a number of reasons, including finding authoritative sources on a topic, keeping abreast of breaking news, and making purchasing decisions. The search results that are returned, and their order, have significant implications: ranking certain results higher or lower can dramatically affect business outcomes (e.g., the popularity of search engine optimization services), political elections (e.g., U.S. Senator Rick Santorum’s battle with Google [60]), and foreign affairs (e.g., Google’s ongoing conflict with Chinese Web censors [67]).

Recently, major search engines have implemented personalization, where the Web search operator modifies the results—or their order—based on the user who is making the query [19, 56]. As previous work has noted [42], an effective personalized search engine is able to decide autonomously whether or not a user is interested in a specific webpage and, if so, display that result at a higher rank. For example, users searching for “pizza” in New
York and in Boston may receive different results corresponding to local restaurants. Search engine operators often choose to personalize results as it has been shown to provide significant benefits to users (e.g., disambiguation of similar search terms, and retrieval of locally relevant results). In fact, the benefits of such personalized rankings has been extensively studied in the research literature [15, 17, 30, 50].

Unfortunately, while the benefits of personalization are well-studied, the potential negative effects of personalization are not nearly as well-understood. For example, search engine operators do not typically label which of the returned results were personalized, or explain why those results were chosen; only operators themselves know the specifics of how the personalization algorithms alter the results. Compounding this problem is the fact that measuring personalization in practice poses many challenges, including obtaining large amounts of personal data, establishing a baseline for personalization, and distinguishing between inadvertent result changes and personalization.

As a result, the opaque personalization of Web search has led to growing concerns over the Filter Bubble effect [22], where users are only given results that the personalization algorithm thinks they want (while other, potentially important, results remain hidden). For example, Eli Pariser demonstrated that during the recent Egyptian revolution, different users searching for “Tahrir Square” received either links to news reports of protests, or links to travel agencies [39]. The Filter Bubble effect is exacerbated by the dual issues that most users do not know that search results are personalized, yet users tend to place blind faith in the quality of search results [36].

Concerns about the Filter Bubble effects are now appearing in the popular press [51, 57], driving growth in the popularity of alternative search engines that do not personalize results. Unfortunately, to date, there has been little scientific quantification of the basis and extent of search personalization in practice.

In this paper, we make three contributions towards remedying this situation. First, we develop a methodology for measuring personalization in Web search results. Measuring personalization is conceptually simple: one can run multiple searches for the same queries and compare the results. However, accurately attributing differences in returned search results to personalization requires accounting for a number of phenomena, including temporal changes in the search index, consistency issues in distributed search indices, and A/B tests being run by the search provider. We develop a methodology that is able to control for these phenomena and create a command-line-based implementation that we make available to the research community.

Second, we use this methodology to measure the extent of personalization on multiple popular Web search engines: Google Web Search, Bing Search, and DuckGo.1 We recruit 300 users with active Google and Bing accounts from Amazon’s Mechanical Turk to run a list of Web searches, and we measure the differences in search results that they are given. We control for differences in time, location, distributed infrastructure, and noise, allowing us to attribute any differences observed to personalization. Although our results are only a lower bound, we observe significant personalization: on average, 11.7% of Google Web Search results and 15.8% of Bing Search results show differences due to personalization, with higher probabilities for results towards the bottom of the page. We see the highest personalization for queries related to political issues, news, and local businesses. We do not observe any noticeable personalization on DuckDuckGo.

Third, we investigate the user features used to personalize, covering user-provided profile information, Web browser and operating system choice, search history, search-result-click history, and browsing history. We create numerous Google and Bing accounts and assign each a set of unique behaviors. We develop a standard list of 120 search queries that cover a variety of topics pulled from Google Zeitgeist [20] and WebMD [64]. We then measure the differences in results that are returned for this list of searches. Overall, we find that while the level of personalization is significant, there are very few user properties that lead to personalization. Contrary to our expectations, for both Google and Bing, we find that only being logged in to the service and the location (IP

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1DuckDuckGo is a relatively new search engine that claims to not track users or personalize results. As such, we do not expect to see personalized results, and we include our measurements of DuckDuckGo primarily as a baseline to compare Google Web Search and Bing Search against.
address) of the user’s machine result in measurable personalization. All other attributes do not result in level of personalization beyond the baseline noise level.

We view our work as a first step towards measuring and addressing the increasing level of personalization on the Web today. All Web search engines periodically introduce new techniques, thus any particular findings about the level and user features used to personalize may only be accurate for a small time window. However, our methodology can be applied periodically to determine if search services have changed. Additionally, although we focus on Web Search in this paper, our methodology naturally generalizes to other search services as well (e.g., news, products). Finally, our methodology may be useful for communities that routinely use search engines as part of their methodology (e.g., natural language processing or recommendation systems).

Roadmap. The remainder of this paper is organized as follows: in Section 2 we provide a background on Web search and personalization, and a discussion of related work. In Section 3 we describe our experimental methodology. In Section 4 we quantify real-world search personalization using results from crowdsourced workers, while in Section 5 we perform controlled experiments to ascertain what features search engines use to personalize results. Next, in Section 6, we examine how the personalization varies over time, across query categories, and by result rank. We conclude with a discussion of results, limitations, and future work on Section 7.

2 BACKGROUND AND RELATED WORK
We begin by providing an overview of web search and personalization, followed by a detailed discussion of related work in the research literature.

2.1 Background
Web search services are some of the most popular destinations on the Web; according to Alexa, Google and Bing are currently the 2nd and 16th most popular sites on the Internet. Google serves billions of search results per day [16], and controls roughly 67% of the US search market, although Bing has risen to control 17% of the market [54]. Alternative search engines like DuckDuckGo and Blekko have experienced some success offering advanced features to power-users, but they have not yet reached mainstream popularity.

Accounts. As the number and scope of the services provided by Microsoft and Google grew, they both began unifying their account management architecture. Today, Google Accounts are the single point of login for all Google services (e.g., Gmail, YouTube, Google Calendar). Once a user logs in to one of these services, they are effectively logged in to all services. A tracking cookie enables all of Google’s services to uniquely identify each logged in user. As of May 2012, Google’s privacy policy allows between-service information sharing across all Google services [68].

Similar to Google, Microsoft provides user accounts for its various services (e.g., Windows Live, Outlook.com, Xbox LIVE, Skype). These various accounts have been consolidated into a single “Microsoft account” (previously called a Windows Live ID); when a user is signed-in to this account, Bing searches are tracked and saved.

DuckDuckGo explicitly eschews the notion of accounts and users cannot "log in"; the company claims to not perform any tracking or profiling of its users.

Personalization. Google first introduced “Personalized Search” in 2004 [26], and merged this product into Google Search in 2005 [19]. In 2009, Google began personalizing search results for all users, even those without Google accounts [27]. Recently, Google started including personalized content from the Google+ social network into search results [53]. For example, users may see Web pages which were shared or “+1’d” by people in their Google+ circles alongside normal Google search results.

Bing Search introduced “Localized Results” [56] and “Adaptive Search” [10] in 2011, customizing search results using the user’s location and previous search history, respectively. In 2013, Bing added “Social Results” to
the results returned to the user, presenting links shared by a user’s Facebook friends alongside normal search results [9].

DuckDuckGo is explicitly designed to not personalize results.

Advertising and User Tracking. Both Google and Microsoft are capable of tracking users as they browse the Web due to their large advertising networks (e.g., DoubleClick and MSN Advertising). Roesner et al. provide an excellent overview of how Google can use cookies from DoubleClick and Google Analytics, as well as widgets from YouTube and Google+ to track users’ browsing habits [46]. Similarly, recent work [37] has shown that it is possible to do browser fingerprinting (essentially looking for unique browser-agents and other headers) as a method for sites to track returning users. In theory, data from any of these systems could be used to drive Web search personalization algorithms.

2.2 Related Work

Personalized search has been extensively studied in the literature [29, 41–43, 48, 58, 61, 62]. Dou et al. provide a comprehensive overview of techniques for personalizing search [14]. They evaluate many strategies for personalizing search, and conclude that mining user click histories leads to the most accurate results. In contrast, user profiles have low utility. The authors also note that personalization is not useful for all types of queries. A recent study investigated the inherent biases of search engines and their impact on the quality of information that reaches people [65] They show that the combined effect of people’s preferences and the system’s inherent bias results in settling on incorrect beliefs about half of the time.

Other features besides click history have been used to power personalized search. Three studies leverage geographic location to personalize search [2, 70, 71]. Two studies have shown that user demographics can be reliably inferred from browsing histories, which can be useful for personalizing content [18, 28]. To our knowledge, only one study has investigated privacy-preserving personalized search [69]. Given growing concerns about the Filter Bubble effects, this area seems promising for future research.

Several studies have looked at personalization on systems other than search. Two studies have examined personalization of targeted ads on the Web [24, 66]. One study examines discriminatory pricing on e-commerce sites, which is essentially personalization of prices [34].

In contrast to prior research which focused on building personalized Web services, work is now emerging that has similar goals to this study, i.e., quantifying personalization on deployed Web services. Majumder et al. propose a latent variable model to infer the features that a service provider is using to personalize content for a given user [32].

However, there is very little concrete information about how the biggest search engines such as Google and Bing personalize their search results. A 2011 post on the official Google blog states that Google Search personalizes results based on the user’s language, geolocation, history of search queries, and their Google+ social connections [52]. The specific uses of search history data are unclear: the blog post suggests that the temporal order of searches matters, as well as whether users click on results. Similarly, the specific uses of social data from Google+ are unknown.

Several studies have examined the differences between results from different search engines. Two studies have performed user studies to compare search engines [3, 63]. Although both studies uncover significant differences between competing search engines, neither study examines the impact of personalization. Sun et al. propose a method for visualizing different results from search engines that is based on expected weighted Hoeffding distance [59]. Although this technique is very promising, it does not scale to the size of our experiments.
3 METHODS

In this section, we describe our experimental methodology. First, we give the high-level intuition that guides the design of our experiments, and identify sources of noise that can lead to errors in data collection. Second, we describe the implementation of our experiments. Lastly, we introduce the queries we use to test for personalization.

3.1 Terminology

In this study, we use a specific set of terms when referring to Web search. Each query to a Web search engine is composed of one or more keywords. In response to a query, the search engine returns a page of results. Figure 1 shows a truncated example page of Google Search results for the query “coughs”, and Figure 2 shows a truncated example page of Bing Search results for the query “tornado.” Each page contains ≈ 10 results (in some cases there may be more or less). We highlight three results with red boxes in both figures. Most results contain ≥ 1 links. In this study, we only focus on the primary link in each result, which we highlight with red arrows in Figures 1 and 2.

In most cases, the primary link is organic, i.e., it points to a third-party website [6]. The WebMD result in Figure 1 falls into this category. However, the primary link may point to another Google or Microsoft service. For example, in Figure 1 the “News for coughs” link directs to Google News, and the “More news about Tornado” link in Figure 2 directs to Bing News. Search engines often include links to other services offered by the same company; this strategy is sometimes referred to as “aggregated search.”

A few services inserted in Web search results do not include a primary link. The “Related Searches” result in Figure 1 falls into this category. Another example is Google Dictionary, which displays the definition of a search keyword. In these cases, we treat the primary link of the result as a descriptive, static string, e.g., “Related” or “Dictionary.”

DuckDuckGo. Search results from DuckDuckGo follow a different format from Google and Bing. On DuckDuckGo, the top of the search result page is dominated by a box of contextual information related to the query. For example, after searching for “barack obama” the contextual box contains information about the president taken from Wikipedia, and links to recent news articles. Below the contextual box is the list of organic search results. Unlike Google and Bing, DuckDuckGo does not return multiple different pages of search results. Instead, the page continually loads more results as the user scrolls down the page.

In this study, we focus on the search results returned by DuckDuckGo, and ignore links in the contextual box. On DuckDuckGo, results are presented in a simple ordered list, so there is no problem of having multiple links in
one result. We focus on the top 10 results returned by DuckDuckGo, so that the analysis is comparable across the three search engines.

3.2 Experiment Design

Our study seeks to answer two broad questions. First, what user features influence Web search personalization algorithms? This question is fundamental: outside of Web search companies, nobody knows the specifics of how personalization works. Second, to what extent does search personalization actually affect search results? Although it is known that Web search companies personalize search results, it is not clear how much these algorithms actually alter the results. If the delta between “normal” and “personalized” results is small, then concerns over the Filter Bubble effect may be misguided.

At a high-level, our methodology is to execute carefully controlled queries on different Web search engines to identify what user features trigger personalization. Each experiment follows a similar pattern: first, create \( x \) accounts that each vary by one specific feature. Second, execute \( q \) identical queries from each account, once per day for \( d \) days. Save the results of each query. Finally, compare the results of the queries to determine whether the same results are being served in the same order to each account. If the results vary between accounts, then the changes can be attributed to personalization linked to the given experimental feature. Note that certain experimental treatments are run without accounts (i.e., to simulate users without accounts). Furthermore, some Web search providers do not allow users to create accounts (e.g., DuckDuckGo).

Sources of Noise. Despite the simplicity of the high-level experimental design, there are several sources of noise that can cause identical queries to return different results.

- **Updates to the Search Index:** Web search services constantly update their search indices. This means that the results for a query may change over time.
- **Distributed Infrastructure:** Large-scale Web search services are spread across geographically diverse datacenters. Our tests have shown that different datacenters may return different results for the same queries. It is likely that these differences arise due to inconsistencies in the search index across datacenters.
- **Geolocation:** Search engines use the user’s IP address to provide localized results [70]. Thus, searches from different subnets may receive different results.
- **A/B Testing:** Web search services sometimes conduct A/B testing [38], where certain results are altered to measure whether users click on them more often. Thus, there may be a certain level of noise independent of all other factors.

The Carry-Over Effect. One particular source of noise comes from the dependency of searches within one “browsing session.” For example, if a user searches for query \( A \), and then searches for query \( B \), the results for \( B \) may be influenced by the previous search for \( A \). Prior research on user intent while searching has shown that sequential queries from a user are useful for refining search result [1, 7, 35, 49, 55]. Thus, it is not surprising that some search engines implement *query refinement* using consecutive keywords within a user’s browsing session. We term the effect of query refinement on subsequent searches as the *carry-over effect*.

An example of carry-over on Google Search is shown in Figure 3. In this test, we search for “hawaii” and then immediately search for “urban outfitters” (a clothing retailer). We conducted the searches from a Boston IP address, so the results include links to the Urban Outfitters store in Boston. However, because the previous query was “hawaii,” results pertaining to Urban Outfitters in Hawai’i are also shown.

To determine how close in time search queries must be to trigger carry-over, we conduct a simple experiment. We first pick different pairs of queries (e.g., “gay marriage” and “obama”). We then start two different browser instances: in one we search for the first query, wait, and then for the second query, while in the other we search only for the second query. We repeat this experiment with different wait times, and re-run the experiment 50
Is there an urban outfitters in Hawaii? - Yahoo! Answers

Top answer: Unfortunately, no, they do not have a store in Hawaii. However, they do ship to Hawaii from their website, if that's any consolation.

Urban Outfitters - Back Bay - Boston, MA

79 Reviews of Urban Outfitters "No matter the line, the front cashier (who is always alone) says "Hi" to everyone coming in. That's not customer service, but rather ..."

Fig. 3. Example of result carry-over, searching for "hawaii" then searching for "urban outfitters."

Fig. 4. Overlap of results when searching for "test" followed by "touring" compared to just "touring" for different waiting periods.

The results of this experiment on Google Search are shown in Figure 4 for the terms "test" and "touring" (other pairs of queries show similar results). The carry-over effect can be clearly observed: the results share, on average, seven common results (out of 10) when the interval between the searches is less than 10 minutes (in this case, results pertaining to Turing Tests are included). After 10 minutes, the carry-over effect disappears. Thus, in all Google-focused experiments in the following sections, we wait at least 11 minutes between subsequent searches in order to avoid any carry-over effects. In our testing, we observed carry-over for both logged in users and users without Google accounts.

We performed the same experiments on Bing and DuckDuckGo, but did not observe any carry-over effects. Thus, we conclude that the carry-over effect is unique to Google Search (at least in fall 2012, when we were conducting measurements).

Controlling Against Noise. In order to mitigate measurements errors due to these factors, we perform a number of steps (some borrowed from [24]): First, all of our queries are executed by the normal Web search webpage, rather than via any search APIs. It has been shown that search engine APIs sometimes return different results than the standard webpage [11]. Second, all of our machines execute searches for the same query at the same time (i.e., in lock-step). This eliminates differences in query results due to temporal effects. This also means that each of our accounts has exactly the same search history at the same time. Third, we use static DNS entries to direct all of our query traffic to a specific Web search provider IP address. This eliminates errors arising from differences between datacenters. Fourth, we wait 11 minutes in-between subsequent queries to avoid carry-over. As shown in Figure 4, an 11 minute wait is sufficient to avoid the majority of instances of carry-over. For consistency, we use this same methodology for Google Search, Bing, and DuckDuckGo, even though the latter two do not exhibit carry-over. Fifth, unless otherwise stated, we send all of the search queries for a given experiment from the same /24 subnet. Doing so ensures that any geolocation would affect all results equally.

Sixth, we include a control account in each of our experiments. The control account is configured in an identical manner to one other account in the given experiment (essentially, we run one of the experimental treatments twice). By comparing the results received by the control and its duplicate, we can determine the baseline level of noise in the experiment (e.g., noise caused by A/B testing). Intuitively, the control should receive exactly the same search results as its duplicate because they are configured identically, and perform the same actions at the same time. If there is divergence between their results, it must be due to noise.
3.3 Implementation

Our experiments are implemented using custom scripts for PhantomJS [40]. We chose PhantomJS because it is a full implementation of the WebKit browser, i.e., it executes JavaScript, manages cookies, etc. Thus, using PhantomJS is significantly more realistic than using custom code that does not execute JavaScript, and it is more scalable than automating a full Web browser (e.g., Selenium [47]).

On start, each PhantomJS instance logs in to a Web search account (e.g., a Google or Microsoft account) using separate credentials, and begins issuing queries to the Web search engine. The script downloads the first page of search results for each query. The script waits 11 minutes in-between searches for subsequent queries.

During execution, each PhantomJS instance remains persistent in memory and stores all received cookies. After executing all assigned queries, each PhantomJS instance closes and its cookies are cleared. The various cookies are recreated during the next invocation of the experiment when the script logs in to its assigned account. All of our experiments are designed to complete in ≈24 hours.

All instances of PhantomJS are run on a single machine. We modified the /etc/hosts file of this machine so that DNS queries to Web search services resolve to specific IP addresses. We use SSH tunnels to forward traffic from each PhantomJS instance to a unique IP address in the same /24 subnet.

All of our experiments were conducted in fall of 2012 and spring of 2013. Although our results are representative for this time period, they may not hold in the future, since Web search engines are constantly tweaking their personalization algorithms.

Accounts. Unless otherwise specified, each Google and Microsoft account we create has the same profile: 27 year old, female. The default User-Agent is Chrome 22 on Windows 7. As shown in Section 5.3, we do not observe any personalization of results based on these attributes.

We manually crafted each of our accounts to minimize the likelihood of being automatically detected. Each account was given a unique name and profile image. We read all of the introductory emails in each account’s email inbox (i.e., in GMail or Hotmail). To the best of our knowledge, none of our accounts were banned or flagged by Google or Microsoft during our experiments.

3.4 Search Queries

In our experiments, each account searches for a specific list of queries. It is fundamental to our research that we select a list of queries that has both breadth and impact. Breadth is vital, since we do not know which queries Web search engines personalize results for. However, given that we cannot test all possible queries, it is important that we select queries that real people are likely to use.

Traditionally, search queries are classified into three different classes according to their intent: navigational, informational and transactional [5]. Navigational queries are not interesting from the perspective of personalization, since navigational queries tend to have a single, “correct” answer, i.e., the URL of the desired website. In contrast,
the results of informational and transactional queries could be personalized; in both cases, the user's intent is to seek out information or products from a potentially large number of websites. Thus, in our experiments we focus on informational and transactional queries.

As shown in Table 1, we use 120 queries divided equally over 12 categories in our experiments. These queries were chosen from the 2011 Google Zeitgeist [20], and WebMD [64]. Google Zeitgeist is published annually by Google, and highlights the most popular search queries from the previous calendar year. We chose these queries for two reasons: first, they cover a broad range of categories (breadth). Second, these queries are popular by definition, i.e., they are guaranteed to impact a large number of people.

The queries from Google Zeitgeist cover many important areas. 10 queries are political (e.g., “Obama Jobs Plan”, “2012 Republican Candidates”) and 10 are related to news sources (e.g., “USA Today News”). Personalization of political and news-related searches are some of the most contentious issues raised in Eli Pariser’s book on the Filter Bubble effects [39]. Furthermore, several categories are shopping related (e.g., gadgets, apparel brands, travel destination). As demonstrated by Orbitz, shopping related searches are prime targets for personalization [33].

One critical area that is not covered by Google Zeitgeist is health-related queries. To fill this gap, we chose ten random queries from WebMD’s list of popular health topics [64].

4 REAL-WORLD PERSONALIZATION

We begin by measuring the extent of personalization that users are seeing today. Doing so requires obtaining access to the search results observed by real users; we therefore conducted a simple user study.

4.1 Collecting Real-World Data

We posted two tasks on Amazon’s Mechanical Turk (AMT), explaining our study and offering each user $2.00 to participate. In the first task, participants were required to 1) be in the United States, 2) have a Google account, and 3) be logged in to Google during the study. The second task was analogous to the first, except it targeted users with Bing accounts. Users who accepted either task were instructed to configure their Web browser to use a HTTP proxy controlled by us. Then, the users were directed to visit a Web page hosted on our research server. This page contained JavaScript that automatically performed the same 80 searches on Google or Bing, respectively. 50 of the queries were randomly chosen from the categories in Table 1, while 30 were chosen by us.

The HTTP proxy serves several functions. First, the proxy records the search engines’ HTML responses to the users’ queries so that we can observe the results returned to the user. We refer to these results as the experimental results. Second, each time the proxy observes a user making a query, it executes two PhantomJS scripts. Each script logs in to the respective search engine and executes the same exact query as the user. We refer to the results observed by these two scripts as the control results, and they allow us to compare results from a real user (who Google/Bing has collected extensive data on) to fresh accounts (that have minimal Google/Bing history). Third, the proxy controls for noise in two ways: 1) by executing user queries and the corresponding scripted queries in parallel, and 2) forwarding all search engine traffic to hard-coded IP addresses for Google and Bing.

SSL versus no-SSL. Although the proxy is necessary to control for noise, there is a caveat to this technique when it is applied to Google Search. Queries from AMT users must be sent to http://google.com, whereas the controls use https://google.com. The reason for this issue is that HTTPS Google Search rejects requests from proxies, since they could indicate a man-in-the-middle attack. Unfortunately, result pages from HTTP Google Search include a disclaimer explaining that some types of search personalization are disabled for HTTP results.

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2This study was conducted under Northeastern University IRB protocol #12-08-42; all personally identifiable information was removed from the dataset.

3We make the source code for this page available to the research community so that our experiment can easily be replicated.
To understand if the differences between SSL and no-SSL Google Search are significant, we conducted a simple pilot study. We automated three Firefox browsers to execute our 120 search queries every day for seven days. Two of the browsers searched using https://google.com, and the third searched on http://google.com (i.e., SSL search serves as the control for this experiment). The three browsers were sandboxed so they could not influence each other (e.g., via cached files or cookies), and all cookies and history were cleared from the browsers before beginning the experiment.

Figure 5 shows the average Jaccard Index and average Kendall’s Tau for each day of test results. Both quantities are averaged over all 120 queries. The “SSL/SSL” line compares the results received by the two accounts that searched using https://google.com. As expected, the results received by the accounts have the same composition (i.e., Jaccard Index is 0.998 on average), although the order of results is somewhat noisy (i.e., Kendall’s Tau is 0.88 on average). The “No-SSL/SSL” line compares the results received by the account that searched using http://google.com to an account that searched using https://google.com. The results show that there are consistent, but minor, differences between the composition and ordering of the two search results. Average Jaccard and Kendall’s Tau are 0.95 and 0.79 for the no-SSL/SSL experiments, respectively.

The takeaway from Figure 5 is that there are slight differences in the search results from SSL and no-SSL Google Search. However, the variation induced by noise is greater than the variation induced by the presence or absence of encryption. Thus, we feel that the experimental methodology used in this section is sound overall, because we are able to control for changes in search results due to noise.

**Alternate Methodologies.** Other researchers have developed alternate techniques to compare search results across users. For example, the authors of the “Bing it On” study [4] had users take screenshots of search results and uploading them to the experimenters. We found such an approach to be a poor fit for our experimental goals, as requesting users to submit screenshots for every search would (a) significantly reduce the coverage of search terms (since users would have to manually upload screenshots, instead of the searches being automatic) and (b) make it more difficult to control for noise (since it would not be possible to run the user query and the control query in lock-step).

**AMT Worker Demographics.** In total, we recruited 300 AMT workers, 200 for our Google Search experiment and 100 for our Bing experiment. The reason for fewer users in the Bing experiment is that we were only able to recruit 100 AMT workers who hold Bing accounts (it appears that Bing accounts are much less common). In both experiments, the participants first answered a brief demographic survey. Our participants self-reported to residing in 43 different U.S. states, and range in age from 18 to 66 (with a bias towards younger users). Figure 6 shows the usage of Google and Microsoft services by our participants. For Google, 84% are Gmail users, followed
by 76% that use YouTube, while for Bing 40% are Hotmail users. These survey results demonstrate that our participants 1) come from a broad sample of the U.S. population, and 2) use a wide variety of Google and Microsoft services. The low usage of Microsoft Windows may be due to issues experienced by Internet Explorer users: written feedback from several of our participants indicated that Internet Explorer users found it difficult to set up the necessary proxy settings for our tasks.

4.2 Results

We now pose the question: how often do real users receive personalized search results? To answer this question, we compare the results received by AMT users and the corresponding control accounts. Figure 7 shows the percentage of results that differ at each rank (i.e., result 1, result 2, etc.) when we compare the AMT results to the control results, and the control results to each other. Intuitively, the percent change between the controls is the noise floor; any change above the noise floor when comparing AMT results to the control can be attributed to personalization.

There are three takeaways from Figure 7. First, we observe extensive personalization of search results. On average, across all ranks, AMT results showed an 11.7% higher likelihood of differing from the control result than the controls results did from each other on Google Search, and 15.8% higher likelihood on Bing. This additional difference can be attributed to personalization. To make sure these differences between the AMT and the control results are in fact statistically significant (and not just a reflection of the sampling), we perform the Chi squared test. We calculate the p-value for each rank for both Bing and Google; we find all of the p-values to be lower.
than 0.0001, indicating the results are statistically significant. Second, as already indicated, we observe more personalization on Bing than on Google Search. Third and finally, top ranks tend to be less personalized than bottom ranks on both search engines.

To better understand how personalization varies across queries, we list the top 10 most and least personalized queries on Google Search and Bing in Table 2. The level of personalization per query is calculated as the probability of AMT results equaling the control results, minus the probability of the control results equaling each other. Large values for this quantity indicate large divergence between AMT and control results, as well as low noise (i.e., low control/control divergence).

As shown in Table 2, the most personalized queries on Bing tend to be related to important political issues (e.g., “job creation” and “tax cuts”) whereas on Google the most personalized queries tend to be related to companies and politics (e.g., “greece”, “human rights,” and “home depot”). In contrast, the least personalized results on both search engines are often factual (“what is”) and health related queries.

We manually examined the most personalized results and observed that most of the personalization on Google is based on location. Even though all of the AMT users’ requests went through our proxy and thus appeared to Google as being from the same IP address, Google Search returned results that are specific to other locations. This was especially common for company names, where AMT users received results for different store locations.

5 PERSONALIZATION FEATURES

In the previous section, we observed significant personalization for real users on Google Search and Bing. We would now like to explore which user features (i.e., aspect of the users’ profile or activity) are most likely to lead to personalized results. To do so, we are unable to use existing real user accounts as we did before, as the history of profile attributes and activity of these accounts are unknown to us. Instead, we create new, synthetic accounts under our control, and use these accounts (whose entire history we do know) to determine which features are most influential.

Although we cannot possibly enumerate and test all possible user features, we can investigate likely candidates. To do so, we enumerated the list of user features that (a) have been suggested in the literature as good candidates for personalization and (b) are possible to emulate given the constraints of our experimental methodology; we discuss the user features we were not able to explore in Section 7. Table 3 lists the different user features that our experiments emulate, as well as which search engines each user feature was evaluated on.

| Most Personalized | Least Personalized |
|-------------------|--------------------|
| **Google** | **Bing** |
| gap | harry |
| hollister | 2008 crysis |
| hgtv | nuclear weapon |
| boomerang | witch |
| home depot | job creation |
| greece | tax cuts |
| pottery barn | issue |
| human rights | abortion |
| h2o | iran and isreal |
| nike | obama |

| **Google** | **Bing** |
|-------------------|--------------------|
| what is gout | what is vegan |
| dance with dragons | theadvocate |
| what is lupus | arash molavi |
| gila monster facts | hollister |
| what is gluten | osteoporosis |
| ipad 2 | what is gluten |
| chéri daniels | hot to dispose of paint |
| psoriatic arthritis | wild kratts |
| keurig coffee maker | gap |
| maytag refrigerator | amana refrigerator |
Table 3. User features evaluated for effects on search personalization. The “Tested On” column details whether we evaluated the given feature on Google (G), Bing (B), and/or DuckDuckGo (D).

| Category                        | Feature         | Tested On | Tested Values                                      |
|---------------------------------|-----------------|-----------|----------------------------------------------------|
| Tracking                        | Cookies         | G, B      | Logged In, Logged Out, No Cookies                  |
| User-Agent                      | OS              | G, B, D   | Win. XP, Win. 7, OS X, Linux                       |
|                                 | Browser         | G, B, D   | Chrome 22, Firefox 15, IE 6, IE 8, Safari 5        |
| Geolocation                     | IP Address      | G, B, D   | MA, PA, IL, WA, CA, UT, NC, NY, OR, GA             |
| User Profile                    | Gender          | G, B      | Male, Female, Other                                |
|                                 | Age             | G, B      | 15, 25, 35, 45, 55, 65                             |
|                                 | Zip Code        | B         | MA, CA, FL, TX, WA                                |
| Search History, Click History,  | Gender          | G, B      | Male, Female                                       |
| and Browsing History            | Age             | G, B      | <18, 18-24, 25-34, 35-44, 45-54, 55-64, ≥65        |
|                                 | Income          | G, B      | $0-50K, $50-100K, $100-150K, >$150K                |
|                                 | Education       | G, B      | No College, College, Grad School                   |
|                                 | Ethnicity       | G, B      | Caucasian, African American, Asian, Hispanic       |

5.1 Collecting Synthetic Account Data
For each user feature we wish to examine, we create \( x + 1 \) fresh user accounts, where \( x \) equals the number of possible values of the feature we are testing in that experiment, plus one additional control account. We refer to all non-control accounts as test accounts. For example, in the Gender experiment, we create four accounts in total: three test accounts (one “male,” one “female,” one “other”) and one control account ("female"). We execute \( x + 1 \) instances of our PhantomJS script for each experiment (one for each account), and forward the traffic to \( x + 1 \) unique endpoints via SSH tunnels. Each account searches for all 120 of our queries, and we repeat this process daily for 30 days. This complete treatment is conducted on Google, Bing, and DuckDuckGo (depending on the particular feature under analysis). As before, we compare the differences in the results between the control account and its counterpart (in our example above, the two "female" accounts) to measure the baseline noise; we then compare the differences in the results between the test accounts and the control to measure personalization.

It is important to note that we cannot compare results across search engines given that their coverage on different topics might vary; thus, our measurements aim for capturing the personalization level within each search engine.

5.2 Measuring Personalization
When comparing the list of search results for test and control accounts, we use two metrics to measure personalization. First, we use Jaccard Index, which views the result lists as sets and is defined as the size of the intersection over the size of the union. A Jaccard Index of 0 represents no overlap between the lists, while 1 indicates they contain the same results (although not necessarily in the same order).

To measure reordering, we use Kendall’s tau rank correlation coefficient. This metric is commonly used in the information retrieval literature to measure the similarity of the orderings of the data when ranked by each of the quantities. To calculate Kendall’s tau coefficient on two ranked lists we take the difference between the number of concordant pairs and the number of discordant pairs and normalize it with the number of possible pairings of the two lists. If the agreement between two rankings is perfect, the coefficient value is 1.
5.3 Basic Features

We begin our experiments by focusing on features associated with a user’s browser, their physical location, and their user profile.

**Basic Cookie Tracking.** In this experiment, the goal is to compare the search results for users who are logged in to a Google/Bing account, not logged in, and who do not support cookies at all. Google and Bing are able to track the logged in and logged out users, since both search engines place tracking cookies on all users, even if they do not have a user account. The user who does not support cookies receives a new tracking cookie after every request, and we confirm that the identifiers in these cookies are unique on every request. However, it is unknown whether Google or Bing are able to link these new identifiers together behind-the-scenes (e.g., by using the user’s IP address as a unique identifier).

To conduct this experiment, we use four instances of PhantomJS per search engine. The first two completely clear their cookies after every request. The third account logs in to Google/Bing and persists cookies normally. The fourth account does not log in to Google/Bing, and also persists cookies normally.

Figure 8 shows the results of our experiments. The upper left plot shows the average Jaccard Index for each account type (logged in/logged out/no cookies) across all search queries on Google when compared to the control (no cookies). In all of our figures, we place a * on the legend entry that corresponds to the control test, i.e., two accounts that have identical features. The figure reveals that the results received by users are not dependent on whether they support cookies, or their login state with Google. However, just because the results are the same, does not mean that they are returned in the same order.

To examine how the order of results changes, we plot the average Kendall’s tau coefficient between each account type versus the control on Google in the lower left plot of Figure 8. We observe that a user’s login state and cookies do impact the order of results from Google Search. The greatest difference is between users who are logged in versus users that clear their cookies. Logged in users receive results that are reordered in two places
(on average) as compared to users with no cookies. Logged out users also receive reordered results compared to the no cookie user, but the difference is smaller. The results in this figure are consistent with the techniques that search engines are likely to use for personalization (i.e., per-user cookie tracking), and give the first glimpse of how Google alters search results for different types of users.

The right column of Figure 8 examines the impact of login cookies on Bing. From the upper right figure (which plots the average Jaccard Index), we see that, unlike Google Search, having Bing cookies does impact the results returned from Bing. The lower right plot in Figure 8 (which plots the average Kendall’s tau coefficient) demonstrates that cookies also influence the order of results from Bing.

We did not run our cookie-based experiments against DuckDuckGo because it does not place cookies on users’ browsers.

**Browser User-Agent.** Next, we examine whether the user’s choice of browser or Operating System (OS) can impact search results. To test this, we created 22 user accounts (11 for Google, 11 for Bing) and assigned each one a different “User-Agent” string. As shown in Table 3, we encoded user-agents for 5 browsers and 4 OSs. Chrome 22 and Windows 7 serve as the controls. For DuckDuckGo, we conduct the same experiment sans user accounts, since DuckDuckGo does not have support for user accounts.

Figure 9 shows the results for our browser experiments on Google, Bing, and DuckDuckGo. Unlike the cookie tracking experiment, there is no clear differentiation between the different browsers and the control experiment. The results for different OSs are similar, and we omit them for brevity. Thus, we do not observe search personalization based on user-agent strings for Google, Bing, or DuckDuckGo.

**IP Address Geolocation.** Next, we investigate whether the three target search engines personalize results based on users’ physical location. To examine this, we create 22 user accounts (11 Google, 11 Bing) and run our test suite while forwarding the traffic through SSH tunnels to 10 geographically diverse PlanetLab machines. These PlanetLab machines are located in the US states shown in Table 3. Two accounts forward through
the Massachusetts PlanetLab machine, since it is the control. As before, we conduct this experiment against DuckDuckGo sans user accounts.

Figure 10 shows the results of our location tests. There is a clear difference between the control and all the other locations on both Google and Bing. On Google Search, the average Jaccard Index for non-control tests is 0.91, meaning that queries from different locations generally differ by one result. The same is true on Bing, where the average Jaccard Index is 0.87. The difference between locations is even more pronounced when we consider result order: the average Kendall’s tau coefficient for non-control accounts is 2.12 and 1.94 on Google and Bing, respectively.

These results reveal that Google Search and Bing do personalize results based on the user’s geolocation. One example of this personalization can be seen by comparing the MA and CA Google Search results for the query “pier one” (a home furnishing store). The CA results include a link to a local news story covering a store grand opening in the area. In contrast, the MA results include a Google Maps link and a CitySearch link that highlight stores in the metropolitan area.

In contrast to Google and Bing, the search results from DuckDuckGo are essentially identical regardless of the user’s IP address. This result is not surprising, since it fits with DuckDuckGo’s stated policy of not personalizing search results for any reason.

Inferred Geolocation. During our experiments, we observed one set of anomalous results from experiments that tunneled through Amazon EC2. In particular, 9 machines out of 22 rented from Amazon’s North Virginia datacenter were receiving heavily personalized results, versus the other 13 machines, which showed no personalization. Manual investigation revealed that Google Search was returning results with .co.uk links to the 9 machines, while the 13 other machines received zero .co.uk links. The 9 machines receiving UK results were all located in the same /16 subnet.
Although we could not determine why Google Search believes the 9 machines are in the UK (we believe it is due to an incorrect IP address geolocation database), we did confirm that this effect is independent of the Google account. As a result, we did not use EC2 machines as SSH tunnel endpoints for any of the results in this paper. However, this anomaly does reveal that Google returns dramatically different search results to users who are in different countries (or in this case, users Google believes are in different countries).

**User Profile Attributes.** In our next set of tests, we examine whether Google Search and Bing use demographic information from users’ profiles to personalize results. Users must provide their gender and age when they sign up for a Google account, which means that Google Search could leverage this information to personalize results. Bing, on the other hand, collects gender, age, and zip code.

To test this hypothesis, we created Google and Bing accounts with specific demographic qualities. As shown in Table 3, we created “female,” “male,” and “other” accounts (these are the 3 choices Google and Bing give during account sign-up), as well as accounts with ages 15 to 65, in increments of 10 years. On Bing, we also create accounts from five different zip codes. The control account in the gender tests is female, the control in the age tests is 15, and the control in the zip code test is in Massachusetts.

The results for the gender test are presented in Figure 11 We do not observe user profile gender-based personalization on Google or Bing. Similarly, we do not observe personalization based on profile age or zip code, and we omit the results for brevity. DuckDuckGo does not allow users to create user accounts, so we do not run these tests on DuckDuckGo.

### 5.4 Historical Features

We now examine whether Google Search and Bing use an account’s history of activity to personalize results. We consider three types of historical actions: prior searches, prior searches where the user clicks a result, and Web browsing history.

![Fig. 11. Results for the User Profile: Gender experiments on Google and Bing.](image)
To create a plausible series of actions for different accounts, we use data from Quantcast, a Web analytics and advertising firm. Quantcast publishes a list of top websites (similar to Alexa) that includes the demographics of visitors to sites [44], broken down into the 20 categories shown in Table 3. Quantcast assigns each website a score for each demographic, where scores >100 indicate that the given demographic visits that website more frequently than average for the Web. The larger the score, the more heavily weighted the site’s visitors are towards a particular demographic.

We use the Quantcast data to drive our historical experiments. In essence, our goal is to have different accounts “act” like a member of each of Quantcast’s demographic groups. The choice of our features was motivated by other web services and online advertisement services that use similar demographic categorizations to personalize content. Studies have shown that user demographics can be reliably inferred from browsing histories, which can be useful for personalizing content [18, 28]. Thus, for each of our experiments, we create 22 user accounts, two of which only run the 120 control queries, and 20 of which perform actions (i.e., searching, searching and clicking, or Web browsing) based on their assigned demographic before running the 120 control queries. For example, one account builds Web browsing history by visiting sites that are frequented by individuals earning >$150k per year. Each account is assigned a different Quantcast demographic, and chooses new action targets each day using weighted random selection, where the weights are based on Quantcast scores. For example, the >$150k browsing history account chooses new sites to browse each day from the corresponding list of URLs from Quantcast.

We execute all three experimental treatments (searching, searching and clicking, and Web browsing) on Google Search, but only execute two (searching, and searching and clicking) on Bing. As previous studies have shown, Google is a ubiquitous presence across the Web [46], which gives Google the ability to track user’s as they browse. In contrast, Microsoft and Bing do not have a widespread presence: out of 1500 top sites ranked by Quantcast, <1% include cookies from Microsoft or its subsidiaries (e.g., Live.com, Outlook.com), versus 63% for Google and its subsidiaries (e.g., YouTube, Doubleclick). Therefore, it is not feasible for Bing to track users’ browsing behavior or personalize search results based on browsing history.
DuckDuckGo does not use cookies, and thus has no way to track users or build up history. Thus, we do not execute any of our historical experiments on DuckDuckGo.

Search History. First, we examine whether Google Search and/or Bing personalize results based on search history. Each day, the 40 test accounts (20 for Google, 20 for Bing) search for 100 demographic queries before executing the standard 120 queries. The query strings are constructed by taking domains from the Quantcast top-2000 that have scores >100 for a particular demographic and removing subdomains and top level domains (e.g., www.amazon.com becomes "amazon").

Figure 12 shows the results of the search history test for five different age brackets. The "No History" account does not search for demographic queries, and serves as the control. The vast majority of the time, all accounts receive almost identical search results across both search engines (except for a few, random outliers in the Bing results). If Google or Bing was personalizing search results based on search history, we would expect the results for the age bracket accounts to diverge from the control results over time. However, we do not observe this over the course of 30 days of experiments. This observation holds for all of the demographic categories we tested, and we omit the results for brevity. Thus, we do not observe personalization based on search history, although it is possible that longer experiments could show larger differences.

Search-Result-Click History. Next, we examine whether Google Search and/or Bing personalizes results based on the search results that a user has clicked on. We use the same methodology as for the search history experiment, with the addition that accounts click on the search results that match their demographic queries. For example, an account that searches for "amazon" would click on a result linking to amazon.com. Accounts will go through multiple pages of search results to find the correct link for a given query.

The results of the click history experiments are the same as for the search history experiments. There is little difference between the controls and the test accounts, regardless of demographic. Thus, we do not observe personalization based on click history, and we omit the results for brevity.

Browsing History. Next, we investigate whether Google Search personalizes results based on Web browsing history (i.e., by tracking users on third-party Web sites). In these experiments, each account logs into Google and then browses 5 random pages from 50 demographically skewed websites each day. We filter out websites that do not set Google cookies (or Google affiliates like DoubleClick), since Google cannot track visits to these sites. Out of 1,587 unique domains in the Quantcast data that have scores >100, 700 include Google tracking cookies.

The results of the browsing history experiments are the same as for search history and click history: regardless of demographic, we do not observe personalization. We omit these results for brevity.
**Targeted Domain Clicking.** Finally, we conduct a variant of our click history experiment. In the previous search-result-click experiment, each account executed 100 "demographic" searches and 120 standard test queries per day. However, it is possible that this methodology is too complex to trigger search personalization, i.e., because each account creates such a diverse history of searches and clicks, the search engines may have trouble isolating specific features to personalize on.

Thus, in this experiment, we simplify our methodology: we create 10 accounts, each of which is assigned a specific, well-known news website. Each account executes 6 news-related queries 4 times on each day (so, 24 searches each day, evenly spaced throughout the day). After searching the account clicks on the link that is its assigned news website in the list of results. For example, one account was assigned www.foxnews.com; 24 times per day this account executed news-related queries, and always clicked on results pointing to www.foxnews.com (if they appeared in the top 10 results). In theory, this creates a very strong signal for personalization, i.e., a search engine could trivially observe that this user favors a specific website, and increase the rank of results pointing to this website.

We conduct the targeted domain clicking test on both Google Search and Bing. We created 10 experimental accounts on each search engine, each of which was assigned a unique target domain, as well as 1 control account that searches but does not click on any links.

Figure 13 shows the results of our targeted domain clicking experiments. To quantify our results, we plot the average difference in rank between the targeted domains as seen by the experimental accounts and the control account. Difference of zero means that a particular domain appears at the same rank for both the experimental account (which clicks on the domain) and the control (which clicks on nothing). Positive difference in rank means the domain appears at higher ranks for the experimental account, while a negative difference means that the domain appears at higher ranks for the control.

As shown in Figure 13, on average, there is close to zero difference between the ranks of domains, regardless of whether they have been clicked on. This result holds true across Google Search and Bing. As shown by the standard deviation lines, even when the rank of the domains differs, the variance is very low (i.e., less than a single rank difference). Furthermore, although this test was run for 30 days, we do not observe divergence over time in the results; if the search engines were personalizing results based on click history, we would expect the difference in rank to increase over time as the experimental accounts build more history. Thus, we conclude that clicking on results from particular domains does not cause Google or Bing to elevate the rank of that domain.

**Discussion.** We were surprised that the history-driven tests did not reveal personalization on Google Search or Bing. One explanation for this finding is that account history may only impact search results for a brief time window, i.e., carry-over is the extent of history-driven personalization on these search engines.

6 QUANTIFYING PERSONALIZATION

In the previous section we demonstrate that Google Search personalization occurs based on 1) whether the user is logged in and 2) the location of the searching machine. In this section, we dive deeper into the data from our synthetic experiments to better understand how personalization impacts search results. First, we examine the temporal dynamics of search results. Next, we investigate the amount of personalization in different categories of queries. Finally, we examine the rank of personalized search results to understand whether certain positions are more volatile than others.

6.1 Temporal Dynamics

In this section, we examine the temporal dynamics of results from Google Search and Bing to understand how much search results change day-to-day, and whether personalized results are more or less volatile than non-personalized search results. To measure the dynamics of search engines over time, we compute the Jaccard Index
Fig. 14. Day-to-day consistency of results for the cookie tracking experiments.

and Kendall Tau coefficient for search results from subsequent days. Figure 14 shows the day-to-day dynamics for our cookie tracking experiment (i.e., the accounts are logged in, logged out, and do not support cookies, respectively). The x-axis shows which two days of search results are being compared, and each line corresponds to a particular test account.

Figure 14 reveals three facts about Google Search and Bing. First, the lines in Figures 14 are roughly horizontal, indicating that the rate of change in the search indices is roughly constant. Second, we observe that there is more reordering over time than new results: average Jaccard Index on Google and Bing is $\approx 0.9$, while average Kendall Tau coefficient is 0.5 for Google and 0.7 for Bing. Third, we observe that both of these trends are consistent across all of our experiments, irrespective of whether the results are personalized. This indicates that personalization does not increase the day-to-day volatility of search results.

**Dynamics of Query Categories.** We now examine the temporal dynamics of results across different categories of queries. As shown in Table 1, we use 12 categories of queries in our experiments. Our goal is to understand whether each category is equally volatile over time, or whether certain categories evolve more than others.

To understand the dynamics of query categories, we again calculate the Jaccard Index and Kendall Tau coefficient between search results from subsequent days. However, instead of grouping by experiment, we now group by query category. Figure 15 shows the day-to-day dynamics for query categories during our cookie tracking experiments. Although we have 12 categories in total, Figure 15 only shows the 1 least volatile, and 4 most volatile categories, for clarity. The results for all other experiments are similar to the results for the cookie tracking test, and we omit them for brevity.

Figure 15 reveals that the search results for different query categories change at different rates day-to-day. For example, there are more new results per day for "politics" related-queries on both Google Search and Bing. Similarly, "politics" and "gadgets" related-queries both exhibit above average reordering each day. This reflects how quickly information in these categories changes on the Web. In contrast, search queries in factual categories
like "what is" and "green" (environmentally friendly topics) are less volatile over time (and are omitted from Figure 15 for clarity).

6.2 Personalization of Query Categories

We now examine the relationship between different categories of search queries and personalization. In Section 5, we demonstrate that Google Search and Bing do personalize search results. However, it remains unclear whether all categories of queries receive equal amounts of personalization.

To answer this question, we plot the cumulative distribute of Jaccard Index and Kendall Tau coefficient for each category in Figure 16. These results are calculated over all of our experiments (i.e., User-Agent, Google Profile, geolocation, etc.) for a single day of search results. For clarity, we only include lines for the 1 most stable category (i.e., Jaccard index and Kendall Tau are close to 1), and the 4 least stable categories.

Figure 16 demonstrates that Google Search and Bing personalize results for some query categories more than others. For example, 88% of results for "what is" queries are identical on Google, while only 66% of results for "gadgets" are identical on Google. Overall, "politics" is the most personalized query category on both search engines, followed by "places" and "gadgets." CDFs calculated over other days of search results demonstrate nearly identical results.

6.3 Personalization and Result Ranking

In this section, we focus on the volatility of results from Google Search and Bing at each rank, with rank 1 being the first result on the page and rank 10 being the last result. Understanding the impact of personalization on top ranked search results is critical, since eye-tracking studies have demonstrated that users rarely scroll down to results "below the fold" [12, 21, 23, 31]. Thus, we have two goals: 1) to understand whether certain ranks are more volatile in general, and 2) to examine whether personalized search results are more volatile than non-personalized results.
To answer these questions, we plot Figure 17, which shows the percentage of results that change at each rank. To calculate these values, we perform a pairwise comparison between the result at rank $r \in [1, 10]$ received by a test account and the corresponding control. We perform comparisons across all tests in all experiments, across all seven days of measurement. This produces a total number of results that are changed at each rank $r$, which we divide by the total number of results at rank $r$ to produce a percentage. The personalized results come from the cookie tracking and geolocation experiments; all others experimental results are non-personalized.

Figure 17 reveals two interesting features. First, the results on personalized pages are significantly more volatile than the results on non-personalized pages. The result changes on non-personalized pages represent the noise floor of the experiment; at nearly every rank, there are more than twice as many changes on personalized pages. Second, Figure 17 shows that the volatility at each rank is not uniform. Rank 1 exhibits the least volatility on Google Search and Bing. The volatility increases until it peaks at 33% in rank 7 on Google Search, and at 26% in rank 8 on Bing. This indicates that both search engines are more conservative about altering results at top ranks.

Given the extreme importance placed on rank 1 search results, we now delve deeper into the rare cases where the result at rank 1 changes during personalized searches (5% of personalized rank 1 results change on Google, while 3% change on Bing). In each instance where the rank 1 result changes, we compare the results for the test account and the control to determine 1) what was the original rank of the result that moved to rank 1, and 2) what is the new rank of the result that used to be at rank 1.

Figure 18 plots the results of this test. In the vast majority of cases, the rank 1 and 2 results switch places: on Google, 73% of new rank 1 results originate from rank 2, and 58% of old rank 1 results move to rank 2. On Bing, 77% of new rank 1 results originate from rank 2, and 83% of old rank 1 results move to rank 2. Overall, on Google, 93% of new rank 1 results come from the first page of results, while 82% of old rank 1 results remain somewhere on the first result page. On Bing, 83% percent of rank 1 results come from or move to somewhere on the first page of results. However, none of the CDFs sum to 100%, i.e., there are cases where the new rank 1 result does not appear in the control results and/or the old rank 1 result disappears completely from the test results. The
latter case is more common on Google, with 18% of rank 1 results getting evicted completely from the first page of results. Both cases, are equally likely on Bing.

Figure 18 reveals similarities and differences between Google Search and Bing. On one hand, both search engines are clearly conservative about changing rank 1 search results, i.e., the vast majority of changes are simply swaps between rank 1 and 2. On the other hand, when the rank 1 result does change, Google and Bing leverage different strategies: Google Search prefers to elevate results already on the first page, while Bing prefers to insert completely new links. We manually examined instances where Bing inserted new results at rank 1, and found that in most cases these new links were to Bing services, e.g., a box of links Bing News results.

6.4 Personalization and Aggregated Search

In Section 3.1, we noted that some of the results from search engines do not point to third-party websites. Instead, some results embed links and functionality from services maintained by the search engine provider. The inclusion of links to other services in search results is sometimes referred to as “aggregated search.” For example, Google often embeds results from Google News, Google Maps, YouTube, and Google+ into pages of search results. Figure 1 shows an example of an embedded Google service: a box of queries that are “Related” to the given search query. Bing offers an array of similar services and embeds to them in search results.

In this section, we examine links to provider services in search results. Specifically, we are interested in whether personalization impacts the placement and amount of links to provider services. These are important questions,
given that regulators have questioned the placement of provider services in search results within the context of antitrust regulation [45], i.e., do providers promote their own services at the expense of third-party websites?

First, we examine the percentage of results at each rank that embed provider services. Figure 19 shows the percentage of results at each rank that embed provider services on Google and Bing. We split our data into personalized and non-personalized pages of results, where results from the logged-in/out and location experiments are considered to be personalized. We aggregate across all 120 experimental queries and all 30 days of experiments.

Figure 19 demonstrates that Google and Bing exhibit different behavior when it comes to embedding provider services. Overall, Bing embeds its own services 19% of the time, whereas Google embeds its own services 9% of the time. However, Google embeds services at rank 1 on ≈15% of result pages, whereas Bing never embeds services at rank 1. Instead, Google tends to embed services uniformly across ranks 2-10, whereas Bing favors embedding services at ranks 3 and 10. On Bing, the rank 3 results point to a variety of different services (e.g., Bing Images, Bing Video, Bing News, etc.), while the service at rank 10 is almost always Related Searches.

Figure 19 also shows that personalization only appears to influence service embedding on Google. On Bing, the amount and placement of embedded services does not change between personalized and non-personalized search results. However, on Google, 12% of links on personalized pages point to services, versus 8% on non-personalized
pages. This trend is relatively uniform across all ranks on Google. This demonstrates that personalization does increase the number of embedded services seen by Google Search users.

Next, we seek to understand whether personalization impacts which services are embedded by search engines. To answer this question, we plot Figure 20, which shows the percentage of results that can be attributed to different services (we only consider links to services, so the bars sum to 100%). As before, we examine results on personalized and non-personalized pages separately, and aggregate across all 120 search queries and all 30 days of experiments.

On Google, the top three most embedded services are Google Images, Google News, and Google Video (which also includes links to YouTube). Bing also generates many links to its equivalent image, news, and video services, however the most embedded service by a large margin is Related Searches (which is almost always placed at rank 10). In contrast, Google only embeds Related Searches into 1% of results pages.

Figure 20 reveals that Google does personalize the types of services it embeds, whereas Bing does not. On Google, "Info" and Google News results tend to be served on more non-personalized pages. Info results present information from Google’s Knowledge Graph, which are usually answers to questions, e.g., “Madrid” if the user searches for “Capital of Spain.” Conversely, “Local,” Dictionary, and Google Video results are served more frequently on personalized pages. Local results present lists of geographically close stores and restaurants that are related to the user’s query, e.g., a list of pizza parlors if the user searches for “pizza.” In contrast to Google, Bing embeds different services at roughly static rates, regardless of personalization.

Google and Bing News. As shown in Figure 20, pages of search results from Google and Bing often include embedded boxes of news from their respective news portals (Google News and Bing News). Each box is characterized by 1-4 links to news stories on third-party websites (e.g., CNN, New York Times, Fox News, etc.) that are relevant to the given query. Typically, one or more of the links will be enhanced with a thumbnail image also taken from a third-party website.

It is known that services like Google News use personalization to recommend news stories that the service believes are relevant to each user [13]. This raises the question: are the news links embedded in pages of search results also personalized? To answer this question, we went through our dataset and located all instances where an experimental account and the corresponding control account were both served embedded news boxes. In these cases, we compared the links in each embedded news box to examine whether news results are being personalized.

The results of this experiment show that search results from Google News and Bing News are not personalized, even if other results on the page are personalized. On both Google and Bing, the Jaccard Index when comparing news links from experimental and control accounts is consistently ≈1, and the Kendall Tau coefficient is consistently ≈1. These results are the same regardless of the characteristics of the experimental account (i.e., location, logged in/out, search history, etc.). Thus, it appears that Google and Bing only personalize news directly on their respective news sites, but not in their search results.

7 CONCLUDING DISCUSSION

Over the past few years, we have witnessed a trend of personalization in numerous Internet-based services, including Web search. While personalization provides obvious benefits for users, it also opens up the possibility that certain information may be unintentionally hidden from users. Despite the variety of speculation on this topic, to date, there has been little quantification of the basis and extent of personalization in Web search services today.

In this paper, we introduce a robust methodology for measuring personalization on Web search engines. Our methodology controls for numerous sources of noise, allowing us to accurately measure the extent of personalization. We applied our methodology to real Google and Bing accounts recruited from AMT and observe that 11.7% of search results on Google and 15.8% on Bing show differences due to personalization. Using artificially
created accounts, we observe that measurable personalization on Google Search and Bing is triggered by 1) being logged in to a user account and 2) making requests from different geographic areas.

However, much work remains to be done: we view our results as a first step in providing transparency for users of Web search and other Web-based services. In the paragraphs below, we discuss a few of the issues brought up by our work, as well as promising directions for future research.

**Scope.** In this paper, we focus on queries to US versions of the Google Web Search, Bing, and DuckDuckGo. All queries are in English, and are drawn from topics that are primarily of interest to US residents. We leave the examination of search engines in other countries and other languages to future work.

**Incompleteness.** As a result of our methodology, we are only able to identify positive instances of personalization; we cannot claim the absence of personalization, as we may not have considered other dimensions along which personalization could occur and we can only test a finite set of search terms. However, the dimensions that we chose to examine in this paper are the most obvious ones for personalization (considering how much prior work has looked at demographic, location-based, and history-based personalization). An interesting extension of our experiments would be to determine how the popularity of the query terms effect personalization.

Given that any form of personalization is a moving target, we aim to continue this work by looking at additional categories of Web searches, examining searches from mobile devices, and looking at other user behaviors (e.g., using services like Gmail, Google+, and Google Maps). We also plan on examining the impact of mechanisms that may disable personalization (e.g., enabling Do-Not-Track headers).

**Generality.** The methodology that we develop is not specific to Google Web Search, Bing, or DuckDuckGo. The sources of noise that we control for are present in other search engines (e.g., Google News Search) as well as other Web-based services (e.g., Twitter search, Yelp recommendations, etc.). We plan on applying our methodology to these and other search services to quantify personalization of different types.

**Recommendations.** We have focused on measuring the personalization that exists on popular Web search engines today, and have avoided trying to determine whether the personalization we observed resulted in better or worse search experiences for the users. We leave such an exploration to future work. However, we do believe that services today should make personalization transparent to the users (i.e., label results that are personalized as such) and allow users to disable personalization if they wish.

**Impact.** In this paper, we focused on quantifying literal differences in search results, e.g., a.com is different from b.com. However, we do not address the issue of semantic differences, i.e., do a.com and b.com contain different information content? If so, what is the impact of these differences? While semantic differences and impact are challenging to quantify, we plan to explore natural language processing and user studies as a first step.

**Open Source.** We make all of the crawling and parsing code, as well as the Google Web Search, Bing, and DuckDuckGo data from Section 5, available to the research community at http://personalization.ccs.neu.edu/

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