Search Media and Elections: A Longitudinal Investigation of Political Search Results in the 2018 U.S. Elections

DANAË METAXA, Computer Science Department, Stanford University, USA
JOON SUNG PARK, Department of Computer Science, University of Illinois at Urbana-Champaign, USA
JAMES A. LANDAY, Computer Science Department, Stanford University, USA
JEFF HANCOCK, Department of Communication, Stanford University, USA

Concern about algorithmically-curated content and its impact on democracy is reaching a fever pitch worldwide. But relative to the role of social media in electoral processes, the role of search results has received less public attention. We develop a theoretical conceptualization of search results as a form of media—*search media*—and analyze search media in the context of political partisanship in the six months leading up to the 2018 U.S. midterm elections. Our empirical analyses use a total of over 4 million URLs, scraped daily from Google search queries for all candidates running for federal office in the United States in 2018. In our first set of analyses we characterize the nature of search media from the data collected in terms of the types of URLs present and the stability of search results over time. In our second, we annotate URLs' top-level domains with existing measures of political partisanship, examining trends by incumbency, election outcome, and other election characteristics. Among other findings, we note that partisanship trends in search media are largely similar for content about candidates from the two major political parties, whereas there are substantial differences in search media for incumbent versus challenger candidates. This work suggests that longitudinal, systematic audits of search media can reflect real-world political trends. We conclude with implications for web search designers and consumers of political content online.

CCS Concepts: • **Information systems** → **Web and social media search**; **Page and site ranking**; **Content ranking**; • **Social and professional topics** → *Political speech*.

Additional Key Words and Phrases: Search media; search engine results; political partisanship

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INTRODUCTION

Algorithmically-curated media content—the core of Facebook's Newsfeed, Google's search engine, and Spotify's Discover Weekly—makes up an ever-growing share of the information we consume online. While such content and the systems that deliver it have much to offer, public concern is mounting about their possible negative impacts on individuals and our society as a whole. Most of the focus thus far has been on social media; in a particularly striking instance this past April, Facebook CEO Mark Zuckerberg was called to testify before the United States Congress in the wake of revelations about possible misuse of sensitive Facebook data during the 2016 election cycle. The

Authors' addresses: Danaë Metaxa, metaxa@cs.stanford.edu, Computer Science Department, Stanford University, USA; Joon Sung Park, jp19@illinois.edu, Department of Computer Science, University of Illinois at Urbana-Champaign, USA; James A. Landay, landay@cs.stanford.edu, Computer Science Department, Stanford University, USA; Jeff Hancock, hancockj@stanford.edu, Department of Communication, Stanford University, USA.

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unprecedented ease and scale of exposing users to targeted media has implications for everything from consumer behaviors to democracy itself.

Compared to social media, web search has received less public attention, though recent outcry in 2018 from U.S. President Donald Trump that Google is "RIGGED" forecasts change. Search engines and search results, while generally not conceptualized as media, are an important source of information for web users. Recent studies have found web users are more likely to find and trust news through search than social media sites [28, 30, 31]. Web search is especially critical in the context of politics, where research has shown it to be among the most commonly-used technologies for finding political information [12].

Search results appear to be particularly important in political contexts. Prior work has identified that differences in the way search results are presented, in particular their ordering, has substantial effects on user perceptions of content credibility and quality [34]. These effects may influence users' information-gathering and opinion-formation process substantially enough to impact the outcomes of close elections [13]. And in addition to their effects on users, search can reveal latent social or cultural trends; this has implications for improving ranking algorithms [41]. Given the way search results are consumed by political information-seeking users and the opaque nature of their production by search engines, we argue for conceiving of search results as a form of media, and studying them accordingly—systematically and longitudinally.

Here we propose search results as a form of media—*search media*—and examine search media in the particularly high-stakes context of politics. In the first portion of this paper, we draw on media theorist Lev Manovich's eight propositions on new media to conceptualize search results as a form of media, laying out the way search results function as media. Having conceived of search results as media, we lay out some of the questions that can be asked of these media, and how to study these cultural artifacts to reveal insights into the political world. We present two empirical analyses of data collected by scraping Google search results leading up to the 2018 U.S. federal midterm elections.

We focus our study on Google as it almost completely dominates the U.S. web search market with a market share of over 90% [10]. Our data are comprised of the first page of search results returned by Google for the names of candidates running for office in that election cycle, collected daily for nearly six months prior to the elections. In the first study, we focus on characterizing search media to better understand what kinds of content comprises search media and how this content changes over time. In the second, we annotate the sources found in our data for political partisanship, and show that search media reflect important aspects of the U.S. media landscape and the political system.

This paper makes three main contributions:

(1) First, we conceptualize search results as a form of media, developing this definition through engagement with theoretical work on new media.
(2) Next, we characterize political search media in the high-stakes context of U.S. politics and the 2018 elections, describing the variety and stability of search media content in political searches.
(3) Finally, we examine the partisanship of sources found in this search media data, showing that search media reflect important aspects of the real-world political landscape that have implications for electoral outcomes.

SEARCH AS MEDIA

We conceptualize search results as a form of new media to frame the study of web search results—in which we consider an entire page of results as a single, coherent artifact—in a manner analogous to the study of newspapers, television, and other media in the past. In particular, we argue that search media falls under the definition of new media—media forms native to digital technologies—laid out by notable media theorist Lev Manovich in his eight propositions on new media [24].

Proposition	Definition [24]	Search results as new media
Culture and computing	New media are "cultural objects enabled by network communication technologies".	Search results are enabled by the web, and are cultural in that their ordering criteria—relevance and authority—are subjective and culturally-defined.
Distribution by digital technology	New media objects use "computer technology for distribution and exhibition".	Search results are both created and distributed through the internet.
Digital data controlled by software	New media are "digital data that can be manipulated by software as any other data".	Search results are essentially data structures containing ordered lists of links.
Mixing cultural conventions and software	New media mix human and computational processes.	Search results pages mix algorithmic processes (crawling, indexing, etc.) with cultural conventions about what constitutes quality.
Ideological tropes of early technologies	New media technologies are accompanied by tropes; e.g., "[it will] allow for 'better democracy'" and "it will contribute to the erosion of moral values".	Current concern over algorithmic content "undermin[ing] democracy" is very reminiscent of these tropes [19].
Faster execution of the previously manual	Technology leads to an increase in speed and efficiency that "does not just leave things as they are... [it] leads to the emergence of qualitatively new phenomena."	Search results, previously compiled for information seekers by librarians, are now available to users instantly.
Metamedia	Many new media are created by remixing existing media, "[using] old media as...primary material".	Search results collect and order existing online content into a new page for consumption by users.
Parallel articulation of post-WWII ideas	Manovich sees parallels between new media of the late 20th century and envisionings of similar ideas in the 1940s-1960s.	The ability to mechanically file and retrieve information from a massive body of human knowledge was first proposed in 1945, when Vannevar Bush imagined the "memex" [7].

Table 1. Considering a page of search results as a technological object fits each of Manovich's eight definitions of new media [24].

New media emerged as a category with the advent of computing and the development of communities of artists working with technology in the 1970s, and includes computer games, animation, and other art forms, as well as other technological artifacts including the internet itself [25]. Encompassing and unifying disparate ideas from technology and communication, new media can be defined and understood in several different ways, all of which contain a central idea: the intersection of computing with culture. In Table 1 we outline each of Manovich's eight propositions for new media, and the way search results fit each.

For example, Manovich characterizes new media as metamedia, "accessing and using in new ways previously accumulated media" [24]. Search results are an excellent example of metamedia; the results page is a single webpage constructed by remixing links to other pages. Its cyclic nature suggests analyzing search results pages as the sum of their component links. Another important proposition is that new media represents a faster execution of previously manual media functions, especially in the way this gain in efficiency changes media phenomena. For example, the current concern over misinformation and the ability for rumors, hoaxes, and propaganda to spread rapidly is a direct result of the automation of media sharing on social media platforms, resulting in users' ability to access an unprecedented quantity of content regardless of quality (unfiltered except by the search engine, but not by any human professional) [40].

As Table 1 shows, the search results page—algorithmically curated hyperlinks ordered by socio-cultural metrics into a single metamedium—satisfies each of Manovich's propositions. This supports our conceptualization of search as media.

Prior Work Studying Political Media

Search media are an important gateway to news online; recent studies have found that web users are more likely to find news through search media than social media [30, 31]. Other work studying users' web browsing histories found that users usually accessed news via a link from another site, and this referring site was an online search 20% of the time (more often than any other kind of referring site) [5]. This makes search media especially critical in the context of politics, where studies have shown that search media is among the most commonly used technologies for finding political information that can shape views and votes. Features as subtle as the ordering of search results can influence users, perhaps even enough to impact the outcomes of close elections [13]. Due to the importance of politics in the context of society and search, we focus here on political search media.

Prior to the widespread use of web search, work in political science considered partisanship in the context of online media and electoral processes. For example, electoral participation, while determined by many factors, is significantly impacted by the mobilization efforts of campaigns and political parties [8]. These efforts can include activating supporters to vote, and negative advertising in an attempt to discourage out-party members from voting [8].

One of the main mechanisms for spreading campaign messages is through targeting liberal and conservative leaning potential voters through online media, a process that may influence polarization of the American public and election outcomes [1]. New media sources have been found to be increasingly polarized, having added more partisan messages to compete with the existing supply of centrist news [4, 36]. One concern is that news consumers gravitate towards "echo chambers," selectively exposing themselves to media supporting their prior beliefs, and the internet provides an unprecedented number of outlets from which to choose [6, 23]. Electorate polarization has widespread implications for democracy—more partisan media has "lowered the share of less interested, less partisan voters and thereby made elections more partisan" [36].

Work in the domain of web search has also touched on politics from several angles. Much of it focuses on the impact of search results on end users and the presence or absence of filter bubbles, the phenomenon in which algorithmic content only exposes users to information that reinforces their existing opinions. Results in this space are mixed; a study analyzing users' web browsing history looking for exposure to different political perspectives found some evidence of such effects [16], while other research has not [12]. Recent work focusing on search personalization and politics has found little evidence of results being personalized in response to queries of a political nature [37].

Challenges in Studying Search Media

Two major challenges in studying search media are their *ephemerality*—they appear in real time in response to a search query, but are not persistent or archived for later review—and that they are *reconstitutive*—they are liable to change based on the media environment, in response to user feedback, or as a result of time or location, among other factors. One strategy used in prior literature to address these challenges and that we deploy in this work is the "algorithm audit" which, following the tradition of audit studies in social sciences, involves querying the search engine repeatedly and recording the results for the purposes of comparison [39].

Algorithm auditing is a particularly important tactic for search media given the ephemerality of search results, which cannot otherwise be studied in retrospect. Prior work has used algorithm audits to study personalization, comparing search results done by different users (at a single point in time for each user) to each other [37]. Other work has used this method to study web spammers' behavior during the 2016 elections, collecting search results for the names of 340 candidates at forty data collection points [27]. Expanding on the scale of prior work, we argue here for the importance of systematic aggregate analysis, collecting data for queries using the names of all election candidates (over 3,000 of them) longitudinally (daily for nearly six months) and giving a unique perspective on search media stability and partisanship over time.

The cyclical and constantly reconstituting nature of search results represents a different kind of challenge. The production of search media can be decomposed into two main dimensions: endogenous factors and exogenous ones. Endogenous factors are those internal to the algorithm itself, such as strategic policy decisions made by Google about what content to surface or bury, user behavior which may feed back into the algorithm, and technical limitations like the rate at which a search engine can crawl and update its indices. Exogenous factors are attributes of "the real world"; in the context of political search media, this includes the behavior of political candidates, changes in current events, and decisions by news media of what to cover and how. All these types of factors are closely intertwined, and it can be difficult to disentangle them. Recent work has attempted to separate user behavior (e.g., choosing input to a search engine) from algorithmic outputs (e.g., the engine's ranking choices) [22]. Other work has collected specific segments of the results page that are heavily curated by the search engine, such as Google's candidate issue guide and "in the news" panels, to study editorial choices made by Google [11]. In this work, we focus exclusively on the least common denominator of search results, the "blue links," but this allows us to make comparisons and aggregate across many different query terms.

RESEARCH QUESTIONS

In this work, we argue for the importance of longitudinal and systematic analysis of political search media with an algorithm audit. While collecting data at a single time point has proved fruitful for comparing along other axes such as source sentiment towards politicians from different political groups (e.g., [11]), or different search engines (e.g., [22]), a wider time window of data collection can surface algorithmic changes as well as reflect current events in the offline world. To do so, data collection in this study spans nearly six months of an election cycle, though the method is extensible and will ideally span several election cycles in the future.

Similarly, while prior work has collected search media data using as queries a wide range of terms related to politics and current events (e.g., [37]), or a subset of political candidates for office (i.e. [27]), the root queries can considerably impact the results, as other work has shown [22]. To make broader statements about the partisanship of sources present in search media and the real-world attributes of the political system, in this work we use as search terms the names of every candidate for U.S. federal office in 2018, analyzing the results in aggregate across this systematic and exhaustive data set.

Our first research question and set of analyses is concerned with understanding the characteristics of political search media.

RQ1: What are the properties and characteristics of search media related to political candidates in the 2018 U.S. Federal election, in particular with regard to types of content and stability of search media over time?

In our second study, our research question revolves around the relationship of search media to the real-world media ecosystem and political landscape, such as incumbency and election. We study this through the lens of a salient dimension of U.S. politics: partisanship.

RQ2: Do search media reflect attributes of the 2018 elections such as distribution of partisan media sources and electoral dynamics?

Having established the theoretical framing behind this work along with the goals of our analysis and the challenges involved in meeting them, we next describe the methodology we deploy.

DATA COLLECTION

Our data was collected following a similar method to that outlined in previous literature, wherein searches for the names of some election candidates were recorded at forty time points leading up to the election [27]. We significantly expand that methodology, collecting Google search results daily for every candidate running for federal congressional office during the 2018 election cycle and covering May 29, 2018 through the election on November 6, 2018 (163 days). We focus our study on Google as it dominates the U.S. web search market with over 90% market share (the next largest search engine, Bing, has around 3%) [10].

Background on U.S. Elections

This work focuses on the United States' federal elections that took place on November 6, 2018. The U.S. federal legislature has two chambers: the House of Representatives and the Senate. Each of the 50 U.S. states elects two senators who serve six-year terms, and between one and 53 representatives (based on the state's population), who serve two-year terms. Terms are staggered such that only a subset of seats in the Senate have elections in a given election cycle (every two years). There are two main political parties in the U.S.—the conservative, right-wing Republican party and the liberal, left-wing Democratic party. While third party candidates run in every election representing a range of other political viewpoints, it is rare for any of these candidates to win federal election. As many candidates from the same party may want to run for election in a given year, the major political parties in most states hold primary elections to choose which candidate to put on the ballot for the general election. Primary elections vary widely both in their timing (for the November 2018 elections, some primaries were held as early as March and some as late as the day of the general election) and logistics (whether primaries are open to any voters or only to registered party member voters, among many other differences). In this research, we collect data for over 3,000 candidates running for 225 seats in the 2018 elections for U.S. House and Senate. Of these, 878 candidates were on the ballot in the general election.

Choosing Search Queries

In initial testing of our data collection pipeline, we observed that the use of name-only queries, as was done in prior work, resulted in many social media or Whitepages-style results for non-politicians with the same names, particularly in the case of lesser-known candidates. Such lesser-known candidates comprise the majority of our data, since we consider every candidate for office rather than a subset as has been done in prior work. As a result and after experimenting with various alternative queries, we chose to include the state abbreviation after the name (i.e., "Peter Yu CO") to increase the relevance of results for lesser-known candidates.

To examine whether adding state abbreviations improved results for lesser-known candidates while not affecting more well-known candidates we collected a day of search results using both methods. As a proxy for being relatively well-known we selected candidates reaching the general election, while for lesser-known candidates we selected candidates losing before the general election. For better-known candidates ($N = 853$), an average of 7.26 domains (out of roughly 10 served by the search engine) were shared between name-only query results and state-included results, while only 5.32 were shared for lesser-known candidates ($N = 2{,}417$)—suggesting that using state abbreviations largely did not affect better-known candidates' results.

Next, to confirm that adding abbreviations improved lesser-known candidates' results we selected a random sample of 10 such candidates and recruited three raters from Amazon Mechanical Turk to review each query result. URLs were rated on a Likert scale, with 3 indicating a URL was "extremely relevant" ("information specific to this candidate"), 2 indicating "moderate" relevance ("at least tangentially related to the candidate"), and 1 indicating no relevance ("i.e. content about someone else with the same name, or otherwise unrelated"). Omitting those shared between both sets of queries (which were rated most highly relevant, at 2.6), results from queries using state abbreviations were on average rated 2.0, and those from name-only queries an average of 1.47, a statistically significant difference ($p < 0.001$). These results suggest that the use of state abbreviations in queries resulted in more relevant data for lesser-known candidates, who comprised the majority of candidates in our data set.

Scraping Search Results

We used five scrapers to collect the blue links on the first page of search results daily. Each scraper had its own IP address, instantiated using the Amazon Elastic Compute Cloud, and rotated through a list of user-agent strings such that each request appeared to come from a normal operating system and modern web browser. Each of the five scrapers collects using a script the first page of Google search results for a fifth of the 3,383 candidates daily. Between each query, the scrapers take a break for about a minute to avoid overloading Google's servers with queries. This data collection process takes approximately 10 hours per day. (Given the volume of search queries sent to Google daily from users around the world, we believe it is highly unlikely that our queries have any impact on the search engine.) Recent work investigating personalization in political web search has found that personalization has "little impact" on such queries [37], but in order for our data to most closely reflect a generic user, we also add a depersonalization parameter ("pws=0") to the end of each query URL to avoid any history-based personalization.

STUDY 1 - CHARACTERIZING SEARCH MEDIA

Revisiting our first research question, in the following analyses we seek to characterize search media related to political candidates in the 2018 U.S. elections. Specifically, we ask, what content comprises this search media and how stable is such content over time?

Content Characteristics

In total, we collected data for 3,383 candidates (2,976 running for the House, 407 for the Senate) who registered with the U.S. Federal Election Commission to appear on the ballot by May 15, 2018. Of these, 878 were on the ballot in the general election. Examining the most prevalent domains in our data, social media sources (e.g., facebook.com and twitter.com), as well as encyclopedic websites (e.g., wikipedia.com and ballotpedia.com) were most common. Also represented were other websites for political information, including votesmart.org, govtrack.us, and congress.gov. The only news media source to appear in the top ten sites by frequency was washingtonpost.com.

Next, to get a better understanding of the types of domains in our data, we hired workers from Amazon Mechanical Turk to label each domain as one of the following categories (decided upon after manually annotating a subset): encyclopedia or knowledge database (e.g., wikipedia.com); news source; politician or campaign website; other political site (e.g., congress.gov, crowdpac.com); social media site; whitepages-style site (e.g., nuwber.com); other. The frequency of domains follows a power law distribution, such that the top 500 by number of non-unique appearances in our data comprise over 70% of sources. For all 534 domains appearing more than 500 times in our data, we hired three annotators, and considered a category label to be decided when two of the three agreed (this was the case for 89% of the domains). The results showed that most domains were judged to be news (47.3%) or campaign (38.5%) sites; the next most common category was other political sites at 6.7%.

Search Media Stability

An important metric in previous studies of search results has been search result stability, in particular in the context of politics where different stakeholders may be motivated to game or rig search results [26], or where changes in search results may reflect important political events or other changes in the political landscape. In this work, we generalize a metric used in prior literature to study stability of search results for each query day by day in our data [3].

Calculating Day-by-Day Similarity. For each query, we calculate the stability of search media throughout our data set using the M metric established in prior literature, which quantifies how similar two pages of search results are to one another, weighting changes among the top links more highly than the lower ones [3]. The metric first computes the difference between two pages, M', as a sum of the change in position each URL from one page to the other. For URLs appearing on both pages, this is proportional to the difference in rank: $|\frac{1}{rank_1(i)} - \frac{1}{rank_2(i)}|$, for some URL i, where $rank_1(i)$ is the URL's rank on the first page, and $rank_2(i)$ is its rank on the second. For URLs not appearing on both pages, the equation presumes such URLs moved from at least the second page of results (in [3], this is presumed to be at least the 11th position): $|\frac{1}{rank_1(i)} - \frac{1}{11}|$ for results appearing on the first page but not the second, and $|\frac{1}{rank_2(i)} - \frac{1}{11}|$ for those on the second but not the first. Altogether this equation for computing the difference of two pages, M', given the URLs on both pages (Z), those only on the first page (S), and those only on the second page (T) is:

$$M' = \sum_Z |\frac{1}{rank_1(i)} - \frac{1}{rank_2(i)}| + \sum_S (|\frac{1}{rank_1(i)} - \frac{1}{11}|) + \sum_T (|\frac{1}{rank_2(i)} - \frac{1}{11}|)$$

This is then normalized by a constant, $c = 4.03976$, and converted into a similarity score, such that two pages with no URLs in common have $M = 0$ and two identical pages yield $M = 1$:

$$M = 1 - \frac{M'}{c}$$

These previously established equations assume two pages of results each with ten URLs. To compute stability in our search results, which are of variable length, we generalize the M metric by making two adjustments. First, we compute the movement of a URL appearing on one page but not the other as if it had come not from the 11th position, but from whichever rank would be at the top of the second page of results—the N_p position, where N is the total number of search results on page p:

$$M' = \sum_Z |\frac{1}{rank_1(i)} - \frac{1}{rank_2(i)}| + \sum_S (|\frac{1}{rank_1(i)} - \frac{1}{N_2 + 1}|) + \sum_T (|\frac{1}{rank_2(i)} - \frac{1}{N_1 + 1}|)$$

We also generalize the normalization factor C for two pages of any length:

$$C = \sum_{i=1}^{N_1} \frac{N_1}{i(N_1 + 1)} + \sum_{i=1}^{N_2} \frac{N_2}{i(N_2 + 1)}$$

$$M = 1 - \frac{1}{C}$$

Stability Over Time. To gain an intuition for the use of the page similarity metric in examining search stability, Figure 1 plots page similarity scores day by day for two candidates in our data set, Nancy Pelosi and Alexandria Ocasio-Cortez. Search media about Candidate Pelosi, an incumbent running for her seventeenth term in Congress, was very stable throughout the data collection; in contrast, search media for Ocasio-Cortez, a challenger candidate who won election to the House of Representatives in a surprising upset victory over the incumbent, shows more variation, especially in the first half of the data collection window.

Having gained an intuition for search media on an individual-query basis, we next examine trends in search media stability in aggregate across all queries. For each date of data collection, we average the search media stability score across all candidates. Unlike in the individual case studies illustrated in Figure 1, which reflect considerable changes in search results day over day, stability averaged across all candidates evens out—with a few notable exceptions. As is visible in Figure 2, aggregating reveals periodic changes in search media every 35 to 40 days during the data collection process. Examining one of these dips in similarity score, we find that the amount search media change is minimal—from a median of 0.973 on September 10 to 0.901 on September 11 (see Figure 2). To the best of our knowledge, this trend has not been reported in prior literature, but its appearance at somewhat regular intervals and only in aggregate suggests it may reflect an endogenous feature underlying the production of search media, such as a monthly synchronization between the servers Google uses to continually re-crawl and re-index the web.

Figure 2 also reflects that search media are similarly stable for candidates by type (comparing challengers, incumbents, and those running for open seats), though the periodic perturbations are weakest for incumbent candidates. Similarly, comparing search media for candidates of different degrees of popularity, using as proxy the candidate's success in the primary (with primary-only candidates likely less well-known and those reaching the general election better-known) we also find little difference in search media stability. Examining the standard deviations in addition to these averages (not pictured in Figure 2 for readability), we also find similar values across the different groups over time.

STUDY 2 - PARTISANSHIP IN SEARCH MEDIA

Having characterized the types of pages present in this data and the way they change over time, our next set of analyses revolved around the distribution of partisan viewpoints present in search media. We wish to see whether these viewpoints reflect something meaningful about the media ecosystem or political landscape; to do so we focus on partisanship, one of the most salient features of U.S. politics. We use existing metrics that match online sources with partisanship scores to automatically annotate as much of our data set as possible at scale; in doing so, we are able to annotate search media with a score that reflects its degree of partisanship, and to track fluctuations of partisanship in our search media data over time and for different types of candidates.

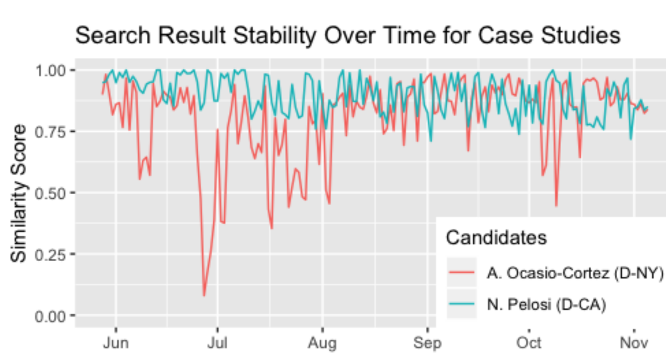

Fig. 1. As examples, search media when querying for well-known incumbent Nancy Pelosi were relatively stable, while search media about challenger Alexandria Ocasio-Cortez were more dynamic.

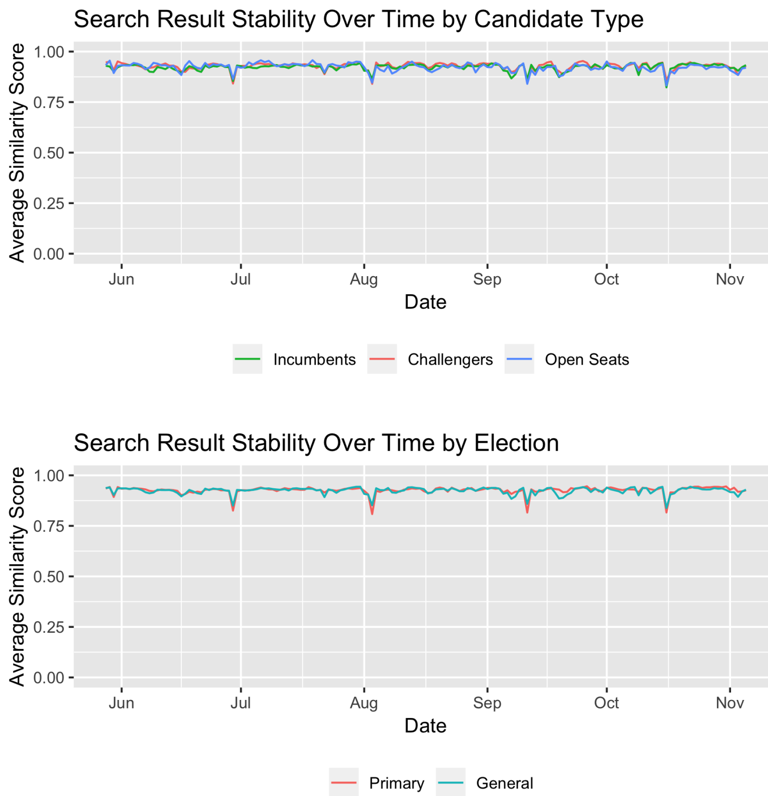

Fig. 2. Aggregating stability over time across candidates by type (incumbents, challengers, and open seats) and by election phase (candidates who only appeared in primaries versus those appearing in the general), we see that search results are relatively stable over time, with small but regular changes, and similar across all groups.

Assigning Partisan Intensity Scores

To assign a score for the degree of partisanship associated with each top-level domain in our data set, we use the *partisan attention scores* for 5,798 media sources compiled by the Berkman Klein study as part of their 2017 report and provided to us by the authors upon request [15]. These scores, which are expressed on a −1.0 to 1.0 scale with those close to −1.0 representing extremely left-leaning sites like motherjones.com (-0.83) and those close to 1.0 representing extremely right-leaning sites like breitbart.com (0.95), are generated based on each source's Twitter shares among over 44,000 users labeled as being likely liberal or likely conservative. Users' political leanings were inferred by identifying users who had retweeted either of the two 2016 general election candidates (@donaldjtrump and @hillaryclinton), but very rarely retweeted both (only 297 users retweeted both candidates). This method follows that of Bakshy et al., who computed scores measuring sources' partisan slants based on Facebook shares by users who had self-identified their political affiliation [2]. The scores in the Berkman Klein report correlate highly with those produced by Bakshy et al., providing evidence for the robustness of the scoring [15].

We are predominantly interested in the degree of partisanship shown in the search media, regardless of the specific party leaning. To express this party-agnostic partisanship, we compute the *partisan* *intensity score* of a media source by taking the absolute value of the source's partisan attention score. Thus our partisan intensity score metric is expressed on a 0 to 1.0 scale, where a score of 1.0 means a source is extremely partisan (regardless of party) and a score close to 0.0 means a source is neutral.

To calculate the overall partisan intensity score of a page of search media, we take the average overall partisan intensity score of all sources on the page. Reflecting prior insights from prior literature that higher-ranked content is more highly visible and therefore salient to users, we take the ranked order of results into consideration as we did in our stability calculations above, weighting the partisan intensity score of each source on the page according to its rank in the ordered list of results.

We exclude any URLs that originated from a media source not covered in the Berkman Klein study of media sources—we are able to categorize 35.2% of our URLs using this method. To better understand the excluded data, we hand-annotated the top 100 most frequently excluded sources. We chose this number because of the power law distribution of sources by frequency of appearance in our data; the top 100 sources accounted for 45.47% of the excluded data. The majority of these sources were social networking sites (including Facebook, Twitter, and LinkedIn), candidates' personal campaign sites, and online shopping sites (such as Amazon). While the exclusion of so many sites is a limitation of this method, we were satisfied that the majority of excluded sites indeed could not be meaningfully labeled with a partisanship score. Following prior work we also removed en.wikipedia.org and ballotpedia.org from the analyses that follow, as these are the top two sites by frequency of appearance and assigning a fixed partisanship score to these encyclopedias misrepresents their breadth of content [38].

Overall Source Polarization

Having labeled these search media with partisan intensity scores, we first examine the distribution of partisanship in our data set. Figure 3 plots the frequency of unique sources by partisan attention score (0.1-sized buckets) as well as the frequency of sources weighted by their number of appearances in our data. In the histogram of unique sources we see a roughly normal distribution of centrist sources offset slightly center-left, and two large peaks of highly partisan sources on the left and, especially, the right. These trends mirror those reported in the Berkman Klein report, which focused on media sources attracting social media attention during the 2016 election season [15]. This suggests that the range of sources from which Google draws is reflective of the broader media landscape; we do not see evidence that sources on either side of the political spectrum are being systematically excluded from search media.

Weighting URLs by their number of appearances in our data set, we see a prevalence of centrist sites, reflecting Google's reliance on mainstream news media sources, which have more moderate partisanship scores. There is also a distinct lack of center-right sources (those with partisanship scores between 0.5 and 0.9) similar to that noted in the Berkman Klein report which describes, "a hollowing out of the center-right and its displacement by a new, more extreme form of right-wing politics" [15]. This trend could stem from the set of websites and assigned scores available from that prior work; however, we also observed this trend, albeit more weakly, when annotating sources using a different list (i.e., [38]) as a sanity-check.

Political Affiliation

Concern over partisanship in media coverage as it relates to the two main U.S. political parties has been widespread for decades. This issue is high-stakes; bias in search media has the potential to silently limit users exposure to other views and perspectives.

Prior work suggests media are not biased against (or for) either party. One of the earliest examples of literature addressing bias by party found network television to cover both parties neutrally during the 1972 U.S. presidential election [20]. Researchers asking similar questions through the 1980s and 1990s have continued to find little evidence of bias in coverage by party affiliation [17, 21]. A meta-analysis

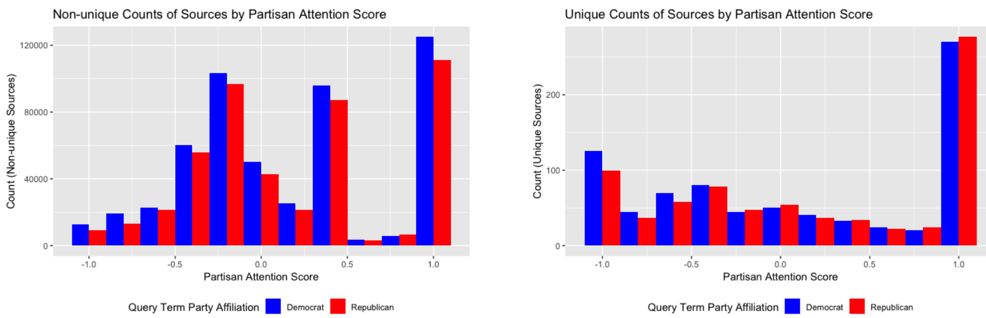

Fig. 3. Examining the distribution of partisan attention in our data reflects some of the same trends reported in prior work about the media ecosystem in social media. We see virtually no difference by party affiliation given queries for names of Democrats versus Republicans.

in 2000 summarized 59 quantitative studies in this domain, and again found "no significant biases" [9]. Using the same standard as related work in this domain, we examine whether search media treat Republicans and Democrats comparably [33]. As reflected in Figure 3, distribution of partisanship in search media sources is very similar for queries for candidates of both major parties. In other words, Google does not point to more conservative sources given a more conservative query, nor more liberal sources given a query for a liberal candidate. This finding extends the previous literature finding relatively party-neutral coverage to the domain of search media. This could potentially reflect a conscious effort by Google to treat political queries comparably regardless of political leaning, or could be caused by the search engine's domain-level assessment of source credibility and resulting tendency to highly-rank sources it has labeled as authoritative, regardless of query. It may also reflect the willingness of media sources from both sides of the political spectrum to cover candidates from their own party as frequently as from the other party.

Incumbency Status and Election Outcomes

Two other very important candidate attributes are highly correlated with each other—incumbency status, and election outcome. We find strong differences in search media partisanship attributes by both these features, but election outcome predictability disappears after controlling for incumbency.

The political science literature predicts that incumbents should be more moderate and more centrist in their positions than challengers, in whose best interest it is to be more extreme to appeal to the base of the party, and that news media may therefore cover them accordingly [18]. We ask, then, whether search media also reflect this trend. As shown in Figure 4, this is confirmed: search media about incumbent candidates show strikingly lower levels of partisanship compared to challengers.

We use an ANOVA on the output of a generalized linear model predicting binomial general election outcome from average partisanship throughout the data collection and incumbency; this shows incumbency has a large effect size that is statistically significant ($F(2{,}865) = 376.2$, $p < 0.001$) and average partisanship is significant as well ($F(1{,}865) = 215.8$, $p < 0.001$).

Open seats (races in which there is no incumbent candidate), are relatively rare, and existing theory does not predict what patterns their media might reflect. Interestingly, search media partisanship for open seat candidates in our data tracks with challengers, suggesting that the media coverage surrounding open seat candidates is similar to the uphill battle faced by lesser-known challengers.

Breaking the data apart into open seat races versus races with incumbents, however, we find that average partisanship is only weakly predictive of outcome—in the case of open seat races

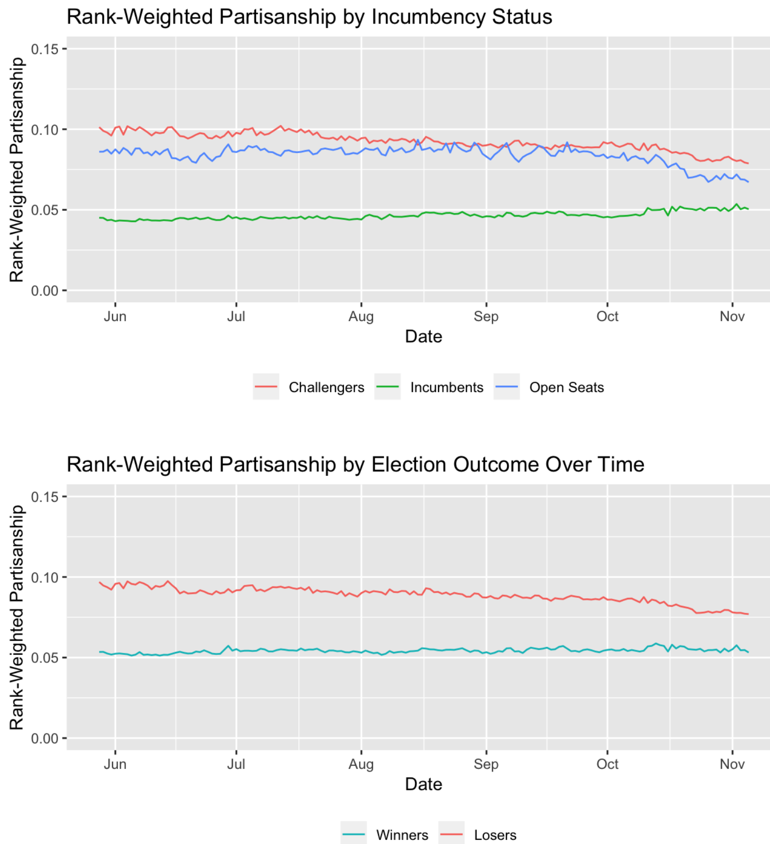

Fig. 4. Search media about incumbent candidates and election winners had significantly lower partisanship throughout our data than challengers, open seat candidates, and election losers.

($F(1, 121) = 2.973$, $p = 0.08$), as well as races with incumbents ($F(1,743) = 3.04$, $p = 0.08$) though incumbency status is still highly significant in the latter ($F(1,743) = 1175.04$, $p < 0.001$).

DISCUSSION

We begin this work by defining search results as a form of media, comprised of algorithmically-curated content, and search engine users as media consumers. Given the importance of political information, we focus on political search media in the context of the 2018 U.S. midterm elections. This theoretical framing informs our choice to study search media systematically, collecting queries for all candidates in those elections, and longitudinally, for nearly six months leading up to the election. These two methodological choices allow us to begin to tease apart some of the endogenous and exogenous factors—those inherent to the search algorithm's inner workings and those reflective of offline events or qualities—present in search media.

In the first of our empirical studies, we set out to characterize this form of media in terms of the sources contained therein, and the way they change over time. We generalize similarity metrics from prior literature used for comparing pairs of search results pages, and track the stability of our queries over time. We find that search media are relatively stable, though in aggregate they show a periodic disturbance that may reflect an aspect of the back-end implementation of Google's search engine.

Given the importance of partisanship as a central feature of U.S. democracy and traditional media, in our second study we label our data with partisanship scores and first examine the distribution of partisan sources in our data, finding trends, such as the inflation of far-right media sources, that echo recent literature on the changing social media landscape. We next connect partisanship in search media to incumbency and then to election outcome, both important real-world phenomena that search media reflect. Taken together, both studies reinforce the merit of our theoretical conceptualization of search as media. Search media function as a form of metamedia, selecting and remixing existing media sources into a new format that, analyzed in our audit-style aggregate method, display emergent trends that reveal the state of the media ecosystem [24].

Our findings have design implications for technologists, and implications for citizens consuming online political content. The need to audit search engines in the first place reflects that these algorithms, despite their importance, are very opaque. Search results are presented to users as a curated document and consumed as if from a trusted media source; the risks are substantial. The method we present, combining a longitudinal algorithm audit with partisanship annotations, is one way of monitoring this risk that companies should make possible (many platforms are much harder to audit than Google's search engine) or perhaps even conduct and publish their own audits regularly. In addition to monitoring, search engines could mitigate the misinformation risk by disrupting users' perceptions of search results as an authoritative media source. For instance, Google could explicitly annotate results pages to indicate geolocation, personalization, or other reasons each result appeared, to give users some insight into the machinations of the algorithm. Facebook's introduction of the "Why Am I Seeing This?" feature provides one concrete example of this idea in practice—users can find an option in the drop down menu of each post and ad on their News Feed with a brief sentence explaining what past behavior or demographic targeting led to the post being surfaced [32]. Similarly, search engines could visually surface meta-information about the perspectives represented on a page of results in the form of a "nutrition label" or visual warning reflecting whether a results page show a breadth of political perspectives, as some prior research has proposed [14, 29, 35]. Such interventions could help users intuitively understand that search media are not authoritative media sources akin to other quality news media—rather, they are complex algorithmic byproducts.

Limitations

The method we propose and employ for studying search media in the context of elections is certainly not the only suitable method for such study; we find it valuable for categorizing and studying partisanship at scale in a large data set, but along with its benefits it has limitations. Notably, the data in this analysis is comprised solely of the main body of search results (the "blue links") scraped from Google's search engine. This is the lowest common denominator of search results—all our queries had this attribute. Searches for a subset of the higher-profile candidates, however, also contain features including panels of recent tweets, knowledge graph panels, and other attributes which we did not collect. Some prior work has studied such content (e.g., [11, 38]) and we encourage future work to continue collecting and analyzing such data. Our choice of search engine also limits the generalizability of these findings—other search engines might behave differently. While Google's enormous market share suggests that it is by far the most dominant search engine and therefore is most important to understand, we hope to expand this work to examine the behavior of other search engines.

Another important limitation involves our reliance on partisanship scores in the second study. We are able to annotate a large but specific subset of sources—those shared widely on other forms of social media, as this widespread social sharing was a prerequisite for the Berkman Klein methodology that developed the scores. We were also able to replicate these trends with newer mappings of domain to partisanship generated with the slightly different method in [38]. However, the fact remains that these aggregate methods can only annotate a subset of all results with a relatively confident score. That our analyses reflect trends consistent with prior work and real-world phenomena suggests that this subset of sites is informative in understanding the media ecosystem behind search, but we cannot claim to understand the entirety of search media pages.

A third major limitation of this work that we hope will lead to fruitful future research: we do not directly study the complex relationship between search and users, including what queries users are likely to make in the context of elections (though we choose queries consistent with prior literature). Closing the loop to study and possibly mitigate search media's impact on users is an area for future work.

Future Work

This work focuses on search media relating to the 2018 U.S. federal elections, characterizing them by type and stability, and in relation to political polarization. The data analyzed here are rich; we hope to expand this work to examine other attributes of search media including sentiment of linked content and ads, and to further examine the attributes described here (for instance by studying stability and partisanship on a weekly or monthly, rather than daily, basis). Additionally, with continued data collection these findings can be expanded to include comparative studies of future elections and other bodies of online content (such as that shared on social media or across the entire web), to begin teasing apart the various exogenous and endogenous factors contributing to the patterns we observe. We also note that, while this work focuses on aggregate analyses of data from thousands of queries over hundreds of days, more fine-grained approaches have potential to more deeply explore the way specific political events influence search media about a specific candidate or race.

The other main area for extension of this work goes beyond the composition of search media to its effect on users. The search media pipeline starts with a search engine crawling and indexing the web, and ends with users issuing queries and receiving information; this work focuses on the first portion of that pipeline rather than the latter part, its consumption. Future work should help identify what queries users actually issue, and better understand the complex impact a page of results can have on users. Finally, while politics is one high-stakes domain for study, future work can leverage the framing of search as media and the analytical framework developed here to apply to other domains impacted by search.

CONCLUSION

Establishing search as media suggests research questions inspired by previous literature to examine the relationship of search media to politics using a systematic and longitudinal methodology. We queried the Google search engine daily leading up to an important political event, the 2018 U.S. midterm elections, using as queries the names of candidates running for office. In our first study we characterize this media for the type of content it contains and its stability over time, finding that search media is relative stable but has periodic shifts that likely reflect endogenous factors related to its production. In our second study, we see the impact of exogenous factors (real-world facts about the candidates in our data set and the political media landscape) on search media. In particular, we find that search media about candidates from different political parties nevertheless display similar trends in partisanship, and also find clear differences in search media partisanship between incumbents and non-incumbent candidates. This framework and these findings suggest the potential for future work studying the impact of search media on users over time.

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