Polarization, Partisanship and Junk News Consumption on Social Media During the 2018 US Midterm Elections

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ABSTRACT

In the United States, social media platforms serve significant volumes of junk political news and information during important moments in political life—particularly elections. In this data memo, we examine the sources of political news and information that were shared by social media users in the period leading up to the 2018 US midterms, evaluate the sources, and identify the primary audiences for content that is sensational, extremist, conspiratorial or that has other qualities of junk news. Analyzing 2.5 million tweets and 6,986 Facebook pages over a 30-day period, we find that (1) the amount of junk news in circulation over social media is greater than it was during the 2016 US presidential election, with users sharing more junk news than professional news overall, (2) junk news once consumed by President Trump's support base and the far-right is now being consumed by more mainstream conservative social media users, and that (3) less than five percent of the sources referenced on social media are from public agencies, experts, or the political candidates themselves.

INTRODUCTION

Large volumes of polarizing, misleading and conspiratorial political news and information flow over social media. Our previous research has demonstrated that a significant amount of the political news and information that circulated on Twitter during the 2016 US election was driven by automated accounts.[1] This content was concentrated in swing states, where social media users shared content from high quality, professional sources of political news and information at an equal level with junk sources.[2,3] We identified particular Russian-origin misinformation campaigns targeted at US military personnel, veterans and their families.[4] In the lead up to President Trump's 2018 State of the Union address, we found that junk news was largely consumed and distributed by hard conservatives and President Trump's supporters.[5]

In this study, we examine the distribution of political news and information on social media before the 2018 US midterm elections. Our research questions are: (1) What kinds of political news and information are social media users in the United States sharing in advance of Election Day? (2) How much of it is extremist, sensationalist, conspiratorial, masked commentary, fake, or some other form of junk news? (3) Which groups of voters in the US are sharing the highest amount of junk news and information?

COMPUTATIONAL PROPAGANDA AND THE 2018 US MIDTERM ELECTIONS

Social media is now a vital platform for news consumption in the United States. According to the 2018 *Reuters Digital News Report*, 68% of US adults use Facebook and 39% of US adults do so for the purpose of seeing news. A significant proportion of the US public also turns to YouTube for political news and information. News about politics and public affairs can also reach social media users inadvertently, even when they do not browse the Internet for that explicit purpose, if their friends or acquaintances post political content on their feeds for instance. Given the importance of social media in contemporary public life, these platforms have become regular targets for coordinated propaganda and influence campaigns.[6] While the reach of junk news during critical moments of public life in the US is wide, we have not seen it entirely overtake the consumption of traditional news, even amongst its most avid consumers.

Since the UK's Brexit referendum and the 2016 US presidential election, social media companies have put significant work into raising the quality of political news and information circulating over their platforms. These initiatives range from fact-checking and digital literacy programs, to transparency efforts around political advertising, and algorithmic downranking of junk news. Platforms have bolstered content moderation to remove spam and automated accounts from social media sites. Despite these efforts, junk news continues to spread in critical moments of public life in the US. On Twitter, a large number of accounts that were linked to the spread of disinformation during the 2016 elections are still actively spreading junk news today.[7]

The November 2018 midterm elections will include campaigns for 35 of the 100 US Senate seats and all of the 435 seats in the House of Representatives. At stake is the issue of which party will control the two chambers of Congress and ultimately oversee the executive powers of the Trump administration. Understanding the role of social media in contemporary political communication requires taking a large sample of the political conversation, cataloguing and evaluating the sources of political news and information being shared, and categorizing the particular audiences for junk news.

SAMPLING AND METHODS

Evaluating Sources of Political News and Information

To answer these research questions, we first build a typology of the most commonly shared sources of political news and information on social media. Since Facebook does not provide the infrastructure for researchers to do this, we actually begin with a large sample of political conversation on Twitter. For this study, we extracted 99,657 URL links from a sample 2,541,544 tweets from 379,777 unique users collected in the lead up to the US midterm election, between September 21-30, 2018, using a combination of relevant political party hashtags, election-specific hashtags, and handles for the individual parties. The full list of hashtags (available on our online supplement) was compiled by a team of three trained coders who are highly familiar with US politics. Prior to launching the data collection, the set of hashtags was refined in a trial run, which revealed the most frequently used election-related hashtags, and the list was revised accordingly.

Twitter's Streaming API was used to collect publicly available tweets. The platform's precise sampling method is not disclosed, however Twitter reports that data available through the Streaming API is, at most, 1% of the overall global public traffic on Twitter at any given time. Tweets were collected if they: (1) contained at least one of the relevant hashtags or at least one Twitter handle of the political parties or political leader; (2) contained the hashtag in the URL shared, or the title of its webpage; (3) were a retweet of a message that contained a relevant hashtag or mention in the original message; or (4) were a quoted tweet referring to a tweet with a relevant hashtag or mention.

The final catalogue of political news and information shared over social media includes sources that have been shared five times or more. Links leading to Twitter itself were excluded, but links to content on other social media platforms, such as Facebook or YouTube, were included and catalogued. By applying the cataloguing decisions made on this latest sample with those made using samples from the last two years, we are able to successfully label 96.1% of all the URLs being shared. Next, we classified the base URLs, accounts, channels, and pages associated with these sources, based on a rigorous and iterative coding process developed and refined through the project's previous studies of six elections in five Western democracies and several countries in Latin America.[8-10]

The team of three coders identified sources of junk news and information, based on a rigorous grounded typology. Sources of junk news deliberately publish misleading, deceptive or incorrect information purporting to be real news about politics, economics or culture. This content includes various forms of extremist, sensationalist, conspiratorial, masked commentary, fake news and other forms of junk news. The typology explaining our content classification is as follows:

Professional News Content

- Major News Brands. This is political news and information by major newspapers, broadcasting or radio outlets, as well as news agencies.
- Local News. This content comes from local and regional newspapers, broadcasting and radio outlets, or local affiliates of major news brands.
- New Media and Start-ups. This content comes from new media and digitally native publishers, news brands and start-ups.
- Tabloids. This news reporting focuses on sex, crime, astrology and celebrities, and includes yellow press publications.

Professional Political Content

- Government. These links are to websites of branches of government or public agencies.
- Experts. This content takes the form of white papers, policy papers or scholarship from researchers based at universities, think tanks or other research organizations.
- Political Party or Candidate. These links are to official content produced by a political party or candidate campaign, as well as the parties' political committees.

Polarizing and Conspiracy Content

- Junk News and Information. These sources deliberately publish misleading, deceptive or incorrect information purporting to be real news about politics, economics or culture. This content includes various forms of propaganda and ideologically extreme, hyper-partisan or conspiratorial news and information. To be classified as Junk News and Information, the source **must fulfill at least three of these five criteria:**
  - *Professionalism*: These outlets do not employ standards and best practices of professional journalism. They refrain from providing clear information about real authors, editors, publishers and owners. They lack transparency and accountability, and do not publish corrections on debunked information.
  - *Style*: These outlets use emotionally driven language with emotive expressions, hyperbole, ad hominem attacks, misleading headlines, excessive capitalization, unsafe generalizations and logical fallacies, moving images, and lots of pictures and mobilizing memes.
  - *Credibility*: These outlets rely on false information and conspiracy theories, which they often employ strategically. They report without consulting multiple sources and do not fact-check. Sources are often untrustworthy and standards of production lack reliability.
  - *Bias*: Reporting in these outlets is highly biased, ideologically skewed or hyper-partisan, and news reporting frequently includes strongly opinionated commentary.
  - *Counterfeit*: These sources mimic established news reporting. They counterfeit fonts, branding and stylistic content strategies. Commentary and junk content are stylistically disguised as news, with references to news agencies and credible sources, and headlines written in a news tone with date, time and location stamps.
- Obvious Russian Sources. This content is produced by known Russian sources of political news and information.

Other Political News and Information

- Citizen, Civil Society and Civic Content. These are links to content produced by independent citizen, civic groups, civil society organizations, watchdog organizations, fact-checkers, interest groups and lobby groups representing specific political interests or agendas. This includes blogs and websites dedicated to citizen journalism, personal activism, and other forms of civic expression that display originality and creation that goes beyond curation or aggregation. This category includes Medium, Blogger and WordPress, unless a specific source hosted on either of these pages can be identified.

- Political Humor & Entertainment. This category includes political jokes, sketch, comedy or entertainment-focused coverage, as well as political talk shows and late-night formats. Despite their humorous and entertaining nature, these formats often serve as central sources of news and information.
- Video/Image Sharing & Content Subscriptions. Includes music streaming portals like Spotify, video streaming services and live streaming, political documentary movies, e-books and audio book subscriptions, as well as image sharing services.
- Fundraising and Petitions. Encompasses civil society fundraising and petition pages, as well as surveying services for various political causes and interests that do not represent an official campaign or candidate.
- Lifestyle & Special Interest. Includes lifestyle and special interest publications like women's and men's magazines, and content focused on art and fashion, fitness, food and wellness, nature and tourism, or hunting, fishing and automobiles.
- Religion. Refers to content with distinctly religious themes and faith-based editorializing presented as political news or information.
- Online Portals, Search Engines and Aggregators. Includes online portals like AOL, Yahoo! and MSN that do not themselves have editorial policies and have no or limited original news content. This category also includes links to Wikipedia.
- Cloud. Encompasses services such as Amazon Web Services, Google Drive and Docs, OneDrive, or archiving services in the cloud.
- Other Political. Refers to content that is political in nature but does not fit any of the other categories, for example services where voters are able to check their polling stations or purchase political merchandise.

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- Other Political. Refers to content that is political in nature but does not fit any of the other categories, for example services where voters are able to check their polling stations or purchase political merchandise.
- Social Media Platforms. These are links that refer to other social media platforms as well as official developer tools. If the content at the ultimate destination can be attributed to another source, it is.
- Not Available. This includes links that are no longer available or have not been successfully archived after repeated attempts, as well as sources that are redirected to other sources and whose original content is unknown.
- Shopping, Services and Applications. Encompasses links to auction websites or sales platforms, such as eBay and Amazon, including software-as-a-service applications, analytics tools and content optimization and monetization tools. This also includes applications and browser extensions.
- Link Shorteners. Includes links like Bitly or Vitweet, when it is not possible to unwrap the original URL. If the source is successfully unwrapped from the link shortener, it is coded in the appropriate category.
- Other Non-Political. Refers to sites that have no political content such as spam, gambling and brand advertising.
- Language. Content from sources in languages that are not English, French, German, Spanish, Portuguese, Hungarian or Mandarin are not labeled, unless verifiable information about a source is accessible.

Each source was coded individually by two separate coders, and any conflicting decision was thoroughly discussed between coders to achieve consensus. In the event that consensus was not achieved, a third executive coder reviewed the source and made a final decision. This allowed us to create a seed list of junk news websites across the political spectrum. This seed list was later combined with an existing list of junk news sources identified during our previous analysis of the 2016 Presidential Election and the State of the Union address, resulting in a list of 113 sources of political news and information that include various forms of propaganda and ideologically extreme, hyper-partisan, and conspiratorial political information.

Facebook Network Mapping

Having catalogued the most prominent sources of political news and information on Twitter, we next searched Facebook public pages to map how that content is being shared over the network. We tracked how the URLs to these websites were being shared over Facebook (see online supplement for details). We first use the Graphika visualization suite to map accounts that followed pages associated with the identified junk news sources.

Visualizing social network data is a powerful way of understanding how people share information and associate with one another. By using selected keywords, seed accounts, and known links to particular content, it is possible to construct large network visualizations that can be examined to find communities of accounts or "groups" that share very similar kinds of content with each other. Social network maps comprise nodes representing the individual accounts, which are connected to other nodes in the map via social relationships. A Fruchterman–Reingold visualization algorithm can be used to represent the patterns of connection between these nodes.[11] It arranges the nodes in a visualization through a centrifugal force that pushes nodes to the edge and a cohesive force that pulls strongly connected nodes together. This mapping process produces focused "segments" of users who share very similar and specific kinds of content with each other. Segments that share some content with each other are aggregated into "groups".

The nodes in a network may all belong to a group with a shared pattern of interests. These groups can be constructed from a number of geographically, culturally, or socially similar segments. For example, segments of GOP Party, GOP State, Conservative Pundits and Conservative Think Tanks could be collectively labeled as a "Mainstream Conservative." This method of segmenting users, coding groups, and generating broad observations about association is an iterative process drawing on qualitative, quantitative and computational methods. These are run many times over a period of time to identify stable and consistent communities in a network of social media users.

To create a map of segments and groups, we use a bipartite graph to provide a structural similarity metric between nodes in the map, which is used in combination with a clustering algorithm to segment the map into distinct communities. For this study, hierarchical agglomerative clustering was used to automatically generate segments and groups from sampled data (see online supplement for details). Different social media platforms have their own unique attributes that are effective in identifying communities that persist over time. For instance, clustering Twitter users by following and follower relationships yields much more stable communities than clustering by mention or retweet relationship. Likewise, clustering Facebook users by the "like" relationship yields similarly stable results. For this study, we have used these attributes to generate maps of stable clusters on Facebook. The outputs of this clustering algorithm have been extensively tested by others in studies of social media maps from Iran, Russia and the United States.[12–13] After clustering, the map-making process uses supervised machine learning techniques to generate labels for segments and groups from a training set labeled by human experts. After these labels are assigned, they are then manually verified and checked for accuracy and consistency.

FINDINGS

Twitter Analysis

Our sample allows us to draw some conclusions about the sources of political news and information that are in circulation. Two things should be noted across categories. First, that the proportion of junk news sources circulating over Twitter has increased by five percentage points since 2016, totaling approximately 25% of all URLs captured during our data collection (*Table 1*). In comparison, links to professionally produced news content accounted for nearly 19% of shares. This is the highest ratio of polarizing, conspiratorial and low-quality content ever found in one of our samples.

Second, surprisingly it seems that professional political content, including links to the pages of government agencies, experts and the candidates themselves are rarely referenced in social media conversations about politics. Indeed, less than five percent of the sources used include these types of political actors. Among these, links to political parties and candidates comprised only around two percent of total shares. Of the URLs categorized as Other, less than two percent linked to other social media platforms, such as Facebook, indicating a low degree of cross-platform posting. Finally, images and video content excluding YouTube links accounted for nearly seven percent of all shares on Twitter during our data collection period.

Table 1: Types of News and Information Shares on Twitter

Type of Source	*N*	*%*
Professional News Outlets		
News Brands	17,917	18.7
Tabloids	524	0.5
Subtotal	18,441	19.3
Professional Political Content		
Political Party or Candidate	2,076	2.2
Government	1,587	1.7
Expert	397	0.4
Subtotal	4,060	4.2
Polarizing & Conspiratorial Content		
Junk News	23,597	24.6
Obvious Russian Content	236	0.2
Subtotal	23,833	24.9
Other Political News & Information		
Citizen or Civil Society	13,754	14.4
Video/Image Sharing	6,398	6.7
Portals, Search & Aggregators	6,287	6.6
Other Political	4,833	5.0
Fundraising and Petitions	2,780	2.9
Remaining Categories	943	1.0
Subtotal	34,995	36.6
Other		
Shopping, Services & Apps	6,891	7.2
Social Media Platforms	1,834	1.9
Remaining Categories	5,670	5.9
Subtotal	14,395	15.0
Total	95,724	100

Source: Authors' calculations from data sampled between 21/09/2018 – 30/09/2018
Note: Major News Brand, Local News, New Media and Start-ups were collapsed into the Professional News Brand category for this table. In the Other Political News & Information parent category, Remaining Categories include Political Humor, Lifestyle, Religion, Online Portals, Cloud Services and Other as these constituted a low percentage of total shares. In the Other Non-Political parent category, Not Available, Shopping, Services, and Applications, Link Shorteners, and Other Non-Political were collapsed into Remaining Categories for the same reason.

Facebook Analysis

We mapped the public Facebook pages by combining: 1) harvested Facebook public page seeds from political tweets shared during the US midterms and a snowball sample of the wider Facebook network around these key online interest groups; 2) a snowball sample of all the Facebook pages associated with party Twitter accounts considered for the Twitter study; 3) iteration of clear US Liberal and Conservative clusters from previous US political maps on Facebook.

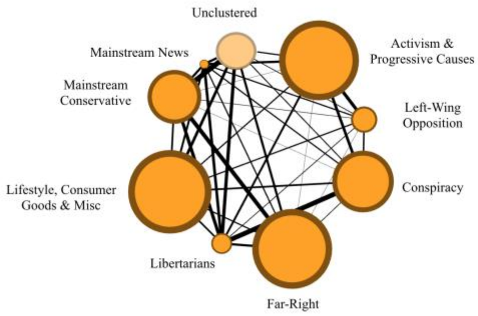
This resulted in a dataset of 6,986 public Facebook pages, from which we collected posts shared in the 30 days between September 29, 2018 and October 29, 2018 using the Facebook Graph API. We extracted all URLs from posts and analyzed the pattern of web citations across the major groupings we identified in the US news ecosystem on Facebook. Additionally, we collected the share counts for all

Table 2: Size, Coverage, and Consistency of Junk News Audience Groups on Facebook

Scores	*Users N*	*Users %*	*Coverage*	*Consistency*
Lifestyle & Consumer Goods	1,311	19	70	6
Activism & Progressive Causes	1,252	18	46	5
Far-Right	1,252	18	89	44
Conspiracy	955	14	67	5
Mainstream Conservative	828	12	83	22
Left-Wing Opposition	381	5	24	6
Libertarians	292	4	63	5
Mainstream News	98	1	20	1
Unclustered	617	9	76	6
Total	6,986	100		

Source: Authors' calculations from data sampled between 29/09/2018– 29/10/2018. Percentages have been rounded to the nearest whole number.
Note: The Unclustered group denotes a group of clusters with very little density and internal connections between the nodes.

Figure 2: US Junk News Audience Groups on Facebook



Source: Authors' calculations from data sampled between 29/09/2018– 29/10/2018. Note: Groups are determined through network association. This is a basic visualization (see online supplement for a full visualization).
Note: The Unclustered group denotes a group of clusters with very little density and internal connections between the nodes.

posts containing the identified URLs from our seed list in order to measure the degree to which junk news content from various sources is shared across the Facebook network. This value includes shares that occur on private pages.

We were able to cluster our sample of Facebook pages into eight groups. The groups emerged through network association, and by interpretation of the kinds of content these accounts distributed, and which pages they marked with a "like." We then tracked how the groups in the sample were sharing content from the identified junk news pages on Facebook. Specifically, we computed the coverage and consistency scores for each group. *Coverage* of a group refers to the percentage of all propaganda domains identified in our junk news sources list that a group posted links to. The *Consistency* of a group refers to the percentage of the total of number of links to all the propaganda domains identified in our junk news sources list, which is shared by the group. A high value for coverage shows that the group is sharing a wide range of propaganda, while a high value for consistency shows that the group is playing a key role in the spreading of such propaganda. Coverage and consistency scores were calculated from the number of links shared from the groups to the junk news sources.

From the coverage and consistency scores in *Table 2*, we can see that the cluster of Far-Right pages have the highest coverage score at 89%, followed by the Mainstream Conservative group at 83%, indicating that these two groups shared the widest array of junk news sources identified in our sample. Not only that but Far-Right pages also display the highest consistency score at 44%, indicating that this group has contributed the most to the spread of junk news. Once again, that group is closely similar to the Mainstream Conservative group of Facebook pages, with a consistency score of 22%. These two audiences combined were responsible for a greater share of junk news than all the other groups taken together. A small audience of left-leaning activists pages, which include Left-Wing Opposition and Activism & Progressive Causes, have also developed an appetite for junk news, having interacted respectively with 24% and 46% of all junk news sources in our seed list. However, these sources represent only a tiny proportion—five percent—of what such groups share overall. A group of Facebook pages that exhibited little to no internal connections with other group members was labelled Unclustered, as it could not be assigned to a definitive cluster in the network.

Finally, we calculated a heterophily score for each combination of group pairings in our analysis of Facebook pages (see online supplement for the heterophily index). A heterophily score above 1.0 indicates strong connections between two groups, while a heterophily score of 1.0 indicates a neutral amount connection between them, and anything below that signals weak or no connection. We observe a high heterophily score between the Libertarian and Conspiracy & Anti-Media groups (1.9), demonstrating strong engagement between these two ecosystems of Facebook pages. Likewise, we find close interaction between the Anti-Trump and Activism and Progressive Causes group (1.3), and the Mainstream Conservative and the Far-Right groups (1.6). This last finding indicates that the Mainstream Conservative group is most strongly connected to the far-right fringe of the US political spectrum.

Figure 2 is a basic visualization of the eight groups on Facebook. The size of each group is determined by the number of Facebook pages that belong to it. The connections between the groups in the figure are computed using the heterophily scores (see *Table 3*). The width of the lines linking groups in the figure represents the strength of connection between them.

CONCLUSIONS

In conclusion, we found that (1) the proportion of junk news circulating over social media has increased in the US since 2016, with users sharing higher proportions of junk news than links to professional content overall; that (2) junk news once concentrated among President Trump's support base has now spread to include communities of mainstream political conservatives; and that (3) less than five percent of the sources referenced on social media are from public agencies, experts, or the political candidates themselves. These findings indicate that, overall, individuals discussing politics on social media ahead of the 2018 US midterm elections referred more to news content of varying quality than to material produced by politicians and government organizations. Furthermore, on Facebook, mainstream conservative audiences who used to be more discriminating are increasingly interacting with extreme groups on the far-right fringe of the US political spectrum.

ONLINE SUPPLEMENTS AND DATA SHEETS

Please visit comprop.oii.ox.ac.uk for additional material relating to the analysis, including (1) high-resolution visualizations of the networks for Facebook, (2) the full list of segments and groups, (3) calculation of heterophily scores, (4) detailed explanation of the hierarchical agglomerative clustering algorithm used to create groupings, (5) a list of the top 30 junk news sites that we found in the dataset.

ABOUT THE PROJECT

The Project on Computational Propaganda (COMPROP) based at the Oxford Internet Institute, University of Oxford, is an interdisciplinary team of social and information scientists researching how political actors manipulate public opinion over social networks. This work includes analyzing the interaction of algorithms, automation, politics, and social media to amplify or repress political content, disinformation, hate speech and junk news. Data memos are designed to present quick snapshots of analysis on current events in a short format, and although they reflect methodological experience and considered analysis, they have not been peer-reviewed. Working papers present deeper analysis and extended arguments that have been collegially reviewed and engage with public issues. COMPROP's articles, book chapters and books are significant manuscripts that have been through peer review and formally published.

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