The COVID-19 Infodemic: Twitter versus Facebook

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Abstract

The global spread of the novel coronavirus is affected by the spread of related misinformation — the so-called COVID-19 Infodemic — that makes populations more vulnerable to the disease through resistance to mitigation efforts. Here we analyze the prevalence and diffusion of links to low-credibility content about the pandemic across two major social media platforms, Twitter and Facebook. We characterize cross-platform similarities and differences in popular sources, diffusion patterns, influencers, coordination, and automation. Comparing the two platforms, we find divergence among the prevalence of popular low-credibility sources and suspicious videos. A minority of accounts and pages exert a strong influence on each platform. These misinformation “superspreaders” are often associated with the low-credibility sources and tend to be verified by the platforms. On both platforms, there is evidence of coordinated sharing of Infodemic content. The overt nature of this manipulation points to the need for societal-level rather than in-house mitigation strategies. However, we highlight limits imposed by inconsistent data-access policies on our capability to study harmful manipulations of information ecosystems.

1 Introduction

The impact of the COVID-19 pandemic has been felt globally, with almost 70 million detected cases and 1.5 million deaths as of December 2020 (coronavirus.jhu.edu/map.html). Epidemiological strategies to combat the virus require collective behavioral changes. To this end, it is important that people receive coherent and accurate information from media sources that they trust. Within this context, the spread of false narratives in our information environment can have acutely negative repercussions on public health and safety. For example, misinformation about masks greatly contributed to low adoption rates and increased disease transmission [19]. The problem is not going away any time soon: false vaccine narratives [18] will drive hesitancy, making it difficult to reach herd immunity and prevent future outbreaks.

It is concerning that many people believe, and many more have been exposed to, misinformation about the pandemic [22, 35, 23, 34]. The spread of this misinformation has been termed the Infodemic [44]. Social media play a strong role in propagating misinformation
because of peer-to-peer transmission [41]. There is also evidence that social media is manipulated [36, 40] and used to spread COVID-19 misinformation [12]. It is therefore important to better understand how users disseminate misinformation across social media networks.

A number of studies have used a variety of perspectives to assess the extent to which the public has been exposed to COVID-19 misinformation on social media. These include quantitative studies of the prevalence of links to low-credibility websites [5, 6, 14, 38] as well as qualitative analyses of posts on Twitter [33, 1, 20]. These different approaches have yielded disparate estimates of misinformation prevalence levels — between 1% and 70%. Meanwhile, surveys of the general public have found exposure levels to be around 30–50% [22, 23, 34]. These widely varying statistics indicate that different approaches to experimental design, including uneven access to data on different platforms and inconsistent definitions of misinformation, can generate inconclusive or misleading results. We follow the reasoning from [14] that it is better to clearly define a misinformation metric, and then use it in a comparative way — to look at how misinformation varies over time or is influenced by other factors.

A common limitation with current studies is that they only focus on a single social media platform [5, 14, 38, 33, 1, 20]. However, the modern information environment is an ecosystem consisting of different platforms over which information propagates concurrently and in diverse ways. Each platform can have different vulnerabilities [2]. A key goal of the present work is to compare and contrast the extent to which the Infodemic has spread on Twitter and Facebook.

A second gap in our understanding of COVID-19 misinformation is in the patterns of diffusion within social media. It is important to understand how certain user accounts, or groups of accounts, can play a disproportionate role in amplifying the spread of misinformation. Inauthentic social media accounts, known as social bots and trolls, can play an important role in amplifying the spread of low-credibility content in general [13, 40, 36], and COVID-19 misinformation in particular [11], on Twitter. The picture on Facebook is less clear, as there is little access to data that would enable a determination of social bot activity. It is, however, possible to look for evidence of manipulation in how multiple accounts can be coordinated with one another, potentially controlled by a single entity. For example, accounts may exhibit suspiciously similar sharing behaviors [27].

We extract website links from social media posts that include COVID-19 related keywords. We identify a link with low-credibility content in one of two ways. First, we follow the convention of classifying misinformation at the source rather than the article level [17]. We do this by matching links to an independently-generated corpus of low-credibility website domains (or sources). Second, in the case of links to YouTube, we flag videos as suspicious if they have been banned by the site, or are otherwise unavailable to the public. This enables us to quantitatively study the prevalence of likely misinformation about COVID-19 and the different ways in which it has been shared on the two commonly used social media platforms.

The main contributions of this study stem from exploring three sets of research questions:

- What is the prevalence of low-credibility content on Twitter and Facebook? Are there similarities in how sources are shared over time? How does this activity compare to that of popular high-credibility sources? Are the same suspicious sources and YouTube videos shared in similar volumes across the two platforms?

- Is the sharing of misinformation concentrated around a few active accounts? Do a few influential accounts dominate the resharing of popular misinformation? What is the
role of verified accounts and those associated with the low-credibility sources on the two platforms?

- Is there evidence of inauthentic coordinated behavior in sharing low-credibility content? Can we identify clusters of users, pages, or groups with suspiciously similar sharing patterns? Is low-credibility content amplified by Twitter bots more prevalent on Twitter as compared to Facebook?

In the next section we describe the methodology and data employed in this paper. The following three sections present results to answer the above research questions. Finally, we discuss the limitations of our analyses and implications of our findings for mitigation strategies.

2 Methods

2.1 Identification of low-credibility information

We focus on news articles linked in social media posts and identify those pertaining to low-credibility domains by matching the URLs to sources, following a corpus of literature [17, 36, 16, 29, 3]. We define our list of low-credibility domains based on information provided by the Media Bias/Fact Check website (MBFC, mediabiasfactcheck.com), an independent organization that reviews and rates the reliability of news sources. We gather the sources labeled by MBFC as having a “Very Low” or “Low” factual-reporting level. We then add “Questionable” or “Conspiracy-Pseudoscience” sources and we leave out those with factual-reporting levels of “Mostly-Factual,” “High,” or “Very High.” We remark that although many websites exhibit specific political leanings, these do not affect inclusion in the list. The list has 674 low-credibility domains and we have shared it separately [26].

2.2 High-credibility sources

As a benchmark for interpreting the prevalence of low-credibility content, we also curate a list of 20 high-credibility information sources. We start from the list provided in a recent Pew Research Center report [21] and used in a few studies on online disinformation [31, 32], and we select popular news outlets that cover the full U.S. political spectrum. In addition, we include the websites of two organizations that acted as authoritative sources of COVID-19 related information, namely the Centers for Disease Control and Prevention (CDC) and World Health Organization (WHO). The full list can be found in Table 1.

2.3 Data collection

We collect data related to COVID-19 from both Twitter and Facebook. To provide a general and unbiased view of the discussion, we chose the following generic terms as keywords: coronavirus, covid (to capture variations like covid19 and covid-19), and sars (to capture sars-cov-2 and related variations).

2.3.1 Twitter data.

Our Twitter data was collected using an API from the Observatory on Social Media [8], which allows to search tweets from the Decahose, a 10% random sample of public tweets.
Table 1: List of high-credibility domains. The political leanings are fetched from All-sides.com ([www.allsides.com/media-bias/media-bias-ratings](http://www.allsides.com/media-bias/media-bias-ratings), accessed Dec. 1, 2020.)

| Domain             | Political leaning |
|--------------------|-------------------|
| huffpost.com       | left              |
| newyorker.com      | left              |
| msnbc.com          | left              |
| newsweek.com       | left              |
| cnn.com            | center left       |
| nytimes.com        | center left       |
| economist.com      | center left       |
| time.com           | center left       |
| washingtonpost.com | center left       |
| reuters.com        | center            |
| apnews.com         | center            |
| npr.org            | center            |
| usatoday.com       | center            |
| wsj.com            | center            |
| foxnews.com        | center right      |
| marketwatch.com    | center right      |
| nypost.com         | center right      |
| dailycaller.com    | right             |
| theblaze.com       | right             |
| dailywire.com      | right             |
| cdc.gov            | N/A               |
| who.int            | N/A               |
Figure 1: Structure of the data collected from Twitter and Facebook. On Twitter, we have the information about original tweets, retweets, and all the accounts involved. On Facebook, we have information about original posts and public groups/pages that posted them. For each post, we also have aggregate numbers of reshares, comments, and reactions, with no information about the users responsible for those interactions.
We searched for English tweets containing the keywords between Jan. 1 and Oct. 31, 2020, resulting in over 53M tweets posted by about 12M users. Note that since the Decahose samples tweets and not users, the sample of users in our Twitter dataset is biased toward more active users.

Our collection contains two types of tweets, namely original tweets and retweets. The content of original tweets is published by users directly, while retweets are generally used to endorse/amplify original tweets by others (no quoted tweets are included). We refer to authors of original tweets as “root” users, and to authors of retweets as “leaf” users (see Fig. 1).

2.3.2 Facebook data.

We used the posts/search endpoint of the CrowdTangle API [7] to collect data from Facebook. We filtered the entire set of English posts published by public pages and groups in the period from Jan. 1 to Oct. 31, 2020 using the above list of keywords, resulting in over 37M posts from over 140k public pages/groups.

Our Facebook data collection is limited by the coverage of pages and groups in CrowdTangle, a public tool owned and operated by Facebook. CrowdTangle includes over 6M public Facebook pages and groups with at least 100k followers/members (public groups with at least 2k members if based in the U.S.), and a very small subset of verified profiles that can be followed like public pages. We include these public accounts among pages and groups. In addition, some pages and groups with fewer followers and members are also included by CrowdTangle upon request from users. This might bias the dataset in ways that are hard to gauge. For example, requests from researchers interested in monitoring low-credibility pages and groups might lead to over-representation of such content.

As shown in Fig. 1, the collected data contains information about original Facebook posts and the pages/groups that published these posts. For each post, we also have access to aggregated statistics such as the number of reshares, comments, and reactions (e.g., “like”) by Facebook users. The numbers of comments and reactions are highly correlated with reshares (Fig. 2), so we focus on reshares in this study.

Figure 2: Pearson correlation coefficients between Facebook metrics aggregated at the domain level for low-credibility domains. The reaction consists of “like,” “love,” “wow,” “haha,” “sad,” “angry,” and “care.” All correlations are significant ($p < 0.01$).
Similarly to Twitter, Facebook pages and groups that publish posts are referred to as “roots” and users who reshare them are “leaves”. However, differently from Twitter, we don’t have access to any information about leaf users on Facebook. We refer generically to Twitter users and Facebook pages and groups as “accounts.”

To compare Facebook and Twitter in a meaningful way, we compare root users with root pages/groups, original tweets with original posts, and retweet counts with reshare counts. We define prevalence as the sum of original tweets and retweets on Twitter, and as the sum of original posts and reshares on Facebook.

### 2.3.3 YouTube data.

We observed a high prevalence of links pointing to `youtube.com` on both platforms — over 64k videos on Twitter and 204k on Facebook. Therefore, we also provide an analysis of popular videos published on Facebook and Twitter. Specifically, we focus on popular YouTube videos that are likely to contain low-credibility content. To approach this in a systematic manner, we assume that videos removed by YouTube are more likely to include low-credibility information. In addition, we also consider private videos to be suspicious, since this can be used as a tactic to evade the platform’s sanctions when violating terms of service.

To identify the most popular and suspicious YouTube content, we first select the 16,669 videos shared at least once on both platforms. We focus on the 1,828 (11%) of these videos that had been removed or made private by querying the YouTube API `Videos:list` endpoint to collect metadata. We rank these videos by their prevalence on each platform. As validation for using unavailability to flag suspicious videos, we manually inspected a small sample (about 1%) of unavailable videos and confirmed their low-credibility through cross-referencing with other YouTube content (e.g., by identifying other low-credibility videos that describe or link to them).

### 2.4 Link extraction

Estimating the prevalence of low-credibility information requires matching URLs, extracted from tweets and Facebook metadata, against our lists of low- and high-credibility websites.
Table 3: Breakdown of Facebook and Twitter posts/tweets matched to low- and high-credibility domains.

|                | Low-credibility | High-credibility |
|----------------|-----------------|------------------|
| **Facebook**   |                 |                  |
| Original posts | 303,119         | 1,194,634        |
| Reshares       | 20,462,035      | 98,415,973       |
| **Twitter**    |                 |                  |
| Original tweets| 245,620         | 734,409          |
| Retweets       | 653,415         | 2,184,050        |

As shortened links are very common, we also identified 49 link shortening services that appear at least 50 times in our datasets (Table 2) and expanded shortened URLs referring to these services through HTTP requests to obtain the actual domains. We finally match the extracted and expanded links against the lists of low- and high-credibility domains. A breakdown of matched posts/tweets is shown in Table 3. For low-credibility content, the ratio of retweets to tweets is 2.7:1, while the ratio of reshares to posts is 68:1. This large discrepancy is due to various factors: the difference in traffic on the two platforms, the fact that we only have a 10% sample of tweets, and the bias toward popular pages and groups on Facebook.

3 Infodemic prevalence

In this section, we provide results about the prevalence of links to low-credibility domains on the two platforms. As described in the Methods section, we sum tweets and retweets for Twitter, and original posts and reshares for Facebook. Note that deleted content is not included in our data. Therefore, our estimations should be considered as lower bounds for the prevalence of low-credibility information on both platforms.

3.1 Prevalence trends

We plot the daily prevalence of links to low-credibility sources on Twitter and Facebook in Fig. 3(a). The two time series are strongly correlated (Pearson $r = 0.87$, $p < 0.01$). They both experience a drastic growth during March, when the number of COVID-19 cases was growing worldwide. Towards summer, the prevalence of low-credibility information decreases to a relatively low level and then becomes more stable.

To analyze the Infodemic surge with respect to the pandemic’s development and public awareness, Fig. 3(b) shows the worldwide hospitalization rate and the overall volume of tweets in our collection. The Infodemic surge roughly coincides with the general attention given to the pandemic, captured by the overall Twitter volume. The peak in hospitalizations trails by a few weeks. A similar delay was recently reported between peaks of exposure to Infodemic tweets and of COVID-19 cases in different countries [14]. The present findings indicate that this delay is related to general attention toward the pandemic rather than specifically toward misinformation.

To further explore whether the decrease of low-credibility information is organic or due to platform interventions, we also compare the prevalence of low-credibility content to that of links to credible sources. As shown in Fig. 3(c), the ratios are relatively stable across
Figure 3: Infodemic content surge on both platforms around the COVID-19 pandemic waves, from Jan. 1 to Oct. 31, 2020. All curves are smoothed via 7-day moving averages. (a) Daily volume of posts/tweets linking to low-credibility domains on Twitter and Facebook. Left and right axes have different scales and correspond to Twitter and Facebook, respectively. (b) Overall daily volume of pandemic-related tweets and worldwide COVID-19 hospitalization rates (data source: Johns Hopkins University). (c) Daily ratio of volume of low-credibility links to volume of high-credibility links on Twitter and Facebook. The noise fluctuations in early January are due to low volume. The horizontal lines indicate averages across the period starting Feb. 1.
the observation period. These results suggest that the prevalence of low-credibility content is mostly driven by the public attention to the pandemic in general, which progressively decreases after the initial outbreak. We finally observe that Twitter exhibits a higher ratio of low-credibility information than Facebook (32% vs. 21% on average). However, this difference may be due to biases in the data collection protocols, as discussed in Methods.

3.2 Prevalence of specific domains

We use the high-credibility domains as a benchmark to assess the prevalence of low-credibility domains on each platform. As shown in Fig. 4, we notice that the low-credibility sources exhibit disparate levels of prevalence. We also see that low-credibility content as a whole reaches considerable volume on both platforms, with prevalence surpassing every single high-credibility domain considered in this study. On the other hand, low-credibility domains generally exhibit much lower prevalence compared to high-credibility ones, (with a
Figure 5: (a) Rank comparison of low-credibility sources on Facebook and Twitter. Each dot in the figure represents a low-credibility domain. The most popular domain ranks first. Domains close to the vertical line have similar ranks on the two platforms. Domains close to the edges are much more popular on one platform or the other. We annotate a few selected domains that exhibit high rank discrepancy. (b) A zoom-in on the sources ranked among the top 50 on both platforms (highlighted square in (a)).

few exceptions, notably thegatewaypundit.com and breitbart.com).

3.3 Source popularity comparison

As shown in Fig. 4, we observed that low-credibility websites may have different prevalence on the two platforms. To further contrast the most popular sources on Twitter and Facebook, we measure the popularity of websites on each platform by ranking them by prevalence, and then compare the resulting ranks in Fig. 5. The ranks on the two platforms are not strongly correlated (Spearman $r = 0.57$, $p < 0.01$). A few domains are much more popular or only appear on one of the platforms (see annotations in Fig. 5(a)). We also show the domains that are very popular on both platforms in Fig. 5(b). They are dominated by right-wing and state sources, such as breitbart.com, washingtontimes.com, thegatewaypundit.com, oann.com, and rt.com.

3.4 YouTube Infodemic content

Thus far, we examined the prevalence of links to low-credibility sources. However, a significant portion of the links shared on Twitter and Facebook point to YouTube videos, which can also carry COVID-19 misinformation. Previous work has shown that bad actors utilize YouTube in this manner for their campaigns [42]. Specifically, anti-scientific narratives on YouTube about vaccines, Idiopathic Pulmonary Fibrosis, and the COVID-19 pandemic have been documented [9, 15, 10].

To measure the prevalence of Infodemic content from YouTube, we consider the unavailability of videos as an indicator of suspicious content, as explained in the Methods section.
Fig. 6 compares the prevalence rankings on Twitter and Facebook for unavailable videos ranked within the top 500 on both platforms. These videos are linked between 6 and 980 times on Twitter and 39 and 64,257 times on Facebook. While we cannot rigorously measure rank correlation due to the exclusion of low-prevalence videos, we do not observe a correlation in the cross-platform popularity of suspicious content from a qualitative inspection of the figure. A caveat to this analysis is that the same low-credibility content can be found within many videos, each having a unique video ID. Some of these videos are promptly removed while others are not. Therefore, the lack of correlation could be driven by YouTube’s efforts to remove Infodemic content in conjunction with attempts by uploaders to counter those efforts.

Having looked at the prevalence of suspicious content from YouTube, we wish to explore the question from another angle: are popular videos more likely to be suspicious? Fig. 7 shows this to be the case on both platforms: a larger portion of videos with higher prevalence are unavailable, but the trend is stronger on Twitter than on Facebook. The overall trend suggests that YouTube may have a bias toward moderating videos that attract more attention. For example, an Infodemic video that is spreading virally on Twitter may receive many abuse reports on YouTube.

4 Infodemic spreaders

Links to low-credibility sources are published on social media through original tweets and posts first, then retweeted and reshared by leaf users. In this section, we study this dis-
semination process on Twitter and Facebook with a focus on the top spreaders, or “superspreaders”: those responsible for the original publication of the most popular Infodemic content.

4.1 Concentration of influence

We wish to measure whether low-credibility content originates from a wide range of users, or can be attributed to a few influential actors. For example, a source published 100 times could owe its popularity to 100 distinct users, or to a single root whose post is republished by 99 leaf users. To quantify the concentration of original posts/tweets or reshares/retweets for a source \( s \), we use the inverse normalized entropy [24], defined as:

\[
C_s = 1 + \sum_{r=1}^{N_s} \frac{P_r(s) \log P_r(s)}{\log N_s},
\]

where \( r \) represents a root user/group/page linking to \( s \), \( P_r(s) \) stands for the fraction of posts/tweets/reshares/retweets linking to \( s \) and associated with \( r \), and \( N_s \) is the total number of roots linking to \( s \). Entropy measures how evenly quantities of content are distributed across roots; it is normalized to account for the varying numbers of roots in different cases. Its inverse captures concentration, and is defined in the unit interval. It is maximized at 1 when the content originates from a single root user/group/page, and minimized at 0 when each root makes an equal contribution. We set \( C_s = 1 \) when \( N_s = 1 \).

Let us gauge the concentration of activity around root accounts through their numbers of original tweets/posts for each source. Similarly, we calculate the concentration of popularity around the root accounts using their numbers of retweets/reshares for each source. We show the distributions of these concentration variables in Fig. 8(a). On both platforms, we find that popularity is significantly more concentrated around root accounts compared to their activity (\( p < 0.001 \) for paired sample t-tests). This suggests the existence of superspreaders: despite the diversity of root accounts publishing links to low-credibility content on both platforms, only messages from a small group of influential accounts are shared extensively.
4.2 Who are the Infodemic superspreaders?

Both Twitter and Facebook provide verification of accounts and embed such information in the metadata. Although the verification processes differ, we wish to explore the hypothesis that verified accounts on either platform play an important role as top spreaders of low-credibility content. Fig. 8(b) compares the popularity of verified accounts to unverified ones on a per-account basis. We find that verified accounts tend to receive a significantly higher number of retweets/reshares on both platforms ($p < 0.001$ for Mann-Whitney U-tests).

We further computed the proportion of original tweets/posts and retweets/reshares that correspond to verified accounts on both platforms. Verified accounts are a small minority compared to unverified ones, i.e., 1.9% on Twitter and 4.5% on Facebook, among root accounts involved in publishing low-credibility content. Despite this, Fig. 8(c) shows that verified accounts yield almost 40% of the total number of retweets on Twitter and almost 70% of reshares on Facebook.

These results suggest that verified accounts play an outsize role in the spread of Infodemic content. Are superspreaders all verified? To answer this question, let us analyse superspreader accounts separately for each low-credibility source. We extract the top user/page/group (i.e., the account with most retweets/reshares) for each source, and find that 19% and 21% of them are verified on Twitter and Facebook, respectively. While these values are much higher than the percentages of verified accounts among all roots, they show that not all superspreaders are verified.

Who are the top spreaders of Infodemic content? Table 4 answers this question for the 23 top low-credibility sources in Fig. 5(b). We find that the top spreader for each source tends to be the corresponding official account. For instance, about 20% of the retweets containing links to thegatewaypundit.com pertain to @gatewaypundit, the official handle associated with The Gateway Pundit website, on Twitter. The remaining retweets have...
Table 4: List of social media handles for the 23 top low-credibility sources from Fig. 5(b). Accounts with a checkmark (√) are verified. Accounts with an asterisk (*) are the top spreaders for the corresponding domains.

| Domain                    | Twitter handle          | Facebook page/group       |
|---------------------------|-------------------------|----------------------------|
| thegatewaypundit.com      | @gatewaypundit ✓        | @gatewaypundit ✓           |
| breitbart.com             | @BreitbartNews ✓        | @Breitbart ✓               |
| zerohedge.com             | @zerohedge ✓            | @ZeroHedge                 |
| washingtontimes.com       | @WashTimes ✓            | @TheWashingtonTimes ✓      |
| rt.com                    | @RT_com ✓               | @RTnews ✓                  |
| swarajyamag.com           | @SwarajyaMag ✓          | @swarajyamag ✓             |
| pjmedia.com               | @PJMedia_com ✓          | @PJMedia ✓                 |
| waynedupree.com           | @WayneDupreeShow ✓      | @WayneDupreeShow ✓         |
| bongino.com               | @dbongino ✓             | @dan.bongino ✓             |
| trendingpolitics.com      | –                       | @trendingpoliticsdotcom    |
| oann.com                  | @OANN ✓                 | @OneAmericaNewsNetworkD ✓  |
| wnd.com                   | @worldnetdaily ✓        | @WNDNews ✓                 |
| sputniknews.com           | @SputnikInt ✓           | @SputnikNews ✓             |
| dailystar.co.uk           | @dailystar ✓            | @thedailystar ✓            |
| politicalflare.com        | @nicolejames            | @nicolejameswriter        |
| thenationalpulse.com      | @RaheemKassam ✓         | @thenationalpulse ✓        |
| americanthinker.com       | @AmericanThinker        | @AmericanThinker ✓         |
| gellerreport.com          | @PamelaGeller ✓         | @pamelageller ✓            |
| cbn.com                   | @CBNOnline ✓            | @cbnonline ✓               |
| 100percentfedup.com       | @100PercFEDUP ✓         | @100PercentFEDUp ✓         |
| Newspunch.com            | –                       | @thepeoplesvoice tv ✓      |
| thepoliticalinsider.com   | @TPInsidr               | @ThePoliticalInsider ✓     |
| hannity.com               | @seanhannity ✓          | @SeanHannity ✓             |
10,410 different root users. Similarly, on Facebook, among all 2,821 pages/groups that post links to thegatewaypundit.com, the official page @gatewaypundit accounts for 68% of the reshares. We observe in Table 4 that most of the top low-credibility sources have official accounts on both Twitter and Facebook, which tend to be verified (15 out of 21 on Twitter and 15 out of 23 on Facebook). They are also the top spreaders of those domains in 16 out of 21 cases on Twitter and 18 out of 23 on Facebook.

5 Infodemic manipulation

Here we consider two types of inauthentic behaviors that can be used to spread and amplify COVID-19 misinformation: coordinated networks and automated accounts.

5.1 Coordinated amplification of low-credibility content

Social media accounts can act in a coordinated fashion (possibly controlled by a single entity) to increase influence and evade detection [27, 25, 37]. We apply the framework proposed by [27] to identify coordinated efforts in promoting low-credibility information, both on Twitter and Facebook.

The idea is to build a network of accounts where the weights of edges represent how often two accounts link to the same domains. A high weight on an edge means that there is an unusually high number of domains shared by the two accounts. We first construct a bipartite graph between accounts and low-credibility domains linked in tweets/posts. The edges of the bipartite graph are weighted using TF-IDF [39] to discount the contributions of popular sources. Each account is therefore represented as a TF-IDF vector of domains. A projected co-domain network is finally constructed, with edges weighted by the cosine similarity between the account vectors.

We apply two filters to focus on active accounts/pages/groups and highly similar pairs. On Twitter, the accounts must have at least 10 tweets containing links, and we retain edges with similarity above 0.99. On Facebook, the pages/groups must have at least 5 posts containing links, and we retain edges with similarity above 0.95. These thresholds are selected by manually inspecting the outputs.

Fig. 9 shows dense connected components in the co-domain networks for Twitter and Facebook. These clusters of accounts share suspiciously similar sets of sources. They likely act in coordinated fashion to amplify Infodemic messages, and are possibly controlled by the same entity or organization. We highlight the fact that using a more stringent threshold on the Twitter dataset yields a higher number of clusters than a more lax threshold on the Facebook dataset. However, this does not necessarily imply a higher level of abuse on Twitter; it could be due to the difference in the units of analysis. On Facebook, we only have access to public groups and pages with a bias toward high popularity, and not to all accounts as on Twitter.

An examination of the sources shared by the suspicious clusters on both platforms shows that they are predominantly right-leaning and mostly U.S.-centric. The list of domains shared by likely coordinated accounts on Twitter is mostly concentrated on the leading low-credibility sources, such as breitbart.com and thegatewaypundit.com, while likely coordinated groups and pages on Facebook link to a more varied list of sources. Some of the amplified websites feature polarized rhetoric, such as defending against “attack by enemies” (see www.frontpagemag.com/about) or accusations of “liberal bias” (cnsnews.com/about-us),
Figure 9: Networks showing clusters that share suspiciously similar sets of sources on (top) Twitter and (bottom) Facebook. Nodes represent Twitter accounts or Facebook pages/groups. Edges are drawn between pairs of nodes that share an unlikely high number of the same website domains. The most shared sources are annotated for some of the clusters. Facebook pages associated with Salem Media Group radio stations are highlighted by a dashed box.
among others. Additionally, there are clusters on both platforms that share Russian state-affiliated media such as rt.com and an Indian right-wing magazine (swarajyamag.com).

In terms of the composition of the clusters, they mostly consist of users, pages, and groups that mention President Trump or his campaign slogans. Some of the Facebook clusters are notable because they consist of groups or pages that are owned by organizations with a wider reach beyond the platform, or that are given an appearance of credibility by being verified. Examples of the former are the pages associated with The Answer radio stations (highlighted in Fig. 9). These are among 100 stations owned by the publicly traded Salem Media Group, which also airs content on 3,100 affiliate stations. Examples of verified pages engaged in likely coordinated behavior are those affiliated with the non-profit Media Research Center, some of which have millions of followers. On Twitter, some of the clusters include accounts with tens of thousands of followers. Many of the suspicious accounts in Fig. 9 no longer exist.

5.2 Role of social bots

We are interested in revealing the role of inauthentic actors in spreading low-credibility information on social media. One type of inauthentic behavior stems from accounts controlled in part by algorithms, known as social bots [13]. Malicious bots are known to spread low-credibility information [36] and in particular create confusion in the online debate about health-related topics like vaccination [4].

We adopt BotometerLite [43], a bot detection model that allows efficient bot detection on Twitter. BotometerLite generates a bot score between 0 and 1 for each Twitter account; higher scores indicate bot-like profiles. To the best of our knowledge, there are no similar techniques designed for Facebook, because insufficient training data is available. Therefore we limit this analysis to Twitter.

When applying BotometerLite to our Twitter dataset, we use 0.5 as a threshold to categorize accounts as likely humans or likely bots. For each domain, we calculate the total
number of original tweets plus retweets authored by likely humans ($n_h$) and bots ($n_b$). We plot the relationship between the two in Fig. 10. The linear trend on the log-log plot signifies a power law $n_h \sim n_b^\gamma$ with exponent $\gamma \approx 1.04$, suggesting a weak level of bot amplification (4%) [36].

While we are unable to perform automation detection on Facebook groups and pages, the ranks of the low-credibility sources on both platforms allow us to investigate whether sources with more Twitter bot activity are more prevalent on Twitter or Facebook. For each domain, we calculate the difference of its ranks on Twitter and Facebook and use the value of the difference to color the dots in Fig. 10. The results show that sources with more bot activity on Twitter are equally shared on both platforms.

6 Discussion

In this paper, we provide the first comparison between the prevalence of low-credibility content related to the COVID-19 pandemic on two major social media platforms, namely Twitter and Facebook. Our results indicate that the primary drivers of low-credibility information tend to be high-profile, official, and verified accounts. We also find evidence of coordination among accounts spreading Infodemic content on both platforms, including many controlled by influential organizations. Since automated accounts do not appear to play a strong role in amplifying content, these results indicate that the COVID-19 Infodemic is an overt, rather than a covert, phenomenon.

We find that, taken as a whole, low-credibility content has higher prevalence than content from any single high-credibility source. However, there is evidence of differences in the misinformation ecosystems of the two platforms, with many low-credibility websites and suspicious YouTube videos at higher prevalence on one platform when compared to the other. Such a discrepancy might be due to different user demographics on the two platforms [30] or to the asymmetric presence of official accounts associated with specific low-credibility websites.

During the first months of the pandemic, we observe similar surges of low-credibility content on both platforms. The strong correlation between the timelines of low- and high-credibility content volume reveals that these peaks were likely driven by public attention to the crisis rather than by bursts of malicious content.

Our results provide us with a way to assess evidence on how effective the two platforms have been at combating the Infodemic. The ratio of low- to high-credibility information on Facebook is lower than on Twitter, indicating that perhaps Facebook was more effective. On the other hand, we also find that verified accounts played a stronger role on Facebook than Twitter in spreading low-credibility content. However, these comparisons are qualified by the different data collection biases. In general, the unavailable videos shared from YouTube tended to have asymmetric prevalence on Facebook and Twitter. In addition to the aforementioned reasons also applicable to websites, a speculative interpretation of this finding is that the videos may have been quickly removed by YouTube before they had a chance to migrate across platforms. Subsequent duplicates of removed content may also play a role, with one version becoming popular on Facebook and another on Twitter.

There are a number of limitations to our work. As we have remarked throughout the paper, both inherent differences between the platforms and differences in data sampling and selection biases make direct and fair comparisons impossible in many cases. The content collected from the Twitter Decahose is biased toward active users due to being sampled
on a per-tweet basis. The Facebook accounts provided by CrowdTangle are biased toward popular pages and public groups, and data availability is also based upon requests made by other researchers. The small set of keywords driving our data collection pipeline may have introduced additional biases in the analyses. This is an inevitable limitation of any collection system, including the Twitter COVID-19 stream (developer.twitter.com/en/docs/labs/covid19-stream/filtering-rules). The use of source-level rather than article-level labels for selecting low-credibility content is necessary [17], but not ideal; some links from low-credibility sources may point to credible information. In addition, the list of low-credibility sources was not specifically tailored to our subject of inquiry. Finally, we do not have access to many deleted Twitter and Facebook posts, which may lead to an underestimation of the Infodemic’s prevalence. All of these limitations highlight the need for cross-platform, privacy-sensitive protocols for sharing data with researchers [28].

Low-credibility information on the pandemic is an ongoing concern for society. Our study raises a number of questions about how social media platforms are handling the flow of information and are allowing likely dangerous content to spread. Regrettably, since we find that high-status accounts play an important role, addressing this problem will probably prove difficult. As Twitter and Facebook have increased their moderation of COVID-19 misinformation, they have been accused of political bias. While there are many moral and ethical considerations around free speech and censorship, our work suggests that these questions cannot be avoided and are an important part of the debate around how we can improve our information ecosystem.

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