Identification and characterization of misinformation superspreaders on social media

Matthew R. DeVerna¹, Rachith Aiyappa¹, Diogo Pacheco¹,², John Bryden¹, Filippo Menczer¹

¹Observatory on Social Media, Indiana University, Bloomington, USA
²Department of Computer Science, University of Exeter, UK

This preprint has not yet undergone peer review

Abstract

The world’s digital information ecosystem continues to struggle with the spread of misinformation. Prior work has suggested that users who consistently disseminate a disproportionate amount of low-credibility content — so-called superspreaders — are at the center of this problem. We quantitatively confirm this hypothesis and introduce simple metrics to predict the top misinformation superspreaders several months into the future. We then conduct a qualitative review to characterize the most prolific superspreaders and analyze their sharing behaviors. Superspreaders include pundits with large followings, low-credibility media outlets, personal accounts affiliated with those media outlets, and a range of influencers. They are primarily political in nature and use more toxic language than the typical user sharing misinformation. We also find concerning evidence suggesting that Twitter may be overlooking prominent superspreaders. We hope this work will further public understanding of bad actors and promote steps to mitigate their negative impacts on healthy digital discourse.

1 Introduction

Misinformation impacts society in detrimental ways, from sowing distrust in democratic institutions to harming public health. The peaceful transition of power in the United States was threatened on January 6th, 2021 when conspiracy theories about the presidential election being “stolen” fueled violent unrest at the U.S. Capitol [9]. During the COVID-19 pandemic, an abundance of health-related misinformation spread online [51, 52], ultimately driving the U.S. Surgeon General to warn Americans about the threat of health misinformation [34]. The public confusion created by this content led the World Health Organization to collaborate with major social media platforms and tech companies across the world in an attempt to mitigate its spread [39].

Recent research suggests that superspreaders of misinformation — users who consistently disseminate a disproportionately large amount of low-credibility content — may be at the center of this problem [15, 45, 21, 12, 51, 6].

In the political domain, one study investigated the impact of misinformation on the 2016 U.S. election and found that 0.1% of Twitter users were responsible for sharing approximately 80% of the misinformation [15]. Social bots also played a disproportionate role in spreading content from low-credibility sources [44]. The Election Integrity Partnership (a consortium of academic and industry experts) reported that during the 2020 presidential election, a small group of “repeat spreaders” aggressively pushed false election claims across various social media platforms for political gain [21, 12].

In the health domain, analysis of the prevalence of low-credibility content related to the COVID-19 “infodemic” on Facebook and Twitter showed that superspreaders on both of these platforms were popular pages and accounts that had been verified by the platforms [51]. In 2021, the Center for Countering Digital Hate reported that just 12 accounts — the
so-called “disinformation dozen”— were responsible for almost two-thirds of anti-vaccine content circulating on social media [6, 33]. This is concerning because eroding the public’s trust in vaccines can be especially dangerous during a pandemic [24] and evidence suggests that increased exposure to vaccine-related misinformation may reduce one’s willingness to get vaccinated [27, 38].

Despite the growing evidence that superspreaders play a crucial role in the spread of misinformation, we lack a systematic understanding of who these superspreader accounts are and how they behave. This gap may be partially due to the fact that there is no agreed-upon method to identify such users; in the studies cited above, superspreaders were identified based on different definitions and methods.

In this paper, we provide a coherent characterization of misinformation superspreaders. In particular, we address two research questions. First, (RQ1) can superspreaders of misinformation be identified in an efficient and reliable manner? To be useful, any method for measuring the degree to which an online account is a superspreader of misinformation should be accurate and predictive. Additionally, given the growing size of datasets related to misinformation, we wish to prioritize methods that are computationally efficient. Here we focus on simple approaches utilizing data that are widely available across platforms. More complex methods may require detailed information about the structure of the entire social network, which is typically unavailable.

Mitigating the negative impact of misinformation superspreaders additionally requires a deeper understanding of these users, leading to our second research question: (RQ2) who are the superspreaders, i.e., what types of users make up most superspreader accounts and how do they behave? A better understanding of the origins of misinformation is an important step toward decreasing its amplification and reach [36].

To answer our first research question, we collect 10 months of Twitter data and evaluate various platform-agnostic metrics (see Data and methods for details) to predict which users will continue to be superspreaders of low-credibility sources after being identified. We do this by ranking accounts in an initial time period with each metric and then comparing how well these rankings predict a user will be a superspreader in a subsequent period. We also compare all metrics to an optimal performance based on data from the evaluation period. The metrics considered are based on Bot Score (likelihood that an account is automated, calculated utilizing BotometerLite [50]), Popularity (number of followers), Influence (number of misinformation retweets earned during the initial period), and False Information Broadcaster (FIB-index), a metric we introduce that is repurposed from scholarly impact studies [17]. We find that the FIB-index and Influence metrics outperform other metrics and achieve near-optimal accuracy in predicting the top superspreaders.

After validating the FIB-index and Influence metric, we address our second research question by conducting a qualitative review of the worst superspreaders. Behavioral statistics and relevant user characteristics are analyzed as well; e.g., whether accounts are verified or suspended. This allows us to provide a qualitative description of the superspreader accounts we identify. 52% of superspreaders on Twitter are political in nature. We also find accounts of pundits with large followings, low-credibility media outlets, personal accounts affiliated with those media outlets, and a range of nano-influencers — accounts with around 14 thousand followers. Additionally, we learn that superspreaders use toxic language significantly more often than the typical user sharing misinformation. Finally, we examine the relationships between suspension, verified status, and popularity of superspreaders. This analysis suggests that Twitter may overlook verified superspreaders with very large followings.

2 Related work

There is a great deal of literature on the identification of influential nodes within a network [28]. While some of this work is not directly related to the social media space, it offers some guidance about how nodes — in our case, accounts — interact within an information diffusion network. Given that the dynamics of diffusion are hard to infer, this work often takes a structural and/or a topical approach.

Structural approaches focus on extracting information about potentially influential users from the topology of social connections in a network [20, 35,
PageRank, an algorithm that counts the number and quality of connections to determine a node’s importance [35]. Several authors have found that the $k$-core decomposition algorithm [1, 42] outperforms other node centrality measures in identifying the most effective spreaders within a social network [37, 22]. This algorithm recursively identifies nodes that are centrally located within a network. Unfortunately, this method is unable to differentiate between individuals in the network’s core.

Topical approaches take into account network structure and also consider the content being shared [16, 49]. For example, Topic Sensitive PageRank [16] calculates topic-specific PageRank scores. Another way to extend PageRank is to bias the random walk through a topic-specific relationship network [49].

Given the ample evidence of manipulation within social media information ecosystems [48, 44, 45, 14], it is important to investigate whether the results mentioned above generalize to misinformation diffusion on social media platforms. Simple heuristics like degree centrality (i.e., the number of connections of a node) perform comparably to more expensive algorithms when seeking to identify superspreaders [5]. These results, though encouraging, rely on model-based simulations and decade-old data. More recent work has proposed methods for identifying fake news spreaders and influential actors within disinformation networks that rely on deep neural networks and other machine learning algorithms [26, 46]. These methods, however, are complex and hard to interpret.

Here we evaluate simple metrics inspired by the literature [37, 5], and address the gaps related to the misinformation space. We consider a Twitter user’s degree within the social (follower) network as well as the misinformation-diffusion (retweet) network. We also introduce the FIB-index metric based on the $h$-index [17], which has also been proposed as a measure of node influence [29]. Finally, we consider a bot score metric [50] that has been shown to capture the role of potential platform manipulation by inauthentic accounts [44].

3 Data and methods

This paper addresses two research questions. To address RQ1, we collect a dataset of misinformation spreading on Twitter. We then compare different metrics for identifying superspreaders of misinformation and provide details about these metrics as well as optimal performance. A dismantling analysis [44, 45] is utilized to quantify how much future misinformation each user is responsible for spreading. To characterize the identified superspreaders (RQ2), we focus on the worst-offending accounts. We manually classify them into different categories and then describe their behavior.

3.1 Misinformation diffusion data

We begin this analysis by building a misinformation diffusion dataset from which we can identify problematic users. Misinformation is defined at the domain level, based on the Iffy+ list of 738 low-credibility sources compiled by professional fact-checkers — an approach widely adopted in the literature [25, 44, 15, 4, 51]. This approach is scalable, but has the limitation that some individual articles from a low-credibility source might be accurate, and some individual articles from a high-credibility source might be inaccurate.

Tweets are gathered from a historical collection based on Twitter’s Decahose Application Programming Interface (API).² The Decahose provides a 10% sample of all public tweets. We collect tweets over a ten-month period (Jan. 2020 – Oct. 2020). We refer to the first two months (Jan–Feb) as the observation period and the remaining eight months as the evaluation period. From this sample, we extract all tweets that link to at least one source in our list of low-credibility sources. This process returns a total of 2,397,388 tweets sent by 448,103 unique users.

3.2 Metrics

Let us present several metrics that can be used to rank users in an attempt to identify misinformation superspreaders.

1. [iffy.news/iffy-plus/](https://iffy.news/iffy-plus/)
2. [developer.twitter.com/en/docs/twitter-api/enterprise/decahose-api/overview/decahose](https://developer.twitter.com/en/docs/twitter-api/enterprise/decahose-api/overview/decahose)
3.2.1 Popularity

Intuitively, the more followers you have on Twitter, the more your posts are likely to be seen and reposted. As a simple measure of popularity, we can use an account’s number of followers, even though it does not fully capture its influence [7]. Specifically, let us define Popularity as the mean number of Twitter followers an account had during the observation period. We extracted the numbers of followers from the metadata in our collection of tweets.

3.2.2 Influence

A measure of influence more directly related to misinformation spreading can be derived from reshares of misinformation-containing posts. Specifically, we compute the Influence of account $i$ by taking the sum of all retweets of posts by $i$ that link to low-credibility sources during the observation period; i.e., the total number of retweets of misinformation earned by $i$. One could also consider quoted tweets, however we focus on retweets because they are commonly treated as endorsements; quoted tweets can indicate other intent such as criticism.

3.2.3 Bot Score

Some research has reported that social bots can play an important role in the spread of misinformation [44]. Therefore, we adopt a Bot Score metric that represents the likelihood of an account being automated [10]. A user’s Bot Score is given by the popular tool BotometerLite,\(^3\) which returns a score ranging from zero to one, with one representing a high likelihood that an account is a bot. The BotometerLite machine learning model relies only on user metadata from the Twitter V1 API [50]. This allows us to analyze the user objects within our historical data, calculating the likelihood that a user was a bot at the time of observation; as opposed to relying on other popular tools that query an account’s most recent activity at the time of estimation [41]. Since we obtain a score from the user object in each tweet, we set user $i$’s Bot Score equal to the mean score across all tweets by $i$ in the observation period.

3.2.4 False Information Broadcaster-index

To quantify an account’s consistent impact on the spread of content from low-credibility sources, we propose a metric inspired by the $h$-index, which was originally developed to measure the influence of scholars [17]. The $h$-index of a scholar is defined as the maximum value of $h$ such that they have at least $h$ papers, each with at least $h$ citations. Similarly, in the context of social media, we define the FIB-index $f_i$ of user $i$ as the maximum value of $f$ such that user $i$ has shared at least $f$ misinformation-containing posts, each of which has been reshared at least $f$ times by other users.

In this study, we apply the FIB-index to the Twitter context and adopt the most common metric on this platform for resharing content, the retweet count. As a result, a Twitter user with a FIB-index of 100 means that the user has posted at least 100 tweets linking to misinformation sources, each of which has been retweeted at least 100 times.

Unlike common measures of influence, such as the retweet count or the number of followers, the FIB-index focuses on problematic repeat-offenders by capturing the consistency with which a user shares misinformation [13]. For example, a user who posts only one misinformation tweet that garners a large number of retweets has a FIB-index of one, regardless of the virality of that individual tweet.

3.3 Accounting for future misinformation

Our approach is to identify superspreaders in the observation period and then quantify how much misinformation they spread during the evaluation period. We construct a retweet network with the data from each period. The observation network (Jan–Feb 2020) and the evaluation network (Mar–Oct 2020) involve approximately 131 thousand and 394 thousand users, respectively. In each network, nodes represent accounts and directed edges represent retweets pointing from the original poster to the retweeter. Each edge $(i, j)$ is weighted by the total number $w_{ij}$ of times any of $i$’s posts linking to low-credibility content are retweeted by $j$.

We create four separate rankings of the 47,012 users that created at least one misinformation-containing post during the observation period based

\(^3\)botometer.osom.eiu.edu/botometerlite
Table 1: Classification scheme utilized during the process of manually annotating superspreader accounts. An account’s political affiliation was recorded if an annotator classified that account as political. The same was done for hyperpartisan accounts in certain other categories, such as media and journalists.

| Classification            | Examples                                                                 | Political Affiliation |
|---------------------------|--------------------------------------------------------------------------|-----------------------|
| Elected official          | Mayors, governors, senators                                              | Recorded              |
| Public service            | City offices, public departments                                         |                       |
| Media outlet              | News outlets, TV news channels                                           | If hyperpartisan      |
| Journalist (hard news)    | Investigative journalists, public health and economics reporters         | If hyperpartisan      |
| Journalist (soft news)    | Sports and entertainment reporters                                       | If hyperpartisan      |
| Journalist (broadcast news)| TV anchors, radio show hosts                                             | If hyperpartisan      |
| Journalist (new media)    | Twitch streamers, podcast hosts                                          | If hyperpartisan      |
| Media affiliated          | Editors, high-level employees, owners of media outlets                   | If hyperpartisan      |
| Public intellectual       | Academic researchers, mainstream opinion columnists                      |                       |
| Political                 | Activists, campaign staffners, political personalities, political pundits, anonymous hyperpartisan accounts | Recorded              |
| Entertainer               | Musicians, comedians, social media personalities                         |                       |
| Sports related            | Baseball players, sports managers                                       |                       |
| Religious leader          | Priests, rabbis, churches                                                |                       |
| Organization              | Organizations not classified elsewhere                                    |                       |
| Other                     | Accounts not classified elsewhere. Primarily personal accounts of non-public figures with moderate followings |                       |
| Deactivated/suspended     | Accounts deactivated/suspended at the time of annotation                 |                       |

on each of the metrics defined above: FIB-index, Popularity, Influence, and Bot Score.

For each ranking, we employ a network dismantling procedure [44, 45] wherein accounts are removed one by one in order of ascending rank from the retweet network. As we remove account \( i \) from the network, we also remove all retweets of misinformation-containing tweets originated by \( i \), i.e., the outgoing edges from \( i \). We can calculate the proportion of misinformation removed from the network with the removal of account \( i \) as

\[
M_i = \frac{\sum_j w_{ij}}{\sum_k w_{kj}},
\]

where the denominator represents the sum of all edge weights prior to beginning the dismantling process. This quantifies how much misinformation each user is responsible for during the evaluation period.

Note that Twitter’s metadata links all retweets of a tweet to the original poster. Therefore, the value \( M_i \) for each account \( i \) is the same across all ranking algorithms. The performance of a metric depends only on the order in which the nodes are removed, determined by the metric-based ranking. We compare how quickly the metrics remove misinformation from the network relative to one another. Metrics that remove misinformation most quickly are considered the best ones for identifying superspreaders. This is because they rank the accounts responsible for the largest proportion of misinformation at the top.

As a non-relative gauge, we also compare each ranking to the optimal ranking for our dismantling-based evaluation. This optimal strategy is obtained by ranking nodes according to descending values of \( M \), where \( M \) is calculated by using the evaluation period instead of the training period. That is, the ac-
count with the largest $M$ value is removed first, followed by the one with the second largest $M$, and so on, until all users have been removed. Note that this optimal ranking is only possible using information from the future evaluation period as an oracle. It serves as an upper bound on the performance that can be expected from any ranking metric.

### 3.4 Account classification and description

The top superspreader accounts according to the rankings described above are classified into one of the 16 different categories detailed in Table 1. We adopted and slightly altered a classification scheme utilized by Gallagher et al. (2021). Health-related and COVID-19-specific categories, i.e., “public health official,” “medical professional,” and “epidemiologist,” were removed. A “media affiliated” category was added to capture accounts that might have some affiliation with low-credibility sources, as seen in previous research [51]. This classification scheme takes into account different types of journalists as well as other influential individuals and entities, such as politicians, media outlets, religious leaders, and organizations. Additionally, accounts in certain categories (“elected official” and “political”) are annotated with their political affiliation: “right” (conservative) or “left” (liberal). The same is done for hyperpartisan accounts in certain other categories, such as media and journalists.

Two authors independently annotated each account. In cases of disagreement, two additional authors followed the same process. The category and political affiliation of these accounts were then derived from the majority classification (three of the four annotators). Accounts for which the disagreement could not be resolved were excluded.

### 3.5 Source-sharing behavior

We investigate the typical misinformation-sharing behavior of a top superspreader account relative to their general sharing behavior. For a given account, we calculate the ratio $r_m$ of tweets linking to low-credibility sources out of all tweets linking to any source. This also allows us to better understand the proportion $1 - r_m$ of non-low-credibility sources that would be lost if the account were removed. This type of content may originate from trusted sources and is assumed to be harmless. An ideal method would identify users that consistently share high-impact misinformation and a minimal proportion of non-low-credibility content.

To calculate $r_m$, we first download all tweets sent by the identified superspreaders during a three-month period (Jan 1, 2020–April 1, 2020). We were able to gather tweets from 123 superspreader accounts that were still active. We then extract all links from the metadata of these tweets. We expand links that are processed by a link-shortening service (e.g., bit.ly) prior to being posted on Twitter. Sources are obtained by extracting the top-level domains from the links. Low-credibility sources are identified by matching domains to the Iffy+ list described earlier. Finally, we calculate the proportion $r_m$ of shared sources that are labeled as low-credibility. The inability to calculate $r_m$ for inactive accounts might introduce bias in this measurement.

### 3.6 Language toxicity

We wish to investigate the content of superspreader posts beyond source-sharing behaviors to understand if they are taking part in respectful discourse or increasing the levels of abusive language in public discussion. We utilize the Google Jigsaw Perspective API [19] to estimate the probability of each tweet in the 10-month dataset being toxic. The API defines toxic language as rude, disrespectful, or unreasonable comments that are likely to make users disengage from an online interaction. We then calculate the toxicity of an account by averaging the score across all of their original tweets. We only consider English-language tweets; five superspreaders tweeting exclusively in other languages are excluded.

### 4 Results

#### 4.1 Dismantling analysis

After ranking accounts in the observation period based on the investigated metrics (FIB-index, Popularity, Influence, and Bot Score), we conduct a dismantling analysis to understand the efficacy of each one (see Data and methods for details). The results of this analysis are show in Fig. 1 (top).
Figure 1: Top: The effect of removing accounts that created misinformation posts during January and February 2020 (observation period) on the proportion of misinformation present during the following eight months (evaluation period). Nodes (accounts) are removed one by one from a retweet network in order of ascending rank, based on the metrics indicated in the legend. The remaining proportion of retweets of misinformation is plotted versus the number of nodes removed. The lowest value for all curves is not zero, reflecting the fact that approximately 13% of the misinformation retweets in the evaluation network are by accounts who did not create misinformation posts during the observation period. Bottom: Likelihood that the difference between the performance of FIB-index and Influence happened by random chance. The most prolific superspreaders according to these two metrics remove a similar amount of misinformation. To compare them for any given number of removed accounts, we conduct Cramer von Mises two-sample tests with increasingly larger samples and plot each test’s p-value on the y-axis. After removing more than 50 accounts (gray area) the Influence metric performs significantly better (p < 0.05). The difference is not significant if fewer accounts are removed.

Bot Score performs the worst: even after more than 2,000 accounts are removed from the network, most of the misinformation still remains in the network. This suggests that bots infrequently originate the misinformation on Twitter. Instead, as previous research suggests, bots may increase views through retweets and expose accounts with many followers to the misinformation, in hopes of having them reshare it for greater impact [44].

We also observe in Fig. 1 (top) that while Popularity performs substantially better than Bot Score, it fails to rank the most problematic spreaders at the top: upon removing the top 10 users, almost no misinformation is removed from the network. In contrast, the FIB-index and Influential metrics place superspreaders at the top of their rankings and the dismantling procedure removes substantial amounts of misinformation from the network immediately.

The Popularity metric draws on the structure of the follower network and therefore contains valuable information about how misinformation might spread. However, the follower network is not a perfect predictor of diffusion networks [37]. The retweet network used by Influence and FIB-index provides a more direct prediction.

Cramer von Mises (CvM) two-sample comparisons show significant differences between the optimal curve and those for FIB-index and Influence
metrics ($p < 0.001$). However, the amount of misinformation removed using either metric is within 2% of the optimal, on average. In fact, removing the top 10 superspreaders eliminates 34.6% and 34.3% of the misinformation based on FIB-index and Influence, respectively (optimal: 38.1%). In other words, 0.003% of the accounts active during the evaluation period posted misinformation that received over 34% of all retweets of misinformation over the eight months following their identification. Removing the top 1,000 superspreaders (0.25% of the accounts who posted during the evaluation period) eliminates 73–78% of the misinformation (optimal: 81%). This represents a remarkable concentration of responsibility for misinformation spreading.

Comparing the performance of FIB-index and Influence to one another across all ranked accounts illustrates that ranking by the Influence metric removes significantly more misinformation on average (CvM: $p < 0.001$). However, it is more useful to compare the performance between these metrics with respect to the highest ranked accounts, since those would be considered as potential superspreaders. Let us again utilize CvM tests to compare the impact of removing samples of top superspreaders of increasing size, up to 1,000 accounts. We first check if the amount of misinformation attributed to the top two ranked accounts according to each metric is significantly different, then the top three, and so on, until we have considered the top 1,000 accounts in each group. As shown in Fig. 1 (bottom), rankings by FIB-index and Influence are not significantly different when comparing the amount of misinformation attributed to the top-ranked accounts. Only after removing accounts ranked 51st or below — who likely would not be categorized as superspreaders — does the performance of these metrics begin to differ significantly.

Overall, these results suggest that, with respect to our sample, both FIB-index and Influence metrics perform well at identifying superspreaders of misinformation. Since removing accounts based on these two metrics yields similar reductions in misinformation, we explore other reasons to prefer one over the other in later sections.

### 4.2 Describing superspreaders

In this section we characterize the misinformation superspreaders in terms of the types of accounts, their misinformation sharing behavior, and use of toxic language. We also investigate the relationship between an account’s follower count and its verified or suspended status. To manually evaluate a manageable number of accounts, we select the top 1% of accounts with a FIB-index above zero, yielding 181 accounts, and then select an equal number of top ranked accounts according to the Influence metric.

#### 4.2.1 Account classification

The groups selected by the two metrics overlap, so there are a total of 250 unique accounts. These were manually classified into different categories following the procedure detailed in Data and methods. After the first round of classifications, two authors agreed on 211 accounts (84.4%, Krippendorf’s $\alpha = 0.79$). Of the remaining 39 accounts reviewed by two additional authors, 21 were classified by a majority of annotators and the rest were excluded, yielding 232 classified accounts.

Fig. 2 reports the number of superspreader accounts in each category. Over half of the accounts (55.1%) were no longer active at time of analysis. Of these 128 inactive accounts, 111 (86.7%) were reported by Twitter as suspended. The suspended accounts were evenly distributed among the superspreaders identified by FIB-index (47.5%, 86 accounts) and Influence (42.5%, 78 accounts). The remaining 17 inactive accounts were deleted. We consider the high number of suspensions as an additional validation of these metrics: Twitter itself considered problematic many of the accounts we labelled as superspreaders.

The accounts still active were classified according to the scheme in Table 1. 52% (54 accounts) fall into the “political” group. These accounts represent users who are clearly political in nature, discussing politics almost exclusively. They consist largely of anonymous hyperpartisan accounts but also high-profile political pundits and strategists. Notably, this group includes the official accounts of both the Democratic and Republican parties (@TheDemocrats and @GOP), as well as @DonaldJTrumpJr, the account
of the son and political advisor of then-President Donald Trump.

The next largest group is the “other” category, making up 14 active accounts (13.4%). This group mostly consists of nano-influencers with a moderate following (median ≈ 14 thousand followers) posting about various topics. A few accounts were classified in this group simply because their tweets were in a different language.

The “media outlet” and “media affiliated” classifications make up the next two largest groups, consisting of 19 active accounts combined (18.3%). Most of the media outlets and media affiliated accounts are associated with low-credibility sources. For example, Breaking911.com is a low-credibility source and the @Breaking911 account was identified as a superspreader. Other accounts indicate in their profile that they are editors or executives of low-credibility sources.

The remainder of the superspreaders consist of (in order of descending number of accounts) “organizations,” “intellectuals,” “new media,” “public service,” “broadcast news,” and “hard news” accounts. Notable among these accounts are: the prominent anti-vaccination organization, Children’s Health Defense, whose chairman, Robert F. Kennedy Jr., was named as one of the top superspreaders of COVID-19 vaccine disinformation [6, 33]; the self-described “climate science contrarian” Steve Milloy, who has been labeled a “pundit for hire” for the oil and tobacco industries [47, 31]; and the popular Fox News television show host, Sean Hannity, who has been repeatedly accused of peddling conspiracy theories and misinformation on his show [11, 43, 30].

Examining the political ideology of superspreaders, we find that 91% (49 of 55) of the “political” accounts are conservative in nature. Extending this analysis to include other hyperpartisan accounts (i.e., those classified as a different type but still posting hyperpartisan content), 91% of accounts (63 of 69) are categorized as conservative.

Fig. 2 also reports political affiliations by superspreader account class. The conservative/liberal imbalance is largely captured within the political accounts group. However, we also see that approximately half of the “media outlet” and “media affiliated” superspreaders consist of hyperpartisan conservative accounts. These results agree with literature that finds an asymmetric tendency for conservative users to share misinformation online compared to liberal users [32, 15, 8].

### 4.2.2 Misinformation sharing behavior

The dismantling analysis focuses on low-credibility content and does not capture the rest of the content shared by an account. This distinction is important because moderation actions, such as algorithmic de-
motion, suspension, and deplatforming, limit a user’s ability to share any content. To better understand the full impact of removing superspreaders, we analyze the likelihood that a superspreader shares a low credibility source. We estimate this likelihood using the proportion $r_m$ defined in Data and methods.

Fig. 3 compares the distributions of proportions of low-credibility links shared by the superspreaders identified by FIB-index and Influence metrics. We see that accounts identified via the FIB-index share relatively more misinformation sources than those identified with the Influence metric; a two-way Mann-Whitney $U$ test confirms that this difference is significant ($U = 2,784, p < 0.01$). Specifically, the median proportion of shared sources that are low-credibility for accounts identified with the FIB-index (median 0.066, mean 0.219, $n = 84$) is approximately two times larger than for those identified with the Influence metric (median 0.030, mean 0.174, $n = 91$). In other words, while removing superspreader accounts based on the two metrics has a similar effect on curbing misinformation, using the FIB-index is preferable because it removes less content that is not from low-credibility sources. This result makes sense in light of the fact that the FIB-index prioritizes accounts who share low-credibility sources consistently.

### 4.2.3 Language toxicity

Let us now explore the language used by superspreaders. We first compare the distribution of mean toxicity scores for accounts identified by the FIB-index and Influence metric. Toxicity scores are estimated with the Perspective API [19] (see details in Data and methods).

We find that FIB-identified superspreaders display similar average toxicity (median = 0.184, mean = 0.197, $n = 178$) to those identified with the Influence metric (median = 0.177, mean = 0.196, $n = 179$); a Mann-Whitney $U$ two-way comparison indicates this difference is not significant ($U = 16,434, p = 0.606, n = 245$).

Fig. 4 shows superspreaders having significantly higher toxicity than all accounts within our dataset (Mann-Whitney $U = 2 \times 10^7$, $p < 0.0001, n = 149,481$). However, at the individual level, we observe no significant correlation between toxicity and FIB-index (Spearman $r = 0.03, p = 0.67$) or Influence (Spearman $r = 0.08, p = 0.26$).

### 4.2.4 Account prominence

Approximately one in five of the superspreader accounts (48 out of 250) have been verified by Twitter. Given such a large proportion of verified accounts, let us investigate the relationship between the prominence (verified status, followers, and retweets) and active/suspended status of these accounts.

Fig. 5 (top) shows that more prominent superspreaders are less likely to be suspended: only 3% of suspended accounts were verified. As shown in Fig. 5 (bottom), superspreaders with many (more than 150 thousand) followers are also less likely to have been suspended. A similar pattern is observed using different thresholds for the number of followers.

Additionally, we find a significant correlation between a superspreader’s number of followers and the amount of misinformation they were responsible for ($M$) during the evaluation period (Spearman $r = 0.42, p < 0.0001$).

### 5 Discussion

In this paper we address two research questions at the core of the digital misinformation problem. Specifically, we compare the efficacy of several metrics in identifying superspreaders of misinformation on Twitter (RQ1). We then employ the best performing metrics to qualitatively describe these problematic accounts (RQ2).

The FIB-index and Influence metrics display similar (and near-optimal) performance in identifying superspreaders. However, the accounts identified by Influence share a larger proportion of tweets that do not link to low-credibility sources. This makes the FIB-index preferable as a tool to identify misinformation superspreaders; mitigation measures would likely remove or restrict the spread of all information shared by those accounts. On the other hand, some bad actors may intentionally introduce harmless content into their feed in hopes of masking their deleterious behavior.

The dismantling analysis illustrates that 10 superspreaders (0.003% of accounts) were responsible for
Figure 3: Misinformation sharing behavior of superspreaders as captured by the distribution of the ratio $r_m$. Users identified via the FIB-index metric share a significantly higher ratio of low-credibility sources than those identified with the Influence metric.

Figure 4: Distributions of language toxicity scores for superspreaders vs. all accounts in the misinformation ecosystem.

originating over 34% of the misinformation shared during the eight months that followed their identification, and 1,000 accounts (0.25%) were responsible for more than 70%. This highlights a stunning concentration of responsibility for the diffusion of misinformation on Twitter. Superspreaders are not only responsible for disseminating most untrustworthy content, but also for posting more toxic language than the average misinformation sharer.

A manual classification of the active superspreaders reveals that over half are heavily involved in political conversation. Despite the fact that the vast majority are conservative, they include the official accounts of both the Democratic and Republican parties. Additionally, we find a substantial portion of nano-influencer accounts, prominent broadcast television show hosts, contrarian scientists, and antivaxxers. This diverse group of users illustrate various motivations for spreading untrustworthy content: fame, money, and political power.

Our analysis shows that removing superspreaders from the platform results in a large reduction in misinformation. However, the potential for suspensions to reduce harm may conflict with freedom of speech values [23]. The effectiveness of other approaches to moderation should be evaluated by researchers and industry practitioners [2]. For instance, platforms could be redesigned to incentivize the sharing of trustworthy content [3].

Internal Facebook documents detailed a program that exempted high-profile users from some or all of its rules [18]. Evidence presented in this paper suggests that Twitter is also more lenient with superspreaders who are verified or have large followings. Social media platforms may be reluctant to suspend prominent superspreaders due to potential negative publicity and political pressure. Paradoxically, the more prominent a superspreader is, the greater their negative impact, and the more difficult they are to mitigate.

6 Acknowledgements

The authors thank Drs. Yong-Yeol Ahn and Alessandro Flammini for their helpful discussions about this project. We also thank the members of the Networks & agents Network (NaN) research group at Indiana University, for feedback on preliminary results, as well as Dr. Yonatan Zunger for helpful input related to the tested metrics.

7 Funding

This work was supported by the John S. and James L. Knight Foundation and Craig Newmark Philanthropies. The funders had no role in study design,
Figure 5: Relationship between suspension, verified status, and popularity of top 250 superspreaders. Top: Percentage of suspended superspreader accounts that are verified. Bottom: Percentage of suspended superspreader accounts based on numbers of followers.

data collection and analysis, decision to publish, or preparation of the manuscript.

References

[1] J. I. Alvarez-Hamelin, L. Dall’Asta, A. Barrat, and A. Vespignani. K-core decomposition of Internet graphs: hierarchies, self-similarity and measurement biases. *Networks and Heterogeneous Media*, 2008. URL http://dx.doi.org/10.3934/nhm.2008.3.371.

[2] J. B. Bak-Coleman, I. Kennedy, M. Wack, A. Beers, J. S. Schafer, E. S. Spiro, K. Starbird, and J. D. West. Combining interventions to reduce the spread of viral misinformation. *Nature Human Behaviour*, 2022. URL https://doi.org/10.1038/s41562-022-01388-6.

[3] S. Bhadani, S. Yamaya, A. Flammini, F. Menczer, G. L. Ciampaglia, and B. Nyhan. Political audience diversity and news reliability in algorithmic ranking. *Nature Human Behaviour*, 2022. URL https://doi.org/10.1038/s41562-021-01276-5.

[4] A. Bovet and H. A. Makse. Influence of fake news in Twitter during the 2016 US presidential election. *Nature Communications*, 2019. URL https://doi.org/10.1038/s41467-018-07761-2.

[5] C. Budak, D. Agrawal, and A. El Abbadi. Limiting the spread of misinformation in social networks. In *Proceedings of the 20th International Conference on World Wide Web*, 2011. URL https://doi.org/10.1145/1963405.1963499.

[6] Center for Countering Digital Hate. The Disinformation Dozen: Why platforms must act on twelve leading online anti-vaxxers, 2021. URL https://www.counterhate.com/disinformationdozen.

[7] M. Cha, H. Haddadi, F. Benevenuto, and K. Gummadi. Measuring user influence in Twitter: The million follower fallacy. In *Proceedings of the International AAAI Conference on Web and Social Media*, 2010. URL https://ojs.aaai.org/index.php/ICWSM/article/view/14033.

[8] W. Chen, D. Pacheco, K.-C. Yang, and F. Menczer. Neutral bots probe political bias on social media. *Nature Communications*, 2021. URL https://doi.org/10.1038/s41467-021-25738-6.

[9] E. Culliford. Online misinformation that led to Capitol siege is 'radicalization,' say researchers. *Reuters*, Jan. 2021. URL https://www.reuters.com/article/us-misinformation-socialmedia-idUSKBN29H2HM.

[10] E. Ferrara, O. Varol, C. Davis, F. Menczer, and A. Flammini. The rise of social bots. *Commun. ACM*, 2016. doi: 10.1145/2818717. URL https://doi.org/10.1145/2818717.

[11] M. Fisher. The making of Sean Hannity: How a Long Island kid learned to channel red-state rage. *Washington Post*, 2017. URL https://www.washingtonpost.com/lifestyle/style/the-making-of-sean-hannity-how-a-long-island-kid-learned-to-channel-red-state-rage/2017/10/09/540cf
[12] S. Frenkel. How Misinformation ‘Superspreaders’ Seed False Election Theories. *The New York Times*, 2020. URL https://www.nytimes.com/2020/11/23/technology/election-misinformation-facebook-twitter.html.

[13] R. J. Gallagher, L. Doroshenko, S. Shugars, D. Lazer, and B. F. Welles. Sustained Online Amplification of COVID-19 Elites in the United States. *Social Media + Society*, 2021. URL https://doi.org/10.1177/20563051211024957.

[14] Y. Golovchenko, C. Buntain, G. Eady, M. A. Brown, and J. A. Tucker. Cross-Platform State Propaganda: Russian Trolls on Twitter and YouTube during the 2016 U.S. Presidential Election. *The International Journal of Press/Politics*, 2020. URL https://doi.org/10.1177/194016120912682.

[15] N. Grinberg, K. Joseph, L. Friedland, B. Swire-Thompson, and D. Lazer. Fake news on Twitter during the 2016 U.S. presidential election. *Science*, 2019. URL https://www.science.org/doi/abs/10.1126/science.aau2706.

[16] T. Haveliwala. Topic-sensitive PageRank: a context-sensitive ranking algorithm for web search. *IEEE Transactions on Knowledge and Data Engineering*, 2003. URL https://doi.org/10.1109/TKDE.2003.1208999.

[17] J. E. Hirsch. An index to quantify an individual’s scientific research output. *Proceedings of the National Academy of Sciences*, 2005. URL https://www.pnas.org/doi/abs/10.1073/pnas.0507655102.

[18] J. Horwitz et al. The Facebook Files. *Wall Street Journal*, 2021. URL https://www.wsj.com/articles/the-facebook-files-11631713039.

[19] Jigsaw. Perspective API, 2017. URL https://www.perspectiveapi.com/.

[20] L. Katz. A new status index derived from sociometric analysis. *Psychometrika*, 1953. URL https://doi.org/10.1007/BF02289026.

[21] I. Kennedy, M. Wack, A. Beers, J. S. Schafer, I. Garcia-Camargo, E. S. Spiro, and K. Starbird. Repeat spreaders and election delegitimization: A comprehensive dataset of misinformation tweets from the 2020 U.S. election. *Journal of Quantitative Description: Digital Media*, 2022. URL https://journalqd.org/article/view/3137.

[22] M. Kitsak, L. K. Gallos, S. Havlin, F. Liljeros, L. Muchnik, H. E. Stanley, and H. A. Makse. Identification of influential spreaders in complex networks. *Nature Physics*, 2010. URL https://www.nature.com/articles/nphys1746.

[23] A. Kozyreva, S. M. Herzog, S. Lewandowsky, R. Hertwig, P. Lorenz-Spreen, M. Leiser, and J. Reifler. Free speech vs. harmful misinformation: Moral dilemmas in online content moderation, 2022. URL https://doi.org/10.31234/osf.io/2pc3a.

[24] H. J. Larson. The biggest pandemic risk? Viral misinformation. *Nature*, 2018. URL https://www.nature.com/articles/d41586-018-07034-4.

[25] D. M. J. Lazer, M. A. Baum, Y. Benkler, A. J. Berinsky, K. M. Greenhill, F. Menczer, M. J. Metzger, B. Nyhan, G. Pennycook, D. Rothschild, M. Schudson, S. A. Sloman, C. R. Sunstein, E. A. Thorson, D. J. Watts, and J. L. Zittrain. The science of fake news. *Science*, 2018. URL https://www.science.org/doi/abs/10.1126/science.aao2998.

[26] S. Leonardi, G. Rizzo, and M. Morisio. Automated classification of fake news spreaders to break the misinformation chain. *Information*, 2021. URL https://www.mdpi.com/2078-2489/12/6/248.

[27] S. Loomba, A. de Figueiredo, S. J. Piatek, K. de Graaf, and H. J. Larson. Measuring the impact of COVID-19 vaccine misinformation...
on vaccination intent in the UK and USA. *Nature Human Behavior*, 2021. URL https://doi.org/10.1038/s41562-021-01056-1.

[28] L. Lü, D. Chen, X.-L. Ren, Q.-M. Zhang, Y.-C. Zhang, and T. Zhou. Vital nodes identification in complex networks. *Physics Reports*, 2016. URL http://www.sciencedirect.com/science/article/pii/S0370157316301570.

[29] L. Lü, T. Zhou, Q.-M. Zhang, and H. E. Stanley. The H-index of a network node and its relation to degree and coreness. *Nature Communications*, 2016. URL https://www.nature.com/articles/ncomms10168.

[30] J. Mayer. The making of the Fox News White House. *The New Yorker*, 2019. URL https://www.newyorker.com/magazine/2019/03/11/the-making-of-the-fox-news-white-house.

[31] C. Mooney. Some like it hot. *Mother Jones*, 2022. URL https://www.motherjones.com/environment/2005/05/some-it-hot/.

[32] D. Nikolov, A. Flammini, and F. Menczer. Right and left, partisanship predicts (asymmetric) vulnerability to misinformation. *Harvard Kennedy School Misinformation Review*, 2021. URL https://doi.org/10.37016/mr-2020-55.

[33] G. Nogara, P. S. Vishnuprasad, F. Cardoso, O. Ayoub, S. Giordano, and L. Luceri. The Disinformation Dozen: An Exploratory Analysis of Covid-19 Disinformation Proliferation on Twitter. In *14th ACM Web Science Conference 2022*, pages 348–358, 2022. URL https://doi.org/10.1145/3501247.3531573.

[34] Office of the Surgeon General. *Confronting Health Misinformation: The U.S. Surgeon General’s Advisory on Building a Healthy Information Environment*. US Department of Health and Human Services, 2021. URL http://www.ncbi.nlm.nih.gov/books/NBK572169/.

[35] L. Page, S. Brin, R. Motwani, and T. Winograd. The PageRank citation ranking: Bringing order to the web. Technical Report 1999-66, Stanford InfoLab, 1999. URL http://ilpubs.stanford.edu:8090/422/.

[36] I. Pasquetto, B. Swire-Thompson, M. Amazeen, F. Benevenuto, N. Brashier, R. Bond, L. Bozarth, C. Budak, U. Ecker, L. Fazio, E. Ferrara, A. Flanagin, A. Flammini, D. Freelon, N. Grinberg, R. Hertwig, K. Jamieson, K. Joseph, J. Jones, R. Grant, D. Kreiss, S. McGregor, J. McNealy, D. Margolin, A. Marwick, F. Menczer, M. J. Metzger, A. Nah, S. Lewandowsky, P. Lorenz-Spreen, P. Orgettado, G. Pennycook, E. Porter, D. G. Rand, R. E. Robertson, F. Tripodi, S. Vosoughi, C. Vargo, O. Varol, B. E. Weeks, J. Wiebey, T. J. Wood, and K. Yang. Tackling misinformation: What researchers could do with social media data. *Harvard Kennedy School Misinformation Review*, 2020. URL https://doi.org/10.37016/mr-2020-49.

[37] S. Pei, L. Muchnik, J. J. S. Andrade, Z. Zheng, and H. A. Makse. Searching for superspreaders of information in real-world social media. *Scientific Reports*, 2014. URL https://www.nature.com/articles/srep05547.

[38] F. Pierri, B. Perry, M. R. DeVerna, K.-C. Yang, A. Flammini, F. Menczer, and J. Bryden. Online misinformation is linked to early COVID-19 vaccination hesitancy and refusal. *Scientific Reports*, 2022. URL https://doi.org/10.1038/s41598-022-10070-w.

[39] M. Richtel. W.H.O. Fights a Pandemic Besides Coronavirus: An Infodemic. *The New York Times*, 2020. URL https://www.nytimes.com/2020/02/06/health/coronavirus-misinformation-social-media.html.

[40] D. M. Romero, W. Galuba, S. Asur, and B. A. Huberman. Influence and passivity in social media. In *Machine Learning and Knowledge Discovery in Databases*, 2011. URL https://doi.org/10.1007/978-3-642-23808-6_2.

[41] M. Sayyadiharakandeh, O. Varol, K.-C. Yang, A. Flammini, and F. Menczer. Detection of novel social bots by ensembles of specialized classifiers. In *Proc. 29th ACM International*
[42] S. B. Seidman. Network structure and minimum degree. *Social Networks*, 1983. URL https://www.sciencedirect.com/science/article/pii/037887338390028X.

[43] M. Shaer. How Far Will Sean Hannity Go? *The New York Times*, 2017. URL https://www.nytimes.com/2017/11/28/magazine/how-far-will-sean-hannity-go.html.

[44] C. Shao, G. L. Ciampaglia, O. Varol, K.-C. Yang, A. Flammini, and F. Menczer. The spread of low-credibility content by social bots. *Nature Communications*, 2018. URL https://doi.org/10.1038/s41467-018-06930-7.

[45] C. Shao, P.-M. Hui, L. Wang, X. Jiang, A. Flammini, F. Menczer, and G. L. Ciampaglia. Anatomy of an online misinformation network. *PLoS ONE*, 2018. URL https://doi.org/10.1371/journal.pone.0196087.

[46] S. T. Smith, E. K. Kao, E. D. Mackin, D. C. Shah, O. Simek, and D. B. Rubin. Automatic detection of influential actors in disinformation networks. *Proceedings of the National Academy of Sciences*, 2021. URL https://www.pnas.org/content/118/4/e2011216118.

[47] P. D. Thacker. Smoked out: Pundit for hire. *New Republic*, 2006. URL https://newrepublic.com/article/104858/smoked-out.

[48] C. Torres-Lugo, K.-C. Yang, and F. Menczer. The Manufacture of Political Echo Chambers by Follow Train Abuse on Twitter. In *Proceedings of the International AAAI Conference on Web and Social Media*, 2022. URL https://arxiv.org/abs/2010.13691. Forthcoming. Preprint.

[49] J. Weng, E.-P. Lim, J. Jiang, and Q. He. Twitter-Rank: Finding Topic-Sensitive Influential Twitterers. In *Proceedings of the Third ACM Conference on Information & Knowledge Management*, 2020. URL https://doi.org/10.1145/3340531.3412698.

[50] K.-C. Yang, O. Varol, P.-M. Hui, and F. Menczer. Scalable and generalizable social bot detection through data selection. In *Proceedings 34th AAAI Conference on Artificial Intelligence*, 2020. URL https://doi.org/10.1609/aaai.v34i01.5460.

[51] K.-C. Yang, F. Pierri, P.-M. Hui, D. Axelrod, C. Torres-Lugo, J. Bryden, and F. Menczer. The COVID-19 Infodemic: Twitter versus Facebook. *Big Data & Society*, 2021. URL https://doi.org/10.1177/20539517211013861.

[52] J. Zarocostas. How to fight an infodemic. *The Lancet*, 2020. URL https://doi.org/10.1016/S0140-6736(20)30461-X.