Prevalence of Low-Credibility Information on Twitter During the COVID-19 Outbreak

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Abstract

As the novel coronavirus spreads across the world, concerns regarding the spreading of misinformation about it are also growing. Here we estimate the prevalence of links to low-credibility information on Twitter during the outbreak, and the role of bots in spreading these links. We find that the combined volume of tweets linking to various low-credibility information is comparable to the volume of New York Times articles and CDC links. Content analysis reveals a politicization of the pandemic. The majority of this content spreads via retweets. Social bots are involved in both posting and amplifying low-credibility information, although the majority of volume is generated by likely humans. Some of these accounts appear to amplify low-credibility sources in a coordinated fashion.

Introduction

As we write this paper, most countries across the world are experiencing an unprecedented outbreak of the novel coronavirus (COVID-19). Millions of people have tested positive for the virus and tens of thousands people have died from it globally (coronavirus.jhu.edu/map.html). At the same time, we have observed an increase of approximately 25% in Twitter volume.

With millions of people stuck in their homes and accessing information via social media, concerns about the spread of misinformation about the pandemic (referred to as “infodemic” (Zarocostas 2020)) have mounted. Social media have been known to facilitate the spread of misinformation (Vosoughi, Roy, and Aral 2018), manipulation (Stella, Ferrara, and De Domenico 2018), and radicalization of users (Thompson 2011). These issues are even more pressing in the current atmosphere since the information flowing through social media is directly related to the health and safety of the people.

In response, quite a few research papers have been made public lately that estimate the prevalence of COVID19-related misinformation on social media (Cinelli et al. 2020; Pulido et al. 2020; Laato et al. 2020) and characterize the behaviors of inauthentic actors (Galli et al. 2020; Ferrara 2020). These studies use different methods on different datasets and yield different perspectives on the issue. However, given the complex nature of the problem, many questions remain unanswered. In this paper, we use a random sample of tweets to estimate the prevalence of COVID19-related low-credibility information on Twitter and further characterize the role of social bots (Ferrara et al. 2016; Shao et al. 2018).

Methods

Identification of low-credibility information

Identification of false information often requires fact-checking from experts, which is extremely time consuming and therefore not viable for this analysis. Instead, we focus on the URLs embedded in the tweets and annotate the credibility of the content not at the URL level but at the domain level following the literature (Shao et al. 2018; Grinberg et al. 2019; Guess, Nagler, and Tucker 2019; Pennycook and Rand 2019; Bovet and Makse 2019; Vosoughi, Roy, and Aral 2018).

We compiled a list of low-credibility (including hyperpartisan) sources from several lists used in recent research. Our list includes sources that fulfill any one of the following criteria: (1) labeled as low-credibility by Shao et al. (Shao et al. 2018); (2) labeled as “Black” or “Red” or “Satire” by Grinberg et al. (Grinberg et al. 2019); (3) labeled as “fake-news” or “hyperpartisan” by Pennycook and Rand (Pennycook and Rand 2019); or (4) labeled as “extremeleft” or “extremerright” or “fakenews” by Bovet et al. (Bovet and Makse 2019). This gives us a list of 570 low-credibility sources.

Data collection

We collected two datasets using different methods to answer different questions.

DS1 consists of tweets containing a set of hashtags and links. Various hashtags are associated to the coronavirus (Chen, Lerman, and Ferrara 2020), but some are focused on certain aspects of the outbreak and some reflect certain biases. To provide a general and unbiased view of the discussion, we chose two generic hashtags #coronavirus and #covid19 as our seeds. Our data
was collected using an API from the Observatory on Social Media, which allows to search tweets from a 10% random sample of public tweets (Davis et al. 2016). This dataset consists of tweets from Mar. 9–29, 2020.

Estimating the prevalence of low-credibility information requires matching the URL domains from the tweets against the list defined above. To include all links from the tweet objects obtained through the API, we used a regular expression to extract any URL-like strings from the tweet text in addition to fetching URLs from the entity metadata. For retweets, we also included the URLs in the original tweets using the same method.

Since shortened URLs are very common, we identified those from 70 most frequent shortening services and expanded the URLs through HTTP requests to obtain the real domains. The expanded URLs were further cleaned. We removed those linking to Twitter itself, which turn out to be the majority, and those linking to other social media sites. While these links might still lead to low-credibility information, there is no easy way to verify, so we exclude them in this study. The remaining links mainly belong to news outlets and authorities like government agencies. The DS1 is the set of tweets that match the COVID-19 hashtags and containing any of these links.

DS2 starts from a collection of tweets containing links to low-credibility sources. The data was collected using the Twitter streaming/filter API from Feb. 1 to Apr. 27, 2020. The URLs were extracted and the corresponding web pages were fetched. To reveal common low-credibility information topics, we analyzed the titles of the linked articles and retained those with keywords “coronavirus” and “covid.” We ranked the links by the number of tweets containing them and extracted the top 1,200. Each URL in DS2 has been shared at least 50 times.

Bot detection
Social bots are social media accounts controlled in part by algorithms (Ferrara et al. 2016). Malicious bots are known to spread low-credibility information (Shao et al. 2018) as well as creating confusion in the online debate about health-related topics like vaccination (Broniatowski et al. 2018). It is therefore interesting to characterize the role of social bots in spreading COVID19-related low-credibility information.

We adopt BotometerLite (Yang et al. 2019), a bot detection model that enables large-scale bot detection. By strategically selecting a subset of the training dataset, BotometerLite achieves high accuracy in cross-validation as well as cross-domain tests. BotometerLite generates a score between 0 and 1 for every account, with higher scores indicating bot-like profiles. For binary classification of accounts we use a threshold of 0.5 in this paper.

Results

Prevalence of low-credibility information
To report on the prevalence of low-credibility information, we obtain reference volume levels using links to the New York Times, a mainstream news source, and the CDC, an official source of critical information related to the outbreak.

Our results show that links to low-credibility sources combined contribute 0.89% of the total tweet volume in DS1 (Fig. 1(a)). For comparison, nytimes.com contributes 0.98% and cdc.gov contributes less than 0.65%. To account for the fact that some users might share certain information repeatedly, we provide the same analysis at the level of users, i.e., the percentage of users who shared the corresponding links at least once, in Fig. 1(b). The results are qualitatively similar. These findings suggest that low-credibility information is not rampant on Twitter, but it does have a volume share comparable with highly reliable sources.

We also show the percentage of retweets for different sources in Fig. 1(c). About 68% of the links to low-credibility information are shared by retweets. For comparison, this fraction is about 54% for nytimes.com and all URLs together in DS1. This suggests that users involved with low-credibility information on Twitter are more likely to share links posted by others. Interestingly, cdc.gov has an even higher retweet rate.

Role of social bots
We report the percentage of tweets posted by social bots for different sources in Fig. 1(d). A significantly higher ratio of the volume of low-credibility information is shared by likely bot accounts, compared to the volume of tweets linking to reliable sources and the overall baseline. Since some accounts post multiple tweets with the same link, affecting the bot ratio estimation, we also perform the same analysis at the user level (not shown in Fig. 1). The bot ratios become 12.1%, 6.5%, 10.6%, and 11.7% for low-credibility,
Coordinated amplification of low-credibility information

Let us build a network of shared low-credibility domains to highlight potentially coordinated groups of accounts amplifying misinformation (Pacheco et al. 2020). We focus on accounts that share at least 3 links. Then we extract domains from shared links to low-credibility sources, and represent an account as a vector of such domains. We finally calculate the cosine similarity between each pair of account vectors and use it as a network weight.

The resulting network is shown in Fig. 3. We note a few densely connected clusters of accounts, which share links to many of the same low-credibility sources. Although this network is not dominated by accounts with high bot scores, manual inspection reveals that several of the accounts generate suspiciously high volumes of partisan content.

Topics from low-credibility sources

We wish to provide a sense of the common topics of linked articles from low-credibility sources. Fig. 4 depicts the most frequent words in the titles of the articles in DS2, excluding the query terms “coronavirus” and “covid.” Popular topics covered by low-credibility sources are U.S. politics, the status of the outbreak, and economic issues.

This analysis suggests a politicization of the pandemic. An example revolves around claims that the COVID-19 pandemic originated from a weaponized virus. One of the most popular sources pushing this narratives is ZeroHedge.com, the third most-shared low-credibility domain in our dataset. Notably, this occurs despite the fact that Twitter suspended the ZeroHedge account for violating the platform’s manipulation policy at the beginning of the pandemic (bloomberg.com/news/articles/2020-02-01/zero-hedge-permanently-suspended-from-twitter-for-harassment).

Discussion

We characterize the prevalence of low-credibility information on Twitter during the novel coronavirus outbreak. The combined prevalence of various low-credibility sources is comparable with mainstream and reliable sources. Consistent with previous research, social bots are more likely to get involved in posting and amplifying low-credibility information. Finally, we find evidence of coordinated activity amplifying low-credibility content.

The analyses presented here are preliminary and have several limitations. First, the sampling method based on two hashtags might introduce unknown biases. Second, the domain-based identification of low-credibility sources is not exhaustive and cannot capture misinformation contained in the content of tweets like text, images, and videos. Third, it is impossible to draw any conclusion about impact from...
Figure 3: Similarity network of accounts sharing links to low-credibility sources. Nodes are colored using a human-like (blue) to bot-like (red) scheme and size is proportional to strength (weighted degree). Edge weights represent cosine similarity among link vectors (see text). Only links with weight above 0.8 are shown, and singleton nodes after this filtering are removed. The final network consists of 180 nodes and 1,343 edges.

the prevalence of misinformation alone. Fourth, bot detection algorithms are never perfectly accurate and may have biases stemming from training data. And fifth, our coordination analysis may be distorted by popular sources. More thorough analyses are needed to confirm as well as expand our findings.

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References

[Bovet and Makse 2019] Bovet, A., and Makse, H. A. 2019. Influence of fake news in twitter during the 2016 us presidential election. Nature Commu. 10(1):1–14.

[Broniatowski et al. 2018] Broniatowski, D. A.; Jamison, A. M.; Qi, S.; AlKulaib, L.; Chen, T.; Benton, A.; Quinn, S. C.; and Dredze, M. 2018. Weaponized health communication: Twitter bots and russian trolls amplify the vaccine debate. Am. J. of Public Health 108(10):1378–1384.

[Chen, Lerman, and Ferrara 2020] Chen, E.; Lerman, K.; and Ferrara, E. 2020. Covid-19: The first public coronavirus twitter dataset. arXiv preprint arXiv:2003.07372.

[Cinelli et al. 2020] Cinelli, M.; Quattrociocchi, W.; Galeazzi, A.; Valensise, C. M.; Brugnoli, E.; Schmidt, A. L.; Zola, P.; Zollo, F.; and Scala, A. 2020. The covid-19 social media infodemic. arXiv preprint arXiv:2003.05004.

[Davis et al. 2016] Davis, C. A.; Ciampaglia, G. L.; Aiello, L. M.; Chung, K.; Conover, M. D.; Ferrara, E.; Flammini, A.; Fox, G. C.; Gao, X.; Gonçalves, B.; et al. 2016. Osme: the iuni observatory on social media. PeerJ Computer Science 2:e87.

[Ferrara et al. 2016] Ferrara, E.; Varol, O.; Davis, C.; Menczer, F.; and Flammini, A. 2016. The rise of social bots. Comm. of the ACM 59(7):96–104.

[Ferrara 2020] Ferrara, E. 2020. #covid-19 on twitter: Bots, conspiracies, and social media activism. arXiv preprint arXiv:2004.09531.

[Gallotti et al. 2020] Gallotti, R.; Valle, F.; Castaldo, N.; Sacco, P.; and De Domenico, M. 2020. Assessing the risks of” infodemics” in response to covid-19 epidemics. arXiv preprint arXiv:2004.03997.

[Grinberg et al. 2019] Grinberg, N.; Joseph, K.; Friedland, L.; Swire-Thompson, B.; and Lazer, D. 2019. Fake news on twitter during the 2016 us presidential election. Science 363(6425):374–378.

[Guess, Nagler, and Tucker 2019] Guess, A.; Nagler, J.; and Tucker, J. 2019. Less than you think: Prevalence and predictors of fake news dissemination on facebook. Science Advances 5(1):eaau4586.

[Laato et al. 2020] Laato, S.; Islam, A.; Islam, M. N.; and Whelan, E. 2020. Why do people share misinformation during the covid-19 pandemic? arXiv preprint arXiv:2004.09600.

[Pacheco et al. 2020] Pacheco, D.; Hui, P.-M.; Torres-Lugo, C.; Truong, B. T.; Flammini, A.; and Menczer, F. 2020. Uncovering coordinated networks on social media. arXiv preprint arXiv:2001.05658.

[Pennycook and Rand 2019] Pennycook, G., and Rand, D. G. 2019. Fighting misinformation on social media using crowdsourced judgments of news source quality. Proc. Nat. Acad. Sci. 116(7):2521–2526.

[Pulido et al. 2020] Pulido, C. M.; Villarejo-Carballido, B.; Redondo-Sama, G.; and Gómez, A. 2020. Covid-19 in-
fodemic: More retweets for science-based information on coronavirus than for false information. *International Sociology* 0268580920914755.

[Shao et al. 2018] Shao, C.; Ciampaglia, G. L.; Varol, O.; Yang, K.-C.; Flammini, A.; and Menczer, F. 2018. The spread of low-credibility content by social bots. *Nature Comm.* 9(1):1–9.

[Stella, Ferrara, and De Domenico 2018] Stella, M.; Ferrara, E.; and De Domenico, M. 2018. Bots increase exposure to negative and inflammatory content in online social systems. *Proc. Nat. Acad. Sci.* 115(49):12435–12440.

[Thompson 2011] Thompson, R. 2011. Radicalization and the use of social media. *Journal of Strategic Security* 4(4):167–190.

[Vosoughi, Roy, and Aral 2018] Vosoughi, S.; Roy, D.; and Aral, S. 2018. The spread of true and false news online. *Science* 359(6380):1146–1151.

[Yang et al. 2019] Yang, K.-C.; Varol, O.; Hui, P.-M.; and Menczer, F. 2019. Scalable and generalizable social bot detection through data selection. *arXiv preprint arXiv:1911.09179*.

[Zarocostas 2020] Zarocostas, J. 2020. How to fight an infodemic. *The Lancet* 395(10225):676.