Connecting the Domains: An Investigation of Internet Domains found in COVID-19 Conspiracy Tweets

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Abstract. Conspiracy theories (CTs) have thrived during the COVID-19 pandemic and have continued to spread on social media despite attempts at fact-checking. The isolation and fear associated with this pandemic likely contributed to the generation and spread of these theories. In this paper, we compare the types of URLs linked in conspiracy-related and non-conspiracy-related tweets. First, we classified COVID-19 tweets as related or unrelated to pandemic conspiracy theories using a state-of-the-art, tuned language model based on Bidirectional Encoder Representations from Transformers (BERT) [13, 21]. Then, we pulled the domains linked by each group and formed a network of the websites using links between them as the edges in the network.

Keywords: conspiracy theories · COVID19 · network analysis

1 Introduction

Soon after the COVID-19 pandemic began in early 2020, the World Health Organization (WHO) acknowledged that they were also fighting an "infodemic" [31]. This "infodemic" of public health misinformation became a pressing issue because false and misleading stories can spread incredibly quickly, and misinformation can negatively impact public health behavior [19]. Some of the initial pandemic-related misinformation themes included the ideas that COVID-19 was a hoax, a Chinese bioweapon, a plan to microchip everyone through vaccines, or was a virus infecting people through 5G [16].

During crises, people have a higher tendency to believe in conspiracy theories, as these theories can provide them with understanding over a complicated and scary problem [15, 23, 29]. For example, a Pew Research survey from the summer of 2020 found that just over a third of those surveyed who had heard the conspiracy theory that influential people planned the virus believed that theory to be either probably or definitely true.

While conspiracy theories help people feel like they are in control, they can negatively impact human behavior. For those who did not believe the pandemic was genuine, these effects included less frequent hand-washing, and less physical distancing [19]. Additionally, conspiratorial beliefs have other dangerous consequences outside of the public health space, such as an association with everyday crime, and increases in extremism and tendency to commit violence [15, 28, 29]. Conspiracy theories can also incite anti-democratic movements [29].

Social media platforms and the Internet more broadly have helped increase both the number of people exposed to conspiracy theories and the speed at which these theories can spread [15]. Because of the harmful effects on offline public health behavior, it is crucial to study the spread of conspiracy theories on social media platforms and off-platform links.

2 Related Work

Conspiracy theories are theories that attempt to explain major political or historical events with claims of covert schemes by influential individuals or groups [3, 9, 12]. Prior research on belief in conspiracy theories has come from various disciplines, including history, sociology, and psychology. This previous research has investigated both which individuals believe in conspiracy theories and why, and what real-world effects (if any) these beliefs can have.

2.1 Belief and Spread of Conspiracy Theories

Conspiratorial belief cuts across various demographic groups - no one is above conspiracy theories. Most Americans believe in one or more conspiracy theories about John F. Kennedy Jr.'s assassination, believing that Lee Harvey Oswald did not act alone [14]. Individuals who believe in one theory tend to also place confidence in several others at the same time, even if they are unrelated or even incompatible [14, 17, 18, 33].

There are several reasons why individuals believe in conspiracy theories, including wanting to understand and feel in control of a situation or maintain a positive image of their group. When information about a confusing event is unavailable, incomplete, or still under investigation, belief in a conspiracy theory that helps explain the event is appealing. Additionally, individuals are substantially more likely to believe an unproven claim about their political opponents over their own political or identity group [14].

Successfully communicated conspiracy theories with a large following can be modeled by Roger's Diffusion of Innovation model. In the model, the innovator is the conspiracy "entrepreneur", or originator of the conspiracy theory. The CT is then distributed by journalistic sources and either adopted or rejected by individuals and groups. Once a CT reaches critical mass, this can lead to some socially dangerous behaviors, such as Pizzagate or the storming of the US Capitol on January 6th, 2021 [24]. The CT is more likely to be picked up if it is straightforward and resonant with an individual's prior beliefs [8].

The role of journalists is to question official statements and government officials and look into possible alternate hypotheses of significant events. Sometimes they uncover misconduct or conspiracies; however, in other cases, their airtime of illogical CTs ends up boosting these theories. Previous studies show that attempting to fact-check or disprove unsound CTs backfires. Some journalistic sources likely are knowingly engaging with conspiracy theories as a way to make money or gain power, as fake news sites can generate significant ad money [24].

Early on in the COVID-19 pandemic, the COVID-related conspiracy theories spread to large audiences online, often without being countered or removed [16]. One study of European social media users found that posts from hostile countries like Russia and Iran received more engagement than posts from regular news sources [25]. Another example is the viral *Plandemic* video that claimed that influential people deployed the virus to profit off of a vaccine. This video received 8 million views across multiple platforms [7, 22].

2.2 Impact and Detection of Conspiracy Theories

Conspiratorial beliefs can often lead to negative offline behavior. While many conspiracy theories do not lead to any real-world actions (ex: JFK assassination, Princess Diana's death, etc.), many others intend to provoke in vs. out-group feelings and demonize the "other". Belief in those theories can encourage violence, extremism, and terrorism [6, 15]. More specifically, recent research on COVID-19 conspiracy theories shows that believers took the pandemic less seriously and did not closely follow public health guidelines on social distancing and hand-washing frequency [19, 23].

Because belief in pandemic conspiracy theories can cause distrust in public health guidelines, detecting these stories and understanding how they spread online is crucial in the fight against mis-/dis-information. One prior study on detection has focused on the narrative structures of real conspiracies vs. conspiracy theories, including coronavirus conspiracy theories [27, 30]. Another study looked at conspiracy discussion in the Reddit community r/conspiracy to better understand how online communities detect and spread new conspiracy theories after dramatic events. However, the researchers noted that a lack of network analysis was a limitation in their work [26]. Many studies, however, tend to focus on detecting mis-/dis-information more generally rather than specifically looking at conspiracy theories [5, 11]. In addition to the substantial research on the belief, spread, and offline impact of conspiracy theories, more network-related research is needed to understand how CTs form and change online and their impact on the overall social media discussion.

2.3 Research Questions

Most prior research on conspiracy theories has focused on why people believe conspiracy theories and the detection and impact of those beliefs. While we find some work on detection and spread on social media, little work exists on where the conspiratorial stories originate on the web.

We trained a BERT-based sequence classification model to identify tweets about COVID conspiracy theories. We then investigated the domains found in conspiracy and non-conspiracy tweets to understand the networks behind conspiracy theories better. Examining the links between domains that host conspiratorial content can help us better determine if these conspiracy theories are spread organically in a bottom-up fashion [32], or in a top-down fashion to either generate revenue or as a part of an influence campaign [24].

In this paper, we address the following research questions:

1. Are there identifiable connections between domains found in tweets classified as conspiracy?
2. Is there evidence of coordination between domains connected by google tracking codes?
3. How do conspiracy domain networks differ from non-conspiracy domain networks?

This research will help us understand the origin of many online conspiracy theories and better understand the motivation and use of domain links to shape and even spread conspiracy theories on social media platforms.

3 Methods

3.1 Data

Data for Classifier Training To train our conspiracy text classification model, we utilized 8,700 hand-labeled tweets, which is the most extensive COVID-19 labeled conspiracy theory data set of which we are aware. Approximately 4,500 tweets were modified from a study by [20] to categorize the types of disinformation about COVID-19 circulating on Twitter. The remaining 4,200 tweets were labeled as part of a summer data science project for undergraduates at Carnegie Mellon University.

Data for Analysis We collected 1,508,765 English language tweets between January 2020 and June 2020. Our research group collected the tweets through the Twitter live stream API with a set of COVID-19 related collection terms. We then applied additional search terms to find tweets with a high probability of containing conspiracy theories. Our model classified approximately 55% of the tweets as conspiracy and 45% as non-conspiracy. We then extracted and expanded all URLs found in our data and used them to create lists of domains found in conspiracy and non-conspiracy tweets.

3.2 Classifier Model

We incorporated the BERT pre-trained language model [13] as the basis of our conspiracy classifier. We included parameter weights pre-trained with 97 million unique COVID-19 related tweets collected between January 2020 and July 2020 [21]. We used the pre-trained weights to create vectorized representations of input text for a downstream sequence-to-sequence classification task. We tuned the model on 8,700 hand-labeled tweets for our conspiracy text classification task.

3.3 Domain Analysis

Bellingcat, an online independent research collective, produced an article outlining how researchers could leverage google tracking codes to find if and how websites are connected [4]. We employed this technique in order to find connections between domains that spread conspiracies during COVID-19.

Google Tracking Codes Google AdSense and Google Analytics are two services that Google provides to domain owners and online content creators. Both services work by providing small snippets of code with unique tracking numbers linked to unique account holders. Google AdSense uses its codes to provide a way for domain owners and content creators to earn money by providing space in their online presence that companies bid on to project their advertisements [1]. Google Analytics works similarly, but the codes are embedded with blocks of Javascript that help facilitate tracking and analytics. The service provides account holders with information such as how long a visitor spends on specific content on their domain and where visitors traveled to next after visiting the account holder's domain [2]

To collect Google tracking codes, we utilized the requests python package combined with our curated list of domains found in conspiracy and non-conspiracy tweets to make requests to the host domain and collect its associated HTML code [10]. Once the HTML code was obtained for a domain, we then used regular expressions to parse out tracking codes if present.

Network Creation We used spyoneweb.com, an internet research tool that collects and collates reports of websites that share google tracking codes and IP addresses. We inputted our list of collected tracking codes into the site's API and received lists of websites associated with each tracking code. We repeated the same process with IP addresses. We use the collected data to generate three edge lists: AdSense x Domain, Analytics x Domain, and Domain x IP address. From the edge lists, we construct a Conspiracy Domain meta-network and a Non-conspiracy Domain meta-network for analysis. Table 1 provides basic metrics for each of the meta-networks and a network consisting of domains unique only to conspiracy tweets, a network consisting of domains unique only to non-conspiracy tweets, and a network representing the intersection of domains found in both conspiracy and non-conspiracy tweets.

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Table 1. This table provides node, link, and density information for the networks constructed from domains found in conspiracy and non-conspiracy tweets in this study.

	Input Domains	Found Domains	Analytics Codes	Adsense Codes	IP Addresses	# of Links	Mean Link Value	Network Density
Conspiracy Network	833	38,023	1,014	319	1,154	57,102	1.338	0.000591
Non-Conspiracy Network	1,330	50,392	1,776	427	1,706	78,590	1.506	0.000389
Unique to Conspiracy	390	13,375	412	164	442	19,376	1.243	0.001383
Unique to Non-Conspiracy	833	25,798	1,174	272	994	36,333	1.435	0.000559
Intersection Network	443	24,648	602	155	712	35,607	1.744	0.000966

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