Note From the Authors, December 6, 2023

Since publication, members of our team have continued working with this dataset for research. In a recent analysis, we discovered an inconsistency in the data used in this paper. Principally the number cited in the paper for the total number of tweets collected was incorrect. The corrected (and accurate) number of tweets we collected is 32.4 million, including 29.1 that we later linked to the 307 “sows doubt” stories. The inconsistency does not change any of the substantive claims in the paper, but we do feel that it is large enough to warrant publishing this corrective note to the paper. The inconsistency also influenced the scale—but not the interpretation or shape—of Figures 5-9, and some of the values cited in Appendix Table A.I.1 and Figure A.I.1. A full list of errata are included in the new Appendix VI.

The core analysis of the paper — the repeat spreaders analysis (table 1) — was not affected by the inclusion of duplicate data. Additionally, the network analysis (figures 2 and 3), and the analysis of overall spread of misinfo-related tweets over time (shown in figure 4) are also unaffected.

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Repeat Spreaders and Election Delegitimization: A Comprehensive Dataset of Misinformation Tweets from the 2020 U.S. Election

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This paper introduces and presents a first analysis of a uniquely curated dataset of misinformation, disinformation, and rumors spreading on Twitter about the 2020 U.S. election. Previous research on misinformation—an umbrella term for false and misleading content—has largely focused either on broad categories, using a finite set of keywords to cover a complex topic, or on a few, focused case studies, with increased precision but limited scope. Our approach, by comparison, leverages real-time reports collected from September through November 2020 to develop a comprehensive dataset of tweets connected to 456 distinct misinformation stories from the 2020 U.S. election (our *ElectionMisinfo2020* dataset), 307 of which sowed doubt in the legitimacy of the election. By relying on real-time incidents and streaming data, we generate a curated dataset that not only provides more granularity than a large collection based on a finite number of search terms, but also an improved opportunity for generalization compared to a small set of case studies. Though the emphasis is on misleading content, not all of the tweets linked to a misinformation story are false: some are questions, opinions, corrections, or factual content that nonetheless contributes to misperceptions. Along with a detailed description of the data, this paper provides an analysis of a critical subset of election-delegitimizing misinformation in terms of size, content, temporal diffusion, and partisanship. We label key ideological clusters of accounts within interaction networks, describe common misinformation narratives, and identify those accounts which repeatedly spread misinformation. We document the asymmetry of misinformation spread: accounts associated with support for President Biden shared stories in *ElectionMisinfo2020* far less than accounts supporting his opponent. That asymmetry remained among the accounts who were repeatedly influential in the spread of misleading content that sowed doubt in the election: all but two of the top 100 'repeat spreader' accounts were supporters of then-President Trump. These findings support the implementation and enforcement of 'strike rules' on social media platforms, directly addressing the outsized role of repeat spreaders.

Keywords: misinformation, disinformation, rumoring, 2020 presidential election, twitter, social networks

Introduction

Misinformation—and its intentional cousin, disinformation—have emerged as critical societal challenges, undermining democratic institutions and processes and making it difficult to address pressing issues such as climate change and global pandemics. In 2020, as the world grappled with the Covid-19 pandemic and accompanying infodemic (Zarocostas 2020), the United States held a general election that became the target of numerous false and misleading claims, including repeated assertions by then-President Trump that the election would be—and then that it was—rigged (Baker and Haberman 2020; Goidel et al. 2019). Prior to the election, Benkler and colleagues (2020) described an elite-driven effort to intentionally sow distrust in the mail-in voting process, terming it a "disinformation campaign" (Benkler 2020:1). The spread of mis- and disinformation continued after election day and grew to include, among other things, a wide range of false, misleading, exaggerated, and unsubstantiated claims that supported a false narrative of extensive and systematic voter fraud—ranging from claims that Sharpie pens were part of a plot to disenfranchise certain voters to allegations that voting machines and voting software were switching votes, en masse, from one candidate to another.

During the two months following the election, as then-President Trump refused to acknowledge the results, these falsehoods were used to mobilize a "Stop the Steal" effort that included pressuring government officials to overturn results (Gardner 2021; Shear and Saul 2021; McFall and Mears, 2021) and eventually led to a violent insurrection attempt within the U.S. Capitol Building on January 6 (Blake 2021; Cramer 2021), as protesters attempted to stop the certification of the results. Nearly a year after the election, 31% of the U.S. population still believe the "big lie" that the election was stolen from then-President Trump (PRRI 2021).

Much of the mis- and disinformation about the election spread online on social media websites like Twitter and Facebook. While platforms introduced new "civic integrity" policies (Chowdhury et al. 2021; Niker and Yarrow 2021; EIP 2020a), and enacted enforcement strategies including the application of credibility labels and other mitigation techniques, these actions were not enough to stop false and misleading claims from spreading. In the lead up to the election, and again after January 6, platforms suspended and otherwise sanctioned large numbers of accounts—eventually taking action against then-President Trump’s accounts. These sanctions effectively removed accounts from the public sphere, making it difficult for future data collections to capture that particular moment in time.

This paper introduces and provides the first descriptive analyses of a unique dataset, captured and curated during this critical window in the history of online misinformation—during the lead-up to and immediate aftermath of the 2020 U.S. election. This dataset, termed *ElectionMisinfo2020*, is made up of over 32.4 million tweets connected to 456 distinct misinformation stories spread about the 2020 U.S. election between September 1, 2020 and December 15, 2020. In particular, this dataset focuses on false, misleading, exaggerated, or unsubstantiated claims or narratives related to voting, vote counting, and other election procedures.

This dataset derives from contemporaneous monitoring and analysis work conducted through the Election Integrity Partnership (EIP), a collaborative team that was identifying and responding to election 2020 misinformation in real-time during that period (CIP et al. 2021). Each tweet is linked to at least one misinformation story that was reported to the EIP. As a result, the dataset includes both the most widely-spread misinformation stories from the election, like those about Dominion Voting Systems, and many smaller stories about lost mail-in ballots, allegations of planned violence that could have suppressed votes, and false statistical claims (Eggers et al. 2021).

This paper describes the techniques we used to generate *ElectionMisinfo2020*, discusses how the dataset combines existing methods for compiling misinformation-related tweets, and demonstrates its usefulness in generating empirical insights. The first of these insights utilizes network analysis to reveal two distinct groups of accounts reflecting U.S. political alignments. We show that while Biden-supporting Twitter accounts did spread false and misleading claims about election procedures, the vast majority of election-related misinformation on Twitter was spread by Trump-supporting accounts. Second, we identify, compare, and examine over time the largest misinformation content groups, collections of stories that had similar narrative or thematic components. Finally, we identify high profile accounts who had highly-retweeted tweets in several distinct misinformation stories—specifically among stories that functioned to sow doubt in election procedures or election results. We label these accounts "repeat spreaders," and show the disproportionate impact these accounts had on total misinformation spread on Twitter during the U.S. election. Taken together, these results spotlight the utility of this new dataset and lay the foundations for its use in further analyses focused on understanding the drivers of misinformation and the patterns of its proliferation before, during, and after the 2020 U.S. election.

Background

Event Background: The 2020 U.S. Presidential Election

When Donald Trump announced his intention to run for president in 2015, most experts doubted his chances; recent history suggested that the success of Republican nominees was tied directly to years of party service and the irreproachability of one's personal and political record. In contrast, Donald Trump was a former Democrat with limited political experience and a checkered personal history. Despite these concerns he managed to unify the Republican base by fomenting anti-government sentiment and presenting himself as a Washington outsider. A key feature of the subsequent 2016 election campaign, which saw him face off with former Secretary of State Hillary Clinton, was the presence of organized disinformation. That disinformation was amplified on social media platforms, including by bot accounts, through coordinated campaigns linked with foreign governments, and in targeted advertisements utilizing user social media profiles. After losing the popular vote but winning the 2016 election through the electoral college, Trump publicly alleged, without evidence, that his deficit in the popular vote was the result of voter fraud (Cottrell et al. 2017).

As President, Trump made ample use of social media, primarily Twitter, to promote content that was often demonstrably false. While Twitter and other social media platforms responded to the 2016 election by trying to reduce bot activity, they did little to question, label, or remove these false statements made by then-President Trump during his first three years in the White House. Furthermore, hyper-partisan accounts supporting then-President Trump, such as the Gateway Pundit, One America News, and Breitbart, used these same digital channels to extend and amplify extant misinformation (Lazar et al 2021). Though the 2020 presidential election was not marked by substantial bot activity or foreign interference, Trump-supporting accounts and media outlets appear to have engaged in the promotion of a "disinformation campaign" (Benkler 2020:1) full of false, misleading, or unverifiable claims about voting fraud. Then-President Trump lost the 2020 election to Joe Biden (both overall and in the electoral college), but false stories attributing that loss to fraud spread online in the aftermath of the election and remained central to online discussions of the election in the following months. This collection of online rumors and conspiracies came to serve as a key rallying point for in-person "Stop the Steal" protests and rallies, the largest of which was the January 6, 2021 riot, attempted insurrection, and storming of the U.S. Capitol Building.

During the election, the authors participated in the Election Integrity Partnership (EIP), a coalition of research entities focused on supporting the real-time information exchange between disinformation researchers, election officials, civil society organizations, and social media platforms. The EIP collected reports of emerging misinformation stories, conducted real-time analysis, and wrote rapid-response reports. In the *ElectionMisinfo2020* dataset, we document and record comprehensive, low-noise sets of tweets connected to each of the misinformation stories reported to the EIP during the 2020 election, making those tweets available for analysis.

Defining Terms: Stories, Rumors, Misinformation, and Disinformation

We use the term *misinformation* for this dataset as an umbrella term, inclusive of rumors, misinformation, and disinformation. However, it is important to note that this use—and in fact, much of the terminology around mis- and disinformation—is contested and in flux. In this section, we present and define our terminology, which is critical for understanding the contours of the *ElectionMisinfo2020* dataset.

One term we invoke here, as the core organizing element of the *ElectionMisinfo2020* dataset, is "story". *Stories* refer to distinct accounts of an event or events, following long standing use in research on rumors (Knapp 1944; Rosnow 1980) and contemporary work on online mis- and disinformation (Polletta et al. 2019; Ananny 2018; Huang and Carley 2020). Often, several stories will share similar content, such as claims that voting machines and voting software were systematically altering votes to advantage a certain candidate—but they may differ as to the specific claim around which technology, which location, and which candidate was implicated. In practice, it is often difficult to differentiate between distinct stories, especially when they map to the same narratives within a disinformation campaign. We discuss that challenge below, in the section titled "Mapping Tweets to Misinformation Stories."

Rumors are stories of uncertain or unverified veracity (Bordia and Difonzo 2004; Kapferer 1987; Starbird et al. 2016). We often think of rumors, particularly in colloquial contexts, as inherently false, but some rumors turn out to be true. Due to the real-time curation of *ElectionMisinfo2020,* the set contains many rumors that were unsubstantiated at the time, including a few that turned out to be true (or partly true), like allegations that a Trump-supporting poll watcher was unlawfully removed from a Philadelphia polling place—and some whose veracity is still uncertain. As such, several prominent *ElectionMisinfo2020* narratives, such as claims that a ballot arrived "pre-filled" for select candidates or that individuals voted multiple times, are unfalsifiable—i.e. the claim is made in such a way that it would be extremely difficult or impossible to disprove.

The term *misinformation* translates, literally, to false information. Misinformation applies to content that is false (like false rumors), but not necessarily intentionally false (Jack 2017). *Disinformation*, on the other hand, is used to characterize content that is false or misleading, and that was intentionally created or strategically amplified for an objective—e.g. political, financial, or reputational gain (Jack 2017; Wardle and Derakhshan 2017). We employ the term "misinformation" here as an umbrella term to include both misinformation and disinformation, but understanding the nuanced differences between the two is valuable. One important distinction of disinformation is that it is not necessarily outright false, but can instead be *misleading*. It is often built around a true or plausible core, but layered with falsehoods and/or exaggerations to create a distorted perception of the truth (Bittman 1985; Starbird et al. 2019). Additionally, disinformation rarely functions as a single piece of content, but more often as part of a broader campaign (Starbird et al. 2019; Calo et al. 2021). The *ElectionMisinfo2020* dataset contains many unsubstantiated and exaggerated claims (for example, about ballots being mistreated by the U.S. Postal Service) that, together, contributed to a false perception of massive and systematic election fraud. In the lead up to the election, Benkler and colleagues described the intentional effort to sow distrust in the mail-in voting process—enacted through the strategic production and amplification of false, misleading, and exaggerated claims—as a “disinformation campaign” (Benkler 2020). We accept that characterization here. A large number of the stories that constitute the *ElectionMisinfo2020* dataset were part of the disinformation campaign to sow distrust in election procedures and, eventually, the results of the election. Importantly, though this disinformation campaign was set in motion by the Trump campaign and "elites" in media and politics, it was sustained by everyday Trump supporters, often sincere believers, who both amplified—and in some cases produced—the false and misleading claims that constituted this campaign.

Previous Research on Online Misinformation and Disinformation

Research on rumoring has a long history and draws from diverse fields—including sociology and social psychology. Early work focused on the spread of rumors and misinformation during conflict and crisis (Knapp 1944; Allport and Postman 1947; Caplow 1947; Kapferer 1987; Starbird et al. 2020). Researchers have posited that uncertainty (such as a lack of official information) and anxiety can motivate rumoring (Andrews et al. 2016), as has been suggested in work detailing how the U.S.'s decentralized election system has created "knowledge gaps and uncertainty that disinformation-peddlers can leverage" (Adler and Thakur 2021). Shibutani described rumoring as a collective, improvisational problem-solving activity whereby people work together to make sense of an unfolding situation (Shibutani 1966).

Early research took two approaches: focusing on rumors that were organically circulating and experimentally studying planted rumors (Starbird et al. 2020). This work follows the tradition of the former and adopts Shibutani's lens to conceptualize rumoring—and the spread of mis- and even disinformation (Starbird et al. 2019)—as a kind of collective sensemaking process.

With the widespread adoption of digital technologies, research on rumoring and misinformation has begun to attend to—and increasingly focus on—the online dimensions of their spread (e.g. Oh et al. 2013; Starbird et al. 2014; Mitra and Gilbert 2015; Maddock et al. 2015; Arif et al. 2016; Vosoughi et al. 2018). Political events in 2016, including documented attempts by state-sponsored organizations to interfere in democratic elections in the U.K. and U.S. (S. Rep. No. 116-290, 2020; Mueller 2019), sparked interest in the online spread of disinformation (e.g. Freelon and Wells 2020; Arif et al. 2018; Starbird et al. 2019; Marwick and Lewis, 2017). In recent years, with increased media attention to what has been perceived as a growing problem, researchers, journalists, and non-profit organizations have converged onto these topics as a new, interdisciplinary field emerges to study these phenomena—often through the analysis of digital trace data.

Challenge of Identifying/Collecting Data on Multiple Misinformation Stories

ElectionMisinfo2020 builds on previous efforts to collect data about online rumors, misinformation, and disinformation. We adapt useful aspects of both small- and large-scale data collection methods to create an extensive collection of misinformation stories that spread around a specific event—the 2020 U.S. election.

Focused data collection has investigated the dynamics of misinformation either within a particular story or comparatively across a small number of stories. Like much of online rumoring research, we focus on Twitter, a platform where most content is publicly shared and data can be accessed at large scale for academic research through Twitter's APIs (Tufekci 2014). One line of work on rumoring on Twitter—extending the perspective of rumoring as a social process—used mixed-method approaches to study a small number of individual rumors or stories to identify patterns and anomalies within and across rumors (e.g. Oh et al. 2010; Oh et al. 2013; Starbird et al. 2014; Maddock et al. 2015). More recent work on online disinformation (e.g. Arif et al. 2018; Starbird et al. 2019; Hunt et. al. 2020) follows this tradition, relying upon highly-curated, comprehensive, low-noise samples of the stories under investigation. We attempt to reproduce this approach for *ElectionMisinfo2020*.

An alternative approach to research on rumoring and misinformation has been to gather much larger sets of social media data using a time frame or single set of keywords. Some of those efforts collected total shares within a certain time frame, like Subbian et al. (2017) who used a single day of content, or Dow et al. (2013), who collected an entire week. Those approaches are useful for studies of viral dynamics, which they have helped elucidate. However, it is difficult to use these approaches when investigating misinformation or rumoring without additional validation that the content is indeed misleading. To get at this gap, others use similarly broad collections but filter or validate these collections with other resources. For example, misinformation researchers have used links to fact checking websites (Friggeri et al. 2014; Vosoughi et al. 2018), in an attempt to ensure that cascades are about misinformation. Yet many cascades may never include a reply with a link to a fact checking website, even if the story in question was fact checked. Finally, some recent studies (Gallagher et al. 2021; Abilov et al. 2021) collect large datasets on a single set of keywords. One standout prior example is Credbank, collected by Mitra and Gilbert (2015), which used computational text analysis and human validation to label millions of tweets for their connection to over one thousand real-world events. Credbank was not focused on political misinformation; it included any real-world event as a potential topic for misinformation.

Our approach with the *ElectionMisinfo2020* dataset was to attempt to apply the best aspects of the techniques above to the collection of a dataset focused on misinformation in the 2020 election. Our process, detailed below, uses hundreds of independent, real-time reports of mis- and disinformation during the 2020 election cycle, and careful validation by researchers to ensure the quality of the data.

Dataset Construction

The *ElectionMisinfo2020* dataset consists of 32.4 million tweets posted between September 1, 2020 and December 15, 2020. Drawn from a broader collection of election-related Twitter data, each tweet was selected for its connection to one of 456 misinformation stories—distinct stories that included false, exaggerated, unsubstantiated or otherwise misleading claims or narratives—promulgated during the 2020 election. In this section, we describe how these stories were (1) first identified through a collaborative reporting process as part of the Election Integrity Partnership (EIP); (2) labeled for content type and deduplicated into distinct stories; (3) each mapped to a comprehensive, low-noise sample of tweets; and (4) validated.

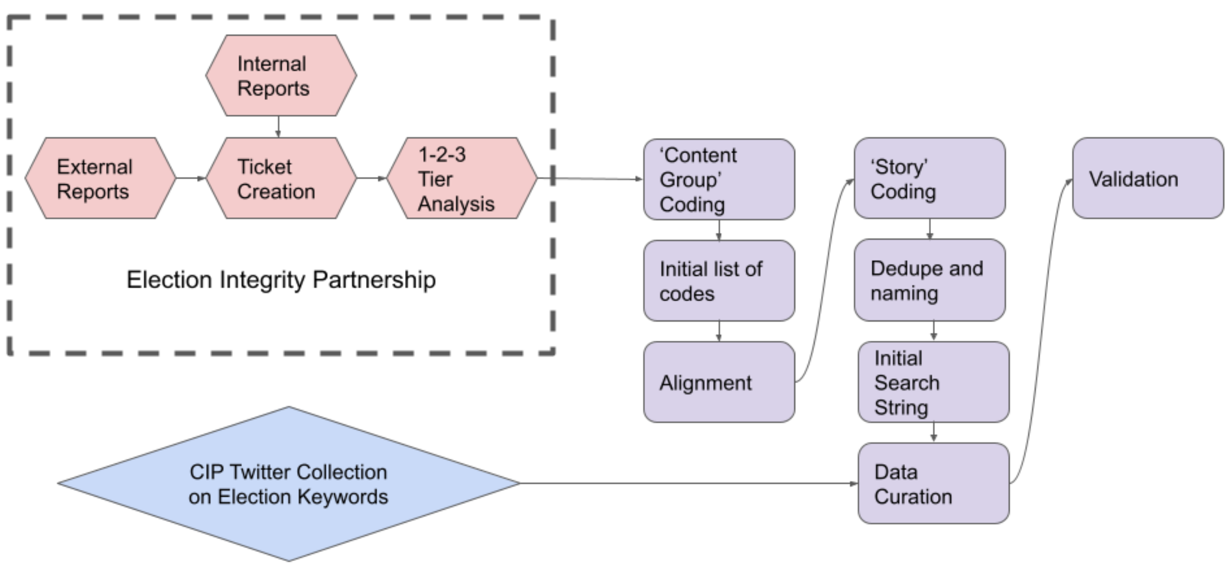

Figure 1. Dataset Creation Flowchart.
A process map of the dataset creation process. It shows how reports generated for the EIP were filtered and coded into stories. Then those stories were linked to comprehensive, low-noise samples of related tweets from the broad election-related Twitter dataset collected by the Center for an Informed Public (CIP).

The Election Integrity Partnership: Identifying Misinformation in Real-Time

The 456 misinformation stories were based on 814 initial reports of misinformation generated by the Election Integrity Partnership (EIP), a coalition of research entities working to identify, analyze, and address misinformation in real-time. The partnership, which was active from July 27, 2020 to November 19, 2020, supported rapid information exchange between researchers, election officials, civil society organizations, and social media platforms. The 112 researchers who made up the EIP team came from four research organizations: Graphika, the Atlantic Council's Digital Forensic Research Lab, the Stanford Internet Observatory, and the University of Washington Center for an Informed Public. Researchers entered with a diversity of backgrounds and skill sets, and received training in monitoring, triaging, and open source investigation principles. The team worked in shift schedules to (1) monitor online platforms and communities for potential election mis- and disinformation, (2) analyze that content, and (3) send findings to the EIP's network of civil society and government affiliated partners.

Since this process occurred concurrently with the emergence of misinformation stories, *ElectionMisinfo2020* includes both extremely large misinformation stories with million of tweets, like those concerning Dominion Voting Systems or misleading allegations that Ilhan Omar's campaign paid for votes, and other stories which never gained traction and have fewer than one hundred connected tweets.

Reports to the EIP came from both within and beyond the partnership: external collaborators made 21% of the reports, and internal researchers contributed 79%. A group of 30 dedicated social media monitors, recruited from a single university and representing a range of academic majors, made most of the internal reports. These researchers, termed "Tier 1 analysts", identified new potential misinformation stories, conducted an initial analysis, and archived related content. To ensure coverage across online ecosystems, each analyst focused on a specific state or interest group, which they developed expertise in and followed throughout the project.

Tier 1 analysts were responsible for evaluating new content against the EIP's scope and prioritization standards (EIP 2020a), defined by the partnership prior to its launch and updated three times between its initial publication in August 2020 and Election Day, on

November 3, 2020. Broadly speaking, the EIP focused on misinformation about election processes and procedures—excluding adjacent topics related to the candidates in the election, such as policy stances, personal histories, and political scandals. The EIP initially focused on four types of election-related stories: (1) procedural interference, (2) participation interference, (3) fraud, and (4) election delegitimization. Later, the collaboration added (5) incitement to violence when it became a salient issue in the overall election-related conversation. *Procedural interference* included stories with false information about when or how to vote. *Participation interference* included anything that could dissuade voters, including intimidation, suppression, false information about long wait times or mail ballot failures. We considered stories within the *Fraud* topic if they encouraged people to commit fraud, for example, by submitting two ballots or destroying ballots. *Delegitimization* stories are those that challenge or question trust in the election or the election process. With these shared definitions in mind, Tier 1 analysts scanned content across a number of online platforms for in-scope, election-related content—eventually logging 643 distinct reports (79% of all EIP reports).

External collaborators could also submit reports to the EIP. Among these, the Center for Internet Security (CIS) contributed the largest number (101 reports or 16% of all EIP tickets). The CIS is a non-profit which runs the Election Infrastructure Information Sharing and Analysis Center (EI-ISAC), the central coordinating body for state and local government officials running U.S. elections. The CIS serves as a central reporting structure for election officials to raise election misinformation concerns. As a result, reports originating from the CIS were dependent on well-resourced, motivated election officials to establish contact with the CIS and take time to report their concerns. Reports from the CIS most often highlighted potential misinformation about Washington, Connecticut, and Ohio voting infrastructure. Additionally, the CIS raised more reports about issues which election officials faced most saliently: this included several reports of online accounts impersonating election officials, phishing emails impersonating the Election Assistance Commission (EAC), and spoofed voter registration websites asking voters to share personal information including addresses and Social Security Numbers. Other collaborators who reported tickets included the State Department's Global Engagement Center, MITRE, Common Cause, the DNC, the Defending Digital Democracy Project, and the NAACP.[2]

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[2] The EIP also contacted the RNC and invited them to join the partnership, but that organization did not respond.

The report-level dataset likely reflects biases of the individual analysts and of the monitoring process more generally. Monitoring topics were diverse, but not comprehensive due to staff limitations: for example, researchers were directed towards spending more monitoring hours on swing states rather than non-swing states on election night. Though the organizers did not record the political orientations of the Tier 1 analysts, our experience working with them suggests that diverse political orientations were present and that the overall group skewed towards the center left. Additionally, language constraints prevented the partnership from monitoring non-English languages as comprehensively as English-language content, and *ElectionMisinfo2020* explicitly excludes stories shared only in languages other than English. Despite these caveats, given the broad diversity of team members and the ongoing calibration conducted with the Tier 1 analysis team, we believe the reports generated by the EIP provide an interesting and unique set of stories which ground *ElectionMisinfo2020's* collection.

Converting Misinformation Reports into Distinct Misinformation Stories

Each misinformation story in *ElectionMisinfo2020* reflects a distinct, time-bounded, informational "event" encompassing the propagation of a single false, misleading, exaggerated, or unsubstantiated claim or narrative. However, many stories were reported to the EIP repeatedly, resulting in multiple reports for the same story. Additionally, some reports contained claims that never appeared on Twitter, requiring us to reduce the quantity of stories included in our database. Using a qualitative coding process, we grouped the initial 814 reports by their narratives and themes into 29 content groups, collapsed duplicate reports into single stories, and excluded stories for which we could find no related tweets.

The EIP reports covered an array of topics, ranging from widely discussed conspiracies about voting machines to localized reports of deceased citizens casting votes. To aid in the organization of the data, we first categorized these stories into content groups, comprised of reports that had similar narrative or thematic components. Researchers created content groups through an inductive process, relying on contextual expertise gained through participation in the EIP. Next, each story was assigned to a content group independently by two coders, with disagreements arbitrated by a third coder. Following this initial categorization, content groups with fewer than five unique stories were redistributed into larger content groupings. The resulting dataset contains 29 unique content groups (see Appendix I for a full list). The two largest groupings, "physical mail-in ballot fraud" and "misleading voting information", ultimately contained 57 stories and 56 stories, respectively.

Once reports were organized into content groups, researchers worked to deduplicate them—grouping together overlapping reports into the same story. For instance, the EIP produced three separate reports concerning a video of shredded ballot applications found in a semi-trailer. Each report sprang from a separate time that the content was shared, one focused on a tweet, one on an article describing the incident, and one on Chinese-language spread of the story. Since each report referenced the same story of shredded ballot applications, we collapsed them into a single misinformation story. Finally, we removed reports that had not spread on Twitter (i.e. reports for which we could not find any related tweets). This filtering and synthesis process helped us reduce the initial 814 reports down to 456 distinct, election-related misinformation stories that spread on Twitter.

Mapping Tweets to Misinformation Stories

Next, we sought to identify—from a more general collection of election-related tweets—a comprehensive, low noise sample of tweets for each misinformation story. To do so, we developed and validated a complex, keyword-based search string for each of the 456 misinformation stories.

Election Discourse: Collecting Election-Related Data through the Twitter Streaming API

The curated *ElectionMisinfo2020* dataset is derived from a larger, more general dataset of election-related tweets which we refer to as the broad election-related Twitter dataset. For several months leading up to—and now more than a year following—the 2020 U.S. election, the Center for an Informed Public (CIP) at the University of Washington collected election-related tweets using the Twitter Streaming API. This dataset included generic terms such as *vote*, *election*, *poll*, *ballot*, and *mail-in* as well as terms related to fraud and voter suppression. During the active election monitoring period (August through December, 2020), researchers added emergent terms including specific hashtags that became focal points for conversations about the election. The CIP tracked more than 160 keywords, spread across numerous collectors (collection instances) to limit the impact of rate limits (around 50 tweets per second for each collector). For the period of interest here, between September 1, 2020 and December 15, 2020, this dataset contains 1.04 billion tweets. For a full list of the keywords used for the collection of the data in the broad election-related Twitter dataset see Appendix II.

This collection has limitations. For certain high-volume terms (e.g. "vote") we dedicated an entire collector to that term, but still regularly hit rate limits. For others, we maintained a relatively balanced set of terms that tended to remain under 50 tweets per second, though occasionally hit limits during specific bursts in activity. Though it is difficult to measure the impact of rate limits, we can estimate them based on retweet comparisons—i.e. for a highly retweeted tweet, comparing the number of retweets we collected during a period of time against the rise in retweet count for that tweet (which is recorded in each retweet's metadata) during that same period of time. We find that even when there is significant rate-limiting, we capture almost all tweets (99.98%) that have at least 10 retweets. This paper, along with a large amount of work on misinformation, focuses on the spread of salient misinformation stories, e.g. those that receive large numbers of retweets, and therefore we find this coverage acceptable. More detail about rate limiting can be found Appendix III.

Curating Election Twitter Data to Identify Tweets Related to Misinformation Stories

From this larger dataset, researchers worked—using an iterative approach—to identify tweets related to each misinformation story. This work was conducted by a small group of coders who had been core members of the EIP and who therefore had a deep understanding of these stories and how they spread. Drawing on information contained in the initial EIP ticket(s) associated with each story, coders generated a date range to isolate the story's spread. Next, coders constructed keyword-based Boolean search strings to capture a comprehensive set of tweets related to the story, while limiting noise (tweets unrelated to the story). Each search string contained keywords linked by Boolean operators (OR, NOT, and AND) and could contain tens of terms to ensure that the tweet sample for each story was comprehensive and low noise.

For example, as the tallying of ballots first commenced on the evening of Election Day a chart was posted on Twitter and Facebook supposedly showing discrepancies between registered voters and votes tallied in Florida precincts. The registration numbers included in the graph were misleading, leading to the impression that fraud had occurred where it had not. To capture the spread of the story, we limited our validation to the period ranging from the morning of November 3, 2020 through November 8, 2020 based on plots detailing the spread of a collection of related tweets. In order to ensure the data we collected on the story matched the discussion, we developed the following search string:

> *more turnout than voters OR more than 100% turnout OR (just sayin. AND every swing state) OR (how does this add up AND fightfortrump) OR disappointed but not surprised OR totally not sus at all) AND (turnout OR registration OR turn out) AND NOT (vandalize OR (florida AND crash)*

Search string curation was an iterative process which enabled coders to test and retest numerous keyword combinations for each story. To assess the precision with which each set of keywords captured tweets relevant to the incident in question, coders were presented with a random selection of ten tweets from the reduced subset. In most cases we examined multiple such samples. When this subset contained unassociated tweets, the keywords were adjusted to either expand the search string to collect a larger sample or add terms with a "NOT" operator to exclude tweets discussing alternative stories.

To ensure that our samples were as comprehensive as possible for each story, we started the process with broad search strings with many "OR" operators. We also used temporal graphical representations of the story to ensure that we did not exclude dates from our search when the story was active. Finally, as we read tweets to make sure they were properly categorized, we also looked for more keywords to include to collect larger and more comprehensive samples.

The final step in the development of the dataset was independent validation to ensure that each story contained no more than 10% noise, or that at least 90% of the tweets linked to each story were indeed about the story in question, while collecting as many tweets as possible. We regarded this 90% threshold as a way of ensuring that we achieved a low-noise sample for each story. Each story was validated by a researcher who had not participated in producing the initial keywords. That validator examined both a random sample of tweets linked to the story and the top ten tweets in terms of retweets for each story. If 90% of that mixed sample was properly linked to the story, then we marked the story as validated. If the generated tweets did not reach this threshold for relevance, the coder iteratively improved the search string until the 90% threshold was met. Once all stories within a particular content group achieved this threshold, it was considered validated and these stories were incorporated into the final dataset. Our deductive approach is effective at excluding tweets unrelated to each misinformation story but cannot guarantee that all tweets related to each story are included in the dataset. We attempted to reduce the risk of missing related tweets by initially deploying broad search strings for each story. However, it is not only possible but likely that some tweets were excluded that were relevant to the topic of the story. While we are unable to estimate the extent of this missingness, our use of tweets, retweets, and quote tweets in our coding should have enabled us to capture the majority of related tweets and leaves us with no reason to suspect that this missingness is biased against any specific subject or story. This process, which included numerous checkpoints and multiple coder interactions, enabled the development of our curated dataset of 456 distinct misinformation stories which spread on Twitter around the 2020 U.S. election, *ElectionMisinfo2020.* A table of story names, search strings, and start and end dates can be found in Appendix V.

This set of 456 stories includes a broad range of misinformation types, and kinds of tweets. Not all the stories are explicitly false or misleading. For example, the EIP tracked allegations of voter intimidation and suppression, some of which were substantiated instances of armed people at or near polling places. Though not false or misleading, those stories could potentially dissuade voters out of fear of harm and therefore were within scope for the EIP's rapid response mission—and so became part of our dataset. Even within stories that were clearly false or misleading, there are tweets linked to those stories in *ElectionMisinfo2020* that are not themselves false, misleading, or clearly sowing doubt in the election. This is because the production and spread of misleading content takes place through a range of discursive strategies. Some tweets in these misleading stories are explicitly false. Others are misleading, but not false—either because they made no claims of fact, perhaps by framing a false statement as a question, or because they simply frame true claims in a misleading way. There are also tweets that function to spread a false or misleading story, but are themselves unambiguously true, for example through quotations of others who have made false claims. Finally, our dataset also includes explicit corrections of false claims. We argue that all of these discursive strategies are important parts of the misinformation story, and so include them in *ElectionMisinfo2020.*

Qualitative Labeling of Stories that "Sow Doubt" in the 2020 Election

Our aim in collecting and curating *ElectionMisinfo2020* was to include as many rumors, misinformation, and disinformation stories as we could based on the incidents reported to the EIP. For our empirical analysis here, however, we focus on the subset of stories that functioned to delegitimize—or sow doubt in—the procedures and/or results of the 2020 election. Studying and reporting on mis- and disinformation can be challenging, and it is critical that research findings within this domain are reported with precision and consideration of how they might be communicated to broader audiences, for example through media coverage. In the wake of the violent events of January 6, 2021, and with knowledge that the findings in this data will be used as part of the accounting of those events, we felt that it was important here to disambiguate delegitimizing content from other kinds of content (e.g. reports of voter suppression or violence at the polls)—especially, for example, when reporting on repeat spreaders.

With a team of researchers, we qualitatively coded each of the 456 stories to identify whether the tweets in that story sowed doubt in election procedures or election results. The coding scheme we used relied on two criteria. We labeled stories as sowing doubt if:

- Some of the most widely spread tweets in the story explicitly alleged the delegitimization of the election.
- A predominant frame in propagation of the story was one that connected it to voter fraud or questioned the integrity of the election.

After developing the codebook, we had at least two coders code each story. The annotator agreement was substantial (Fleiss's Kappa = 0.64) (Landis and Koch 1977). A panel of three coders arbitrated stories where the original two coders disagreed. This process labeled 307 of the 456 misinformation stories as sowing doubt in the election. Most of the stories labeled as not sowing doubt were false reports of voting information – misstatements of the time that polls close or the deadline for voter registration. The 149 stories which contained misinformation but did not sow doubt in the election included 3.3 million tweets, while the 307 stories which we marked as sowing doubt in the election contained 29.1 million tweets. The analyses below focus on those 307 stories and 29.1 million tweets.

Results

To demonstrate the usefulness of the content and structure of the *ElectionMisinfo2020* dataset we describe the dataset's network structure, partisanship, and common areas of content. We also report on repeat spreader accounts within this data—accounts that A) spread large amounts of misinformation in the most distinct stories; and

B) were operated by public figures who were either verified or had sufficiently large follower counts. Finally, we present short case studies of four widely spread and discussed stories: (1) a narrative claiming Dominion voting systems were changing votes; (2) a story spread on Election Day that included allegations of undelivered mail-in ballots; (3) "Sharpiegate": allegations that a large number of votes were invalidated due to the use of felt-tipped pens for filling out ballots; and (4) allegations made by a "whistleblower" who worked for USPS in Pennsylvania.

Political-Ideological Structure

We used an inductive, network-based approach to estimate partisanship for the accounts that shared tweets within the stories we identified and curated. We began with a dataset of ~500M retweets, a subset of the broad election-related Twitter dataset containing terms related to the presidential election, limited to tweets matching the terms: "vote", "voting", "mail", "ballot", "poll", and "election." From this dataset, we create a *coengagement projection* graph (Beers et al. 2022)—a network where two nodes are connected if at least 10,000 accounts have retweeted both nodes (see Figure 2, below).

We leveraged the clusters identified in our network to estimate partisanship for the Twitter accounts in our dataset in two stages. For the first stage, we assigned a partisan label—whether the account seemed to support President Biden or then-President Trump—for each account who appeared directly in our coengagement projection network. We marked accounts that appeared in the coengagement projection network based on their location within either the Biden-supporting or Trump-supporting clusters, shown in Figure 2. As some accounts had strong connections to both the Biden- and Trump-supporting clusters, we only marked accounts as partisan based on their network position if more than 90% of their weighted ties were within one cluster. We excluded twelve accounts based on that cutoff. Many were mainstream news accounts, like those from C-SPAN (@cspan), the Associated Press (@AP_Politics), NBC news (@NBCNews), Newsweek (@Newswek), and The Hill (@thehill). This assigned partisan values for 4,474 accounts. For the second stage, we estimated partisanship for other accounts based on how often they retweeted accounts who were marked in the first step. We marked an account as a Trump supporter if that account had retweeted tweets from any users from our coengagement projection network, and if 80% of those retweets were of Trump-supporting accounts. Similarly, we marked an account as a Biden supporter if 80% of its retweeted tweets were from users in our network of Biden-supporting accounts. If an account met neither threshold, we did not mark them for either Trump or Biden. This second step allowed us to mark 1,580,365 accounts, or 57% of all accounts. Though many accounts remained unmarked, those accounted for a small portion of all tweets: we were able to mark the partisanship of the accounts for 94% of the tweets in *ElectionMisinfo2020*.

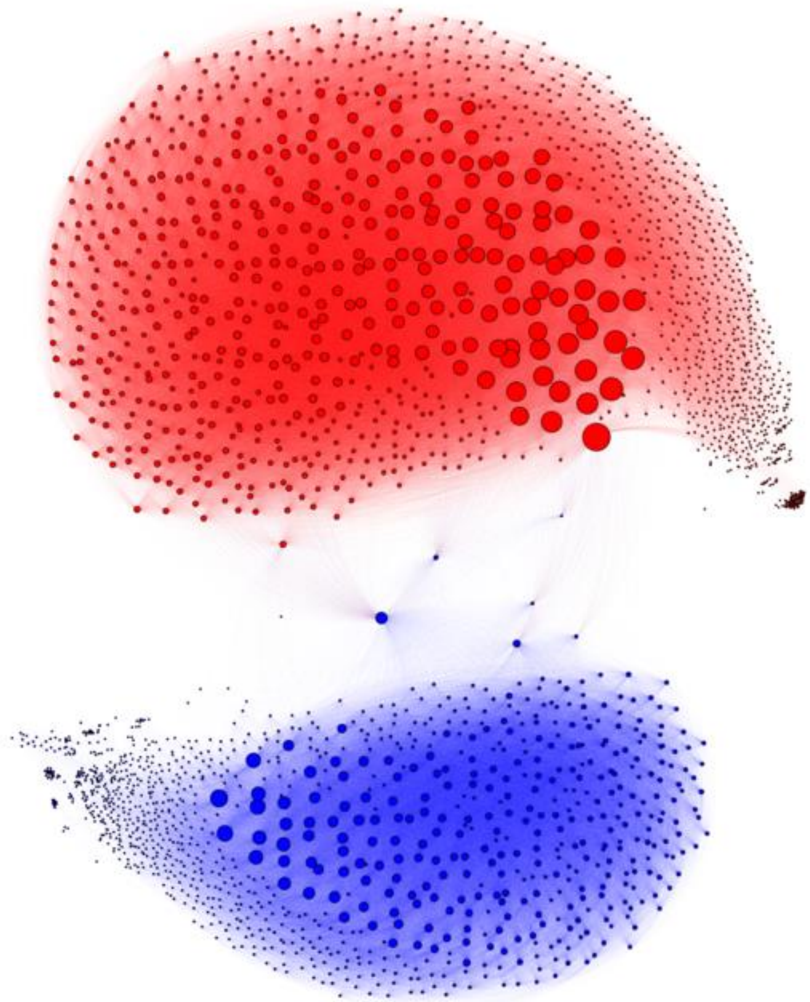

Figure 2. Coengagement Projection Graph of Election Discourse.

A visualization of a coengagement projection graph (Beers et al. 2022) where two accounts share a tie if at least 10,000 accounts retweet both accounts at least once. Nodes are sized by their degree, with edges weighted to the number of accounts retweeting both nodes. We used Gephi to visualize this data (Bastian et al. 2009), with the ForceAtlas2 layout algorithm (Jacomy et al. 2014). Using this retweet projection, major political accounts cluster into two, large, partisan groups using the Louvain modularity clustering algorithm with resolution 1.0. The cluster on the top, colored red, includes former President Trump and many of his high profile supporters, while the bottom, blue cluster includes President Biden and many of his high profile supporters. For both clusters, the average node had over 99.6% of its edge weights linking to other nodes in the same cluster (99.68% for Biden-affiliated nodes, 99.89% for Trump-affiliated nodes), with < 0.4% on average linking to the other cluster.

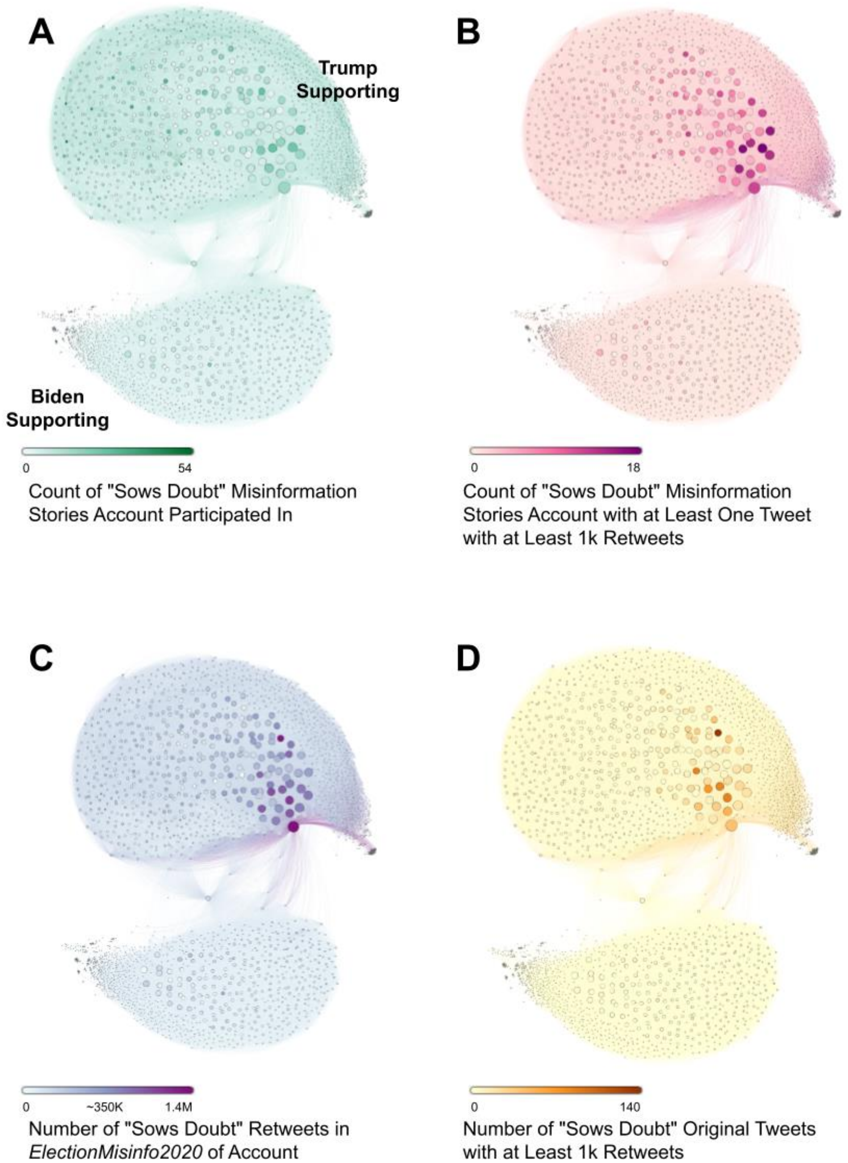

Figure 3. Four views of participation in "Sows Doubt" misinformation stories.

The same coengagement projection graph shown in Figure 2, but colored by accounts' participation in the misinformation stories contained in *ElectionMisinfo2020* that we marked as sowing doubt in the election. 3A is shaded based on the number of misinformation stories marked as "sows doubt" in which the account had any tweet, retweet, quote tweet, or reply. 3B is shaded by the count of "sows doubt" misinformation stories in which an account had an original tweet, quote tweet, or reply which received at least 1k retweets. 3C is shaded by the total number of retweets of all of an account's tweets, quote tweets, and replies received in

ElectionMisinfo2020 connected to stories marked as "sows doubt". Finally, 3D is shaded by the number of an account’s tweets, quote tweets, and replies which received at least 1k retweets and were connected to a story marked as "sows doubt".

To understand how different *ElectionMisinfo2020* stories marked as sowing doubt in the election spread through pro-Trump and pro-Biden Twitter communities, we map those stories onto the coengagement projection graph. Figure 3 shows the same network as in Figure 2, but shades nodes by their participation in "sows doubt" misinformation stories using four different metrics. All four methods show some involvement from accounts in both clusters, but also a disproportionately large amount of misinformation activity in the Trump-supporting cluster.

In Figure 3A, accounts are colored based on how many stories they participated in—through original tweets or by retweeting others. We can see that many of the darkest nodes, those that participated in the largest number of "sows doubt" misinformation stories, are located in the Trump-supporting cluster. However, some nodes in the Biden-supporting cluster are also colored; there were active participants in both clusters who shared multiple election-related stories that were determined to be false or misleading.

In Figure 3B, we only count stories where an account posted an original tweet with at least 1k retweets—in other words, where an account contributed original content that was highly retweeted as part of a misinformation story. This is also the metric we use for our repeat spreaders analysis below. By this measure, the darkest nodes are also some of the largest nodes in the Trump-supporting cluster, including then-President Trump’s account itself. And indeed, our repeat spreader analysis below reveals that former President Trump’s account was repeatedly influential in the spread of stories that sowed doubt in election procedures/results.

Figure 3C focuses on the number of total retweets an account garnered for participating in "sows doubt" stories in *ElectionMisinfo2020*, a measure of its overall influence in the spread of election-delegitimizing misinformation. Finally, Figure 3D indicates the relative number of original tweets each account posted which were part of a "sows doubt" story and got more than one thousand retweets, a combined signal of activity and influence.

Taken together, these graphs show that, across multiple metrics of how much election misinformation spread on Twitter, it is clear that stories marked as sowing doubt in the election spread more within pro-Trump communities than pro-Biden communities. There are some accounts in the pro-Biden cluster who did spread misinformation effectively, though when compared with the pro-Trump cluster, these accounts were much fewer in number and far less central in their community's structure.

Election Misinformation by Time and Partisanship

We used the partisanship labels to estimate the spread of misinformation we marked as "sowing doubt" in the election by pro-Biden and pro-Trump communities over time from September to December and for each of our content groups and misinformation stories. We only used partisanship from accounts we were able to classify either directly through their membership in a network cluster from the network shown in Figure 2, or who retweeted accounts from one of those clusters more than 80% of the time, as discussed in the "Political-Ideological Structure" section above.

Using those classified accounts, we made plots of partisan share of misinformation spread linked to "sows doubt" stories about the US election over time, and for each of our content groups and misinformation stories.

Figure 4 shows our measure of partisan spread, during our study period, of tweets by Trump-supporting and Biden-supporting accounts related to the 307 misinformation stories we identified as sowing doubt in the election.

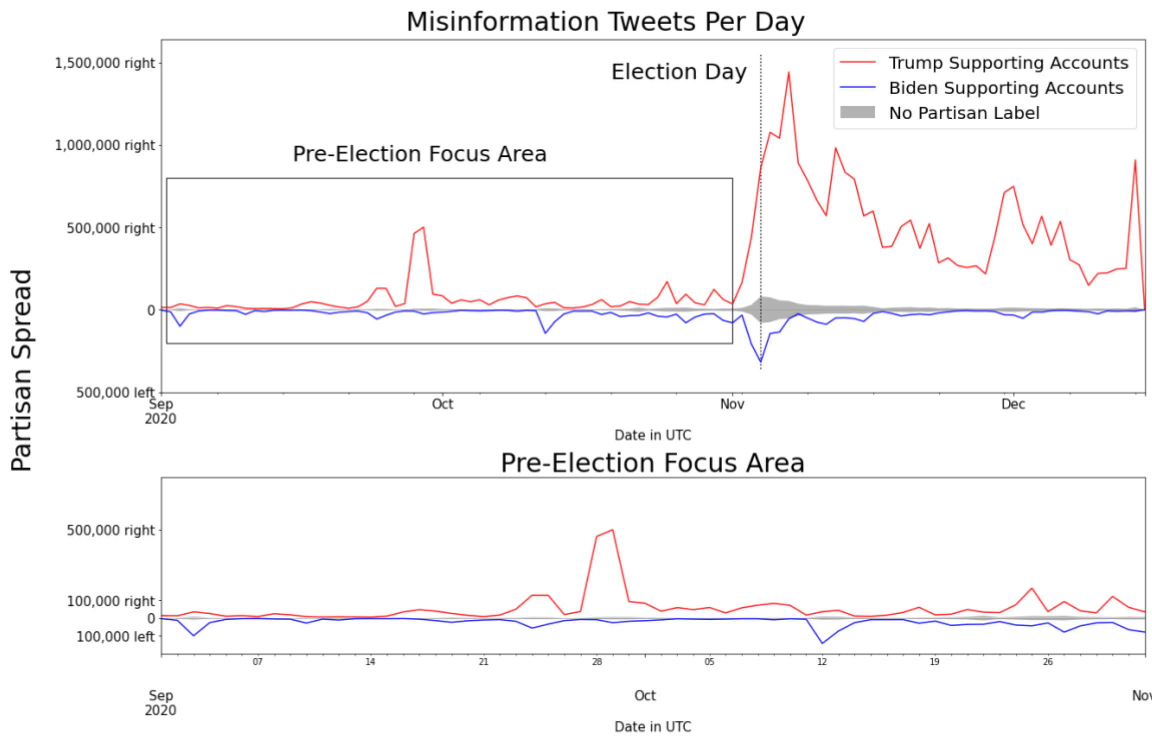

Figure 4. Temporal plot of tweets connected to 'sows doubt' stories.

Temporal plot of the number of tweets in "sows doubt" stories for each day from September 1, 2020 to December 15, 2020, using our partisan labels to estimate the partisanship of each tweet. Specifically, the y-axis shows how many of those tweets were from Trump supporters, in red and upwards, or Biden supporters, in blue and downwards. We show tweets from accounts whose partisanship that we were unable to classify as a gray ribbon.

Examining misinformation spread over time shows that before the election there were already a large number of misinformation tweets each day from both Trump and Biden supporters, and that both sides saw an increase in late October and early November—going into and immediately following the election. The median number of pre-election tweets each day related to incidents we marked as sowing doubt in the election was 30k from Trump supporters and 7.5k from Biden supporters. These early tweets, especially among Trump supporters, contained many of the themes that were popular after the election on November 3.

On and immediately after Election Day, the volume of misinformation increased for both Trump and Biden supporters. However, the proportion was highly skewed toward pro-Trump accounts: even on Election Day, when the outcome of the race was uncertain, there were over 750k million tweets connected to sows doubt incidents from Trump supporters and roughly 250k from Biden supporters. Once the results clearly showed that Biden would win, the partisan difference in misinformation volume increased: Biden supporters generally stopped engaging with misinformation on Twitter other than to challenge key narratives. Trump supporters, on the other hand, frequently tweeted during this period—which held some of our largest volume misinformation stories like Dominion, Sharpiegate, and others, including accusations of partisan counting methods, and suggestions that large numbers of ballots were cast in the name of dead people.

Largest Content Groups

We intentionally organized *ElectionMisinfo2020* to capture both the spread and the content of misinformation. Content groups, collections of stories that have similar narrative or thematic components, are the broadest categories of misinformation in the dataset. The temporal dynamics of the five largest content groups are shown in Figure 5. All five of these content groups included stories that functioned to sow doubt in election procedures and/or results.

The largest content group, "Technology", includes misinformation stories alleging that votes were changed digitally, about hacking allegations, and about the false claims concerning Dominion voting systems. The second largest group focused on allegations of political actors illegally collecting individual ballots, or "Ballot Harvesting", including the allegations made by Project Veritas (Astor 2020), and allegations that operatives targeted and misled elderly voters. The third largest group was made up of stories which alleged that votes had been cast in the name of dead people. This group included many allegations of votes recorded for specific deceased individuals, as well as claims that large numbers of people with birthdays in 1900 had ballots cast for them. The fourth largest group collected stories surrounding how votes were counted, labeled "Partisan Vote Counting/Recording." Many of those stories were allegations about improper handling of ballots, or delays in counting timed to benefit one candidate. The fifth largest content group of stories we called "USPS Accusations". It focused on false accusations that the U.S. Postal Service (including its leadership and/or employees) was improperly interfering with the election and was mostly spread by Biden-supporting accounts.

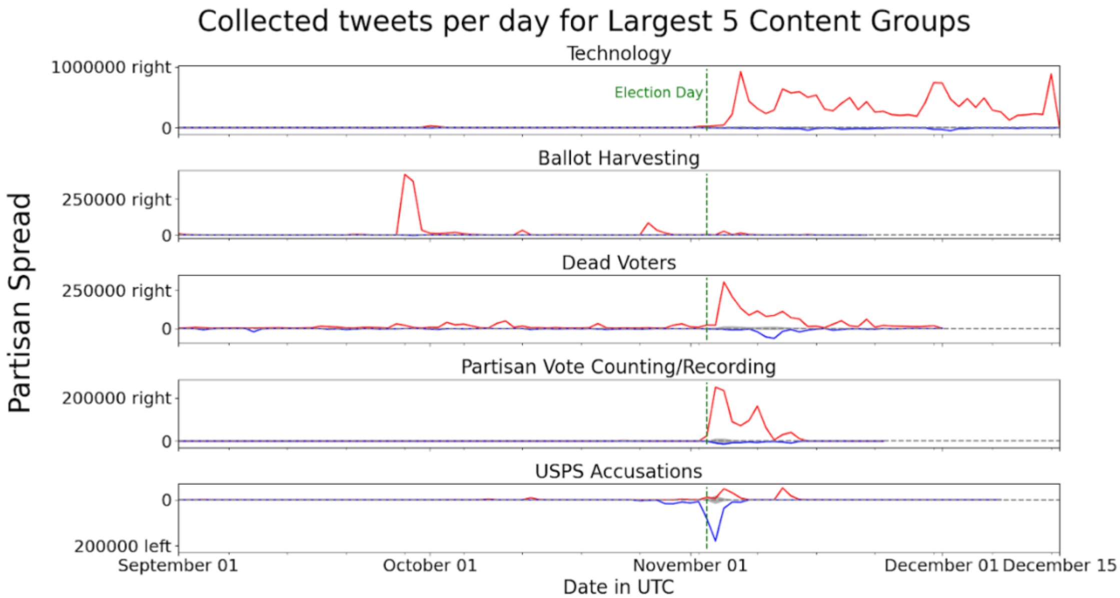

Figure 5. Temporal plot of tweets in the five largest content groups.
Temporal plot of the number of tweets in the five largest content groups for each day from September 1, 2020 to December 15, 2020, using our partisan labels to estimate how many of those tweets were from Trump supporters, in red and upwards, or Biden supporters, in blue and downwards. We show tweets from accounts whose partisanship that we were unable to classify as a gray ribbon.

Four out of the top five content groups were primarily spread by Trump-supporting accounts. Only allegations about USPS involvement in election fraud skewed towards Biden supporters. More information about the content groups, including over-time plots for each one can be found in Appendix I, while the keywords and content groups for each misinformation story are in Appendix V.

Repeat Spreaders

We used our dataset to identify accounts that repeatedly spread false and misleading information about the election through multiple, distinct stories. Efforts to discredit the election took shape over time and across many different false/misleading narratives, and misinformation stories prior to the election seemed to fertilize the ground for the prolific spread we saw after the election. To measure the impact accounts had on that misinformation ecosystem, we chose to measure the impact of specific accounts in their influence in the spread of multiple, distinct misinformation stories. Compared to counting overall tweets (or retweets of that account) which could come from a single very large tweet from a single misinformation story, looking at large tweets across multiple stories allows us to reveal the accounts that repeatedly spread election-related mis- and disinformation. We identified accounts who had at least one original tweet, quote tweet, or reply in a "sows doubt" *ElectionMisinfo2020* story which received more than 1,000 retweets, a threshold we considered a reasonable measure of an account's influence. Since we are interested in repeated spread of false and misleading narratives—in part because the disinformation often takes place through a campaign and incorporates multiple different narratives—we looked at how many distinct stories each account was influential in spreading, i.e. in which they posted a tweet that met the 1,000 retweet threshold. We refer to this as a measure of "repeat spreaders."

This method has a different focus than other measures of influence commonly used in the study of rumors and misinformation, differentiating it from those using the total number of retweets or shares associated with each account or by using the h-index (Gallagher et al. 2021). The total number of retweets or shares is a reasonable measure of an account's influence in a particular discursive space and is commonly used in journalistic studies of misinformation (see, for example, CCDH 2021). However, the power-law distribution of social media spread and sharing means that using the raw count of retweets or a similar sharing metric can easily be biased towards accounts with a small number of tweets with very large spread. Moreover, in our data those very large tweets also tend to be associated with the most widely spread misinformation stories. Since we are interested in accounts who are influential across multiple misinformation stories, this measure is insufficient. However, we investigate both alternatives in Appendix IV.

Table 1 shows the top 35 "repeat spreader" accounts, ordered by the number of "sows doubt" stories they shared with an influential (>1000 retweets) tweet. The top 35 accounts alone were responsible for 9,304,879 out of 32,581,921—or 28.6%—of all "sows doubt" connected retweets and quote tweets we collected. All of the top 35 are Trump supporters—the first Biden-supporting account, a user who had roughly 175k followers during the election, ranked 52th. The partisanship is underscored by the fact that the list includes former President Trump and his two adult sons, as well as his lawyer Rudy Giuliani. This list also shows the connection between the 2020 election and the Qanon movement: 9th ranked @prayingmedic regularly spread Q-related material. Finally, this list also shows the role of right-leaning media outlets like the Gateway Pundit and Breitbart News, or their presenters, such as Candace Owens and Mark Levin. Similarly, Trump-supporting political and online activists like Steven Crowder and Charlie Kirk appear on the list.

Table 1. Repeat Spreaders of 'Sows Doubt' Stories

Rank	User Screen Name	Verified User	Stories With Large Tweet (>1000 RTs)	Large Tweets (>1000 RTs)	Number of Retweets	Stories With Any Tweet or Retweet
1	RealJamesWoods	Yes	24	30	363,349	29
2	gatewaypundit	Yes	21	85	408,586	38
3	TomFitton	Yes	19	28	140,259	25
4	JackPosobiec	Yes	18	42	165,274	35
5	EricTrump	Yes	17	28	463,353	26
6	realDonaldTrump	Yes	16	55	2,286,540	22
7	DonaldJTrumpJr	Yes	16	24	357,766	45
8	catturd2	No	15	22	75,290	24
9	prayingmedic	No	14	45	118,844	28
10	JamesOKeefeIII	No	13	54	452,749	15
11	ChuckCallesto	Yes	13	37	295,710	21
12	MichaelCoudrey	Yes	13	28	184,850	32
13	ANONOMIZED[3]	No	12	33	71,300	16
14	robbystarbuck	Yes	11	17	78,707	44
15	stillgray	Yes	11	18	75,688	40
16	RichardGrenell	Yes	10	25	289,835	16
17	RealCandaceO	Yes	10	9	248,614	10
18	michellemalkin	Yes	10	28	87,237	18
19	scrowder	Yes	10	17	67,322	12
20	pnjaban	Yes	10	11	46,164	28
21	charliekirk11	Yes	9	28	394,231	12

[3] To protect accounts that may have reasonable expectations of privacy, we anonymize accounts that 1) are not verified; 2) are not public figures, including elected officials and self-described journalists; and 3) had <250,000 followers during the period where we collected their tweets.

22	RyanAFournier	Yes	9	10	107,962	32
23	PhillyGOP	No	9	9	36,650	17
24	joshdcaplan	Yes	9	9	30,696	18
25	johncardillo	Yes	9	9	24,726	39
26	RudyGiuliani	Yes	8	14	264,090	8
27	Project_Veritas	Yes	8	26	119,348	12
28	ScottAdamsSays	Yes	8	18	110,475	15
29	jsolomonReports	No	8	25	97,756	10
30	marklevinshow	Yes	8	16	96,395	8
31	seanmdav	Yes	8	10	67,669	42
32	Timcast	Yes	8	11	65,480	10
33	mschlapp	Yes	8	12	56,613	21
34	BreitbartNews	Yes	8	17	45,945	14
35	DiamondandSilk	Yes	8	11	44,071	14

Case Studies

Building on the repeat spreaders analysis, we briefly investigate four of the 307 misinformation stories labeled as sowing doubt, showing their partisan spread over time, as red and blue lines in Figures 6-9, and the proportion of that spread that can be tied (via retweets) to our top 150 repeat spreaders, which we represent with light red and blue fill. We used 150 accounts because they were also responsible for almost exactly half of the retweets and quote tweets in the data. Larger amounts of pink or blue shading suggest that the story, at that point of time, was more influencer-driven, since a large portion of the tweets were connected to the top 150 repeat spreaders. On the other hand, relatively small amounts of shading suggest a more organic story, with more of the retweets being connected to less prominent accounts.[4] We also provide a brief content overview of each

[4] The Top 150 repeat spreaders are a good measure of the top 150 influential users in the spread of original misinformation content. However, note that we identified only 11 of those users as Biden supporters. As

story and highlight particularly influential tweets. Being able to combine the context of repeat spreaders to an investigation of a particular story is one strength of the *ElectionMisinfo2020* dataset.

Dominion Voting Systems

By far the largest story in our dataset, and indeed the largest misinformation story of the 2020 election, was the allegation that election software developed by Dominion Voting Systems had systematically changed votes from candidate Trump to candidate Biden. Past allegations of fraud tied to voting systems have been raised on the left (Rodhe 2004), but in 2020 this story spread almost exclusively among pro-Trump accounts and echoed previous long-standing rumors pertaining to voting machine vulnerabilities. The story began with an error by an official in Antrim County, MI which resulted in temporarily inaccurate vote tallies. The error was not related to Dominion's software, but resulted from a mistake in the process of updating the software on vote tabulation computers (Michigan Department of State 2020).

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such, that group is a less-good measure of the influencer-driven or organic nature of misinformation spread among Biden-supporters than among Trump-supporters.

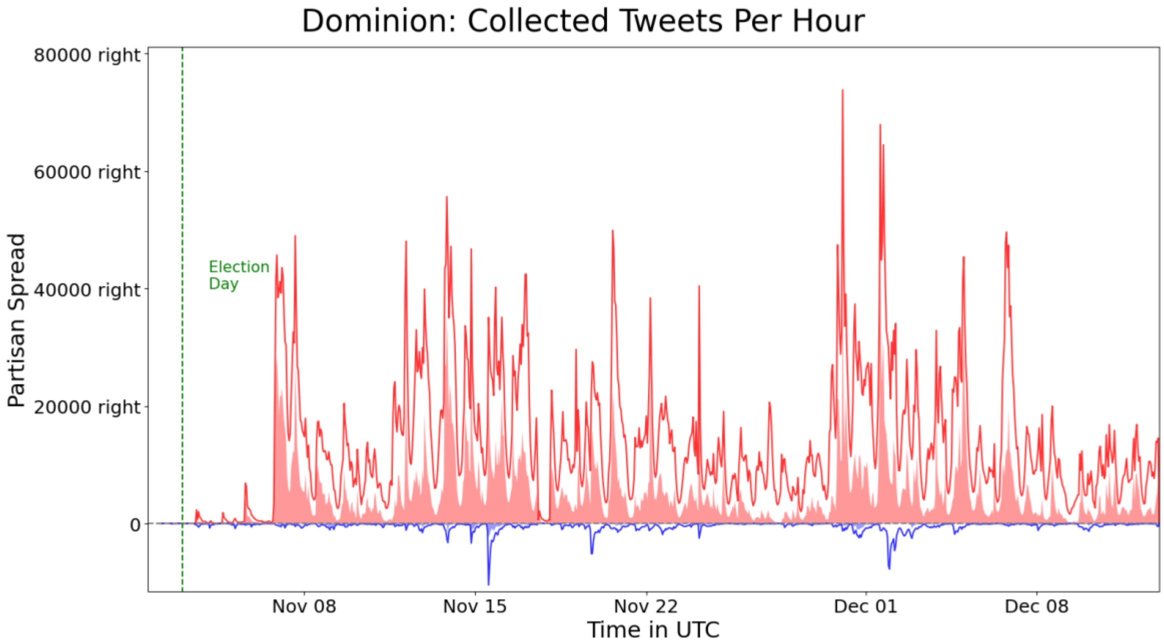

Figure 6. Tweets per hour linked to the Dominion story.

Temporal plot of the number of tweets per hour in the "Dominion" story, using our partisan labels to estimate how many of those tweets were from Trump supporters, in red and upwards, or Biden supporters, in blue and downwards. The light red and blue fill reflects the portion of total spread that can be connected to an original tweet by one of the top 150 repeat spreaders.

The earliest small spikes in Figure 6 were related to that story about Antrim County and an incident in Georgia, which was characterized by similar claims. The story grew with a tweet by repeat spreader @robbystarbuck reading:

> One Michigan county clerk caught a glitch in tabulation software so they hand counted votes and found the glitch caused 6,000 votes to go to Biden + Democrats that were meant for Trump and Republicans. 47 MI counties used this software. All must check now! (November 6 6:00 UTC)

That tweet was retweeted over 44k times. It highlighted the earlier Antrim County issue, calling it a "glitch", but erroneously connected it to other counties in Michigan. Combining these allegations transformed the story about an essentially insignificant and isolated mistake into what seemed to be evidence of systemic fraud. A similar tweet by fellow repeat spreader @stillgray followed:

> This is big. The software used to tabulate the votes in one county sent at least 6,000 Trump votes to Biden. 47 counties used the software. Other states may have, too. Was it a glitch or a 'feature'?

This tweet, which was retweeted 37k times, also takes the Antrim event as a signal of a larger issue spreading throughout and beyond the state of Michigan. A quote tweet (of this tweet) by Donald Trump Jr. was retweeted another 28k times. After this point, the narrative was picked up by then-President Trump, who used the term "dominion" in 24 tweets, which garnered collectively a total of 849k retweets between November 6 and December 15, 2020.

Dominion, then, was a prime example of an isolated incident which was reframed to suit the narrative that election fraud was systematic and widespread. It was spread early on by repeat spreaders, and then repeatedly emphasized by then-President Trump. The influencer-driven nature of the Dominion story is clear in Figure 6: a relatively high proportion of spread, even early on, can be attributed to activity from repeat spreaders, as shown by the pink fill. This narrative was the most tweeted (and retweeted) misinformation story in our data, possibly because, to those who believed or wanted to believe it, such a software glitch alone seemed plausibly severe enough to overturn the election.

Undelivered Ballots

Though none of the top 35 repeat spreaders we identified were Biden supporters, a few election 2020 misinformation stories did spread widely among Biden-supporting accounts. The largest of these concerned allegations that hundreds of thousands of mail-in ballots would be delayed and left uncounted. These claims were often connected to suggestions that such delays were purposeful, often directly accusing Postmaster General Louis DeJoy, a Trump-appointee, of intentionally sabotaging the mail-in vote.

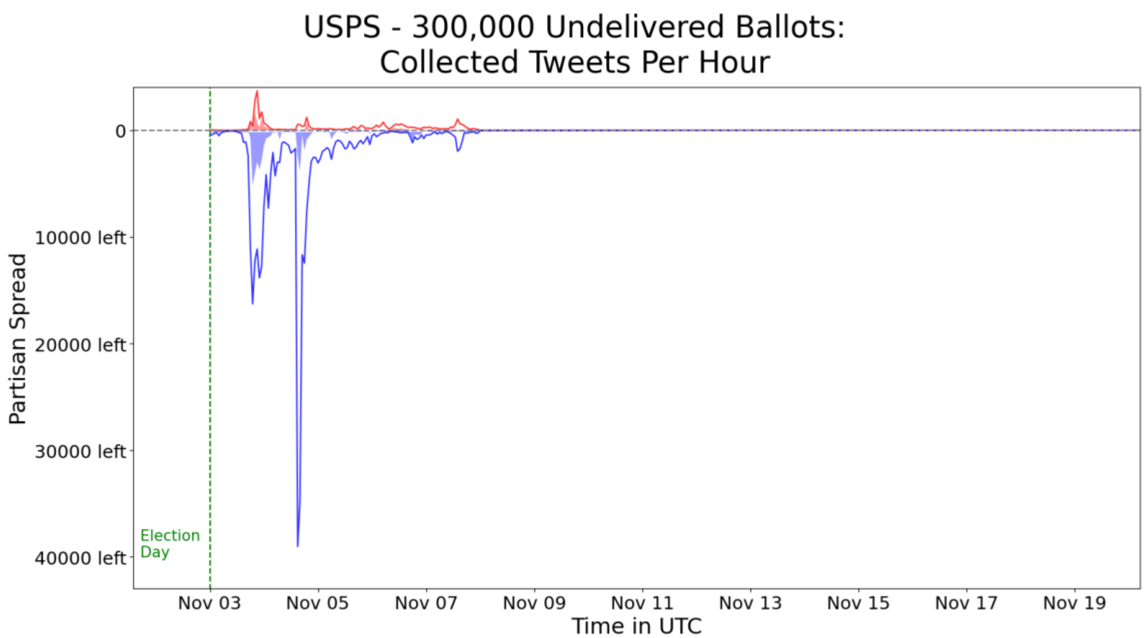

Figure 7. Tweets per hour linked to the Undelivered Ballots story.
Temporal plot of the number of tweets per hour in the "USPS undelivered ballots" story, using our partisan labels to estimate how many of those tweets were from Trump supporters, in red and upwards, or Biden supporters, in blue and downwards. The light red and blue fill reflects the portion of total spread that can be connected to an original tweet by one of the top 150 repeat spreaders.

This misinformation story, shown in Figure 7, seems to have begun with an apparently accurate accounting of delays published by John Kruzel, a reporter for *The Hill*. Kruzel's tweet showed a list of ballots which had not yet received a delivery scan and referenced that a hearing would soon take place to address the problem. Though Kruzel's tweet was technically accurate, it was misleading since the number of ballots listed as undelivered tended to be much smaller than the vote margins in those areas (so they would not have impacted the final results). Additionally, the USPS claimed that many of the ballots on the list were delivered but may not have had a delivery scan. While the original tweet was technically accurate but somewhat misleading (around impact), many quote tweets of Kruzel's original took the allegations much further (i.e. suggesting intentional fraud). For example, Ari Berman's quote tweet read:

> `Louis DeJoy should be held in contempt of court & face criminal charges for obstructing an election if these ballots are not delivered on time`

This implied that the delay could be attributed to Dejoy's role as the Postmaster General. This was a common narrative from Biden-supporting accounts, which, though less common, were still represented in 11 of the top 150 repeat spreader accounts.

Sharpiegate

Another prominent story in our data (see Figure 8), termed "SharpieGate" by some of its proponents, reveals a slightly different dynamic—beginning somewhat organically and later receiving amplification by influential accounts. SharpieGate began early on Election Day, when voters in several polling locations noted that the Sharpie pens they had been given to vote were bleeding through the ballots—and some began to share concern (and later suspicion) that their votes had not been counted. Officials in Arizona (the state the narrative focused on most heavily) noted that bleed through would not affect their votes as the ballots were designed to be used with Sharpie pens as they allow marks to dry faster than with ink pens (Leingang and Fifield 2020).

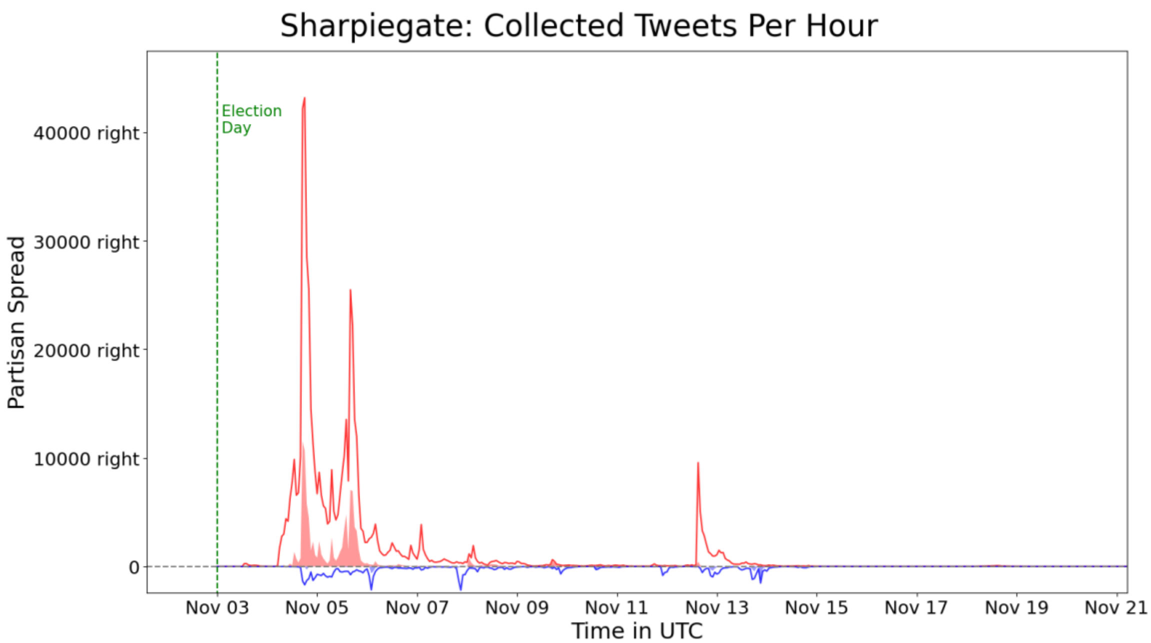

Figure 8. Tweets per hour linked to the Sharpiegate story.

Temporal plot of the number of tweets per hour in the "Sharpiegate" story, using our partisan labels to estimate how many of those tweets were from Trump supporters, in red and upwards, or Biden supporters, in blue and downwards.The light red and blue fill reflects the portion of total spread that can be connected to an original tweet by one of the top 150 repeat spreaders.

Early on, the spread of SharpieGate was largely bottom up—moving through tweets and retweets of low-follower accounts and often accompanied by a tone of concern or, in some cases, suspicion. Note that there is little light red shading (retweets of repeat spreader accounts) in the early spread of this rumor (Figure 8), underscoring its initially organic nature. This changed as the narrative went into its first (and highest) peak on November 4.

In the early hours of the day after the election, shortly after Arizona was called for President Biden, the tone of the Sharpie conversation began to shift from concern and suspicion towards outright accusation that Trump voters were being purposefully disenfranchised by being forced to use Sharpie pens. As that day progressed, more influencers began to participate in the propagation of that false narrative.

However, even at its peak, a relatively small proportion of the tweets, quote tweets and retweets in the Sharpiegate story came from our top 150 repeat spreaders, who account for 50% of all retweets and quote tweets in *ElectionMisinfo2020.* Instead, the Sharpiegate story seems to have been unusual among large narratives in that it had larger numbers of tweets spread by less influential accounts. This may be connected to the experiential nature of the story.

Sharpiegate also had a notable late spike, around November 13, when influencers revived the story as part of a general effort at that time to weave together different misinformation stories into conspiracy theories. For example, @CodeMonkeyZ claimed that the ballots marked with Sharpies would have been saved in a separate folder, allowing investigators to uncover the plot. Of course, that was not the case.

USPS PA Whistleblower

Our fourth and final case study reveals a very different dynamic. Many of the misinformation stories tracked in the *ElectionMisinfo2020* dataset began with real incidents. This was the case with the examples presented so far: a mistake by a county official, real counts of ballots without delivery scans, or Sharpie pens bleeding through ballots. Other incidents were completely manufactured. This seemed to be true of several of the "whistleblower" stories that we tracked, some of which were initially spread by the group Project Veritas or its leader, James O'Keefe III. The USPS PA Whistleblower story, shown in Figure 9, featured unfounded allegations by a man claiming to be a USPS worker in Pennsylvania.

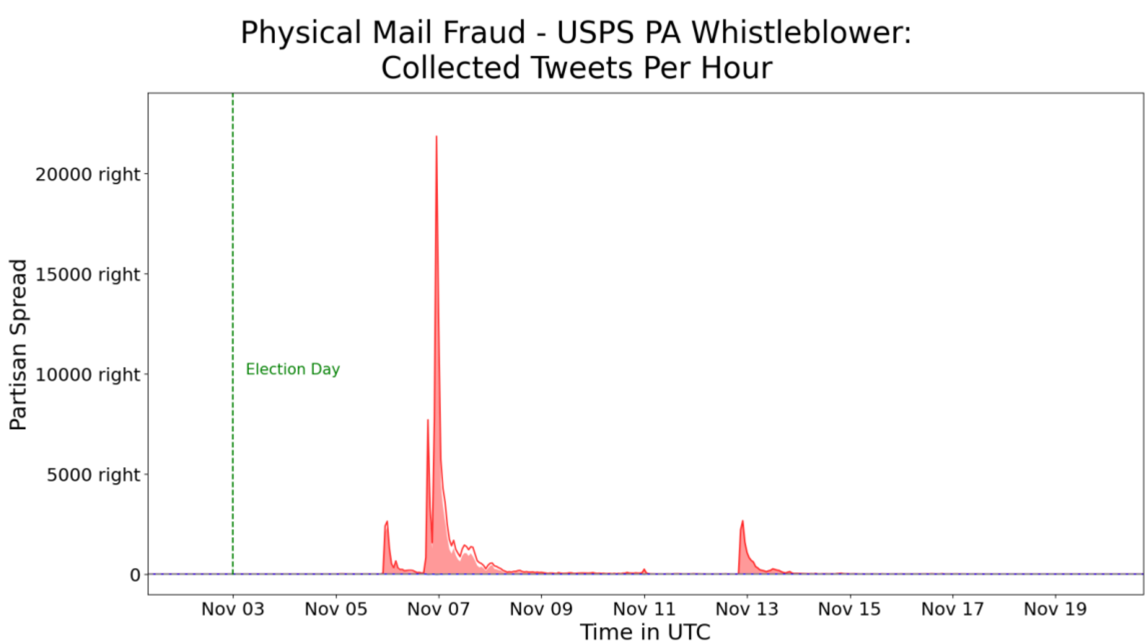

Figure 9. Tweets per hour linked to the PA Whistleblower story.

Temporal plot of the number of tweets per hour in the USPS PA Whistleblower story, using our partisan labels to estimate how many of those tweets were from Trump supporters, in red and upwards, or Biden supporters, in blue and downwards. The red and blue fill reflects the portion of total spread that can be connected to an original tweet by one of the top 150 repeat spreaders.

This story was almost entirely driven by tweets from James O'Keefe III, first teasing and then releasing a video of Richard Hopkins, a USPS employee in Pennsylvania. The video and the tweets both contained allegations that the Pennsylvania Postmaster had ordered the backdating of mail-in ballot envelopes so that more of them could be counted. Hopkins walked back his allegations on November 9, admitting that he had no evidence that backdating had occurred or been ordered. However, O'Keefe's tweet and the Project Veritas video featuring his claims were still being retweeted on November 13, as part of a general attempt at spreading content questioning the outcome of the election on that day.

Discussion and Conclusion

This work presents a first look at a novel dataset, curated in real-time by trained researchers, covering hundreds of distinct misinformation stories that spread about the 2020 U.S. election. As we hope to have demonstrated, the scope of the *ElectionMisinfo2020* dataset gives it the potential to be used to analyze the origins, pathways to amplification, and real-world overlap of the online misinformation that surrounded the 2020 U.S. election and its political outcomes—including the related events on January 6, 2021. As such, we hope that the initial findings developed here will serve to inspire further research into the social media dynamics that drive and sustain misinformation—and specifically election-related misinformation. The combination of front-end identification, verification, and processing ensures that the database, while not entirely comprehensive, contains data related to misinformation stories across a variety of narratives built around many different real world (and in some cases imaginary) events. Moreover, this process enabled us to include smaller incidents, as defined by their reach and interactions on Twitter, which have often been overlooked and therefore missing from previous datasets. In addition to the scope of the stories included in the dataset, the keyword selection and validation processes give us confidence that the majority of the stories contained in *ElectionMisinfo2020* consist of tweet sets that are largely reflective of the breadth of each story as they spread on the platform in real-time.

Initial analyses, presented here, provide additional evidence for various trends identified using smaller datasets. Specifically, the main takeaways from the dataset reiterate observed asymmetric spreading by the political right as well as the outsized influence of repeat spreader accounts. With regards to partisanship, we have shown that by identifying specific accounts by the candidates they most frequently interact with, we can conclude that prior evidence noting the pervasiveness of misinformation on the right was representative of a larger asymmetry, both by highly followed and less followed accounts. Though there is evidence in these data to suggest that left affiliated accounts may have been more active in the misinformation space had Biden failed to win the election, the differences in partisan amplification were evident long before the election, as evidenced by claims that the election would be rigged in the build-up to November 3rd, as well as prior to final vote counts. This was particularly evident amongst highly followed accounts, which this dataset helps tie to the spread of misinformation.

On issues of enforcement, evidence from the repeat spreaders identified in the data is aligned with previous work (Gallagher et al. 2021; CCDH 2021; EIP 2020b; CIP et al. 2021) in noting that many high impact accounts rely on interactions with misinformation stories to grow followers and sustain engagement with their account. Where incentives remain tied to follower interactions, lesser interventions, such as content labeling, are not likely to have a significant impact on the willingness of these accounts to interact with questionable content. Rather, enforcing rules more stringently on accounts which repeatedly violate rules, as well as increasing enforcement on influential, large-follower accounts could be a fruitful avenue for platforms to explore. Our own previous work, published as a "rapid response" blog (EIP 2020b) and a white paper (CIP et al. 2021), helped spotlight this role played by large influencer accounts in repeatedly spreading misinformation. Since then, others (Gallagher et al. 2021; CCDH 2021) have also brought attention to the prevalence of top-down or elite spread of misinformation. Some platforms have realized that repeated violations need to be treated differently with so called "strike systems," where platforms have policies to more heavily sanction accounts which repeatedly violate speech policies. These are quite common, from mainstream social platforms like Twitter and YouTube, and even on "free speech" platforms like Parler (Buckley and Schafer 2021). While these policies are not always implemented for misinformation content, the existence of these systems for other contexts would make adding them for misinformation (and specifically for disinformation) more feasible. Moreover, combining strike systems with existing policies may be more effective than isolated approaches (Bak-Coleman et al. 2021). Rather than exempting high profile accounts from enforcement, as some platforms have done (Horwitz 2021), the large influence and potential for harm that large accounts possess suggest that these accounts ought to be held to at least as strict, if not stricter, standards than less influential accounts. In practice, however, of the top 35 repeat spreader accounts in Table 1, most continue to post on Twitter to a wide audience. Only seven were suspended in the wake of the election, and only two of those seven for apparent violations of Twitter's policies around disputed election claims (Dellinger 2021; Mastrangelo 2021; Twitter 2021b).

Moreover, as evidence from the *ElectionMisinfo2020* dataset shows, top-down interactions are not the only way for misinformation to gain traction, as coordinated efforts by partisan accounts were shown to have sustained high profile misinformation on Twitter—prior to the wave of suspensions following January 6 (Tollefson 2021). This dataset offers the first real chance to examine the dynamics of other extant account groups like this, along with repeat spreaders, whose dynamics we hope to interrogate further in future work. A focus on other types of misinformation, already split among content groups within our dataset, could yield information on the specific dynamics driving the amplification of various forms of misinformation online. For example, we also collected several stories related to either real, threatened, or fictional instances of political violence. These stories, which at the time largely appeared to be isolated incidents, have taken on more weight in the aftermath of the January 6, 2021 insurrection. In our final count we tallied 118 unique stories in the broader *ElectionMisinfo2020* dataset related to violence or threats of violence, split between the content groups intimidation (38), suppression (21), riots (18), discussions of a potential coup (16), protests (16), and discussions of civil war (9). Given the wider literature on the influence of violence in the destabilization of elections these stories represent an incisive threat to electoral integrity that should be the focus of further research in the buildup to future elections.

In all, we view this new dataset as an inclusive resource for researchers interested in examining the broad scope of misinformation circulated during the months before and after the 2020 U.S. election. Rather than focusing on specific incidents, the live identification and post hoc validation processes should enable research that utilizes both misinformation stories with outsized impact as well as those which failed to inspire extended discussion. As a result, this data should first allow researchers to carefully examine the factors that enable certain stories to "take off" while others fade into online obscurity. Second, by exposing the pathways that specific misinformation stories take to national notoriety, we hope this database will also serve to provide insight into the characteristics of the accounts who amplify these stories along this chain. Though this database enables further examination of the most active and influential of these accounts, less is known about the accounts with less prominent profiles who often serve as a crucial link to repeat spreaders—a compelling question for future research. In addition, from a policy perspective, each misinformation story and associated tweet set can serve in studies that aim to examine the impact of specific policies or outcomes on the acceleration of misinformation.

Despite efforts to limit gaps in the development and creation of this dataset, there remain limitations. As noted in the methodology section, though the EIP's team of content analysts was trained to identify and tag potential misinformation in as neutral a manner as possible, there is no way to ensure that analysts treated information from both political sides equally. Additionally, though misinformation stories were cataloged from websites and social media platforms as far ranging as NextDoor, Parler, and Reddit, this dataset is limited to misinformation that, at least briefly, appeared on Twitter. Though Twitter does appear to have been used to disseminate the majority of these stories, there were several stories which originated on separate platforms which we were never able to track to the platform. However, we can get an idea of how prevalent cross-platform spread is by looking at the links in our data to other social media websites: 192 (62%) of the misinformation stories included at least one tweet with a link to YouTube, 87 (28%) included a link to Facebook, and 61 (20%) linked to Instagram. More than 25 (8%) stories were linked each to Tiktok, Parler, and Reddit as well. Another limitation is that our curation process does not enable us to differentiate between misinformation tweets furthering the spread of a particular story and corrective tweets attempting to limit its spread. Though preliminary evidence from this process suggests that these corrections represent only a small fraction of the total discussion, the tweets associated with each story should be considered as representing the totality of the discussion surrounding each story, rather than solely a collection of tweets containing misinformation.

Collectively, the *ElectionMisinfo2020* dataset presents an uncommonly comprehensive collection of 456 misinformation stories and 32.4 million related tweets related to the 2020 U.S. election. Here, we demonstrated the potential of this dataset through the identification and analysis of the 2020 election's repeat spreaders, which had an undue influence over the stories we identified and tracked. By drawing data directly from the stories reported and cataloged in real time by the EIP, this dataset serves as both a snapshot of circulating misinformation and a resource for researchers and policymakers alike interested in examining the online ecosystem in which these rumors and conspiracy theories flourished.

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