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A Network Approach for Studying the Spread of Cross-Platform Visual Misinformation

visual misinformation, rumors, cross-platform, social network analysis, livestream

Extended Abstract

Most research analyzing the spread of problematic information (e.g., rumors, misinformation, disinformation, and propaganda) on social media platforms has focused on textual content. Yet visual content — such as photos, memes, GIFs, and videos — can be more persuasive and memorable than textual content [1]. Visual content has been used to expand reach and cohesion on social movements, including "Stop the Steal" campaign that led to the January 6th attack on the United States (U.S.) Capitol [1]. Recent work exploring the spread of visual content online, such as videos from YouTube and Rumble or photos from Facebook and Imgur, employ two techniques that each have their own limitations. One technique relies on tracing URLs between social media platforms and video- or image-sharing platforms [2], but an obvious limitation is that content which spreads through other means of sharing (e.g., screenshots, screen recordings, or re-uploaded content) cannot be traced. Another technique relies on examining images and videos through visual similarity clustering and hash-based image search, but divorces the visual content from its underlying network dynamics [3, 4].

Yet, as Marshall McLuhan argues in Understanding Media, the *medium* is the message [5]. If we are to truly understand how messages in the form of visual content spread across multiple platforms, we must consider the *networked medium* through which it spreads. In this work, we first propose a network approach to represent the spread of cross-platform visual content, and second, we use this methodology to analyze visual content in a case study of voter fraud rumors during the 2022 U.S. midterm elections.

A Network Approach. Our approach for representing the spread of visual content as a network consists of three features (see Fig. 1 for the implementation). First, we represent each post (e.g., on social media, on a blog, news site, or other website) as a node, with each platform represented by a unique color. The size of the node is proportional to the sum of the total engagement metrics for that post. As engagement metrics are not consistently available and because they are not consistently tracked across platforms, and to account for temporal differences in data collection between different platforms, we normalize engagement metrics on per-platform basis. Second, we represent the spread or sharing of visual content from one post to another as a directed edge from the source node to the destination node. Third, visual content typically spreads publicly online in three ways: (1) intra-platform shares using platform-native features (e.g., retweet on Twitter, share on Facebook, retruth on TruthSocial); (2) inter- and intra-platform shares using URLs (e.g., sharing a link on Twitter to a Facebook post); and (3) other sharing mechanisms (e.g., screenshots, screen recordings, or re-uploaded content) where the origin platform may or may not be determinable. We collectively refer to these three methods as *cross-platform* spread, which we represent as different edge styles. If there is more than one potential source for a photo or video within the data set, we represent this uncertainty as a dotted edge from two or more source nodes to one or more destination nodes.

Case Study of Cross-Platform Voter Fraud Rumors. During the 2022 U.S. midterm elections, Mike Lindell — the CEO of MyPillow and a prominent voter fraud influencer [6] — held a widely-viewed livestream on election night that highlighted vote count visualizations obtained through a third-party service for a number of hotly contested races in the U.S., such as Georgia and Pennsylvania. Whenever an abrupt change in vote count tallies occurred, Lindell and company described it as evidence of fraud (even though it was not [7]). His livestream was picked up both by prominent influencers and regular users on several social media platforms, who shared screenshots, memes, and video clips of the livestream, potentially reducing trust in election processes and outcomes.

To better understand how these misleading visualizations spread across the social media landscape, we collected posts from six platforms (Twitter, Parler, TruthSocial, Gettr, Rumble, Telegram) using the Twitter and SMAT APIs [8, 9]. Our query was limited to a curated set of keywords relating to Lindell's livestream, mentioned in the week following its air date on November 8th, 2022. In total, we collected over 16,500 social media posts, including over 2,700 images and videos. Figure 2 represents how we visualized a random sample of 12 posts through manual labeling of images and videos to determine where that imagery originated from, and highlights the usefulness of visualizing even a small number of nodes with our network structure. We are currently leveraging a combination of qualitative data analysis, URL back-tracing, and image similarity algorithms to examine how the photos and videos spread across platforms. For videos, we are exploring how to take automatic screenshots at periodic intervals (e.g., 60 seconds for videos longer than 10 minutes and 5 seconds for shorter videos), and use perceptual hashes of the screenshots to identify whether one video was clipped from another or if a screenshot or photo came from a particular video.

This is but one example of how misleading visualizations spread across the internet, and we expect to encounter similar scenarios in the future. Future work should explore how to build automated pipelines to support network analysis of visual content.

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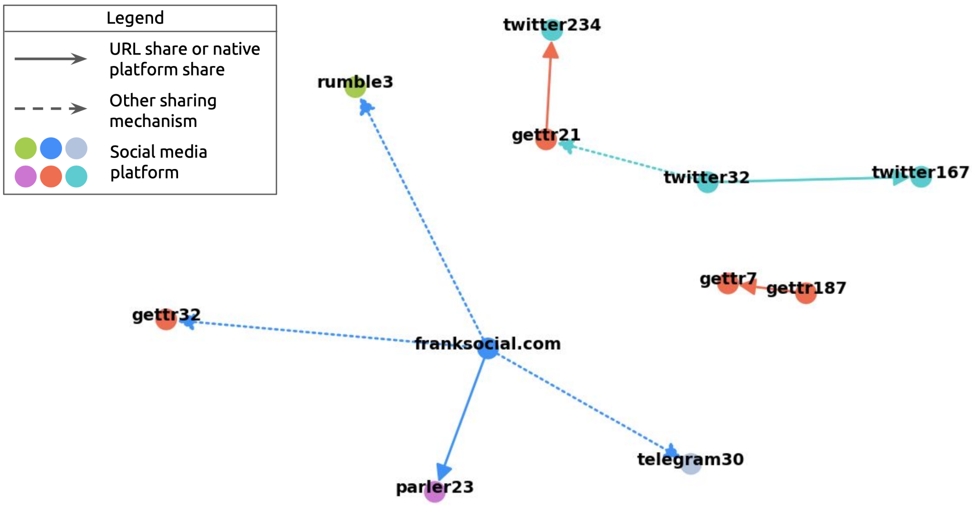

Figure 1: An example implementation of our network structure representing the spread of visual content across platforms. Nodes are unique posts colored by platform. Directional edges represent the sharing of posts or media between nodes and are colored by the source node platform. The style of the directional edge indicates how the content was shared, with a solid line indicating a URL or native platform share and a dotted line indicating other sharing mechanism.

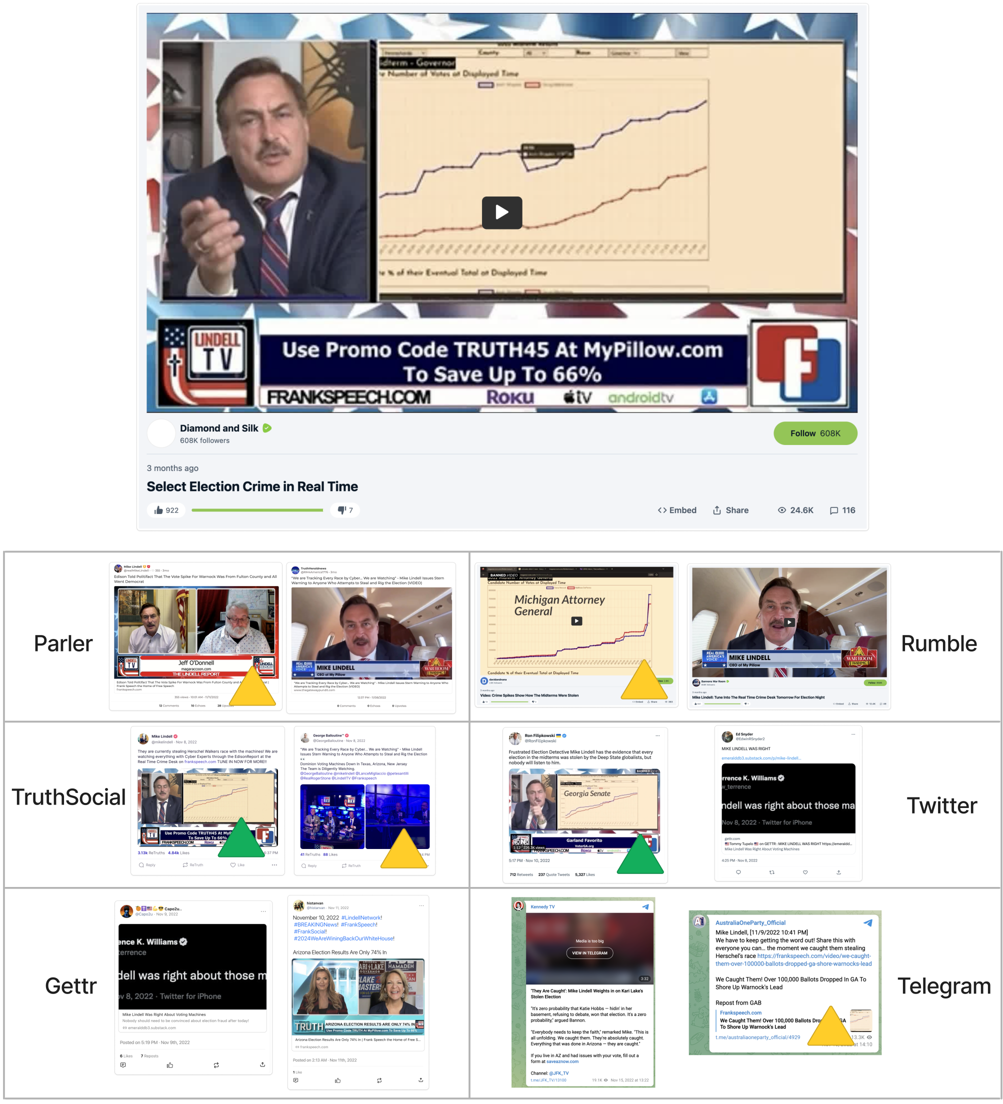

Figure 2: We qualitatively inspected a random sample of 2 posts from six platforms each (12 total) and determined where that imagery originated from. In this random sample, only two posts (green triangles) include a direct URL reference back to a copy of Lindell's livestream hosted on Rumble (depicted above), while four include photo and video screen captures from the livestream without a URL reference (yellow triangles). Finally one Parler post and one Rumble post make indirect references to an earlier Instagram livestream of Lindell; and four other posts reference Lindell's voter fraud claims in the text but do not include imagery or URLs related to the livestream. It is clear from just this small sample that a URL-based approach and visual similarity clustering alone may not enough. Instead, a combination of the two along with back-tracing are required to truly understand how visual content spreads online.