Fringe News Networks: Dynamics of US News Viewership following the 2020 Presidential Election

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ABSTRACT
The growing political polarization of the American electorate over the last several decades has been widely studied and documented. During the administration of President Donald Trump, charges of "fake news" made social and news media not only the means but, to an unprecedented extent, the topic of political communication. This extreme political polarization continued through the election and all through the period up to the attempted takeover of the Capitol on January 6, 2021. In this paper, we analyze this tumultuous phase in American history through the lens of news viewership. We consider the official YouTube channels of six US cable news networks across a wide political spectrum with a specific focus on three conservative fringe news networks. We analyze how the viewers reacted to the different ways the election outcome was covered by these news outlets. This paper makes two distinct types of contributions. The first is to introduce a novel methodology to analyze large social media data to study the dynamics of US news networks and their viewers. The second is to provide insights into what actually happened regarding these news networks and their viewship during this volatile 64 day period. Our empirical evidence suggest that recent natural language processing advancements can be harnessed in a synergistic way to mine political insights from large scale social media data.

CCS CONCEPTS
• Applied computing → Sociology;  
• Computing methodologies → Natural language processing;  
• Human-centered computing → Empirical studies in collaborative and social computing.

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1 INTRODUCTION
On January 6, 2021, the Capitol riot shook the US political landscape in an unprecedented way. As an immediate effect, the growing scrutiny on news and social media dividing the American citizens further intensified. Within the next few days, several social media outlets revoked or restricted the then President Trump’s access to their platforms. In this paper, we analyze the politically uncertain time between the 2020 Presidential election and the Capitol riot through the lens of news viewership. Specifically, we investigate an interesting intersection of news and social media – YouTube channels of six US cable news networks. Over the last few years, these news networks have made significant inroads into the YouTube platform through offering news content via their own YouTube channels. Viewers are able to interact with the news content through “likes”, “dislikes”, comments and subscription. Apart from the big three news networks, namely, Fox News, CNN, and MSNBC, we consider three conservative fringe news networks, namely, Blaze TV, Newsmax TV, and OANN (One America News Network), and analyze the dynamics of news viewership during this volatile 64 days between the Presidential election and the riot. In addition, we consider the now-restricted YouTube channel of former President Trump. As control, we consider the user activities on these YouTube channels in the 64 days prior to the election.

Via a substantial corpus of 14.5 million comments posted by 2.2 million users, and engagements signals such as likes, dislikes, and subscription, we thus attempt to paint a picture of the news viewership during this political crisis. We combine both linguistic signals and engagement signals in our analysis to understand a broad range of research questions involving shifts in user attitudes, engagement, and migration.

Our paper presents a comprehensive analysis of news outlets hosted by a mainstream platform, YouTube. We believe that in the future, not only the official YouTube channels of these news
networks registered at FCC will enjoy a steady stream of audience, the audience share of influencers (e.g., Bryan Tyler Cohen and Steven Crowder) and news like opinion outlets (e.g., Next News) will also continue to grow. Thus understanding this interaction space between news and opinion consumers and the providers to figure out what led to user-generated content presented in Table 1 is timely and important. With the 2022 midterm election being months away, and the current political climate showing little sign of reconciliation, we believe our analysis exhibiting synergistic applications of a wide array of techniques presents an important case study on mining political insights at scale.

1.1 Political Background

As documented by a wide range of studies [3, 9, 10, 22, 23, 26, 27, 31], there was an unprecedented political polarization in the US in the year leading up to the election. The election was held on November 3rd. The initial election returns that were coming in that evening were unexpectedly strong for the President for Florida compared with virtually all prior polling. The mood in the White House was upbeat. But, as reported by the New York Times “. . .[the] mirage of victory was pierced when Fox News called Arizona for former Vice President Joseph R. Biden Jr. at 11:20 p.m., with just 73 percent of the state’s vote counted.” Fox News made this call before other national networks had done so. In fact, it wasn’t until November 12th, nine days after Election Day, that the other networks with decision desks — NBC, ABC, CBS and CNN — called the state for Biden too.

As reported by The Times, “Mr. Trump and his advisers erupted at the news. If it was true that Arizona was lost, it would call into doubt on any claim of victory the president might be able to make.”

1.2 Contributions

Our paper makes the following two key contributions.

Methodological: Although there is a tremendous amount of information in the news videos and accompanying viewer comments on YouTube, it is unclear how to characterize this vast unstructured data in a way that allows us to capture and study the key dynamics in US politics. Here we introduce a novel methodology for characterizing these dynamics, based on applying recently-developed AI methods [7, 22, 30] for text analysis to this YouTube data to extract more structured information at scale about its content, and combining this extracted information with other available data such as the shifting number of subscribers to different YouTube channels, producing a more quantitative, objective, and structured understanding of these dynamics.

Substantive: Our second contribution lies in the context of the polarization of American politics and its denouement in the Capitol riot. We provide insights into what actually happened regarding US political social media channels and their viewerships during the 64 days between the US Presidential election on November 3rd, 2020 and the entry into the US Capitol of violent demonstrators on January 6th, 2021.

1.3 Key Findings

Our paper’s analyses find the following key conclusions.

• Following November 3rd, there was a notable loss of Fox’s YouTube channel’s market share, and the departure of previously loyal Fox viewers to what here-to-fore were considered fringe networks (OANN, Newsmax, and Blaze). As an example, the viewership of Newsmax increased by over a factor of seven from the pre-election period to January 6th, 2021.

• Compared to networks such as CNN, MSNBC, and Fox News, we find that the networks OANN, Newsmax, and Blaze had more features of being “echo chambers,” in the sense that their viewerships more nearly uniformly agreed with what they were watching, with lower proportions of their viewerships critiquing what was being presented to them.

• We find that viewer opinion about the legitimacy of the election is polarized into two groups, with viewers of MSNBC, CNN, and Fox News far more in agreement that Biden should be considered “president-elect” than OANN, Newsmax, and Blaze. In a similar vein, OANN and Newsmax are strong outliers in terms of usage of the trigram “stop the steal.”

• Based on cloze tests [34] using the probe The biggest problem of American is [MASK], training a language model [11] based on the comments provided by MSNBC viewers, the top three answers are “Trump,” “COVID,” and “unemployment”, while a language model trained on comments provided by OANN yields “communism,” “corruption,” and “socialism.” The other networks fall into positions...
along this continuum that are consistent with expectations. A similar behavior is observed when cloze tests are employed to analyze who won the election. These findings are corroborated further with a Natural Language Inference algorithm.

• The language present in the comments on YouTube videos hosted by the official channel of President Trump is more similar to fringe media outlets than any mainstream media outlet. Viewers of Trump’s YouTube channel made a substantial switch to Newsmax.

1.4 Paper Roadmap
The rest of the paper is organized as follows. After presenting the rationale for our selection of YouTube channels and describing our data sets in Section 2, we delve into each of the three broad research questions that motivate our findings in Section 3. Section 4 puts our work in context with related work in the area of analyzing political corpora. Sections 5, 6 and 7 describe the experiments and analysis employed to answer the respective research questions. Following our experimental results, we discuss the broader implications and major takeaways of our findings in Section 8. We conclude with Section 8.2 outlining some of the limitations of our work.

2 DATA SET AND DESIGN CONSIDERATIONS

2.1 Choice of News Outlets
We consider the official YouTube handles of six US cable news networks in our analysis: (1) Fox News; (2) CNN; (3) MSNBC; (4) Newsmax TV; (5) OANN; and (6) Blaze TV. Our choice of the first three news outlets—Fox News, CNN, and MSNBC—also known as the “big three”, is guided by the fact that these three are the top three US cable news networks in terms of viewship. All the YouTube channels we consider have considerable presence on YouTube. We denote the combined subscriber count of more than 20 million. OANN and Newsmax TV were the two news networks primarily accused of airing extensive unsubstantiated voter fraud claims. These two news networks were also repeatedly mentioned by the former President Trump via tweets. We include Blaze TV in our analysis because of its comparable popularity on YouTube (see, Table 2).

2.2 Data Set Details
Our data set consists of official YouTube channels of six US cable news networks listed in Table 2, subscription count of these YouTube channels, comments posted by viewers of individual news videos posted by each channel, and “likes” and “dislikes” associated each with these videos. In addition to these six YouTube channels, we consider the official YouTube channel of former President Trump. We used the publicly available YouTube API to download comments, and video “likes” and “dislikes” information. Each comment is identified by a unique comment id and each user is identified by a unique user handle provided by YouTube API.

Table 2: List of news networks considered. Video counts during $T_{31}$ reflect the number of videos uploaded on or before 5th January 2021 starting from 31st August 2020.

| YouTube channel | Number of subscribers | Number of videos during $T_{31}$ | Total number of comments |
|-----------------|----------------------|----------------------------------|--------------------------|
| CNN             | 11.7M                | 824                              | 3,368,178                |
| Fox News        | 6.71M                | 2,066                            | 4,059,446                |
| MSNBC           | 3.97M                | 3,890                            | 2,776,968                |
| OANN            | 1.36M                | 1,728                            | 427,908                  |
| Newsmax         | 1.77M                | 746                              | 971,617                  |
| Blaze TV        | 1.34M                | 518                              | 634,650                  |
| Donald J. Trump | 2.68M                | 2,212                            | 2,382,821                |

Our analyses primarily focus on two non-overlapping time intervals. We denote the time interval of 31st August, 2020 to 2nd November, 2020, i.e., the 64 days leading up to the 2020 US election, as $T_{before}$, refers to the time interval starting from November 3rd, 2020 to January 5th, 2021. Starting from 31st August, 2020 to 5th January, 2021. We denote the combined time interval of these 128 days as $T_{31}$. Overall, our data set consists of 14,557,966 comments on 11,964 videos posted by 2,278,034 users.

3 RESEARCH QUESTIONS

3.1 President-elect Biden
Before we delve deeply into our user-focused research questions, we present first a simple yet powerful count-based analysis of a phrase from the news video transcripts that indicates that different news networks indeed characterized the election outcome differently. Our selected phrase is “President-elect Biden” (and a few high-frequency variants of these—e.g., “President-elect [wildcard] Biden” to make room for Joseph or Joe or Joseph R.). We argue that after November 7th, 2020, when the Associated Press called the election for Biden, any reference to President-elect Biden in any news video indicates support for the legitimacy of the Biden victory.

Table 3 lists the percentage of times that a news video mentioning Biden refers to him as “President-elect” at least once. We note that, while the two mainstream media outlets exhibit comparable mentions of the phrase “President-elect”, the three conservative fringe networks show remarkably fewer mentions of this term indicating a possible stance of not accepting the official outcome of the election. The of the three big networks, Fox News is a well-known conservative network. However, on portraying the election outcome, we note that surprisingly, Fox did not side with its far-right counterparts and used the phrase as much as MSNBC did.

3.2 Research Question 1 (RQ 1)
Given that Fox has described the election’s legitimacy in the same way as other mainstream networks, coupled with the fact that

$^7$Apart from CNN, for each news video, we also extracted video transcripts using a Python package. The package did not give reliable results for CNN, hence we omit CNN in our analyses on the news transcripts.

$^8$Of course, there could be counter-examples—for instance, an anchor saying “I am never going to refer to him as President-elect Biden until Supreme Court hears the case”. We manually inspected 100 randomly sampled unique references across 100 videos and confirm that is not the case.
Table 3: Analysis of the overall stance toward accepting the election outcome of Biden being the President-elect across different news networks. Percentages shown are the percentage of times that a news video mentioning Biden refers to him as 'President elect.' These results indicate that both mainstream media outlets Fox News and MSNBC referred to Biden as President-elect relatively more than the fringe media outlets.

| YouTube Channel | Measure |
|-----------------|---------|
| CNN             |         |
| Fox News        | 29.1%   |
| MSNBC           | 28.8%   |
| OANN            | 2.7%    |
| Newsmax         | 6.5%    |
| Blaze TV        | 13.9%   |

Trump requested his followers to abandon Fox, a natural follow-up question is whether there was a user migration from Fox to fringe networks. Unlike Reddit or Twitter, the network structure of YouTube users is opaque. YouTube APIs do not allow tracking individual user subscriptions and video views and likes are anonymized. Furthermore, a disgruntled user still may want to stick to the same news network without completely shunning it albeit with a lower engagement. To understand these nuances, we have the following broad research question: **RQ 1**: How did the user engagement of news viewsherships evolve between $T_{\text{before}}$ and $T_{\text{after}}$?

Specifically, we break down the above research question into two related sub-parts:

**RQ 1.1:** Were there any shifts in viewer engagement of news networks post election?

**RQ 1.2:** Were there any systematic migrations from mainstream media outlets to fringe media outlets?

### 3.3 Research Question 2 (RQ 2)

A central challenge in this paper is to obtain quantifiable linguistic signals from unstructured texts and combine them with the user engagement signals to construct an accurate portrayal of this complex time period. Our work involves multiple news networks airing competing narratives about the election legitimacy and how that affected the dynamics of the news viewsherships. We are interested in aggregating opinions about the legitimacy of the election in individual news viewsherships from these unstructured texts. Hence, we have the following research question: **RQ 2**: How did the aggregate opinions of news viewsherships about the election outcome manifest linguistically during $T_{\text{after}}$?

### 3.4 Research Question 3 (RQ 3)

While existing academic research and news articles have examined questions such as Trump’s tweets’ influence on financial markets [5] or how watching videos on Trump’s political rallies influences YouTube video recommendations [35], to our knowledge, characterizing the viewshership of Trump official YouTube channel has little or no existing literature. As our final research question, we are therefore interested in learning if it is possible to estimate how similar Trump’s YouTube viewers are to different news viewsherships. Leveraging a recently proposed technique based on machine translation [22], we thus seek to compare and contrast linguistic signals from Trump’s YouTube channel to answer: **RQ 3**: Based on the comments on the viewed videos, which news networks were “linguistically most similar” to those of President Trump’s YouTube channel?

### 4 RELATED WORK

Previous research on US cable news reported divergent views both in audience and in content [13, 19]. However, these works focused on the television medium and primarily relied on surveys. In terms of the nature of our data set, our work is closest to [22] in its use of comments on YouTube news videos of major US cable news networks. We also leverage the linguistic framework and a measure to estimate viewership agreement from this work. Our work contrasts with [22] in the following key ways: (1) our focus on an important (and timely) and non-overlapping period of 64 days prior and after the 2020 US election; (2) our emphasis on three fringe news networks, two of which were (Newsmax and Blaze TV) previously ignored in [22] and one briefly analyzed; and (3) our use of a wider variety of NLP tools in analyzing a broader range of research questions rather than presenting a quantifiable framework to gauge linguistic polarization.

Previous work on deplatforming has analyzed effects of large-scale bans of communities on other social media platforms such as Reddit [8]. Our work on analyzing the migration of Fox News viewers to Newsmax adds a subtle nuance that in this case users are not being deplatformed by the platform owners. It is rather (potentially) triggered by calling the election as per the Associated Press. Echo chambers in social media is a widely studied topic [6, 14, 20]. Our work is similar to past work on analyzing the presence of echo chambers [25] in conservative forums with a key distinction that our choice of platform is heavily mainstream.

Our work draws inspiration from several recent NLP contributions analyzing political corpora [22, 29] or misinformation [16]. For instance, [29] presented an application of language models [11] to mine insights and aggregate opinions using language models fine-tuned on an Indian political social media data set. Cloze tests [34], aka fill-in-the-blank test, involves a single-word completion task of a sentence or a sentence stem. When presented with a cloze test, BERT [11], a prominent language model, outputs a sequence of possible completions ranked by probability. [29] has shown that BERT can be fine-tuned on social media unstructured texts and cloze tests can be used to aggregate opinions. Similarly, [16] presents a link between stance detection and text entailment in the context of detecting COVID-19 misinformation. We demonstrate the synergy between these methods on a critical domain of political crisis.

### 5 USER ENGAGEMENT SIGNALS (RQ 1)

#### 5.1 Post Election Engagement Shift (RQ 1.1)

**RQ 1.1:** Were there any shifts in viewshership engagement of news networks post election?

We investigate the above research question through three signals: (1) video likes and dislikes; (2) news network subscriber count; and (3) average comment count.

**Video likes and dislikes:** Following [22], we use the same viewshership disagreement measure to estimate disagreement in a network.
Table 4: Analysis of viewership agreement. For a given news network and time duration, each cell summarizes the \( \sum_i I(v^i, C, T) \) and \( \frac{v^i_{like}}{v^i_{like} + v^i_{dislike}} \). We observe that CNN, Blaze TV and MSNBC do not show any noticeable change in average number of comments; (2) Fox News exhibits a curious pattern where the market-share drops. Also, there can be several other possible news sources even on YouTube. That said, our measure allows us to track the growth of these six networks revealing insights into the nature of growth of these fringe networks in the last 128 days.

Table 5: Analysis of engagement. For a given news network and time duration, each cell summarizes the channel activity as \( a / b \) where \( a \) denotes the number of videos uploaded and \( b \) denotes the average number comments on videos. We note that Newsmax and OANN enjoyed a remarkable increase in average number of comments per video. Note that, OANN was banned for a week by YouTube because of spreading COVID-19 misinformation.

| YouTube channel | \( T_{before} \) | \( T_{after} \) | \( \Delta_{disagreement} \) |
|-----------------|------------------|------------------|-----------------------------|
| CNN             | 0.20             | 0.17             | +0.03                       |
| Fox News        | 0.18             | **0.28**         | **-0.10**                   |
| MSNBC           | 0.10             | 0.09             | +0.01                       |
| OANN            | 0.02             | 0.02             | 0                           |
| Newsmax         | 0.01             | 0.02             | -0.01                       |
| Blaze TV        | 0.02             | 0.05             | -0.03                       |

Let \( v^i_{like} \) and \( v^i_{dislike} \) denote the total number of likes and dislikes received by a given video \( v^i \). Let for a given channel \( C \), \( I(v^i, C, T) \) returns 1 if video \( v^i \) is uploaded within duration \( T \), otherwise it returns 0. The disagreement factor of a channel \( C \) for a given time duration \( T \) is thus calculated as \( \frac{\sum_i I(v^i, C, T) v^i_{dislike} + v^i_{like}}{\sum_i I(v^i, C, T) v^i_{like} + v^i_{dislike}} \). The interpretation of a low value of this measure is overall, videos are generally liked by substantially more viewers than disliked in the channel. A higher value indicates mixed user response with an increasing fraction of disapproving viewership. As a nice property of this measure, [22] further points that the ratio \( \frac{v^i_{like}}{v^i_{like} + v^i_{dislike}} \) for an individual video and the overall measure are both bounded within [0,1] and one arbitrarily heavily liked or disliked video can at most influence the overall average by \( \frac{1}{n} \) where \( n \) is the total number of videos uploaded in that particular duration (as shown in Table 4, the minimum value for \( n \) in our case is 294).

Table 4 presents the disagreement factor for each channel for time duration \( T_{before} \) and \( T_{after} \) and the difference in disagreement (denoted by \( \Delta_{disagreement} \)) obtained by subtracting the disagreement in \( T_{after} \) from \( T_{before} \). A positive \( \Delta_{disagreement} \) indicates that the channel has gained popularity while a negative value indicates a decline in popularity. We note that apart from Fox News, \( \Delta_{disagreement} \) is within \( \pm 0.03 \) for all other news networks.

Comments on videos: The two time slices are focusing on, both are expected to generate high viewership. \( T_{before} \), i.e., the time slice leading up to the election would naturally attract viewers while as a result of casting widespread doubts over the legitimacy of the election, the engagement during \( T_{after} \) would be high as well. Also, note that, since any video uploaded during \( T_{before} \) would have more time to accrue comments than any video uploaded during \( T_{after} \), it is not surprising if the average number of comments for videos uploaded during \( T_{after} \) is slightly less than the average number of comments for videos uploaded during \( T_{before} \) for a given channel. However, Table 5 shows three distinct patterns. We notice that (1) CNN, Blaze TV and MSNBC do not show any noticeable change in average number of comments; (2) Fox News shows noticeable decline in comment engagement; and (3) OANN and Newsmax show an increase by more than factors of 2 and 3, respectively.

Number of subscribers: Comments on a news video or likes or dislikes are response to an individual unit of content supplied by a given channel – a single video. YouTube viewers can subscribe for specific channels indicating that they are willing to receive updates on the channel’s activities (e.g., receive notification when a new video is uploaded). In that sense, subscription to a channel is perhaps a more longer term engagement signal than liking (or disliking) or commenting. Let for each channel \( C, C_{sub} \) denote the total number of subscribers of \( C \) at time \( t \). We define market-share of subscribers of a given channel \( C_i \) at time \( t \) as:

\[
\text{marketShare}(C_i, t) = \frac{C_{i,sub}}{\sum_j C_{j,sub}}
\]

where \( C_i, C_j \in \{\text{Newsmax, Blaze, CNN, OANN, Fox, MSNBC}\} \). We admit that our definition oversimplifies certain things since a specific user can subscribe to multiple news networks at the same time. Also, there can be several other possible news sources even on YouTube. That said, our measure allows us to track the growth of these six networks revealing insights into the nature of growth of these fringe networks in the last 128 days.

Table 6 summarizes the market-share of the news networks on three particular days: (1) 31st August 2020, the first day of \( T_{before} \); (2) 3rd November, 2020, the first day of \( T_{after} \) and the day of 2020 US election; and (3) January 5th, 2021, the last day of \( T_{after} \). We note that (1) all fringe news networks gained market-share as time progressed with Newsmax’s gain being equal to a factor of 6 (Figure 1 presents its growth); (2) the big-three (CNN, Fox News, and MSNBC) lost market share when compared against their individual market-shares on 5th January, 2021 with what was on 31st August, 2020; and (3) Fox News exhibits a curious pattern where the market-share slightly rises on 3rd November, 2020 and then dips.

5.2 User Migration (RQ 1.2)

**RQ 1.2:** Was there any systematic migrations from mainstream media outlets to fringe media outlets?

Table 5, Table 4, and Table 6 all point to a decline in Fox News’s popularity during \( T_{after} \) as compared to \( T_{before} \). We are curious to examine where did these viewers go? Let \( N_{i,fox} \) and \( N_{i,newmax} \) denote the total number of comments made by user \( u_i \) on Fox News videos and Newsmax videos uploaded during \( T_{logs} \), respectively. We focus on highly active users who commented both on Fox News and Newsmax videos to obtain a user set \( U \) such that \( u_i \in U \) if \( N_{i,fox} > 0, N_{i,newmax} > 0 \) and \( N_{i,fox} + N_{i,newmax} \geq 10 \). In plain words,
Figure 1: The growth of Newsmax in terms of #subscribers. The vertical lines indicate important dates. The two Presidential debates took place on September 29th and October 22nd. The election took place on 3rd November and AP called the election for Biden on 7th November. The electoral college vote took place on December 14th.

Table 6: Analysis of market-share in terms of subscriber count. We define the market-share of a channel in a particular time $t$ as the ratio of its subscriber count to the sum of subscriber count at time $t$ of all the news channels considered.

| YouTube channel | 31st August, 2020 | 3rd November, 2020 | 5th January, 2021 |
|-----------------|------------------|-------------------|------------------|
| CNN             | 47.68%           | 46.13%            | 43.66%           |
| Fox News        | 27.47%           | 27.63%            | 24.96%           |
| MSNBC           | 15.58%           | 15.20%            | 14.74%           |
| OANN            | 3.71%            | 3.94%             | 5.03%            |
| Newsmax         | 1.10%            | 2.28%             | 6.60%            |
| Blaze TV        | 4.46%            | 4.99%             | 5.00%            |

Table 7: Analysis of comment-share between pair of networks. For a network pair ($C_1, C_2$) the share is summarized as $a / b$ where $a$ denotes comment share of $C_1$ and $b$ denotes comment share of $C_2$.

| YouTube channel | $T_{before}$ | $T_{after}$ | $T_{earliest}$ | $T_{latest}$ |
|-----------------|--------------|-------------|----------------|--------------|
| Fox News - Newsmax | 91% / 9%     | 57% / 43%   | 89% / 11%      | 59% / 41%    |
| CNN - MSNBC     | 45% / 55%    | 46% / 54%   | 45% / 55%      | 47% / 55%    |

our user set contains users who have made at least one comment on Fox News and Newsmax and the total number of comments made on Fox News and Newsmax by the user exceeds or equals 10. We obtain 69,766 users satisfying these conditions. We then analyze their activities by slicing $T_{128}$ in two different ways. One natural choice is the temporal slices $T_{after}$ and $T_{before}$. Our second choice of time slice divided $T_{128}$ along the activity timeline of a given user. We consider the earliest 20% and the latest 20% comments made by each user during $T_{128}$ and analyze the relative share of comments in Fox News and Newsmax.

Table 7 summarizes our findings. In order to contrast our results, as a control group, we consider the channel pair of CNN and MSNBC and analyzed the comment shared of user group of 99,101 users following the conditions described above. We notice that during the distribution of comments in CNN-MSNBC pair was stable across $T_{before}$ and $T_{after}$. However, we notice a stark contrast in Fox-Newsmax pair. During $T_{before}$, Newsmax has a minuscule presence while $T_{after}$ exhibits a near equal comments share with Fox. The qualitative trend of this analysis remains unchanged even when we consider our user activity-based timeline. Hence, our analyses indicate that several users from Fox News moved to Newsmax.

6 LINGUISTIC SIGNALS (RQ 2)

RQ 2: How did the aggregate opinions of news viewshers about the election outcome manifest linguistically during $T_{after}$?

We investigate this research question (1) using relative frequency of a popular trigram to discredit the election outcome; (2) cloze tests on deep models trained on individual discussion data sets; and (3) casting the problem as a text entailment task.

6.1 Stop the steal

Table 8: Example of comments using the trigram “stop the steal”.

| Example Comment |
|-----------------|
| theres obviously massive voter fraud trump is the legal winner stop the steal (CNN) |
| stop the steal stop the democrat traitors and their chinese allies (CNN) |
| joe biden is weak corrupt and c c p china knows this biden is illegitamite due to cheating d n c stop the steal trump has to win (Fox News) |
| newsmax tv and rudy gulianni is telling the truth stop the steal what a shameful and disgraceful election (Fox News) |
| this guy is a great american stop the steal screw you msnbc (MSNBC) |
| stop the steal we all know trump won in a landslide (MSNBC) |
| trump won this election stop the steal enforce martial law drain the swamp (OANN) |
| stop the steal of our democracy let these perpetrators loose their citizenship and be forced out of our country (OANN) |
| donald j trump must win stop the steal i voted for justice freedom and for the world liberty (Newsmax) |
| the only way democrats can win a majority is through voter fraud stop the steal (Newsmax) |
| buy ammo patriots this is exactly what the second amend-ment is for a tyrannical government stop the steal (Blaze TV) |
| save the american republic stop the steal the globalist marxist liberal dnc coup must be stopped (Blaze TV) |

We start with a simple analysis of the usage of the following trigram: “stop the steal”. The choice of this phrase is guided by the “stop the steal” protests aimed at discrediting the 2020 election.
Table 9: Cloze test results for the probe *The biggest problem of America is [MASK]*. A separate version of BERT was fine-tuned, using viewer comments from each network. Top three results (ranked by probability) output by fine-tuned BERT are presented for each news network.

| MSNBC          | CNN         | Fox News   | OANN        | Newsmax    | Blaze TV   |
|----------------|-------------|------------|-------------|------------|------------|
| trump, covid,  | corruption, | racism,    | communism,  | corruption, | corruption, |
| unemployment   | corruption,  | communism, | socialism,  | corruption, | socialism,  |
|                | socialism,  |            |             | socialism,  |            |
|                |             |            |             |             |            |

Table 10: Analysis of "stop the steal" across news networks.

| YouTube channel | Rank |
|-----------------|------|
| MSNBC           | 111  |
| CNN             | 134  |
| Fox News        | 123  |
| MSNBC           | 75   |
| OANN            | 63   |
| Newsmax         | 111  |
| Blaze TV        | 63   |

Table 10 shows that while this trigram is considerably popular across all six channels, OANN and Newsmax particularly stand out.

6.2 Cloze Tests and Natural Language Inference

The masked word prediction of high-performance language models, such as BERT [11], has a parallel in the form of cloze tests [34] aka fill-in-the-blank questions used in the human psycholinguistics literature [32]. When presented with a sentence (or a sentence stem) with a missing word, a cloze task is essentially a fill-in-the-blank task. For instance, in the following cloze task: *In the [MASK], it snows a lot, winter is a likely completion for the missing word. In fact, when given this cloze task to BERT, BERT outputs the following five seasons ranked by decreasing probability: winter, summer, fall, spring and autumn. In our work, we are interested in gauging the aggregate attitude of a network viewership toward the outcome of the 2020 election. For each channel, we fine-tune BERT with the comments on videos uploaded during *T*\textsubscript{after}, BERT’s vulnerability in handling negations is documented in [21]. Following [29], we remove all comments that contains any valence shifter.

We first make a small digression to discuss a result that sheds light on the stark contrast of opinions across these news networks. On a cloze test *The biggest problem of America is [MASK]*, we notice that the top three results succinctly capture the divergent views of the news audience across news networks. While *socialism* consistently appeared in all conservative networks, *trump, covid, and racism* appeared in their liberal counterparts.

To rank the aggregate opinion on the 2020 US election, we consider the following two cloze tests: (1) *Trump has [MASK] the 2020 election* (denoted by *cloze*\textsubscript{trump}) (2) *Biden has [MASK] the 2020 election* (denoted by *cloze*\textsubscript{biden}). Let *cloze*\textsubscript{test}(c, w) denote the probability of the word w output by BERT. In order to appropriately calibrate the model, we compute the score for Trump as  

\[ \text{score}_{trump} = \text{cloze} \text{test}(\text{cloze}_{\text{trump}}, \text{won}) \]

and Biden as  

\[ \text{score}_{biden} = \text{cloze} \text{test}(\text{cloze}_{\text{biden}}, \text{won}) \]

The scores for Trump for different news networks give us the following order: MSNBC < CNN < Fox < OANN < Blaze < Newsmax indicating that compared to mainstream media outlets, discussions on fringe news channels exhibit more doubts on the legitimacy of the election.

We further corroborated our results with a well-known natural language inference model [12]. Given a premise and a hypothesis, the natural language inference (NLI) task involves predicting entailment, contradiction, or independence. For example, the hypothesis *some men are playing a sport* is entailed by the premise *a soccer game with multiple males playing* [7]. Our work draws inspiration from a recent work [16] that cast the task of COVID-19 misinformation detection as an NLI task stating that the class labels informative, misinformative and irrelevant has a natural one-to-one correspondence to entailment, contradiction and semantic irrelevance, respectively. For a given news network, using individual comments from our data set as premise, we tested the following two hypotheses:

**Hypothesis 1:** I prefer Trump as my president. (denoted by H\textsubscript{1})

**Hypothesis 2:** I prefer Biden as my president. (denoted by H\textsubscript{2})

For a given channel C and a hypothesis H, we randomly sampled 5,000 comments from user discussions on videos uploaded on C during *T*\textsubscript{after}, and compute the fraction of comments that entails H. Obtained order for H\textsubscript{1}: MSNBC < CNN < Fox < OANN < Blaze < Newsmax < Blaze TV.

Obtained order for H\textsubscript{2}: Blaze TV < OANN < Fox < Newsmax < MSNBC < CNN.

7 TRUMP’S YOUTUBE CHANNEL (RQ 3)

**RQ 3:** The comments on videos of which news network is linguistically most similar to the comments on the videos in the official YouTube channel of President Trump?

In this experiment, we leverage a recently-proposed framework based on machine translation that quantifies the differences between large-scale social media discussion data [22]. This framework assumes that two sub-communities (e.g., Fox viewers and CNN viewers) are speaking in two different languages (say, $L$\textsubscript{CNN} and $L$\textsubscript{Fox}) and obtains single-word translations using a well-known
machine translation algorithm [33]. In a world not fraught with polarization, any word \( w \) in \( L_{\text{cnn}} \) should translate to itself in \( L_{\text{fox}} \). However, if a word \( w_1 \) in one language translates to a different word \( w_2 \) in another, it indicates \( w_1 \) and \( w_2 \) are used in similar contexts across these two languages signalling (possible) disagreement. These disagreed pairs present a quantifiable measure to compute differences between large scale corpora as greater the number of disagreed pairs the farther two sub-communities are.

Formally, let our goal be computing the similarity measure between two languages, \( L_{\text{source}} \) and \( L_{\text{target}} \), with vocabularies \( V_{\text{source}} \) and \( V_{\text{target}} \), respectively. Let translate\((w)\)\(\text{source} \to \text{target}\) denote a single word translation of \( w \in V_{\text{source}} \) from \( L_{\text{source}} \) to \( L_{\text{target}} \). The similarity measure between two languages along a given translation direction computes the fraction of words in \( V_{\text{source}} \) that translates to itself, i.e.,

\[
\text{Similarity}(L_{\text{source}}, L_{\text{target}}) = \frac{\sum_{w \in V_{\text{source}}} \mathbb{1}(\text{translate}(w) \in V_{\text{source}}) \land \text{translate}(w) \to \text{target}}{|V_{\text{source}}|}
\]

The indicator function returns 1 if the word translates to itself and 0 otherwise. The larger the value of Similarity \((L_{\text{source}}, L_{\text{target}})\), the greater is the similarity between a language pair.

In this work, we consider the official YouTube handle of former President Trump. We follow the same steps and hyper-parameter settings described in [22] and in Table 11, we quantify the similarities between language present in the official YouTube channel of Donald Trump (denoted by \( L_{\text{trump}} \)) and the six US cable news networks. We use the same monikers for the languages in the four news networks considered in [22] (\( L_{\text{cnn}}, L_{\text{fox}}, L_{\text{msnbc}}, \) and \( L_{\text{oann}} \)) and denote the language of the discussions on Blaze TV and Newsmax news videos as \( L_{\text{blaze}} \) and \( L_{\text{newmax}} \), respectively.

Table 12: Percentage share of comments in \( D_{\text{before}} \) (column \( T_{\text{before}} \)) and \( D_{\text{after}} \) (column \( T_{\text{after}} \)). \( \Delta \text{commentShare} \) is obtained by subtracting the comment share in \( T_{\text{before}} \) from \( T_{\text{after}} \).

| YouTube channel | \( T_{\text{before}} \) | \( T_{\text{after}} \) | \( \Delta \text{commentShare} \) |
|-----------------|----------------------|----------------------|-------------------------------|
| CNN             | 17.69                | 17.81                | 0.12                          |
| Fox News        | 49.90                | 34.60                | -15.3                         |
| MSNBC          | 14.95                | 14.19                | -0.76                         |
| OANN            | 5.48                 | 8.54                 | 3.06                          |
| Newsmax         | 3.88                 | 17.81                | 13.93                         |
| Blaze TV        | 8.10                 | 7.05                 | -1.05                         |

It is well-known that corpus size is one of the most important contributing factors to ensure the quality of word embedding [28]. Further, [22] indicates that typical to most deep learning systems, one of the limitations of the machine translation based framework is it is data-hungry. We thus focus on the entire year of 2020. Table 11 underscores the following two points: (1) the language present in the YouTube videos hosted by the official channel of President Trump is more similar to fringe media outlets than any mainstream media outlet with the ordering (most similar to least similar): \( L_{\text{newmax}} > L_{\text{oann}} > L_{\text{blaze}} > L_{\text{fox}} > L_{\text{cnn}} > L_{\text{msnbc}}; \) and (2) compared to the liberal news outlets, the conservative news networks are more similar to each other. Also, note that, Trump’s YouTube channel is not a news network. Hence, it does not cover issues as varied as a typical news network would. Therefore, it is not surprising that the similarity between \( L_{\text{trump}} \) and other news-languages are lesser than the similarity between news networks.

We were curious to learn about the news media diet of Trump viewers. We first focus on a user set \( U_{\text{Trump}} \) that has made five or more comments on videos from Trump’s channel uploaded during the entire life time of the channel up to Jan 5, 2021. We obtain 113,443 such users. Of these user set, we next construct a subset with user commenting at least once on any of the six news networks during \( T_{128} \). Pruning \( U_{\text{Trump}} \) with this filtering criterion gives us a set of 99,961 overall users (denoted by \( U_{\text{news}} \)). Next, we construct a data set, \( D \), consisting of comments made by users in \( U_{\text{news}} \) on videos (uploaded within \( T_{128} \)) of any of the six news networks. We finally divide \( D \) into \( D_{\text{before}} \) and \( D_{\text{after}} \) consisting of comments posted during \( T_{\text{before}} \) and \( T_{\text{after}} \), respectively. Table 12 presents the percentage shares of comments in \( D_{\text{before}} \) and \( D_{\text{after}} \) for each of the networks. We note that Fox News lost the maximum comment share while Newsmax’s gain was the highest. This result indicates viewers of Trump’s network made a substantial switch to Newsmax.

8 DISCUSSION AND CONCLUSIONS

8.1 Conclusions

This paper leads to two different types of conclusions: conclusions about what actually transpired during the 128 days covered by our data set, and conclusions about methodologies for analyzing such large scale social media to study political and other social sciences.

Before we delve deeply into our substantive conclusions, we emphasize that through this work, we have demonstrated that
recent advancements in NLP methods enable us to analyze a vast amount of data with minimal manual supervision. However, each of these methods has certain blindspots (e.g., BERT’s vulnerability to negation or the translation based method’s requirement of a large of amount data). Our work demonstrates the synergy of these methods in obtaining corroborating evidences from multiple sources and thus gaining valuable insights. While these techniques have been used in isolation on different political corpora [16, 22, 29], in this work, we present a combined approach to analyze a data set on a political crisis the country has not seen for years.

8.1.1 Understanding What Happened. Through a series of corroborating experiments described above, we reach the following conclusions.

C1: Fringe networks did not cover the election the same way as the mainstream networks. (Section 3).

C2: Our linguistic signals indicate that audience of the fringe networks exhibit more doubt about the election outcome as compared to the audience of mainstream outlets. (RQ 2, Section 6)

C3: Our user engagement signals indicate that a considerable fraction of news viewers migrated from Fox to the far more echo-chamberish Newsmax which cast continual doubt over the legitimacy of the election. Fox News was the only mainstream media outlet that lost considerable popularity. (RQ 1, Section 5)

C4: Viewer comments on President Trump’s official YouTube handle are linguistically more similar to viewer comments on fringe networks than those of the more mainstream media outlets. Trump’s viewers remarkably switched from Fox to Newsmax. (RQ 3, Section 7)

Combining these conclusions, we make the following points. First, it is not surprising to observe the user migration from Fox to Newsmax. Studies exist that indicate that users often seek for news that confirm their biases [36]. From linguistic signals and from the fact that the fringe networks still remained echo chambers, we can infer that users who believed that the election was stolen, and migrated to fringe networks, possibly continued believing the election was stolen. What is surprising is that the users’ doubts, fuelled by continued news content about unsubstantiated voter fraud claims, riled up the users to make shockingly disturbing comments such as january 6th washington dc march for trump be there locked and loaded do not comply with treasonous police.

Second, acknowledging that YouTube as a platform operates at a mammoth scale (e.g., every 1 minute on YouTube 500 hours worth of content is uploaded[13]), algorithmic intervention of misinformative content or moderation of hate and/or dangerous speech could be an uphill task. That said, we argue that detecting anomalous news consumption patterns such as the abrupt rise of Newsmax in popularity is a substantially easier task than automatically identifying presence of unsubstantiated claims from videos. Our work thus raises an important point that during a political crisis, news consumption patterns may reveal useful signals.

Finally, our work is an important study in the context of this unique crisis to Western democracy which shows that with the current almost-ubiquitous penetration of the internet, vacuums may fill up rapidly. If a mainstream media is unwilling to present an alternate version of the election outcome, certain fringe networks can fill up the void and enjoy a sudden meteoric rise in popularity possibly through presenting an alternate version of reality. As compared to OANN and Newsmax, the rise in popularity of Blaze TV was relatively muted. While the content and audience of this network is not much different from the other two fringe networks, former President Trump never spoke or tweeted favorably about this network. Our analysis cannot present causal evidence. Neither can it rule out the possibility that a different fringe network will not enjoy a similar run as Newsmax in a subsequent political crisis in the near future.

8.2 Limitations of Our Study

8.2.1 Methodological limitations: For some of our experiments, we build upon pre-trained language models trained on vast amount of texts. Recent works have indicated that these models have a wide range of biases which may percolate to downstream tasks [4]. While our machine translation based experiments train the models from scratch, our experiments using cloze tests and entailment are trained on top of pre-trained models.

8.2.2 Platform limitations: As we mentioned earlier, YouTube APIs do not reveal identities of the video viewers, and likes and subscriptions are anonymized. We thus relied on comments on videos as a signal to track user migration. Since a vast majority of YouTube users do not comment but watch videos, this analysis fails to capture such users.

8.2.3 Single platform versus multiple platforms. In the web-space, YouTube does not reside in vacuum. Beyond video recommendations from the platform itself, activities in outside platforms may influence video popularity. For instance, celebrity recommendations via tweets can spike YouTube engagement. There is a growing trend in analyzing cross-platform behavior of both user [1] and information flow [15, 17]. Our study is confined to a single medium. Our study will be richer if multiple signals from different social media platforms are combined.

8.2.4 YouTube opinion outlets: In our study, we focused on YouTube channels of US cable news networks. However, even within YouTube, these channels are not the only source of news and opinions on US politics. Prominent influencers from both sides of the aisle (e.g., Bryan Tyler Cohen and Steven Crowder) enjoy massive YouTube popularity. News like channels that are not registered to FCC (e.g., The Next News Networks, and The Young Turks) also enjoy millions of subscribers. Furthermore, the political comedians [22] also cover a fair share of political events on YouTube. Our analyses can be enriched by considering these types of political opinion outlets.

8.2.5 Disentangling the effects of YouTube recommendations: Prior studies indicate that while users are aware of the recommendation system but their understanding of the system is limited [2]. It is thus possible that the YouTube video recommendation algorithms may have a strong influence in the news viewership dynamics.

Prior studies on quantifying YouTube recommendations in suggesting radicalized content [24] has reported that YouTube’s algorithm actively discourages viewers to view radicalized content. However, here, we are discussing channels belonging to US cable...
news networks registered to FCC. A detailed study on more than 56k videos has investigated how personalized contributions to affirming misinformation [18]. The key conclusion of this study is that apart from vaccine misinformation, watching misinformation videos typically begets more misinformation video recommendations. This result actually sheds further intrigue into our current case study because we do not know if the YouTube algorithms made any efforts to prevent voter fraud misinformation.

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