Hyperpartisanship, Disinformation and Political Conversations on Twitter: The Brazilian Presidential Election of 2018

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Abstract

This paper examines the role of hyperpartisanship and polarization on Twitter during the 2018 Brazilian Presidential Election. Based on a mixed-methods approach, we collected and analyzed a dataset of over 8 million tweets about Jair Bolsonaro, a far-right candidate from the Social Liberty Party. Our results show that there is a strong connection between polarization, hyperpartisanship and disinformation. As the centrality of hyperpartisan outlets on Twitter grew, more traditional media outlets became less central and conversations became more polarized. We also confirmed that hyperpartisan outlets often shared disinformation or biased information, presented as a "truth-telling" alternative to journalistic outlets. And while disinformation was more frequently observed in the far-right group, it was also present in the anti-Bolsonaro cluster, especially towards the runoff period.

Introduction

On October 28th, 2018, Jair Bolsonaro, a far-right candidate from the Social Liberty Party (PSL) was elected as the 38th President of Brazil, winning over his left-to-central opponent Fernando Haddad by nearly 11% of the votes. The 2018 presidential election happened in two rounds: one on October 7th, and the other on October 28th. During the first round, out of thirteen candidates, Bolsonaro received the majority of votes, with Fernando Haddad, from the Workers' Party (PT), right behind him. During the second round, Bolsonaro was elected with 55.13% of the votes, becoming the 5th president directly elected by the Brazilian population since the begin of the New Republic period in 1985.

The 2018 presidential election was marked by the heavy usage of social media during the campaign, particularly by Bolsonaro and his supporters, a strong presence of hyperpartisan news outlets, and an active circulation of disinformation[1]. Notably, during the election period, Bolsonaro suffered an attempt on his life[2] on September 6th of 2018, and – as a result – concentrated his campaign efforts through social media while recovering. Thus, Bolsonaro's use of social media and the Brazilian election are good examples of how social media may influence political discourse in the country. We particularly focus on the use of Twitter, given that it is an intrinsically public platform that provides space for hyperpartisan outlets, politicians, activists and others to spread information and disinformation about candidates and their policies (Soares, Recuero and Zago, 2018; Soares, Recuero and Zago, 2019).

For this paper, we examine how accounts we identified as "hyperpartisan" and that called themselves "news outlets" influenced political discussions on Twitter. While similar cases of how hyperpartisan outlets influenced online political discussions have been documented around the world (see Bastos and Mercea, 2017; Giglietto et al., 2019), in this study we explore their roles in the spread of disinformation. This case study is part of a larger two-year project examining the Brazilian social media ecosystem and political conversations. Our overarching goal is to determine the role hyperpartisanship and polarization may have played in shaping public debates on social media.

Based on a dataset of 8 million tweets collected in the last week before each round of the presidential election, we examine the following research questions: (1) How "central" were hyperpartisan outlets in discussions about Bolsonaro on Twitter, compared to traditional media outlets? (2) Did the centrality of these outlets change during the two rounds and how? (3) Were these hyperpartisan outlets connected to disinformation?

Related Literature

[1] https://www.nytimes.com/2018/10/19/technology/whatsapp-brazil-presidential-election.html (Accessed on September 2, 2019)
[2] https://www.economist.com/the-americas/2018/09/08/jair-bolsonaro-is-stabbed-at-a-rally (Accessed on September 2, 2019)

Social Media, Political Conversations and Polarization

The impact of social media on political conversations and democracy has been a topic of interest among researchers around the world. One of the key concerns in this area is how social media may be driving political conversations towards polarization, and providing a perfect environment for disinformation to spread, undermining democracies (Tucker et al., 2018). This concern is especially relevant to young democracies, such as Brazil.

Democracy has always been linked to the quality of debates and conversations that could lead to political engagement. In modern democracies, this participation is usually mediated by traditional mass media, which allows for communication between candidates and the public (Maia, 2008). Social media has changed this landscape by providing a new space for conversations and social interaction, one with different affordances such as anonymity and asynchronicity (Papacharissi, 2004). The discussion about how social media influenced political engagement seems to have initially been positive, partially because political conversations on these platforms were expected to increase diversity and enrich the political debate (Papacharissi, 2002; Chadwick, 2009; Stromer-Galley, 2003). However, subsequent studies showed different results; some studies found that conversations on social media tend to cluster people with the same political views, potentially increasing homophily and leading to greater polarization (Adamic and Glance, 2005; Gruzd and Roy, 2014; Bastos, Mercea and Baronchelli, 2017; Soares, Recuero and Zago, 2019).

Some studies credited polarization to social media algorithms and affordances, which would restrict the diversity of content one has access to across social media sites (Sunstein, 2017). On the other hand, studies also identified that users are actively filtering the content they share, reinforcing their political position (Benkler, Faris and Roberts, 2018; Soares, Recuero and Zago, 2018). Online groups of like-minded individuals that reverberate only their own beliefs are often referred to as "echo chambers" (Sunstein, 2001, 2009). In this sense, echo chambers are common in social media political conversations, especially in polarized contexts (Bail et al., 2018). The selective exposure to information that these groups have is also connected to how disinformation and hyperpartisan media circulates. Barberá and colleagues' (2015) work examined political conversations on Twitter and classified them as "national conversation" or "echo chambers". National conversations were characterized as those with diverse points of views, whereas echo chambers were conversations that were more polarized. The researchers found an asymmetry in this polarization, with liberals more likely to be exposed to content from the opposing side compared to conservatives. A greater polarization in the right and the far-right was also found in other studies examining political conversations on social media (Faris et al., 2017; Himelboim et al., 2017; Benkler, Faris and Roberts, 2018; Soares, Recuero and Zago, 2019).

Polarization in online discussions may undermine the quality of the public debate because it may create the perception of "false consensus" within a group (Soon and Goh, 2018). Actors in a polarized group have more contacts with like-minded people than with people who think differently. Because polarized contexts tend to isolate people, it may also support the perfect environment for disinformation to spread. Several studies have shown, for example, that polarized individuals may be more susceptible to disinformation as they have a less variate "media diet" (Benkler, Faris and Roberts, 2018; Tucker et al., 2018; Soares, Recuero and Zago, 2019).

Social Media, Hyperpartisanship and Disinformation

Hyperpartisan media is defined as outlets that "depart from traditional notions of journalistic balance and presents a biased picture of one side of a political debate" (Bhatt et al., 2018). Their content is mostly biased and sensationalist, clearly supportive of a political party or a political view (Mourão and Robertson, 2019). The language used is often exogenous of traditional journalism, with adjectives, exclamation marks, or one-sided information. Furthermore, hyperpartisan outlets frequently define mainstream media as untrustworthy in order to legitimatize their biased views (Benkler, Faris and Roberts, 2018). The spread of hyperpartisan sources is also connected to increasing polarization of the conversation (Bastos and Mercea, 2017). Hyperpartisan websites often cite each other, creating clusters of partisanship (Bhatt et al., 2018).

Hyperpartisan outlets have also been implicated in the spread of disinformation via social media channels such as Twitter (Bastos and Mercea, 2017; Bhatt et al., 2018; Recuero and Gruzd, 2019), often by offering "alternative" stories to what has been reported in traditional news outlets (Larsson, 2019). The hyperpartisan outlets are especially dangerous because their biased content sometimes becomes more visible than content produced by mainstream media (Allcott and Gentzkow, 2017). It happens both because of the form in which they present their content (Mourão and Robertson, 2019) and the action of users who share it to reinforce their political narrative (Soares, Recuero and Zago, 2019). This combination is also linked to the creation of echo-chambers (Benkler, Faris and Roberts, 2018).

The spread of disinformation has been studied by several authors and through several perspectives. While some like to call it "fake news" (Falis, 2009), others believe this is part of a broader phenomenon called "information disorder" (Derakhshan and Wardle, 2017). Information disorders may take three distinct forms: disinformation, misinformation, and malinformation (Derakhshan and Wardle, 2017). Disinformation focuses on content that was created deliberately to mislead, while misinformation is usually connected to false information that did not intend to mislead, like satire, for example. Mal-information, on the other hand, is false information created and particularly aimed at someone. For the authors, disinformation can take several forms: Not only does it comprise of fabricated information, but it can also include other strategies, such as reframing a real story with a false context, or by connecting it to another piece of false information. In this paper, we will use disinformation in this same sense. Thus, disinformation can be fabricated information or misleading information, created through framing a fact through a false context, or creating a false connection between two facts (Derakhshan and Wardle, 2017).

Disinformation spread may occur through several avenues; apart from hyperpartisan outlets, there are other actors associated with disinformation, such as bots, activists, and political leaders (Tucker et al., 2018). Activists in political conversations tend to filter the content they interact with, mostly reinforcing their own position and frequently ending up fortifying echo chambers (Soares, Recuero and Zago, 2018). Similarly, bots and fake accounts are often used to influence political conversations by falsely fueling some political positions and creating the perception of "false consensus" (Soon and Goh, 2018; Tucker et al., 2018; Bastos and Mercea, 2017). Although the direct consumption of disinformation might be limited to smaller groups (Guess, Nyhan and Reifler, 2018), their action as a "vocal minority" might affect the political conversation as a whole (Guess et al., 2018; Eady et al., 2019). Political leaders or opinion leaders in echo chambers usually achieve centrality by producing radicalized or biased content that reinforces the political views of the group (Soares, Recuero and Zago, 2018). In this environment, users are more likely to be misled and misinformed (Flynn, Nyhan and Reifler, 2017), which may also affect their political decisions. Therefore, it is important to analyze how hyperpartisan outlets affected political conversation during the Brazilian elections and how it was related to the spread of disinformation.

Method

To examine if and how hyperpartisan outlets influenced political conversations on Twitter during the 2018 Presidential Election in Brazil, we ask:

RQ 1 – How "central" were hyperpartisan outlets in discussions about Bolsonaro on Twitter, compared to more traditional media outlets?

RQ 2 – Did the centrality of these outlets change during the two rounds, and how?

RQ 3 – Were these hyperpartisan outlets connected to disinformation?

To answer these questions, we analyzed the public conversations about Jair Bolsonaro during two periods of the 2018 Presidential Election in Brazil: 1) the last week before the first round of voting (September 30th - October 7th, 2018), and 2) the last week before the runoff (October 20th - 28th, 2018). We chose these periods because they correspond to the period with more activity in the campaigns. Altogether, we collected over eight million tweets mentioning "Bolsonaro", with the help of Twitter's Search API and via the Social Feed Manager application (Prom, 2017). The summary of the data is presented in Table 1.

	# of Tweets	# of Accounts
1st round	2,377,740	845,705
2nd round	5,679,053	1,398,107

Table 1: Dataset Summary

Next, we used custom Python scripts to discover conversational networks based on the collected data. To examine the centrality of hyperpartisan outlets in the resulting network, we used Social Network Analysis (SNA; Wasserman and Faust, 1994). In our networks, users are the nodes and interactions between them (retweets, replies, and mentions) are the edges. To examine potential polarization within these conversations, we first used a modularity algorithm (Blondel et al., 2008) to identify groups of highly connected accounts. We focused on the two largest clusters in each network. We then examined average degree centralities (indegree and outdegree) and clustering coefficient within each of the two clusters (as if they were separate networks). The overall clustering coefficient for each cluster was calculated as the average of clustering coefficients for each node in the cluster, which in turn was measured by the level of connectivity among the neighboring nodes (Watts and Strogatz, 1998).

We also used Connected Concept Analysis (CCA; Lindgreen, 2016) to identify the most prevalent concepts discussed among members of each cluster. To conduct CCA, we used our custom Python script. First, the concepts were identified based on the number of occurrences in the dataset. The threshold for each concept to be included in the analysis was 100 occurrences because we were interested in the most prevalent topics circulated in each cluster. Further, we manually grouped related concepts (e.g., "election" and "elections").

The final step in CCA was to connect concepts into a network representation based on their co-occurrence in tweets (excluding retweets). These steps were repeated for each cluster separately. We used the resulting "semantic" networks to identify the most prevalent political topics discussed by Twitter users in each cluster in the conversational networks. The discovered topics confirmed that each of the two largest clusters contained tweets representing the opposite political views: one group of accounts that primarily circulated pro-Bolsonaro content (pro-Bolsonaro cluster) and another group that mostly shared content in opposition to Bolsonaro and his policies (anti-Bolsonaro cluster).

We used indegree centrality as a measure of influence in the network because it is based on the number of retweets, replies and mentions one receives in the conversation (Cha et al., 2010). Notably, some research has shown that indegree and other measurements of influence, such as eigenvector centrality, tend to produce a similar list of influencers on Twitter (Dubois and Gaffney, 2014). We also explored outdegree centrality as a measure of users' participation (Soares, Recuero and Zago, 2018). Outdegree centrality focuses on how many tweets with a connection (retweets, replies or mentions) were created by a given account. A high outdegree may show activists (Soares, Recuero and Zago, 2018). Although some of these accounts are likely to be automated (bots), what matters to our analysis is how such accounts may give more visibility to certain media outlets, affect political discussions and potentially spread disinformation (Tucker et al., 2018; Guess et al., 2018; Soares, Recuero and Zago, 2018, 2019; Eady et al., 2019).

Finally, we qualitatively examined the top 500 accounts (based on indegree) within each group to identify media outlets. To accomplish this, we used content analysis (Krippendorff, 2013). We classified accounts that belong to media outlets into "hyperpartisan media" and "traditional media". Hyperpartisanship was determined by analyzing the description of the account and their last 20 published tweets. Specifically, following the prior work in this area (Bhatt et al., 2018; Larsson, 2019; Mourão and Robertson, 2019), we checked: 1) if the account supported a political party, candidate or ideology, clearly stated in the description or its tweets, 2) if the account identified itself as content-focused, sharing and producing "news"; 3) if the account used emotional and/or sensationalist language, and 4) if it shared biased information in support of a political party, candidate or ideology. Traditional media outlets were classified based on either the "checked" verification logo provided by Twitter for some official accounts, or the identification of a traditional news source, such as a newspaper, TV or radio news.

For all accounts that belong to hyperpartisan outlets, we examined the 20 most retweeted stories from each of these outlets to check for presence of disinformation. We considered any type of disinformation including: fabricated information, biased framing and use of false connections or contexts to mislead readers (Derakhshan and Wardle, 2017; Mourão and Robertson, 2019). Disinformation was classified based on the fact-checking sources such as Agência Lupa[3] and Aos Fatos[4]. To identify disinformation, we read the tweets and checked their content against fact-checking sources. Two independent coders analyzed the messages to identify disinformation (resulting in the inter-coder reliability Kappa score of .574). A third "tie-breaker" coder was used to resolve any disagreement between the first two coders.

Results

Polarization and Hyperpartisanship

When examining the conversation networks in each of the timeframes, we found a high clustering of nodes around two groups, depicting a "polarized crowds" or "echo chamber" structure rather than a "network conversation" structure (Smith et al. 2014; Himelboim et al., 2017; Barberá et al., 2015). The nodes representing Twitter accounts are displayed on the left side of Figures 1-4.

Further, when we examined the tweets through CCA (Lindgreen, 2016). CCA concepts are displayed on the right side of Figures 1-4. Based on CCA, we found a clear pro-Bolsonaro discourse in the pro-Bolsonaro group in both rounds. The discourse produced by accounts in the other cluster in both networks focused on several politicians, with a strong anti-Bolsonaro sentiment.

In particular, during the first round, the main concepts in the pro-Bolsonaro group were strongly connected to Bolsonaro's discourse (Figure 1), such as: 1) religious, pro-military, pro-guns, anti-left concepts; 2) the presence of supporting hashtags around Bolsonaro (#supportBolsonaro, #Bolsonaroismypresident, etc.); 3) the most cited/retweeted people were Bolsonaro's supporters (i.e., his sons, people who worked in his campaign). The most central discussion focused on the attempt on Bolsonaro's life, described as terrible and connected to a conspiracy led by the Left.

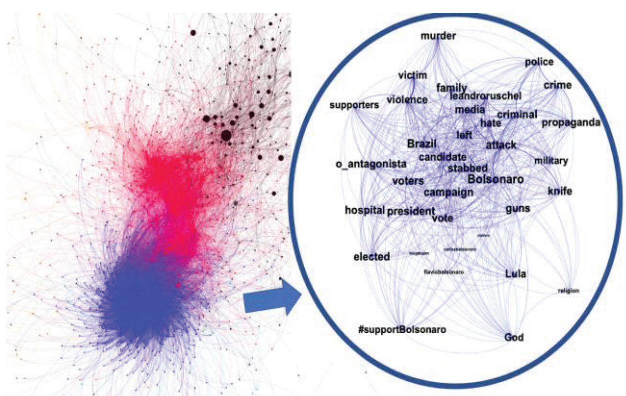

Figure 1: Pro-Bolsonaro cluster during the first round (cluster on the left), with related CCA concepts shown on the right.

[3] https://piaui.folha.uol.com.br/lupa/ (Accessed on September 2, 2019)
[4] https://aosfatos.org/ (Accessed on September 2, 2019)

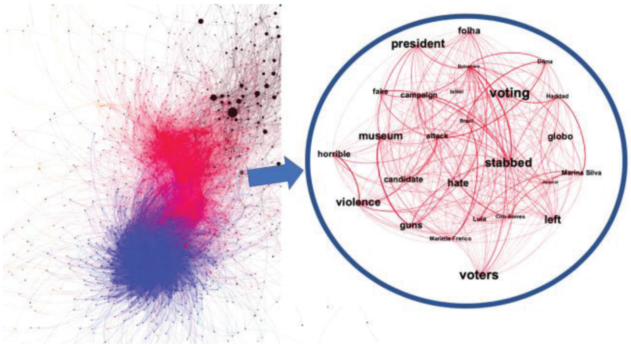

Figure 2: Anti-Bolsonaro cluster during the first round (cluster on the left), with related CCA concepts on the right.

On the other hand, the anti-Bolsonaro cluster was characterized by a discourse against Bolsonaro (Figure 2). The central discussion was also about the attack on Bolsonaro, but mostly discussing the pro-gun defense of the candidate. Although there were many similar concepts, we can see that the frame of the discussion was different (for example, questioning Bolsonaro's "fake" attack). Most of the other candidates (e.g., Ciro Gomes, Fernando Haddad, Marina Silva, and Geraldo Alckmin) appeared in the discussion as well. Other left-leaning discussions, such as the assassination of Marielle Franco and the fire that consumed the National Museum were also present.

Data from the second round (runoff) shows similar results (Figures 3 and 4). First, there are two different clusters, indicating that users from each group were more involved in the conversation that supported their candidates. In the pro-Bolsonaro cluster, there is a strong presence of concepts associated with the candidate's discourse (Figure 3), as in the first round (e.g., "Bible", "guns", the association with "trump"), as well as hashtags such as "bolsonaroYES" and "leftNO".

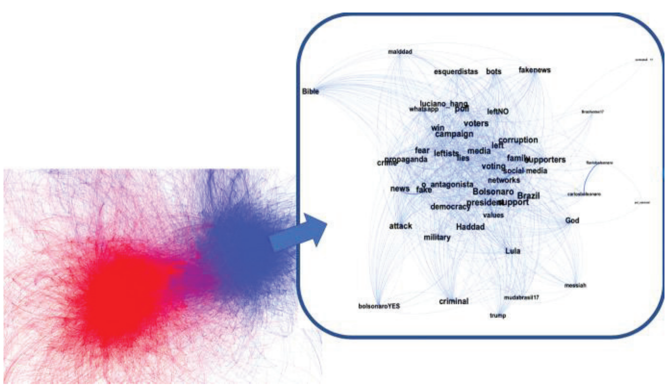

Figure 3: Pro-Bolsonaro cluster during the second round (cluster on the left), with related CCA concepts shown on the right.

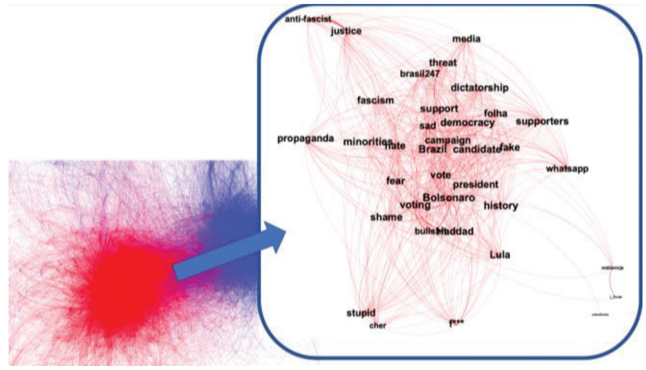

Figure 4: Anti-Bolsonaro cluster during the second round (cluster on the left), with related CCA concepts on the right.

The anti-Bolsonaro cluster (Figure 4) included concepts reflecting negative emotions towards Bolsonaro such as "fascism" and "dictatorship", as well as the hashtags "anti-fascist" which were used to refer to the movement against the candidate. Concepts such as "minorities", "human rights", "fear", and "threat" were also present, as well as hashtags such as "#elenão" (not him), which were part of the protests against Bolsonaro during this period.

Tables 2 and 3 show that these clusters have a higher indegree/outdegree average than the other clusters, suggesting more active participation by accounts within each cluster (Soares, Recuero and Zago, 2018, 2019). Interestingly, both clusters increase their average indegree and outdegree from Round 1 to Round 2, but this increase was higher in the anti-Bolsonaro cluster. Therefore, during both periods, accounts in the pro-Bolsonaro cluster were more interconnected (higher indegree/outdegree average) than accounts in the rest of the network. The same is true with clustering coefficient: the metric increased from the first to the second round and was higher within the pro-Bolsonaro cluster. The higher average degree and clustering coefficient from the first to the second round suggests the network became more polarized, as the users were more connected within their clusters and more active in sharing like-minded content. This tendency was especially prevalent among pro-Bolsonaro users, which suggests they were more active in reproducing content within the cluster. This finding is in line with previous findings that far-right clusters tend to be more engaged in sharing their own content and have less contact with different points of views (Faris et al., 2017; Benkler, Faris and Roberts, 2018; Soares, Recuero and Zago, 2019).

The pro-Bolsonaro clusters also had a much higher standard deviation for the average indegree and outdegree, indicating that they were more centralized. This means the distribution of nodes was more skewed compared to the anti-Bolsonaro cluster. Therefore, the pro-Bolsonaro clusters relied on a small group of highly active nodes to spread content in both rounds.

1st round	Whole network	Anti-Bolsonaro	Pro-Bolsonaro
Average indegree	3.15	3.69	9.95
St. Deviation	140.01	122.10	214.31
Average outdegree	3.15	3.76	10.06
St. Deviation	10.71	8.40	26.81
Clustering Coefficient	0.017	0.012	0.047

Table 2: 1st round clusters

2nd round	Whole network	Anti-Bolsonaro	Pro-Bolsonaro
Average indegree	4.0	4.79	10.33
St. Deviation	1.99	249.39	307.65
Average outdegree	4.0	4.72	10.66
St. Deviation	1.37	13.23	27.51
Clustering Coefficient	0.032	0.029	0.052

Table 3: 2nd round clusters

Influencers and Hyperpartisan Content

We further examined the 500 nodes with the highest indegree in each cluster to identify media outlets. In the pro-Bolsonaro group, 66 accounts belonged to media outlets in the first round, and 33 in the second round. In the anti-Bolsonaro group, 42 accounts belonged to media outlets in the first round, and 59 in the second round. Also, the pro-Bolsonaro cluster contained more hyperpartisan media outlets than the anti-Bolsonaro cluster.

As shown in Table 4, there was an increase in the circulation of hyperpartisan content during the second round of the election. In the anti-Bolsonaro group, hyperpartisan nodes jumped from 29% of the total retweets to 39.7%. An even greater increase was observed in the pro-Bolsonaro cluster, where the hyperpartisan nodes had 45% of the retweets in the first round, and 64.3% of the second round.

In the pro-Bolsonaro cluster, hyperpartisan outlets contributed 57,796 retweets, almost as many as the number of retweets by traditional media outlets (63,368). In the first round, there was a larger number of retweets from media outlets, while in the second round, hyperpartisan news were more central. The most retweeted tweets of the majority of these outlets usually contained some form of disinformation, either through framing (for example, exaggerating poll numbers or giving opinions as hard news) or even through fabricated stories (for example, some of the most popular stories focused on how parties were somehow involved in a conspiracy that ended with the attack against Bolsonaro), as discussed in the next section.

	Pro- Bolsonaro		Anti-Bolsonaro	
	1st round	2nd round	1st round	2nd round
Traditional media outlets	39	15	29	41
Total RTs	57260	6108	35409	38486
%	55%	35.6%	71%	60.1%
Hyperpartisan outlets	27	18	13	18
Total RTs	46678	11118	14200	24921
%	45%	64.3%	29%	39.7%

Table 4: Media and Hyperpartisan Outlets

Results suggest that the influence of hyperpartisan content grew over time as the election became increasingly more polarized around pro-Bolsonaro and anti-Bolsonaro groups. Circulating hyperpartisan content rather than traditional media content seems to be connected to the emergence of echo chambers, when other sources of information are filtered out of the cluster. This data also supports the theoretical discussion on how echo chambers and polarization may be connected to political radicalization (Sunstein, 2017; Benkler, Faris and Roberts, 2018). Ultimately, as the polarization grew, the consumption of news from traditional outlets reduced in both clusters and the circulation of hyperpartisan content increased.

We further examined the position of nodes in the clusters. The pro-Bolsonaro cluster contained the hyperpartisan nodes with higher indegree (in the center of the circled cluster) both in the first and second dataset (Figures 5 and 6). However, we found that the number of hyperpartisan nodes also increased in centrality in the anti-Bolsonaro cluster during the second round. Traditional media outlets, on the other hand, lost centrality in both clusters (black nodes). While the mainstream outlets are closer to the anti-Bolsonaro cluster in both networks, they are "pushed" to the margins during the second round, being less retweeted than other accounts. In the pro-Bolsonaro cluster, traditional media outlets also appear to be less central than the hyperpartisan nodes.

In summary, as the election got more polarized, the conversation also became more polarized and extreme. Furthermore, the more polarized the network became, the more prevalent hyperpartisan media outlets appeared, particularly in the pro-Bolsonaro cluster.

Hyperpartisanship and Disinformation

Finally, we examined the 20 most retweeted stories for all hyperpartisan outlets that appeared in our dataset. We investigated which stories contained disinformation. For this analysis, we only considered accounts that published original tweets, not accounts that mostly retweeted others. Many hyperpartisan outlets would simply retweet stories originally published by other sources, probably to give them more visibility. Thus, for this analysis, we excluded 10 outlets in the pro-Bolsonaro groups, and 3 in the anti-

Bolsonaro groups, since they did not share original stories. Also, some outlets did not have 20 original tweets in our dataset, in these cases we analyzed as many messages as they had. In total, we analyzed 1128 unique tweets.

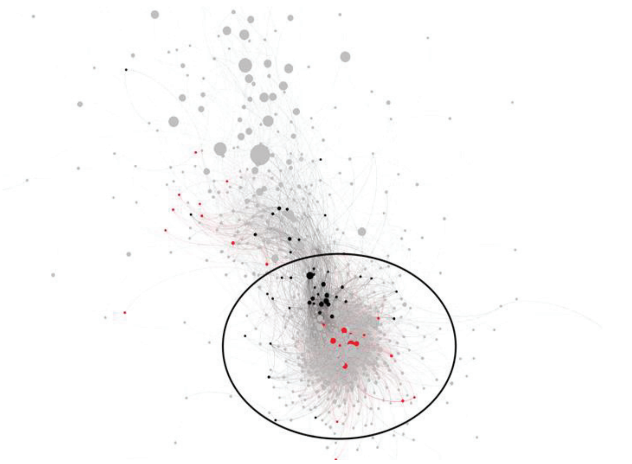

Figure 5: Clusters during the first round (Top 1% nodes showed). The pro-Bolsonaro cluster is circled.

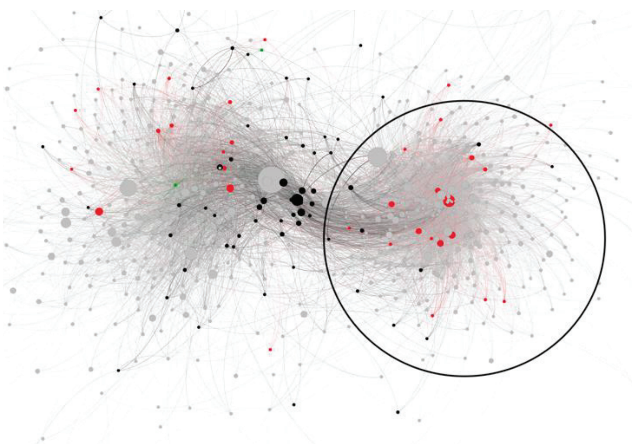

Figure 6: Clusters during the second round (Top 1% nodes showed). The pro-Bolsonaro cluster is circled.

In order to identify disinformation, two authors of this paper independently coded the messages. Disinformation was considered to be false stories or stories with false framing or stories with false connections, so we used fact-checking outlets that debunked disinformation to guide our coding. The overall intercoder reliability was a moderate to substantial Kappa score of .574. The highest score was for the hyperpartisan messages from outlets within the pro-Bolsonaro cluster during the first round (.642); and the lowest was for the anti-Bolsonaro cluster during the second round (.514). To ensure high quality of the coding, we recruited a third coder to review the disagreements between the two initial coders and classify the messages.

The first discovery is that many hyperpartisan accounts shared some disinformation (Figures 7 and 8). We found that the most retweeted stories often offered an alternative story (that hyperpartisan accounts framed as the "real" version), as opposed to traditional media stories that were trending at the same time. For example, the most shared stories initiated by pro-Bolsonaro outlets during the first round were about how the attack on the candidate was a result of a left-wing conspiracy to kill him (52 original tweets, over 30,000 retweets). In contrast, some hyperpartisan outlets in the anti-Bolsonaro cluster shared views of how the attack on Bolsonaro was staged (17 original tweets, over 400 retweets).

Beyond conversations regarding when Bolsonaro was stabbed, disinformation shared by the pro-Bolsonaro outlets included false poll results (fabricated information) or propaganda (misleading or false connection information framing Bolsonaro in a "good" light). The anti-Bolsonaro hyperpartisan outlets also shared false poll numbers, as well as predictions about a terrible future the country could face with a Bolsonaro victory made by political pundits. There were also false stories of people who allegedly decided to change their vote from Bolsonaro to Haddad, which was denounced by many fact-checking outlets.

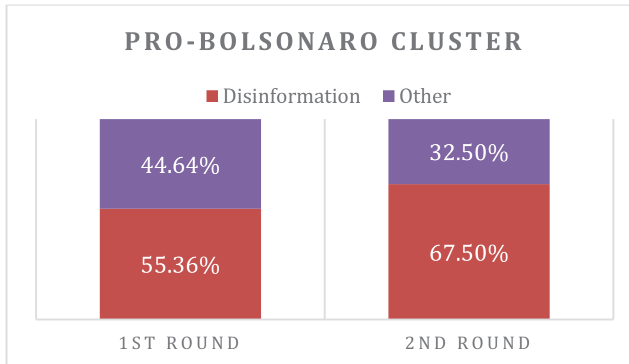

Figure 7: Hyperpartisanship disinformation in the Pro-Bolsonaro cluster

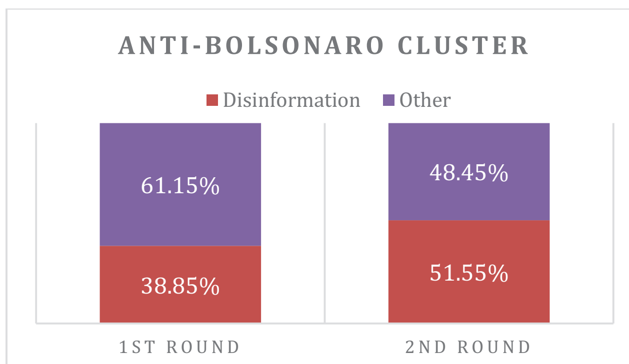

Figure 8: Hyperpartisanship disinformation in the Anti-Bolsonaro cluster

Second, the pro-Bolsonaro hyperpartisan outlets shared proportionally more tweets with disinformation in both rounds, compared to the anti-Bolsonaro hyperpartisan outlets. This result is in line with other studies, that showed that disinformation is strongly connected to Hyperpartisanship (Faris et al., 2017; Himelboim et al., 2017; Benkler, Faris and Roberts, 2018; Soares, Recuero and Zago, 2019).

Third, the number of tweets containing disinformation had increased during the second round in both pro and anti-Bolsonaro camps. Therefore, we conclude that polarization, hyperpartisanship and disinformation increased from the first to the second round.

In summary, the results suggest that hyperpartisan outlets played an active role in spreading disinformation (see also Bastos and Mercea, 2017; Bhatt et al., 2018; Recuero and Gruzd, 2019). Importantly, disinformation campaigns happened in both pro and anti-Bolsonaro cluster and they increased during the second round.

Conclusions

We sought out to examine three research questions focused on the role of hyperpartisan outlets in political conversations on Twitter.

For the first question, regarding how central hyperpartisan outlets were and how much they influenced the conversation, we discovered that as the centrality of hyperpartisan outlets grew, more traditional media outlets became less central and conversations became more polarized in general. We also determined that two major clusters were involved in political conversations about Bolsonaro in Brazil. One was strongly supportive of the candidate, whereas the other was against him. Our data showed how the two clusters circulated more information aligned with their political views, confirming the presence of so-called "echo chambers" (Barberá et al., 2015). The hyperpartisan outlets that circulated in one cluster generally did not circulate content in the other, creating conditions for disinformation to spread more easily, since it seemed to offer narratives that resonated with the political views of the clusters, suggesting "false consensus" and political alignment in the discourses (similarly to Bastos and Mercea, 2017; Soon and Goh, 2018; and Tucker et al., 2018).

For the second research question, we wanted to understand how centrality of media outlets changed during the two rounds. We found that pro-Bolsonaro hyperpartisan outlets became more central in their own cluster as the election progressed and spread more hyperpartisan content than the anti-Bolsonaro hyperpartisan outlets in their cluster. And while we found that the influence of hyperpartisan accounts grew over time in both clusters, it grew much more in the pro-Bolsonaro cluster. This suggests that conversations became more extreme and more polarized among Bolsonaro's supporters. Furthermore, we found that tweets from the hyperpartisan outlets that supported pro-Bolsonaro narratives, even if fake, tended to gain more visibility than other accounts, particularly because of the high activity of the nodes in this cluster. This is also in line with some previous work showing that hyperpartisan content may be connected to radicalization of groups, as the pro-Bolsonaro cluster was connected to disinformation campaigns and these campaigns to polarization (Bastos and Mercea, 2017; Benkler, Faris and Roberts, 2018; Larsson, 2019; Soares, Recuero and Zago, 2019).

For the third research question, our results support the idea that hyperpartisan content often produces biased information (Larsson, 2019). While disinformation was more frequently observed in the far-right cluster, it also increased its presence in the anti-Bolsonaro cluster during the runoff period. Because hyperpartisan content often circulates within closely-knit groups of like-minded individuals, there may be an effect of "false consensus" (Soon and Goh, 2018), where online participants start to believe in the narratives supported by the majority of group members. This phenomenon may also be motivated by "confirmation bias", the tendency for people to receive, validate and reproduce information that confirms their own viewpoints (Nickerson, 1998). In political contexts, where discussions tend to be ideological, this may be an important factor to consider when studying how and why hyperpartisan content and disinformation circulates on social media.

The current study contributes to the growing body of literature on polarization in the context of political conversations on social media (Barberá et al., 2015; Bastos and Mercea, 2017; Himelboim et al., 2017) by demonstrating how polarization and related communication processes on Twitter have intensified over time during the 2018 Brazilian Presidential Election. This is similar to Garimella and Weber's study (2017) that also demonstrated how polarization increased overtime in the context of political discussions on Twitter in the US. Also similar to Benkler, Faris and Roberts (2018) who examined the 2016 US election-related tweets and Facebook posts, we observed asymmetry in polarization based on one's political ideology: the right-wing pro-Bolsonaro group contained more hyperpartisan outlets and shared more disinformation compared to the left-wing group.

Regarding the role of accounts belonging to hyperpartisan media, we found that these actors are highly likely to share disinformation, as previous studies also suggested (Benkler, Faris and Roberts, 2018; Tucker et al., 2018; Larsson, 2019). Moreover, our results show that hyperpartisan outlets tend to be more central than mainstream media outlets, making the disinformation they circulate more visible. This is similar to what Allcott and Gentzkow (2017) and Larsson (2019) found in the 2016 US election and Norwegian contexts respectively.

Our study has some limitations. It was focused on a particular case of the 2018 Brazilian presidential election. We also acknowledge a potential limitation due to data collection, as Twitter API might filter or limit the data it provides unknowingly to the research team. Another limitation is the lack of statistical testing of differences in network metrics. Moreover, while our paper relied on a clustering coefficient to assess network polarization, future work ought to examine additional metrics of network robustness to validate our results. Nevertheless, our study contributes to research by providing an in-depth view of how hyperpartisanship may be connected to polarization, and how the structure of echo chambers may influence the circulation of disinformation and discourse radicalization in political conversations. Such polarized environments may pose a threat to the health of democracy (Papacharissi, 2002; Chadwick, 2009; Stromer-Galley 2003), as the new public sphere becomes more susceptible to disinformation campaigns (Tucker et al., 2018).

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References

Adamic, L. A., and Glance, N. 2005. The political blogosphere and the 2004 U.S. election: divided they blog. *Proceedings of the 3rd international workshop on Link discovery*. doi:10.1145/1134271.1134277.

Allcott, H., and Gentzkow, M. 2017. Social Media and Fake News in the 2016 Election. *Journal of Economic Perspectives*, 31(2): 211-36.

Bail, C. A.; Argyle, L. P.; Brown, T. W.; Bumpus, J. P.; Chen, H.; Hunzaker, M. B. F.; Lee, J.; Mann, M.; Merhout F.; and Volfovsky, A. 2018. Exposure to opposing views on social media can increase political polarization. *PNAS*, 115, 37, 9216–9221.

Barberá, P.; Jost, J. H.; Nagler, J.; Tucker, J. A.; and Bonneau, R. 2015. Tweeting From Left to Right: Is Online Political Communication More Than an Echo Chamber? *Psychological Science,* 26, 10, 1531-1542. doi: 10.1177/0956797615594620.

Bastos, M.; Mercea, D. and Baronchelli, A. 2017. The Spatial Dimension of Online Echo Chambers. [*physics.soc-ph*]. arXiv:1709.05233v1. Available at: https://arxiv.org/ftp/arxiv/papers/1709/1709.05233.pdf.

Bastos, M. T. and Mercea, D. 2017.The Brexit Botnet and User-Generated Hyperpartisan News. *Social Science Computer Review,* 37(1), pp. 38–54. doi:10.1177/0894439317734157.

Benkler, Y.; Faris, R.; and Roberts, H. 2018. *Network Propaganda*: Manipulation, disinformation, and radicalization in American politics. New York: Oxford University Press.

Bhatt, S.; Joglekar, S.; Bano, S.; and Sastry, N. 2018. Illuminating an Ecosystem of Partisan Websites. *arXiv preprint* arXiv:1803.03576.

Blondel, V. D.; Guillaume, J.L.; Lambiotte, R.; and Lefebvre, E. 2008. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment* (10), P1000.

Cha, M. H.; Benevenuto, F.; and Gummadi, K. P. 2010. Measuring user influence on twitter: The million follower fallacy. In *Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media*. Washington: AAAI, p. 10-17.

Chadwick, A. 2009. 'Web 2.0: New Challenges for the Study of E-Democracy in an Era of Informational Exuberance' *I/S: A Journal of Law and Policy for the Information Society* 5 (1), pp. 9-41.

Derakshan, H., and Wardle, C. 2017. Information Disorder: Definitions. Conference paper. Available at: https://firstdraftnews.org/wp-content/uploads/2018/03/The-Disinformation- Ecosystem-20180207-v2.pdf.

Dubois, E., and Gaffney, D. 2014. The Multiple Facets of Influence: Identifying Political Influentials and Opinion Leaders on Twitter. *American Behavioral Scientist*, *58*(10), 1260–1277. https://doi.org/10.1177/0002764214527088.

Eady, G.; Nagler, J.; Guess, A.; Zilinsky, J.; Tucker, J. A. 2019. How Many People Live in Political Bubbles on Social Media? Evidence From Linked Survey and Twitter Data. *SAGE Open*, 9(1), DOI:10.1177/2158244019832705.

Faris, R. M.; Roberts, H.; Etling, B.; Bourassa, N.; Zuckerman, E.; and Benkler, Y. 2017. *Partisanship, Propaganda, and Disinformation: Online Media and the 2016 U.S. Presidential Election*. Berkman Klein Center for Internet and Society Research Paper. Retrieved from https://dash.harvard.edu/handle/1/33759251.

Garimella, K., and Weber, I. 2017. A Long-Term Analysis of Polarization on Twitter. In Proceedings of the 11th International AAAI Conference on Web and Social Media (ICWSM-17). Available at: https://aaai.org/ocs/index.php/ICWSM/ICWSM17/paper/view/15592.

Giglietto, F.; Valeriani, A.; Righetti, N.; and Marino, G. 2019. Diverging patterns of interaction around news on social media: insularity and partisanship during the 2018 Italian election campaign, *Information, Communication & Society,* 22:11, 1610-1629, doi: 10.1080/1369118X.2019.1629692.

Gruzd, A., and Roy, J. 2014. Investigating Political Polarization on Twitter: A Canadian Perspective. *Policy and Internet*, 6, 1, 28-45.

Guess, A.; Lyons, B.; Nyhan, B.; and Reifler, J. 2018. *Avoiding the echo chamber about echo chambers*: Why selective exposure to like-minded political news is less prevalent than you think. Miami: John S. and James L. Knight Foundation.

Guess, A.; Nyhan, B.; and Reifler, J. 2018. Selective exposure to misinformation: Evidence from the consumption of fake news during the 2016 US presidential campaign. European Research Council 9.

Hampton, K.; Shin, I.; and Lu, W. 2017. Social media and political discussion: when online presence silences offline conversation, *Information, Communication & Society*, 20:7, 1090- 1107.

Himelboim, I.; Smith, M.; Rainie, L.; Schneiderman, B.; and Espina, C. 2017. Classifying Twitter Topic-Networks Using Social Network Analysis. *Social Media + Society*, 3(1). Doi: 10.1177/2056305117691545.

Krippendorf, K. 2013. *Content Analysis. An Introduction to Its Methodology* (3rd ed). California, CA Sage Publications.

Lambiotte, R.; Delvenne, J. -C.; and Barahona, M. (2009) Laplacian Dynamics and Multiscale Modular Structure in Networks. Available at: https://arxiv.org/abs/0812.1770.

Larsson, A. 2019. News Use as Amplification – Norwegian National, Regional and Hyperpartisan Media on Facebook. *Journalism Mass and communication quarterly* - Pre-print version on: https://www.academia.edu/38221050/News_Use_as_Amplification_Norwegian_National_Regional_and_Hyperpartisan_Media_on_Facebook.

Lindgreen, S. 2016. Introducing Connected Concept Analysis: A network approach to big text datasets. *Text&Talk*; 36(3): 341–362. Doi:10.1515/text-2016-0016.

Maia, R. C. M. 2008. Visibilidade midiática e deliberação pública. In: Gomes, W. Maia, R. C. M. Comunicação e democracia: Problemas & Perspectivas. São Paulo: Paulus, 117-162.

Mourão, R. R., and Robertson, C. T. 2019 Fake News as Discursive Integration: An Analysis of Sites That Publish False, Misleading, Hyperpartisan and Sensational Information, *Journalism Studies*, doi: 10.1080/1461670X.2019.1566871.

Nickerson, R. 1998. Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology,* 2 (2): 175, 1998.

Papacharissi, Z. 2002. The virtual sphere: The internet as a public sphere. *New Media & Society*, 4(1), 9–27. Doi:.1177/14614440222226244.

Papacharissi, Z. 2004. Democracy online: civility, politeness, and the democratic potential of online political discussion groups. *New Media & Society*, 6(2), 259–283. Doi:10.1177/1461444804041444.

Papacharissi, Z. 2009. The Virtual Sphere 2.0: The Internet, the Public Sphere and beyond. In: Chadwick, A. Howard, N. (eds). *Routledge Handbook of Internet Politics* (p. 230-245). London, UK, and New York, NY: Routledge.

Prom, C. 2017. Tool Report: Social Feed Manager, *MAC Newsletter:* Vol. 45: No. 2, Article 9.

Recuero, R., and Gruzd, A. 2019. Cascatas de Fake News Políticas: um estudo de caso no Twitter. *Galáxia* (São Paulo) n.41, pp.31-47. Epub May 23. Doi: 10.1590/1982-25542019239035.

Soares, F. B.; Recuero, R.; and Zago, G. 2018. Influencers in Polarized Political Networks on Twitter. In *Proceedings of the International Conference on Social Media & Society*, Copenhagen, Denmark (SMSociety). doi: 10.1145/3217804.3217909.

Soares, F. B.; Recuero, R.; and Zago, G. 2019. Asymmetric Polarization on Twitter and the 2018 Brazilian Presidential Elections. In *Proceedings of the 10th International Conference on Social Media & Society*, Toronto, Canada (SMSociety). doi: 10.1145/3328529.3328546.

Soon, C., and Goh, S. 2018. Fake news, false information and more: Countering human biases IPs. *Working Papers No. 31*. Available at: https://lkyspp.nus.edu.sg/docs/default-source/ips/ips-working-paper-31_fake-news-false-information-and-more_260918.pdf.

Stromer-Galley, J. 2003. Diversity of Political Conversation on the Internet: Users' Perspectives, *Journal of Computer-Mediated Communication,* Volume 8, Issue 3, 1 April 2003, JCMC836, https://doi.org/10.1111/j.1083-6101.2003.tb00215.x.

Sunstein, C. 2001. Echo Chambers. Princeton: Princeton University Press.

Sunstein, C. 2009. Republic.com 2.0. Princeton: Princeton University Press.

Sunstein, C. 2017. #Republic. Princeton: Princeton University Press.

Tucker, J. A.; Guess, A.; Barbera, P.; Vaccari, C.; Siegel, A.; Sanovich, S.; Stukal, D.; and Nyhan, B. 2018. Social Media, Political Polarization, and Political Disinformation: A Review of the Scientific Literature. Available at SSRN: https://ssrn.com/abstract=3144139 or http://dx.doi.org/10.2139/ssrn.3144139.

Wasserman, S., and Faust, K. 1994. Social Network Analysis. Cambridge*: Cambridge University Press*.

Watts, D. J., and Strogatz, S. H. 1998. Collective dynamics of 'small-world' networks. *Nature* 393:440-442.