Elites Tweet to get Feet off Streets: Measuring Elite Reaction to Protest Using Social Media

Kevin Munger, Richard Bonneau, John T. Jost
Jonathan Nagler, Joshua A. Tucker*

September 17, 2015

Abstract

1 Introduction

Social media has changed the way that protests are conducted, and how they have been studied. There is a wealth of quantitative empirical research on the affordances social media offers protesters, but comparatively little on the use of social media by elite actors in non-democratic regimes. The qualitative framework of active social media use to enhance regime resilience provided by (Gunitsky, 2015) is compelling, but it has yet to be rigorously tested. We aim to do so and thus make inferences about the strategic goals of opaque, using a similar approach to (Roberts, Stewart, and Airoldi, 2015), who model the text of Chinese newspapers to infer the propaganda objectives of the Chinese regime.

Specifically, we test theories that pro-regime elites use social media to counter-mobilize their supporters against the protests organized by the opposition, and that they engage in efforts to control the discourse online by providing counter-narratives

*This paper was written in conjunction with NYU's Social Media and Political Participation (SMaPP) lab, of which Munger is a PhD student member and the remaining authors are Principal Invesetigators. km2713@nyu.edu

that discredit the narrative being supported by the opposition. The particular context of our analysis is the Venezuelan anti-Maduro protests of 2014.

These protests are the ideal case to demonstrate the strategic use of Twitter by elites. Although Venezuela edged toward authoritarianism in the 21st century, its elites continue to have free speech, although the regime does exert pressure on traditional media outlets. Venezuela is also among the top five countries in terms of Twitter penetration (PeerReach, 2013), and as in common in Latin America, its politicians are more likely to speak their minds directly on Twitter rather than have a media team craft a sanitized Twitter presence. Venezuelan politicians are well-represented on Twitter: as of April 2015, Henrique Capriles, the runner-up in the last two elections, was the most “followed” person in Venezuela, and Hugo Chávez was a close second, despite having died in March 2013.

To ensure a balanced sample of elites, we investigate the Twitter accounts of Venezuelan *diputados*, members of the unicameral National Assembly. 139 of 165 *diputados* had Twitter accounts, and they tweeted over 100,000 times during the 5 months under study, giving us ample analytical leverage. We find evidence of the strategic use of Twitter by the two coalitions reflecting their proximate and ultimate goals, and in so doing provide quantitative support for the qualitative framework presented in Gunitsky (2015): opposition *diputados* attempt to reinforce the protest’s message, but only as long as it is in their interest, while regime *diputados* attempt to take back the narrative from the protesters and structure it in their favor. We operationalize these measures using Latent Dirichlet Allocation to model the topics that the *diputados* tweeted about during the protest.

The paper proceeds as follows: Section 2 provides a background of the situation in Venezuela; Section 3 discusses the relevant literature; Section 4 outlines our hypotheses in detail; Section 5 presents the data; Section 6 explains the methodology; Section 7 gives results; Section 8 concludes.

2 Literature on the Role of Social Media in Politics

Though social media has changed the way that political communication happens in liberal democracies, its impact in non-democratic regimes has been even more pronounced. Because social media are more challenging to control than are traditional media, they are offer more ** affordances (Josh–you'd wanted me to replace this with "opportunities," and that definitely flows better, but "affordances" is a technical term that that reviewer was extremely keen on–is it worth keeping? ** for people to become informed and engage in protest (Christensen and Garfias, 2015; Tufekci and Wilson, 2012). Social media also enhances the tactical coordination capacity of protester by decreasing the information asymmetries between protesters and the police (Earl et al., 2013) and allowing crowds to function as organizations (Agarwal et al., 2014; Bennett, Segerberg, and Walker, 2014).

Because the Arab Spring was a largely unexpected event, and one in which social media played a visible role, much of the early scholarship on the topic was enthusiastic about its revolutionary potential (Gerbaudo, 2012; Khondker, 2011; Lotan et al., 2011). Non-democractic regimes do, however, have the capacity to respond to the threat that social media can pose. Deibert et al. (2010) develop a three-generation framework for how regimes reduce the threat of social media. The first generation is to restrict access to the Internet (Howard, Agarwal, and Hussain, 2011) and the second is to censor certain kinds of information posted online (King, Pan, and Roberts, 2013). These approaches are fairly crude, and aim to return to the equilibrium in which social media did not exist.

The "third generation" strategies, including information campaigns and actively paying supporters to post online, show how social media can be used as a tool for regime activism (Greitens, 2013). For example, Oates (2013) details how post-Soviet regimes have taken advantage of weak civil societies to control the online discourse, and Sanovich et al. (2015) demonstrates the dramatic changes in online engagement strategy in Russia since 2000. Depending on the technological and organizational capacities of the two sides, this regime activism might even tip the balance of power in favor of the regime (Morozov, 2011; Rahimi, 2011).

A comprehensive discussion of social media's potential to increase regime resilience using these "third generation" strategies is Gunitsky (2015). Social media can help stave off revolution by giving the regime information about specific grievances that they can address without relying on local bureaucrats with an incentive to falsify information. Once there are protesters in the streets, social media allows the regime to counter-mobilize their supporters into demonstrating in favor of the regime. These demonstrations take place both in the real world, making it more difficult for the opposition to control the physical space without resorting to violence against other citizens, and on social media, preventing the opposition from framing the discourse the way they want to.

Muddying the informational waters can serve a crucial function in staving off revolution. The literature on global games illustrates the importance of both first-order information about the quality of the regime and higher-order information about the beliefs of other citizens in solving the coordination problem necessary for a successful revolution (Edmond, 2013). A sizable counter-demonstration in favor of the regime can introduce sufficient uncertainty among potential protesters to keep them home and prevent a potential revolution from reaching the threshold necessary for success.

The implications of social media's affordances for citizens to engage in protest have been well-studied, both theoretically and empirically. There has been comparatively little effort to examine the regime's active use of social media in the ways described by Gunitsky. One possible reason for this is that elite (both pro- and anti-regime) communication is explicitly propagandistic, and thus its content cannot be taken at face value. But it is precisely this aspect that makes elite communication especially useful for the quantitative analysis of regime strategy: the words may be cheap talk but the motivation is serious, as the fortunes of the regime may hang in the balance.

3 Recent Venezuelan History

Venezuela has been a democracy since 1958.[1] The first 40 years were dominated by the *punto fijo* system, with political power alternating between two clientelistic parties. 1998 saw the election of Hugo Chávez and a shift in Venezuelan economic and social policy.

Chávez won re-election in 2006 and 2012 with very high voter turnout, even as inflation and crime rates rose to high levels (Corrales and Penfold-Becerra, 2011). Chávez's tenure also saw the transition of Venezuela from representative democracy to what Mainwaring (2012) calls participatory competitive authoritarianism, a system which could be subsumed in the general category of a "hybrid" regime. Chávez's health declined rapidly in 2012, and he died in early 2013.

Vice president Nicolás Maduro won the 2013 special election against Henrique Capriles, a popular state governor and Chávez's opponent in 2012, but his margin of victory was only 1.5%, and there were claims of fraud and illegitimacy made by the losing party.

[1] For a visual timeline of the events discussed here, see Appendix C.

Under Maduro, continuing inflation and high violent crime rates led to rising discontent (Corrales, 2013). The sparks that ignited the 2014 protests were the January 6 robbery-murder of a former Miss Venezuela and the attempted rape, on February 5, of a university student on a campus in Táchira in the southeastern part of the country. The latter event led to a small student protest against high crime rates that provoked a violent governmental response (Perez, 2014). This inspired a much larger protest that eventually spread to Caracas. Radical opposition leaders, especially the faction headed by María Corina Machado and Leopoldo López, had been in the planning stages for a movement to advocate for regime change (known as *La Salida*), and they rode the wave of student protest to put their plans into action. Note that the moderate opposition elites, including all of the *diputados* in this study, were not involved in the planning or execution of these early protests; thus, the large-scale protests we study were similarly exogenous to both the pro- and anti-regime *diputados*.

The protests escalated quickly, and López became sufficiently outspoken and high-profile that the regime jailed him on February 18th. His arrest was precipitated by him tweeting directly at Maduro: ".@Nicolasmaduro Don't you have the guts to arrest me? Or are you waiting for orders from Havana? I tell you this: The truth is on our side"[2] (authors' translation). Twitter allowed López to spread his message directly and quickly to a wide mass of people – note the almost $45,000$ retweets – with no risk that it would be distorted or misrepresented.

[2]The tweet begins with a period so that it is visible to everyone; normally, tweets that begin with @[username] are only visible to people who "follow" both parties.

During the height of the protests, opposition groups advocating *La Salida* in Caracas set up permanent blockades (*guarimbas*) designed to paralyze the city and heighten the economic crisis. In response, the regime allowed armed paramilitary groups called *colectivos* to attack, rob, and kill opposition protesters. The violence led to thousands of injuries and at least 40 deaths.

The first major sit-down between the regime and the moderate opposition took place on April 10th, though no conclusion or agreement was announced. April 19th and 20th were a major revolutionary holiday (Beginning of the Independence Movement Day) and Easter, respectively, and this weekend represented the high water mark of the protests.

The protests began to wind down in May after a compelling display of strength by the government, but they revealed deep divisions within the country and among the opposition factions, neither of which was truly unified. Capriles and the moderate opposition that includes all of the opposition *diputados* continued to push for democratic reforms and non-violent methods of progress, whereas *La Salida* wanted nothing less than the removal of the ruling party, through constitutional means if possible but through violent street protests if necessary (Ciccariello-Maher, 2014). The moderates tried to draw as much attention to the protests as possible, out of opposition solidarity or in order to improve their baragaining power or electoral chances in the future. In any case, *La Salida* was never the first choice of the opposition *diputados* under study.

4 Hypotheses

We aim to perform a quantitative test of Gunitsky (2015)'s framework, in the context of the 2014 Venezuelan protests. These protests represented an existential threat to the regime; *La Salida* was calling for regime change outside of the structure of regularly scheduled elections, and the protesters in the street had established a strong narrative frame that the regime had failed via its mishandling of the economy and failure to reign in violent crime. In this context, we should expect to see the pro-regime elites use social media to counter-mobilize their supporters and retake the narrative from the opposition. Because the opposition's central complaints about inflation and crime were self-evidently true, a response that attempted to dispute the merits of their claim via organizing a large-scale demonstration praising the safety of life in Caracas would ring false to everyone. Rather, following the logic of the models developed in Edmond (2013), we expect the regime elites to tweet about a variety of different topics, to broaden the discourse and loosen the opposition's hold on it.

The opposition elites, in contrast, should focus on the protests and their specific message, at least as long as they believe it to be in their interest. Recall that the opposition *diputados* we study were not involved in planning or executing the protest, but are rather part of the moderate opposition which had been dedicated to effecting change through elections. We expect to see a contrast in the strategic reactions of the two coalitions of *diputados* to the onset of the protests as they pursue their respective goals, and we have three different approaches to measuring that contrast.

The primary quantity we use to measure these strategies is *focus*: the extent to which each coalition's tweets are about few or many different topics. We use Latent Dirichlet Allocation (LDA)–an unsupervised technique that uses the co-location of words to find topics in a given series of texts–on each day's worth of tweets to model the topics discussed on Twitter. We then operationalize *focus* in two ways. The first is the topic diversity of the tweets from each coalition on each day. Explained in more detail below, topic diversity summarizes the amount of different information a given text contains. Higher topic diversity corresponds with less focus.

Following Gunitsky (2015)'s theoretical framework, we expect the regime's counter-mobilization and discourse framing efforts to result in a higher topic diversity score.

Hypothesis 1 *Compared to their pre-protest levels of topic diversity, the opposition diputados' tweets will become more focused and their topic diversity scores will decrease, while the regime diputados' tweets will become less focused and their topic diversity scores will increase.*

We also operationalize *focus* by looking at which topics are most prominent during each day's worth of tweets from each coalition. During the protest, we expect the regime to make many different topics their main talking point for the day. For the opposition, however, we expect very few different topics to be their main talking point for the day. H_1 is concerned with the overall topic distribution, while H_2 tests the consistency of top topics.

Hypothesis 2 *Each day during the protest, the opposition diputados' tweets will be centered on very few different topics, and the regime diputados' tweets will be centered on many different topics.*

There are also important indicators of strategy that are unique to the medium of Twitter. The most relevant is the use of "hashtags" (#'s), which structure discussion between people who might not know each other. There are two different strategies for using hashtags: include them in tweets to indicate the subject of your tweet, or invent specific, lengthy ones that themselves define subjects of discussion. We expect the opposition *diputados* to use short, "labeling" hashtags to draw attention to the narrative being created by the protesters, and for the regime *diputados* to use long[3], "discourse-structuring" hashtags to counter-mobilize their supporters into broadening the discourse.

Hypothesis 3 *During the protests, the regime diputados will use long hashtags more frequently than the opposition.*

These three hypotheses represent a way to quantify the regime strategies outlined in Gunitsky (2015). If we find that the two coalitions use Twitter in significantly different ways in these three measures, this is evidence of that authoritarian regimes engage in an active strategy on social media to frame the discourse and counter-mobilize their supporters. Additionally, if we find the regime's Twitter use becomes less *focused* during the protest, both in terms of topic diversity and the number of different topics they center their message on, that provides empirical support to the logic of information diffusion suggested by Edmond (2013).

5 Data Collection

For each of the 99 regime and 66 opposition *diputados* in Venezuela's unicameral legislature, we performed a manual search for an associated Twitter account. In some cases, there were multiple accounts associated with a single politician–either a campaign account and a governing account or an official account and a personal account–but there was only one that was both active and which possessed a significant number of followers, and we chose that one. If there was any ambiguity as to whether a Twitter account belonged to a politician or an ordinary citizen with the same name, we checked to see if the account was followed by one of the party elites from either side.[4] We were able to locate accounts for 139 of the 166 *diputados* (84%): 63 of 66 for the opposition

[3]We discuss what constitutes "long" below, but in general these hashtags are 3+ word phrases.

[4]It turns out that several Venezuelan politicians share names with professional baseball and soccer players.

Table 1: **Number of Tweets by Venezuelan *Diputados***

Diputados	N	1st Quartile	Median	3rd Quartile	Mean	Total Tweets
Regime	65	109	308	799	664	43,174
Opposition	56	215	584	1234	1,117	62,534

Period of Analysis: December 19, 2013 - May 29, 2014

(95%, similar to US Members of Congress), and 76 of 99 (77%) for the regime.[5] For the subsample whose tweets are analyzed in this paper–those who tweeted after December 18, 2013–there are 135 accounts, 65 regime and 56 opposition.

We used Twitter's REST API[6] via `tweepy`[7], in the Python programming language, to collect the most recent tweets for each account. Using the `/statuses/user_timelines` endpoint[8], Twitter's API allows fetching the latest 3,200 tweets for a given account. We did this on April 19th and then again on May 29th, at which point the protests had largely subsided. As a result, we obtained more than 3,200 tweets for some accounts. Many of the accounts had fewer than 3,200 tweets, so we have their entire history. Twitter's API also provides the metadata associated with each account, including their "biography," where they claim to be located, and the date they joined Twitter. We entered each *diputado's* party as an additional variable in the dataset.

Table 1 (below) summarizes of the number and distribution of the tweets collected. Although the regime had a higher number of individuals with active accounts, the opposition produced roughly 40% more total tweets during our period of observation, and this difference only became pronounced once the protests started. The difference is not just driven by a few prolific opposition accounts; comparing the 1st quartiles, medians, and 3rd quartiles of the regime and opposition indicates that the opposition is more active throughout the distribution.

It is also important to note the distribution of tweets by each coalition over time. The timeline of our analysis can be divided into four periods: (1) December 19-January 6, before the protests; (2) January 7-February 18, protests begin; (3) February 19th-April 19th, ongoing protests; (4) protests subside; the breaks between these protests

[5]To check the validity of our selection, we had a research assistant recreate our analysis. There were only 2 discrepancies, the adjudication of which was obvious.

[6]https://dev.twitter.com/docs/api/1.1

[7]https://github.com/tweepy/tweepy

[8]https://dev.twitter.com/docs/api/1.1/get/statuses/user_timeline

are noted by vertical lines in all of the figures on January 6, February 18, and April 19. For more details, see Appendix C, which contains an annotated visual timeline of the events and a summary of concurrent observed elite twitter behavior.

Notice that before the protests, the tweet density was similar and low for both the government and opposition. Both sides saw a flare-up around the time of the murder of Miss Venezuela on January 6th, which then subsided. The opposition began to tweet more often well in advance of the February 14 protest explosion, and sustained a higher level of tweeting throughout the time period. The government also increased its rate of tweeting, but never reached the same level as the opposition. During periods 3 and 4, both coalitions maintained a steady rate of tweeting; note that in this figure, there is no noticeable change around the third vertical line, April 19th.

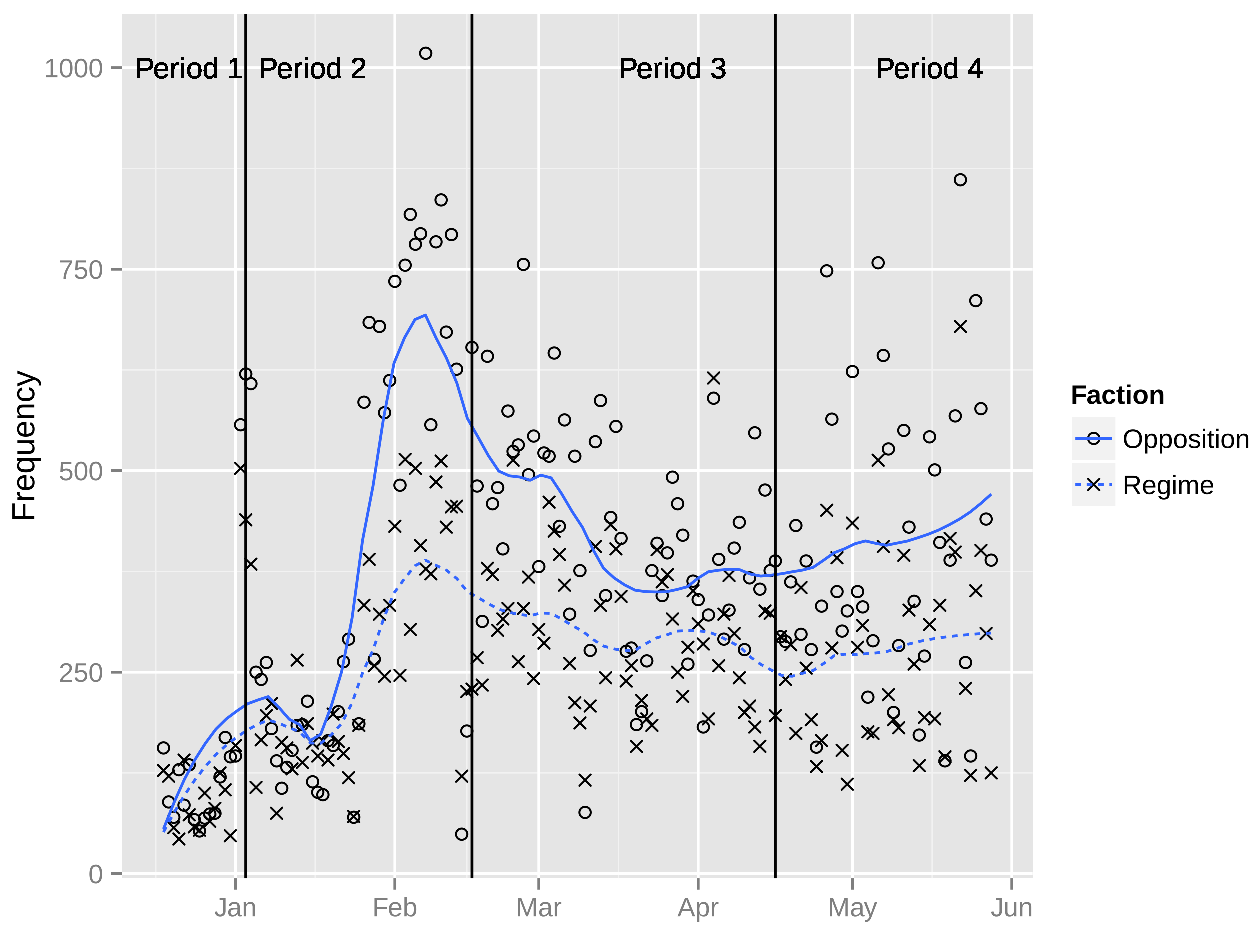
6 Analysis

To estimate the number of overall topics being discussed on a given day by each coalition, we employed Latent Dirichlet Allocation (Blei, Ng, and Jordan, 2003) to generate topics and label each day's worth of tweets with a certain distribution over those topics. LDA is an unsupervised, "bag-of-words" machine-learning algorithm used for topic modeling that is increasingly popular in the social sciences. This approach is well-suited to analyzing the communication of a group of elites over time because it is unsupervised (that is, the researcher does not decide which topics to study *ex ante*) and because it allows the entire corpus of information to be used.

The input to LDA is a corpus of documents composed of tweets aggregated as described below, each of which is a vector of N terms (within which order is irrelevant) taken from a vector of length V that contains all the terms in the corpus. LDA also requires the specification of two parameters: K, the number of topics to be modeled, and α, a concentration parameter that determines the shape of the probability distribution central to LDA. LDA analysis is conducted by treating each document as a probability distribution over latent topics and each topic as a distribution over words. That is, LDA assigns k weights to each word, one for each topic it is instructed to find, and k weights to each document in the corpus.

In this case, the "documents" consist of the text of the *diputados*' tweets. The start date of our analysis is December 19, 2013, 2 months before the start of the height of the protests as marked by López's arrest, and the end is May 29th, 2014, approximately

Figure 1: Tweets per Day by Each Coalition



The number of tweets sent by *dipudatos* from each faction per day. The vertical lines correspond to January 6 (the murder of former Miss Venezuela), February 18th (the arrest of López), and April 19th (Beginning of the Independence Movement Day). Trend lines for each coalition created with loess.

a month after the protests subsided. We divided each day's worth of tweets by each coalition into a separate document. There are 162 days included in the analysis, and thus 324 documents. Once aggregated into these documents, the terms comprising the tweets from that coalition-day are treated identically: order ceases to matter, as does the number of tweets. For example, a dozen tweets that each say only "Venezuela" spread over a single day by a dozen different *diputados* from the same coalition has the same impact as a single tweet that says "Venezuela" a dozen times.

This approach does ignore potentially useful information by disregarding which individual *diputado* from a coalition produced each tweet. Given that our aim is to measure the degree of coordination among the coalitions, however, this information is not germane.[9] The technique also loses information by conflating all the tweets from each day. This is unavoidable: there is not enough information in a single tweet to treat it as a document, and the machine learning literature indicates that aggregating tweets leads to better performance for LDA (Hong and Davison, 2010).[10]

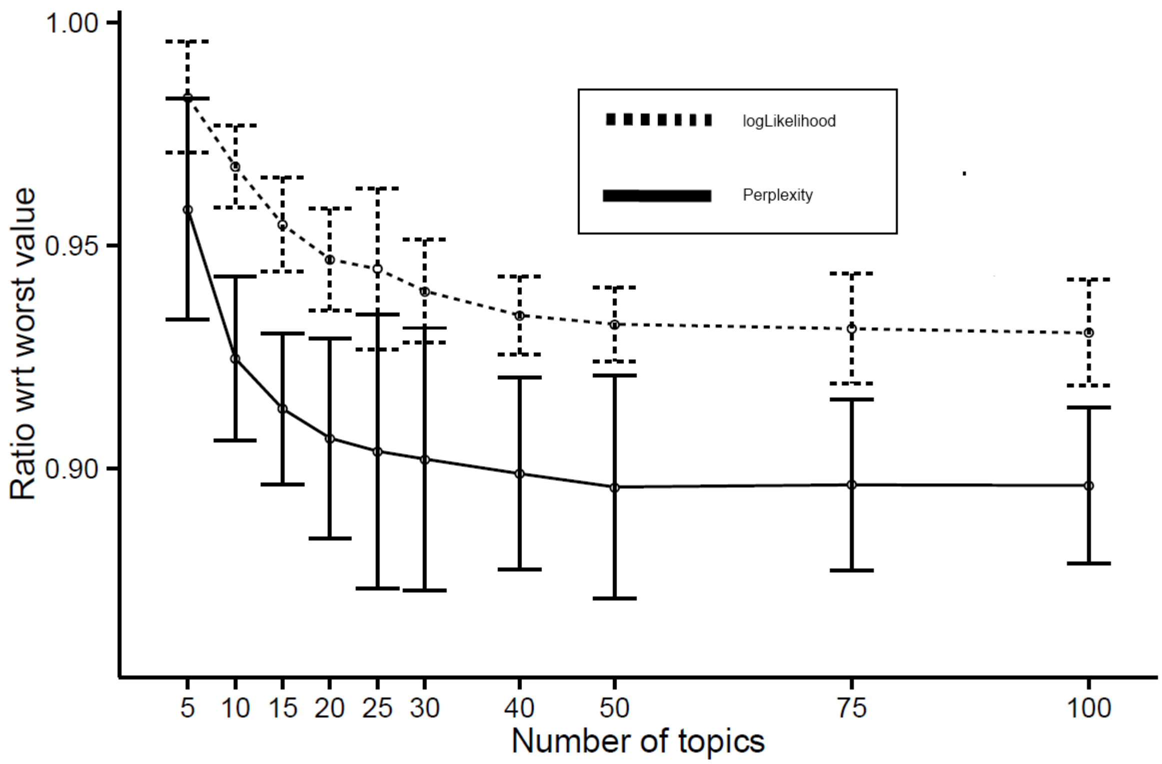
To determine the number of topics k, we performed ten-fold cross-validation of both log-likelihood and perplexity analyses on the holdout sample.[11] Although the model fit improves monotonically in the number of topics, the gains from adding more topics diminish at around 50 topics (see Figure 1). There exist standard rules for choosing k, such as the conservative "one-standard-error" rule outlined in Hastie et al. (2009), but this choice is contingent on the question LDA is being used to answer. LDA has been used most commonly to identify specific topics, prioritizing the recognizability of the topics created; in this context, the main priority is to avoid overfitting the data by choosing a conservative k. Our aim is to study the change in *focus* over time, so this concern is less relevant, and creating more topics allows for greater variation in the quantity of interest, even if those topics are sparsely represented and hard to identify.

[9]This would be a problem if there were fewer accounts, or if one account were doing all the tweeting. Ideally, the tweets would be distributed among the accounts in a closer approximation to the normal distribution than the observed logarithmic distribution, but because the shape of the distribution is similar for the two coalitions, this weakness does not impair our comparative analysis.

[10]There are recent innovations in machine learning that attempt to improve on LDA performance modeling topics generated from short-length texts like tweets, either by using word dyad co-occurance (Cheng et al., 2014) or by pre-pooling the tweets by hashtags (Mehrotra et al., 2013); once these techniques are tested and fully validated, they could represent improvements on the naive tweet-pooling technique used in this manuscript.

[11]Perplexity is a measure of how well the LDA algorithm trained on the training sample is able to predict the holdout sample. Cross-validation works by dividing the sample up into several subsections (in this case, ten), iteratively using nine of the subsamples to predict the tenth, and seeing how accurate those predictions are.

Figure 2: Testing Different Numbers of Topics



The dotted line connects log-likelihood estimates for the model fitted with different number of topics, the dark line connects perplerxity estimates for the model fitted with different number of topics.

As a result, we follow a guideline of doubling the number of topics that the conservative approach recommends, and select k=100.[12] Our results are not an artifact of this choice; the central finding of different degrees of *focus* in Figure 3 is statistically significant for k= 30 and k= 50, though the time period for which this is true is narrower than for k =100.

Following standards in the social science literature, we use the collapsed Gibbs sampler (Griffiths and Steyvers, 2004; Phan, Nguyen, and Horiguchi, 2008), a modification of the sampling method proposed in Blei, Ng, and Jordan (2003). Using the R package 'topicmodels' developed by Hornik and Grün (2011), we ran LDA in a single chain for 1000 iterations. The text was pre-processed using 'topicmodels' by removing numbers and punctuation, by converting all the text to lowercase, and by "stemming" the

[12]For α, we follow the standard established by Griffiths and Steyvers (2004) and set $\alpha = .5$, where $50/k = .5$.

words so that different forms of the same word are not treated as entirely different words; stemming is especially important when dealing with Spanish objects that have four different endings depending on the number and gender of the subjects. After this pre-processing, the corpus (collection of words) consisted of $N = 50,902$ terms.

In creating the topics, the algorithm estimates k=100 γ's for each document. For each of the 324 documents w, γ_{wk} is the probability that document w pertains to topic k; note that $\sum_{k=1}^{100} \gamma_{wk} = 1$. There are 32,400 of these γ's.

To analyze how *focused* the coalitions are over time, we measure the Shannon Entropy (Shannon, 1948) of the γ distribution of each document. Commonly used in the natural sciences to measure the diversity of an ecosystem by the relative counts of each species in that ecosystem, Shannon Entropy (what we refer to throughout the paper as topic diversity) is well suited to measuring how *focused* these documents are. It efficiently captures information about the entirety of the distribution while avoiding the imposition of arbitrary thresholds. The formula for Shannon Entropy is $-\sum_{i=1} p_i \log_2(p_i)$. In this case, because the γ's in each document must sum to 1, $p_i = \gamma_{wk}$ and the topic diversity score for each document is

$$\text{Topic Diversity} = -\sum_{k=1}^{100} \gamma_{w,k} \log_2(\gamma_{wk})$$

The possible topic diversity scores range from 0 (if the γ distribution is unitary) to $\log_2(k = 100)$ (if the γ distribution is uniform). Generally, lower topic diversity scores mean a less uniform distribution, and in the case being analyzed here, a more *focused* message.

7 Results

We divide the timeline under study into four time periods: (1) December 19-January 6, before the protests; (2) January 7-February 18, protests begin; (3) February 19th-April 19th, ongoing protests; (4) protests subside; the breaks between these protests are noted by vertical lines in all of the figures in this section.

7.1 Tweet Focus–topic diversity

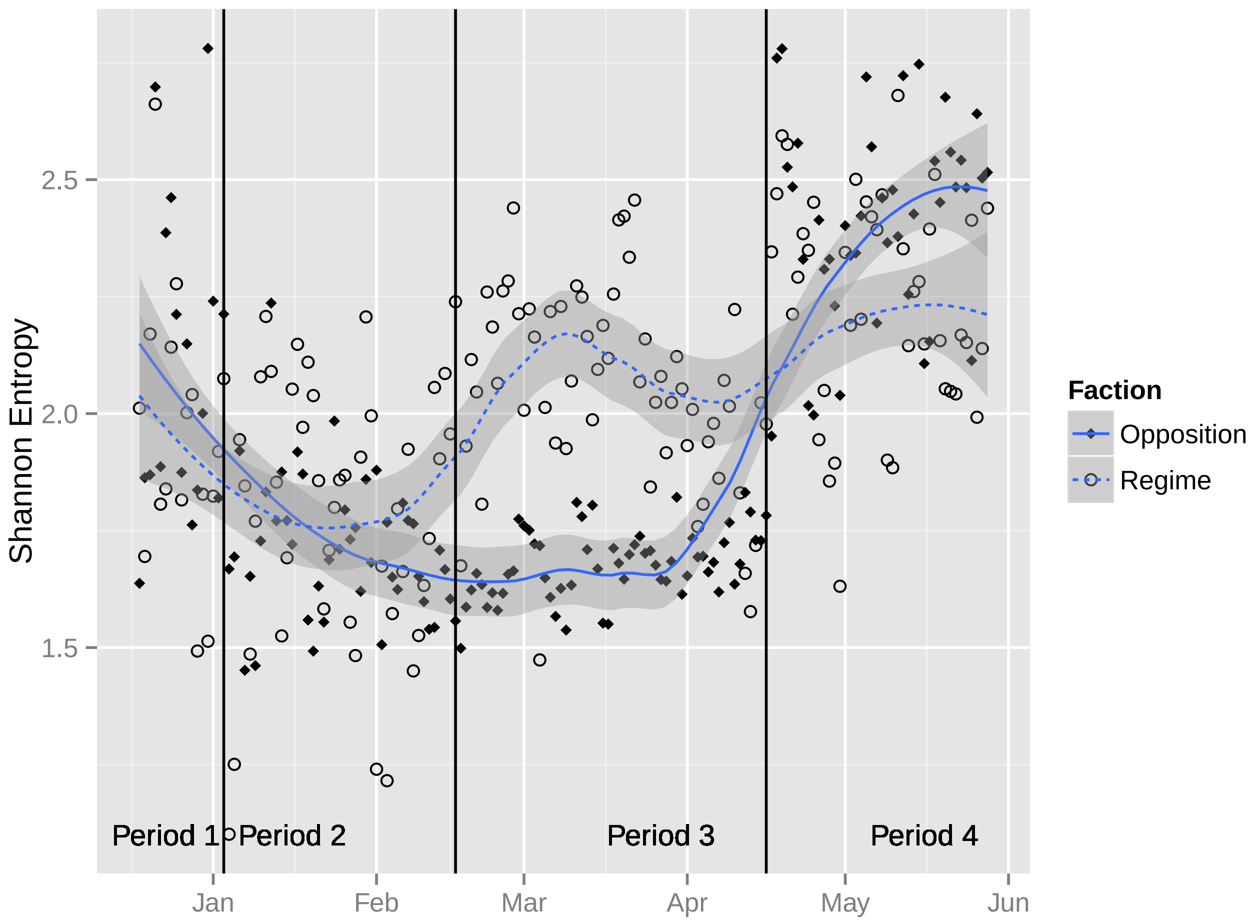
The central prediction in $H - 1$, derived from the framework in Gunitsky (2015) and suggested by the model in Edmond (2013), is that the tweets sent by the regime will become less focused during the crisis. The results from the topic diversity scores are shown in Figure 3. Recall that lower topic diversity reflects more focused twitter behavior (i.e. tweets are concentrated across a smaller number of topics). The trend for both the regime and opposition *diputado* diversities are identical in the first and most of the second period: each coalition is becoming more *focused* as the regional protests over crime and inflation spread to the capital. In the week or so before López's arrest, the government's trend abruptly changes: after nearly two months of indistinguishable levels of *focus*, the regime becomes statistically significantly less *focused* than the opposition during the height of the protests.

Explicit t-tests of the two predictions in H_1 are sensitive to the exact choice of when the protests start; we did, however, define the four time periods used throughout our analysis before running any models. Though the protests gradually gained momentum over time, the arrest of López certainly comes the closest to being a defining moment for the beginning of Period 3, the height of the protests. The average topic diversity for the regime is significantly higher in Period 3 than Period 1, and the topic diversity for the opposition is significantly lower in Period 3 than Period 1. (Both at a 95% confidence level, 2-tailed [Should I put the actual numbers in????])). With the caveat that there is necessarily a degree of subjectivity in this designation of the start of the protest, we find support for H_1.

In the fourth period, after Beginning of the Independence Movement Day and Easter, there is a discontinuity in the opposition topic diversity measures. This suggests that the messaging strategy of the opposition may have changed. Because there was no corresponding public event around which they might have coordinated, the discontinuity is consistent with a high degree of private coordination among these *diputados*.[13] Although we cannot conclusively explain why this happened solely by looking at these data, a reasonable interpretation is that the opposition "gave up" on the aggressive strategy of *La Salida* to oust the Maduro government. Promoted and executed almost entirely by the radical faction of the opposition, *La Salida* was never the first choice

[13] This is a novel method, and it could be that these methods applied to any time period's worth of tweets would provide trends that could be interpreted as supportive of a given narrative. The placebo check in Appendix B, applying the same analysis as in Figure 3, demonstrates a lack of trend in the four months after the period studied here.

Figure 3: Focus–as Modeled by topic diversity–Over Time



The vertical lines correspond to the murder of Miss Venezuela, the arrest of López, and Beginning of the Independence Movement Day, respectively. Trend lines and 95% confidence intervals were created with loess.

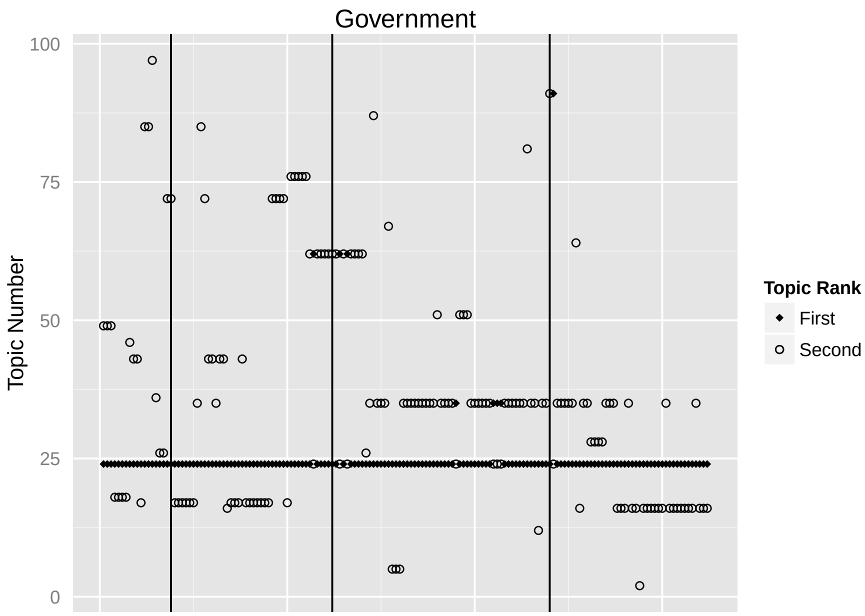
of the moderate opposition elites, and almost all of the opposition *diputados* studied here were moderates. Indeed, the most radical *diputado*, María Machado, was actually removed from her post by the regime. The opposition *diputados* wanted to present a unified front against the regime and thus were careful to *focus* attention on the protest without going so far as to openly call for violent revolution. They may also have been using the pressure that the protests represented to improve their bargaining power with the regime with respect to policy. This explanation comports with the timing of the first major sit-down between the regime and the moderate opposition on April 10th. Though these talks were widely seen as a failure in that they did not produce any concrete changes, they could have represented a public show of power to determine the relative strengths of the bargaining parties. If this was the case, then the talks may have convinced the moderate opposition that the government was willing and able to maintain the status quo. The discontinuity in the fourth section of Figure 3 may indicate that the moderate opposition abandoned their strategy of supporting the radical wing of the opposition in favor of a return to their earlier broad-based criticism of the regime.

This unexpected development does not undermine the support for H_1; we had no expectations about how the coalitions would respond to the end of the protest. In fact, that we noticed the change in the behavior of the opposition illustrates a strength of the style of unsupervised text analysis of elite communication employed in this paper: it allows us to detect trends that take place at a scale that might elude a human analyst, and to at least make guesses as to the underlying strategy driving this change.

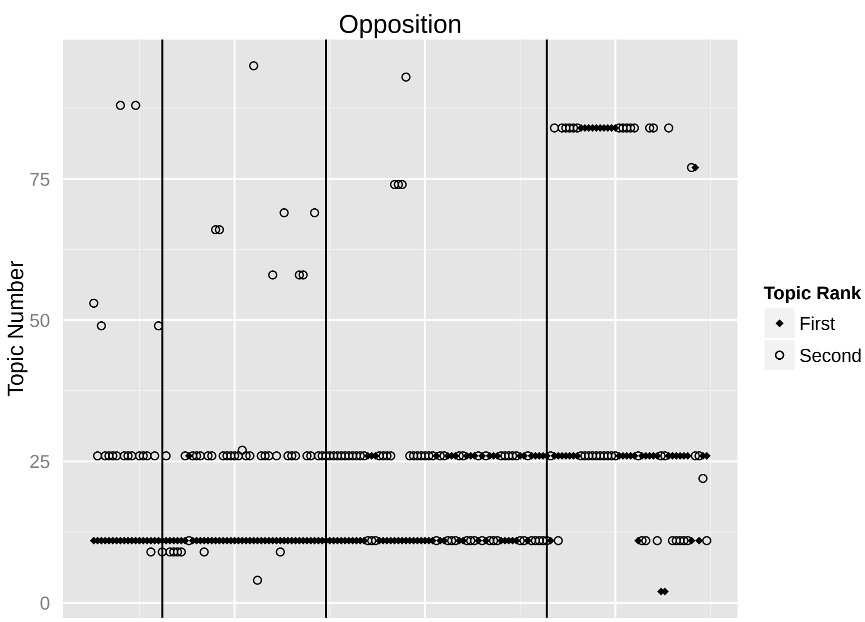
7.2 Tweet Focus–Content of Top Topics

Using the topic diversity to operationalize *focus* captures information about the entire distribution of topics, but it is agnostic about which topics are the most important for each day. Discussion could be evenly split between topics 1-50 on one day and evenly split between topics 51-100 the next and yield identical topic diversity scores. Both conceptions are essential to understanding the two coalitions' communication strategy, and Figure 4 provides a more detailed look at which topics are most central to each coalition's discussion on each day. The x-axis shows the timeline of the protests, and each day has two corresponding marks on the graph: the diamond indicates the topic that captured the highest percentage of the coalitions' tweets for that day, and the circle indicates the topic with the second highest percentage. We would find support

Figure 4: Top Topics Over Time



The vertical lines correspond to January 6 (the murder of former Miss Venezuela), February 18th (the arrest of López), and April 19th (Beginning of the Independence Movement Day). Cell entries indicate whether that topic number was the number 1 (diamond) or number 2 (circle) topic that day. The three most popular government topics, from top to bottom, are: 62, which paints López as a fascist; 35, which describes the opposition as terrorists; and 24, which equates the Maduro regime with Chávez and Venezuela more generally.



The three most popular opposition topics, from top to bottom are: 84, that the regime ruined the economy; 26, which promotes the student protest; and 11, encouraging people to work and vote with Capriles and his faction.

Table 2: **Top Terms for Relevant Topics**

#	Terms
	Top Government Topics
#	Terms
24	*nicolasmaduro*, Chavez, the people, PSUV, president, Venezuela, new, *dcabellor*, Maduro, homeland
35	Venezuela, *jmontillapsuv*, peace, terrorism, protest camp, Venezuelan, opposition, violent, rightist, violent protesters
62	peace, fascist, violent, violence, fascism, Venezuela, Leopoldo, march, rightist, López
	Top Opposition Topics
#	Terms
11	today, work, vote, the people, *hcapril*, unity, day, diputado, good, Venezuela
26	government, Venezuela, student, Maduro, protest, path, today, country, this way, diputado
84	*prmerojusticia*, *juliocmontoy*, *americodegrazi*, increase, law, *williamsdavil*, earn, day, economy, path

These terms have been translated from Spanish by the lead author; terms in italics refer to specific Twitter accounts. The original Spanish terms can been found in Appendix A.

for H_2 if, during the protest, there were fewer different topic numbers that made it to the top two topics for the opposition than for the regime.

The government did hold more consistently to their number one topic, but it also featured a wider range of second topics (25) in comparison with the opposition (18). During the height of the protest (period 3), though, there were only 4 opposition top topics compared to 11 for the government. Taking López's arrest as the start of the protests, we find support for H_2. Note that this is not simply an artefact of the government tweeting more; as noted above, the opposition actually produced 40% more total tweets, making this difference during period 3 even more striking.

Table 2 lists the most common terms used in each of the most important topics.[14] Topic 24 cements the Chávez-Maduro connection and includes the President of the National Assembly (Cabello), the acronym of the regime's party (PSUV) and the words for "the people" and "homeland." Topic 62 is a clear indictment of López; five of the terms are designed to paint him as a "violent right-wing fascist." Topic 35 is a more general condemnation of the opposition's violent ("terrorist") tactics, including two variations on *guarimba*, the Venezuelan term for the permanent protest camps that

[14] Keep in mind that we over-partition the data by choosing to model 100 topics; these summaries are illustrative, but not central to our analysis.

also served as blockades designed to paralyze the government in Caracas.

For the opposition, Topic 11 seeks to connect "the people" with moderate opposition leader Henrique Capriles and asks them to "vote" and "work," and to do these things "today." Topic 26 describes the student protests as the way forward for the country and specifically addresses the government and governmental officials. Topic 84 is harder to interpret, but a majority of the terms have to do with government-mandated wage increases. Every year, the government raises mandatory salaries for the majority of workers on May 1st, but in 2014 the nominal increase was only 30%, far less than the unofficial inflation rate of around 60%. Topic 84 also addresses *Primero Justicia*, a prominent opposition party headed by Capriles, and several affiliated *diputados*.

The specific topics reaching the top two are indicative of particular communication strategies they adopted at different points. The government switched from its overwhelming favorite topic (24: the regime is Venezuela) and adopted a new topic (62: López is a fascist) around the time of López's arrest. At the same time, its second topic (35: the opposition are terrorists) solidified during the main phase of the protest. For the opposition, however, the largest change is again seen in the wake of Easter/Beginning of the Independence Movement Day, as its previous top topic (11: work with Capriles) is abandoned when a new topic (84: the regime ruined the economy) comes to the top of the discussion. There are various other topics that are similarly event-specific[15], but our choice of a large value for k makes this kind of analysis, sometimes central to LDA models of political discussions over time, less essential.

7.3 Hashtags

The final piece of evidence of differential Twitter strategies we test is the use of hashtags to assess support for H_3, which predicts that the regime will use longer hashtags in their attempt to counter-mobilize their supporters and take control of the discourse. On Twitter, hashtags are used to coordinate discussion between strangers on a given subject. For example, the most common hashtag used by the regime elites in this sample was "#psuv," the acronym for the ruling party. By including "#psuv" in a tweet, they ensure that their tweet will be shown in a list of all tweets containing "#psuv" to anyone who searches for or clicks on that hashtag. Figure 5 presents the trends in the use of hashtags.

[15]For example, the regime-sponsored topic around Christmas highlighted by the term "Chavidad," a portmanteau of Chávez and *Navidad*, the Spanish word for Christmas.

Figure 5(a) shows overall hashtag use by the two coalitions; each symbol indicates the number of hashtags tweeted by each coalition on each day. In general, both coalitions use a higher number of hashtags during the protest, and the increase is actually more pronounced for the opposition. However, there are two common types of hashtags: simple topic words that characterize the general subject to which a tweet pertains ("#Venezuela"), and phrases explicitly designed to promote discussion of a specifically crafted topic ("#MaduroProtectorDeVenezuela"). To find support for H_3, we should observe the regime using the latter type of hashtag more often. #MaduroProtectorDeVenezuela, for example, was used by the regime to promote the notion that Maduro and his government were Venezuela's only defense against violent protesters.

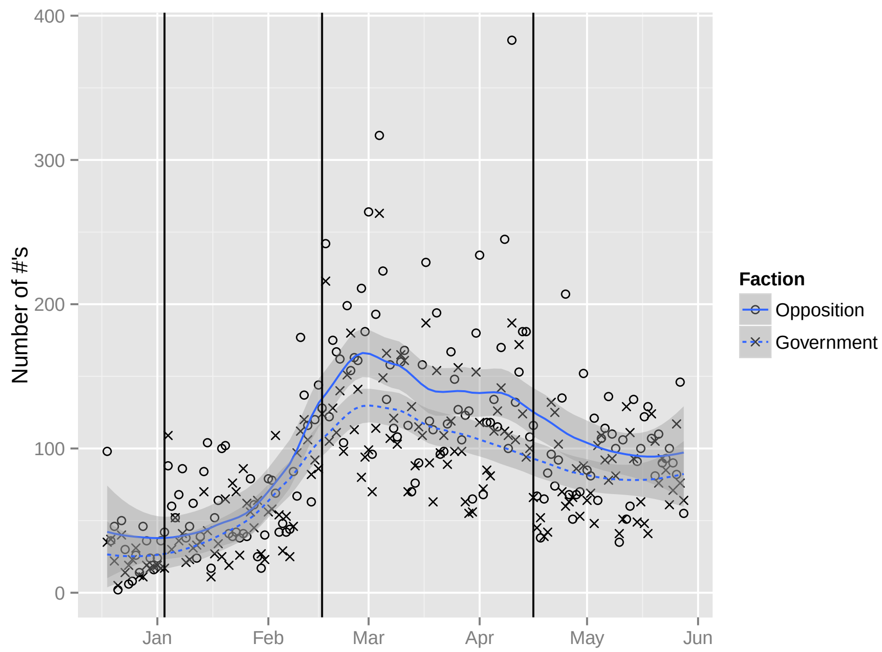
Figure 5(b) demonstrates that the regime was more likely to use long hashtags, but only once the protest started. For each coalition-day, it shows the number of hashtags that were at least twenty characters long. Twenty characters is strongly indicative of a hashtag that consists of at least three substantive words, but see Appendix D for evidence that our results are robust to different choices for this cut-off. In period 1 and most of period 2, the two coalitions were equally likely to use a long hashtag, but once the protests get started, the regime ramps up their counter-mobilization strategy and uses these lengthy hashtags to redefine the discourse.

To illustrate, the regime *diputados* used the following hashtags at different times to encourage their followers to talk about specific topics: #DesconectateDeLaGuarimba encouraged people to abandon the protest camps in Caracas; #ChavezViveLaPatriaSigue claimed that the spirit of Chavez lived on and that patriots should support Chavistas; #GringosyFascistasRespeten called their opponents US sympathizers and fascists and said that they need to respect Venezuelan sovereignty; #VzlaBajoAtaqueMediatico claimed that the international press was being unfairly supportive of the opposition as part of an effort to unseat the anti-US regime. While each of these acknowledged that the protests were going on, each was an attempt to develop a critical frame and to generate discussion of the situation that was unrelated to the demands and complaints of the protesters.

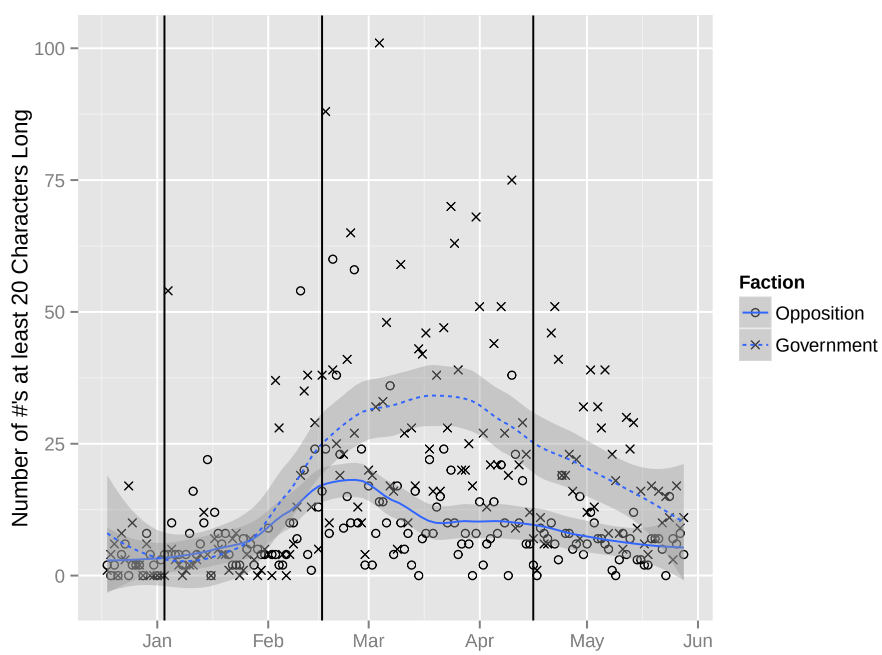
Though hashtag use on Twitter is obviously endemic to the platform and has no direct parallels in other contexts, it does provide insight into the quantity of interest: the strategic use of social media by the regime to counter-mobilize its supporters and structure the discourse. The fact that the opposition was no more likely to adopt this strategy means that it is not simply the case that elites in general use long hashtags in times of crisis; rather, elites use social media strategically to accomplish their respective

Figure 5: Hashtag Use

(a) Overall Hashtag Use



(b) Number of Hashtags at Least 20 Characters Long



(a) shows the total number of hashtags tweeted per day by the two coalitions. (b) restricts this analysis to the number of hashtags that were at least twenty characters long.

goals.

7.4 Evidence for Counter-Mobilization and Discourse Structuring

In the above section, we test our hypotheses and find support for all three. Figure 3 shows that *focus* as measured by topic diversity increased for the opposition and decreased for the regime *diputados* during the protest. Figure 4 shows the same thing, but with *focus* operationalized as the number of different topics around which a day's discussion was centered. Figure 5 shows that, while overall hashtag levels do not change much, the use of lengthy hashtags increases significantly for the regime but not the opposition.

Each of these three hypotheses was motivated by the framework provided by Gunitsky (2015): the regime *diputados* would use social media to counter-mobilize their supporters and take back the discourse from the opposition. By using the response of the opposition *diputados* as a standard of comparison, we find evidence that the regime *diputados* did indeed make strategic choices in keeping with the Gunitsky framework.

8 Conclusion

The stated goal of the *La Salida* movement, to remove the regime from power before the next election, was not accomplished during the summer of 2014. Although underlying macroeconomic and political concerns persist, the regime effectively demonstrated their repressive capacity. Our findings show that part of their strategy appears to have been to use social media to counter-mobilize their supporters to balance the physical presence of the protesters in the streets, and to try to wrest control of the narrative away from the protester's emphasis on the poor economic and security situation. The moderate opposition *diputados*, on the other hand, used social media to draw more attention to this established narrative, but only as long as it was in their interest–their sudden change after the Easter holiday demonstrates that they not permanently committed to the strategy of *La Salida*.

This change in strategy could not have been detected without the use of social media data. While this paper has set out to establish that social media is used by authoritarian regimes as a part of a strategy of regime resilience, and thus that social media use by elites in these countries is intrinsically important, it also affords opportunities to learn about strategic goals in otherwise opaque political contexts.

We cannot measure whether or not the Twitter strategies employed by the regime were effective; that question is outside the scope of this paper, but would be an excellent avenue for future research.

The quantitative textual analysis developed in this paper is a novel implementation of well-established machine learning techniques. Although looking at the topic diversity scores and distribution of top topics is less qualitatively interesting than traditional methods, it has the advantages of being objective and easily replicable. Moreover, what this approach allows us to study–the amount of information being transmitted–is essentially impossible for humans to measure. Machine learning allows researchers to extract patterns from elite communication, even if the literal content of that communication is propagandistic.

Future research should take even more advantage of idiosyncratic social media use by elites to try to better understand the unobservable inner workings of non-democratic regimes. An excellent example of this approach is Malesky and Schuler (2010), who use the behavior of Vietnamese legislators in questioning sessions to make inferences about their incentives and that of the regime more generally. That institution is peculiar to Vietnam, but social media is not, and it offers a similar avenue for analysis.

A: Top Terms for Relevant Topics

Top Government Topics	
#	Terms
24	nicolasmadur, chavez, puebl, psuv, president, venezuel, nuev, dcabellor, madur, patri
35	venezuel, jmontillapsuv, paz, terror, guarimb, venezolan, oposicion, violent, derech, guarimber
62	paz, fascist, violent, violenci, fascism, venezuel, leopold, march, derech, lopez
Top Opposition Topics	
#	Terms
11	hoy, trabaj, vot, puebl, hcapril, unid, dia, diput, buen, venezuel
26	gobiern, venezuel, estudiant, madur, protest, via, hoy, pais, asi, diput
84	prmerojustici, juliocmontoy, americodegrazi, aument, ley, williamsdavil, mer, dia, econom, via

Appendix

A Original Terms for Table 2

Table A contains the untranslated terms in Table 2.

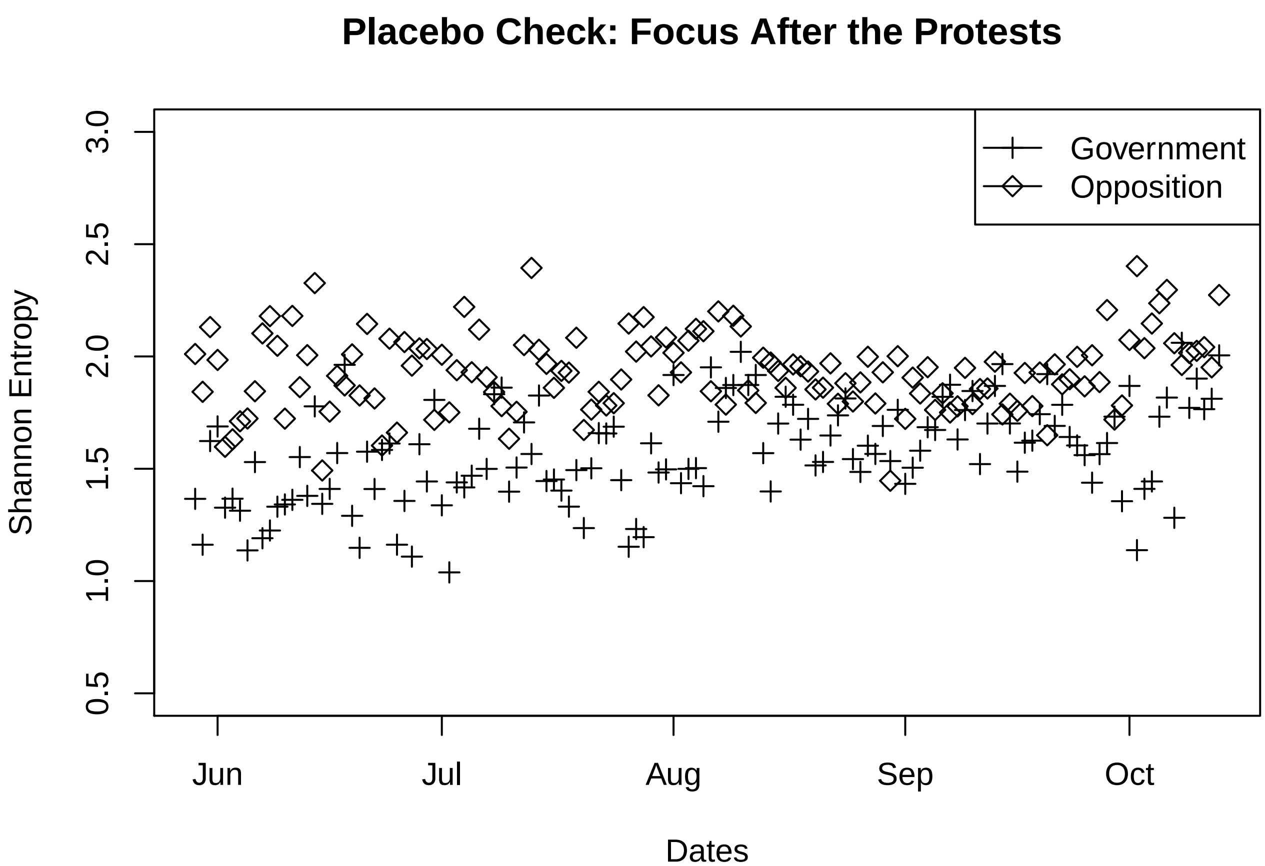
B Placebo Check for Focus

The results of the primary analysis in Table 2 depict trends in Twitter usage. The claim is that these trends correspond to important real-world events, so it's important that a similar (or similarly distinctive) graph does not obtain for data collected from a less tumultuous time period.

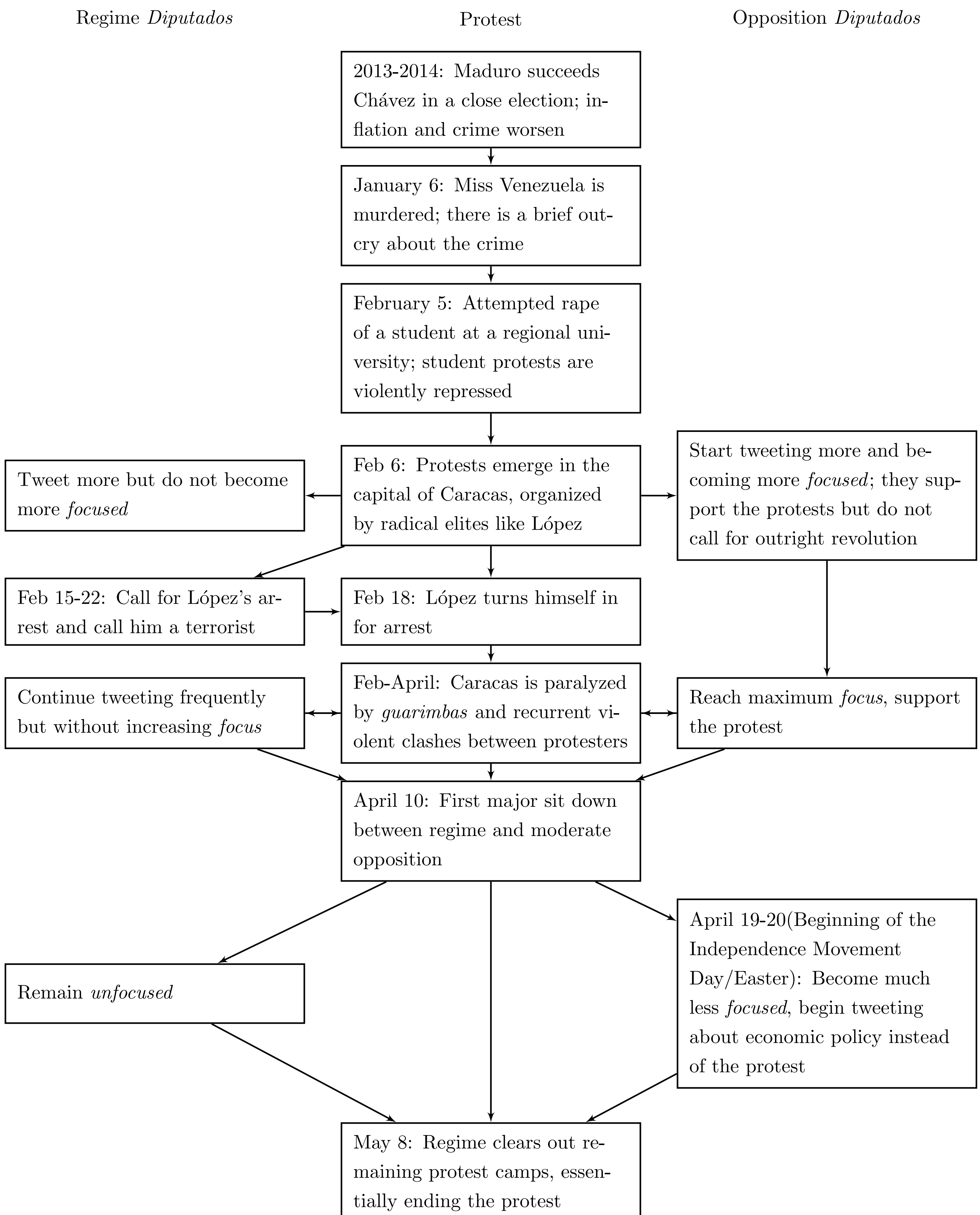
To that end, we collected the tweets from the same accounts from May 30th to October 13th, an arbitrary end date that was simply the present day. We collected 88,328 new tweets, 46,679 from the regime and 41,649 from the opposition. The ratio of regime to opposition is thus close to 1:1, compared to 2:3 in the original analysis. We ran the same LDA model as before, and used the same measure of topic diversity to track *focus*. The results are depicted in Figure B below.

Very little changes during the four months, providing supporting evidence that the dynamism observed during the crisis is unique and important. Though the government and opposition evince similarly stable trends in Figure B, the opposition tends to have slightly higher topic diversity scores and thus be less *focused*, further marking their high *focus* during the protests as significant.

Figure B


Placebo Check: Focus After the Protests
Government
Opposition
Shannon Entropy
0.5
1.0
1.5
2.0
2.5
3.0
Jun
Jul
Aug
Sep
Oct
Dates

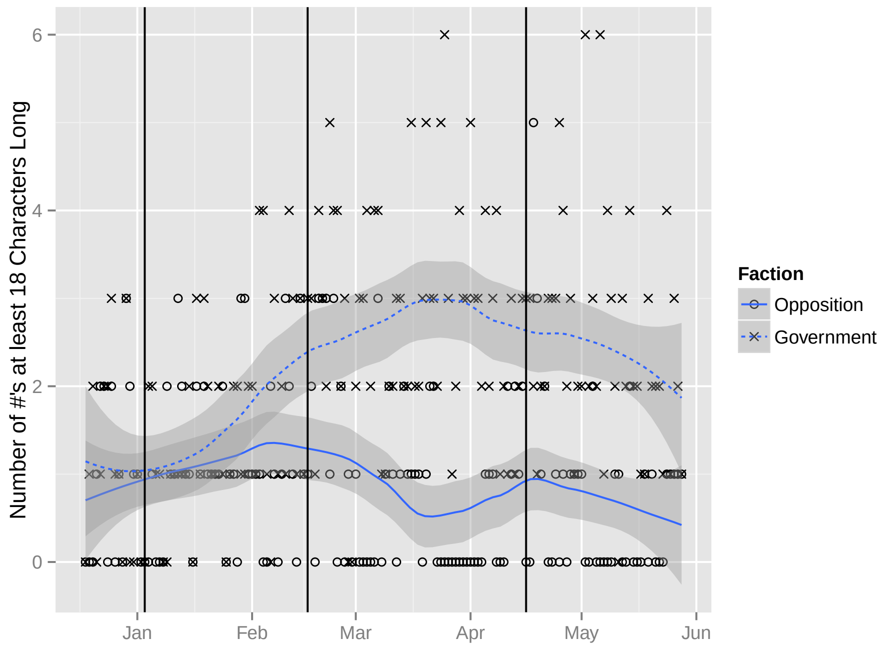
C Timeline of Events

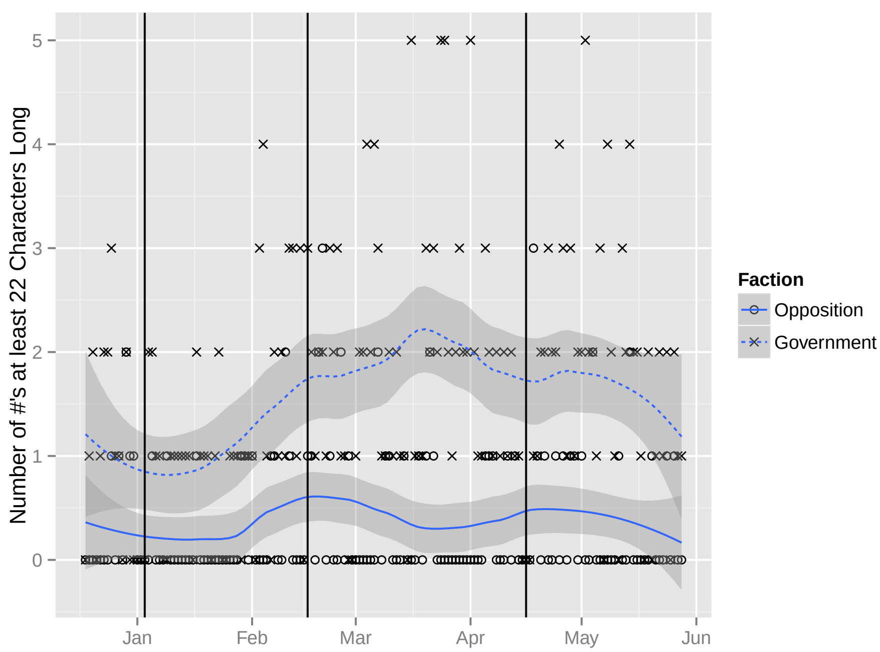


D Robustness Check–Hashtag Length

The analysis of the strategic use of “long” hashtags sets the cut-off point at twenty characters; our findings are robust to different cut-off points. Below in Figure D are two different versions of Figue 5(b); the top one has a cut-off of eighteen characters, and the bottom one has a cut-off of twenty-two characters. In neither case is the result substantially different from that shown in the body of the paper, although the time period in which there is a significant difference between the two strategies is longer for the case of twenty-two characters.

D: Robustness Check–Hashtag Length





The vertical lines correspond to January 6 (the murder of former Miss Venezuela), February 18th (the arrest of López), and April 19th (Beginning of the Independence Movement Day). The top panel shows the number of hashtags, out of the top 10 most common hashtags used by each coalition on a given day, that were at least eighteen characters long; the bottom panel, twenty-two characters long.

References

Agarwal, Sheetal D, W Lance Bennett, Courtney N Johnson, and Shawn Walker. 2014. "A model of crowd enabled organization: Theory and methods for understanding the role of twitter in the occupy protests." *International Journal of Communication* 8: 27.

Bennett, W Lance, Alexandra Segerberg, and Shawn Walker. 2014. "Organization in the crowd: peer production in large-scale networked protests." *Information, Communication & Society* 17 (2): 232–260.

Blei, David M, Andrew Y Ng, and Michael I Jordan. 2003. "Latent dirichlet allocation." *the Journal of machine Learning research* 3: 993–1022.

Cheng, Xueqi, Yanyan Lan, Jiafeng Guo, and Xiaohui Yan. 2014. "BTM: Topic Modeling over Short Texts." *IEEE Transactions on Knowledge and Data Engineering* p. 1.

Christensen, Darin, and Francisco Garfias. 2015. "Can You Hear Me Now?: How Communication Technology Affects Protest and Repression." *SSRN* .

Ciccariello-Maher, Georeg. 2014. "LaSalida? Venezuela at a Crossroads." *The Nation* .

Corrales, Javier. 2013. "Chavismo After Chavez." *Foreign Affairs* .

Corrales, Javier, and Michael Penfold-Becerra. 2011. *Dragon in the tropics: Hugo Chavez and the political economy of revolution in Venezuela.* Brookings Institution Press.

Deibert, Ronald, John Palfrey, Rafal Rohozinski, Jonathan Zittrain, and Miklos Haraszti. 2010. *Access controlled: The shaping of power, rights, and rule in cyberspace.* Mit Press.

Earl, Jennifer, Heather McKee Hurwitz, Analicia Mejia Mesinas, Margaret Tolan, and Ashley Arlotti. 2013. "This protest will be tweeted: Twitter and protest policing during the Pittsburgh G20." *Information, Communication & Society* 16 (4): 459–478.

Edmond, Chris. 2013. "Information manipulation, coordination, and regime change." *The Review of Economic Studies* 80 (4): 1422–1458.

Gerbaudo, Paolo. 2012. *Tweets and the streets: Social media and contemporary activism.* Pluto Press.

Greitens, Sheena Chestnut. 2013. "Authoritarianism Online: What Can We Learn from Internet Data in Nondemocracies?" *PS: Political Science & Politics* 46 (02): 262–270.

Griffiths, Thomas L, and Mark Steyvers. 2004. "Finding scientific topics." *Proceedings of the National academy of Sciences of the United States of America* 101 (Suppl 1): 5228–5235.

Gunitsky, Seva. 2015. "Corrupting the Cyber-Commons: Social Media as a Tool of Autocratic Stability." doi:10.1017/S153792714003120.

Hastie, Trevor, Robert Tibshirani, Jerome Friedman, T Hastie, J Friedman, and R Tibshirani. 2009. *The elements of statistical learning.* Vol. 2 Springer.

Hong, Liangjie, and Brian D Davison. 2010. Empirical study of topic modeling in twitter. In *Proceedings of the First Workshop on Social Media Analytics.* ACM pp. 80–88.

Hornik, Kurt, and Bettina Grün. 2011. "topicmodels: An R package for fitting topic models." *Journal of Statistical Software* 40 (13): 1–30.

Howard, Philip N, Sheetal D Agarwal, and Muzammil M Hussain. 2011. "When do states disconnect their digital networks? Regime responses to the political uses of social media." *The Communication Review* 14 (3): 216–232.

Khondker, Habibul Haque. 2011. "Role of the new media in the Arab Spring." *Globalizations* 8 (5): 675–679.

King, Gary, Jennifer Pan, and Margaret E Roberts. 2013. "How censorship in China allows government criticism but silences collective expression." *American Political Science Review* 107 (02): 326–343.

Lotan, Gilad, Erhardt Graeff, Mike Ananny, Devin Gaffney, Ian Pearce et al. 2011. "The Arab Spring— the revolutions were tweeted: Information flows during the 2011 Tunisian and Egyptian revolutions." *International Journal of Communication* 5: 31.

Mainwaring, Scott. 2012. "From representative democracy to participatory competitive authoritarianism: Hugo Chavez and Venezuelan politics." *Perspectives on Politics* 10 (04): 955–967.

Malesky, Edmund, and Paul Schuler. 2010. "Nodding or needling: analyzing delegate responsiveness in an authoritarian parliament." *American Political Science Review* 104 (03): 482–502.

Mehrotra, Rishabh, Scott Sanner, Wray Buntine, and Lexing Xie. 2013. Improving lda topic models for microblogs via tweet pooling and automatic labeling. In *Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval*. ACM pp. 889–892.

Morozov, Evgeny. 2011. "Whither Internet Control?" *Journal of Democracy* 22 (2): 62–74.

Oates, Sarah. 2013. *Revolution stalled: The political limits of the Internet in the post-Soviet sphere*. Oxford University Press.

Perez, Valentina. 2014. "The Grim Reality of Venezuelan Protests." *Harvard Political Review* .

Phan, Xuan-Hieu, Le-Minh Nguyen, and Susumu Horiguchi. 2008. Learning to classify short and sparse text & web with hidden topics from large-scale data collections. In *Proceedings of the 17th international conference on World Wide Web*. ACM pp. 91–100.

Rahimi, Babak. 2011. "The agonistic social media: cyberspace in the formation of dissent and consolidation of state power in postelection Iran." *The Communication Review* 14 (3): 158–178.

Roberts, Margaret E, Brandon M Stewart, and Edoardo Airoldi. 2015. "A model of text for experimentation in the social sciences." *Unpublished manuscript* .

Sanovich, Sergey, Denis Stukal, Duncan Penfold-Brown, and Joshua Tucker. 2015. "Turning the Virtual Tables: Government Strategies for Addressing Online Opposition with an Application to Russia.".

Shannon, Claude. 1948. "A Mathematical Theory of Communication." *The Bell System Technical Journal* pp. 379–423.

Tufekci, Zeynep, and Christopher Wilson. 2012. "Social media and the decision to participate in political protest: Observations from Tahrir Square." *Journal of Communication* 62 (2): 363–379.