Candidate Networks, Citizen Clusters, and Political Expression: Strategic Hashtag Use in the 2010 Midterms

By
LETICIA BODE,
ALEXANDER HANNA,
JUNGHWAN YANG,
and
DHAVAN V. SHAH

Twitter provides a direct method for political actors to connect with citizens, and for those citizens to organize into online clusters through their use of hashtags (i.e., a word or phrase marked with # to identify an idea or topic and facilitate a search for it). We examine the political alignments and networking of Twitter users, analyzing 9 million tweets produced by more than 23,000 randomly selected followers of candidates for the U.S. House and Senate and governorships in 2010. We find that Twitter users in that election cycle did not align in a simple Right-Left division; rather, five unique clusters emerged within Twitter networks, three of them representing different conservative groupings. Going beyond discourses of fragmentation and polarization, certain clusters engaged in strategic expression such as "retweeting" (i.e., sharing someone else's tweet with one's followers) and "hashjacking" (i.e., co-opting the hashtags preferred by political adversaries). We find the Twitter alignments in the political Right were more nuanced than those on the political Left and discuss implications of this behavior in relation to the rise of the Tea Party during the 2010 elections.

Keywords: campaign communication; hashjacking; online communities; social media; Tea Party; Twitter; U.S. elections

The contemporary media environment is changing rapidly, with the mass media age giving way to networked communication structured around social media, causing concern among many scholars that democratic discourse is being undermined and political alignments are growing increasingly polarized (Stroud 2011; Sunstein 2007; Prior 2007).

Leticia Bode is an assistant professor of communication, culture, & technology at Georgetown University, with affiliate appointment in the Department of Government. Her research focuses on the intersection of politics, technology, and communication.

Alexander Hanna is a PhD candidate in sociology at the University of Wisconsin–Madison. Alex is interested in social movements, media, and computational social science.

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Others have pointed out the possibility of multiple, simultaneously occurring public spheres, facilitated by the variety of social platforms available to the average citizen today (Dahlgren 2005; Papacharissi 2002). These online venues also allow for observation of the political communication behaviors of users and, by extension, the examination of their participation in multiple discursive communities. The online world provides a new arena in which we can watch coalitions emerge, and examine the nature of political discourse and alignments.

One important platform with the potential to allow for both exchanges of views between elites and citizens and the emergence of communities within public space is Twitter. Twitter provides a direct (and public) method for political actors to connect with citizens, and for those citizens to organize into online alignments. Use of Twitter has grown rapidly, with more than 310 billion tweets sent since its creation. By September 2013, 18 percent of U.S. adults active online were using Twitter, with nearly half visiting the site daily, making it among the most active networking platforms (Pew Center Internet and American Life Project 2013).

As Twitter use has grown, so has its adoption in campaign communication and electoral politics. One overlooked realm of this usage is the use of the political hashtag (user-generated keywords organized around the # symbol). Hashtags allow users to cluster around specific topics—essentially to create discursive clusters around a shared interest. For this reason, we contend that Twitter encourages the creation of multiple public spheres among the politically inclined through the use of hashtags, and that membership in these alignments is defined by shared concerns, social identity, and expressive strategies rather than solely ideological affinity.

This study takes a focused and unique sample from Twitter—candidates in U.S. congressional and gubernatorial contests in 2010 and a random selection of their followers—to explore the composition and clustering of these networks. We do so by analyzing 9 million tweets produced by more than 23,000 users. Focusing on a core element of Twitter communications, the use of hashtags, we examine the formation of de facto communities based on language use within this network. We pay particular attention to the presence of strategic expression such as "retweeting" (sharing someone else's tweet with one's followers) and "hashjacking" (co-opting hashtags preferred by political adversaries). Using these methods, we are able to describe emergent online political communities in the midst of a key midterm election.

JungHwan Yang is a PhD candidate in the Department of Journalism and Mass Communication at the University of Wisconsin–Madison. His research interests include computational methods and political communication.

Dhavan V. Shah is Maier-Bascom Professor at the University of Wisconsin–Madison, where he is director of the Mass Communication Research Center. He is housed in the School of Journalism and Mass Communication, with appointments in Industrial and Systems Engineering, Marketing, and Political Science. His work concerns framing effects on social judgments, digital media influence on civic and political engagement, and the impact of health information and communication technologies on chronic disease management.

Fragmentation, Polarization, and Candidate Networks

Jürgen Habermas (1962) advanced the notion of the public sphere as an area in which individuals congregate to discuss issues, identify problems, and attempt to agree on a course of political action. Recent work points to a growing fragmentation and pluralization of the public sphere, traced to the rising dominance of online communication (Dahlgren 2005; Papacharissi 2002; Habermas 2006). Yet there is considerable disagreement on the extent of pluralization of the public sphere (Neuman, Bimber, and Hindman 2011), with a number of scholars asserting social media contributes to polarization (Baum and Groeling 2008), with online publics splitting along traditional political lines—a Right-Left political divide (Tremayne et al. 2006; Adamic and Glance 2005; Farrell and Drezner 2008; Hindman 2008). Depending on one's vantage point, then, social networking platforms and news portals either foster multiple public spheres, or reinforce and exacerbate partisan divides, or represent some combination of the two (Baum and Groeling 2008; Robertson, Vatrapu, and Medina 2010). Whichever claim is correct, these technologies also amplify individuals' ability to connect with a range of social units, bringing together collectivities and networks of relations (Shah et al. 2005).

Despite the concerns about the role of digital media on fragmentation and polarization, coupled with the fact that the vast majority of candidates for the U.S. Congress in 2010 employed Twitter in their campaigns, few studies have examined the types of political expression that occur within the networks connecting candidates and citizens. Most research on the political use of Twitter has focused on the behaviors of members of Congress, both what encourages them to adopt Twitter and what helps them to be "successful" in such use (Lassen and Brown 2011; Williams and Gulati 2010; Chi and Yang 2010, 2011).

Several other studies have examined Twitter use within the electoral context, attempting to predict electoral outcomes (Tumasjan et al. 2010; Metaxas, Mustafaraj, and Gayo-Avello 2011; DiGrazia et al. 2013), considering the structure of political networks (Conover et al. 2011), and examining patterns of political activity by candidates (Bruns and Highfield 2013; Graham et al. 2013). Notably, these studies focused on candidates' behaviors, dedicating considerably less attention to the expression and clustering of their follower networks. Although social networking platforms provide a means for candidates to connect with citizens, these venues also provide a means for these citizens to communicate with one another, self-organize, and engage in adversarial politics.

Explaining Strategic Expression in Online Communities

It is with this in mind that we examine whether social networking supports the maintenance of existing partisan divides, deeper political realignments, or partisan decoupling. Much of what motivates this study, then, is an interest in identifying varied and potentially overlapping online communities and the forms of strategic expression used within them. These communities are expected to share language, rhetorical techniques, political priorities, and interactional goals. Because "hashtags are used to bundle together tweets on a unified, common topic," we use them to identify and describe these discursive clusters (Bruns and Burgess 2011, 5). Hashtags allow users outside of follower networks to engage on a particular topic and to identify their tweets as belonging to a broader conversation (Boynton and Richardson 2014). In this way, hashtags facilitate conversation among unconnected individuals, resulting in an important form of digital political communication and behavior.

Thus, an understanding of connections among political publics on Twitter emerges organically, by virtue of their own expressive behavior, rather than by researchers imposing a known spectrum of understanding, such as political ideology or partisan affiliation, on their actions. This work advances past efforts to examine the clustering of online publics by (1) drawing a larger, more complete sample of political elites; (2) examining randomly selected follower networks and their message posts; (3) clustering these networks based on their hashtag use; and (4) examining patterns of strategic expression use within these unique clusters. Through this approach, we can better study online political clusters and their strategic practices.

We have two main expectations regarding the mapping of hashtag use within these candidate networks. First, we expect major clusters to emerge outside of the traditional ideological extremes of the Left-Right spectrum. This view is not at odds with other work documenting a Left-Right divide (Adamic and Glance 2005; Conover et al. 2011), for we certainly expect clusters representing liberals/progressives and libertarian/conservatives. However, we also expect to identify local clusters of users who engage in types of political behavior or communication within, between, or beyond the classic understanding of ideological Right and Left, representing online communities that share particular beliefs, identities, and values. As such, we expect that hashtag use within candidate networks will also reveal intra-ideological disputes, emergent political movements, mobilization around specific ideas, contestation over particular electoral races, or affinity for particular media outlets.

As has been observed of discourse in cyber-culture, opportunities for "flame wars," nastiness, and incivility are rife (Willard 2007; Anderson et al. 2013). Along these lines, we expect some users will aggressively encroach on other clusters' coded language, injecting their perspectives into opposing communities. "Hashjacking"—co-opting the hashtags preferred by political adversaries—and retweeting may be discursive strategies favored by users who wish to maximize diffusion of their views, either for proselytizing or to confront opponents.

Data and Measures

Twitter data

Twitter data were collected over 72 days around the 2010 election from the candidate networks of all candidates for governor, Senate, and House who had a

Twitter account, for a total of 386 candidates, of whom 347 represented a major party.[1]

Followers for each candidate were randomly sampled at two separate times during the election cycle, proportionally decreasing in each instance as the sample approached the maximum sample size of fifty. This resulted in a total sample of 23,466 followers.[2] Though this approach is limited in capturing the activities of a broader range of users, the data are more comprehensive than taking a random sample of the whole Twitterverse since we were able to capture every single tweet of the sampled users. Nearly 9 million tweets (text of the tweet and metadata) were gathered through the Twitter Streaming API.

In political settings, hashtags are used to identify political allegiances, form discursive clusters, label particular races, name media sources, and otherwise focus and direct exchanges on topics of interest. Analysis of the co-occurrence of particular hashtags and their frequency of use within clusters provides a glimpse into the self-structuring of online clusters around shared ideas and strategies. Given our focus, we generated a weighted frequency of hashtag use within each sampled user for the purposes of multidimensional scaling. We constructed a two-mode matrix of users by hashtags used as the starting point for our analysis.

Normalizing hashtag use by user, rather than using a count, helps to distinguish users who tweet once and use a particular hashtag from users who tweet a thousand times, hashtagging each time, but use a particular hashtag only once. As we are interested in how hashtagging behavior can represent political alignments on Twitter, we believe this is an important distinction when attempting to differentiate between types of political users, with the former group more likely systematically engaging in a particular hashtag community, but the latter not doing so to the same extent. Because some hashtags are used with much greater frequency than others, we further weight by the overall population's use of a particular hashtag so as to give those hashtags greater importance in our classification scheme.

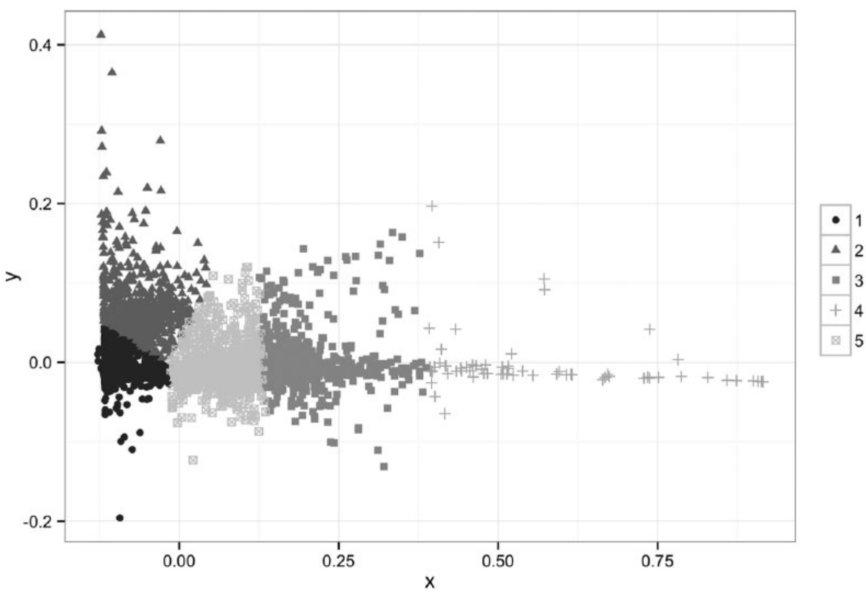
Analysis

Multidimensional scaling of hashtag use

To examine the clustering of Twitter users together we performed a multidimensional scaling (MDS) analysis (Kruskal and Wish 1981) for the use of hashtags by unique users in our dataset. We attempt to identify users who are similar to each other by virtue of what they actually say (shared use of particular hashtags). To generate the MDS, we focused on the heaviest users of hashtags and concentrated on this group's use of the most prominent hashtags. We aimed for 5,000 users and 500 hashtags, based on when the distribution of user volume and hashtags tended to even off. We used a final sample of 4,979 users and 474 unique hashtags to achieve clear demarcations. Using more users or hashtags did not change the analysis substantively.

We performed the analysis using nonmetric MDS, which attempts to retain rank order of entries as ordered by distance while simultaneously minimizing the

FIGURE 1
MDS Map of the Political Twitter Users



NOTE: Clusters created using k-means.

badness-of-fit (stress) iteratively (Kruskal and Wish 1981).[3] We vectorized user hashtag usage by generating a weighted two-mode matrix of user hashtag frequency over total hashtag usage.[4] We used the output of the MDS as the input for a clustering algorithm. K-means clusters aim to partition points into *k* groups such that the sum of squares from points to the assigned cluster centers is minimized, relying on least-squares estimation. A scree plot (not shown) flattened out after five clusters. Additional clusters did not significantly reduce the within-group sum of squares.

We chose to use two dimensions in the mapping, which minimized the stress sufficiently (2.099)[5] and allowed us to more easily interpret the spatial position as an indicator of similar behavior. Plotting of MDS analysis allows us to discern distinct groupings of individuals based on their shared Twitter behavior and to observe which entities are closer to each other. Consistent with our expectations to observe clusters beyond a Left-Right division, the mapping shown in Figure 1 supports a more nuanced interpretation than suggested by partisanship alone. The five clusters vary mostly along the horizontal axis, though there is considerable variation along the vertical dimension as well. Although it certainly hints at polarization in political Twitter (a point we return to below), it also illustrates how much users differ—the analysis indicates that a traditional partisan dichotomy is not sufficient to explain online political expression, at least in terms of hashtag use in 2010 on Twitter. To better understand the differences among the five clusters observed in the mapping, we look more closely at their language use, strategic expression, and frequency of hashtag use.

Local interpretation of clusters

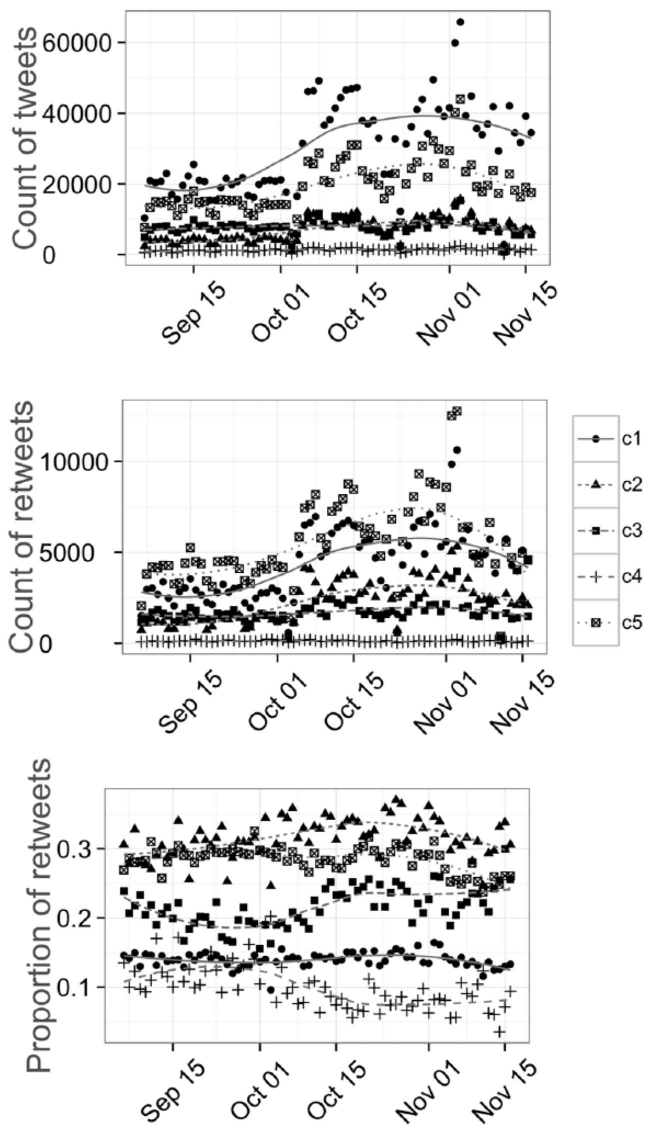
We examined the proportion of hashtags used within each cluster and the prominence of particular hashtags to gauge distinctive language use (see the appendix for the top thirty hashtags across clusters). A simple comparison of the proportion of the most popular hashtags of each cluster suggests some basic ideological differences among the clusters. Conservative hashtags, such as #tcot (top conservatives on Twitter) and #teaparty (Tea Party movement), dominate Clusters 3, 4, and 5, suggesting their ideological leaning toward the Right. In contrast, #p2 (progressives 2.0) is most prominent in Cluster 2, suggesting a liberal leaning. Cluster 1, the largest cluster, shows no particular leaning in terms of top three hashtag use.

Diversity of hashtags used within each cluster also varies. For example, when looking at clusters where #tcot is used most frequently, the dominance of #tcot within each cluster differs considerably: #tcot constitutes more than 80 percent of all hashtag use in Cluster 4, but only 34 percent and 25 percent in Clusters 3 and 5, respectively. To highlight this, Figures 2, 3, and 4 show features of the five clusters' posting behaviors and hashtagging. Figure 2 displays over-time variation in volume of tweets and retweets, and the proportion of retweets to total volume, with each point indicating the daily value and the line indicating the smoothed value. Similarly, Figure 3 shows the volume and proportion of the three most prominent hashtags, #tcot, #p2, and #teaparty. Figure 4 shows the volume and proportion of "hashjacking" behaviors, when #tcot and #teaparty intersect with #p2. Substantial differences in the use of key ideological markers emerge.

Cluster 1 can be best characterized by its low level of strategic expression. Although largest in terms of total number of tweets (N = 2,188,224), only a small portion of this cluster's users engaged in retweeting and hashtagging. Just over 10 percent of all tweets were retweets, and the top three hashtags cumulatively accounted for just under 16 percent of total hashtagging. Among the 515,121 hashtagged tweets, #teaparty is most prominent, followed by #tcot and #p2. Popular retweets of this cluster were mostly liberal, including retweets of Barack Obama (@BarackObama), liberal media personalities (e.g., @KeithOlbermann, @StephenAtHome), and progressive blogs (@thinkprogress).

Cluster 2, with 347,395 hashtagged tweets, is clearly defined by liberal/progressive politics. It makes extensive use of the #p2 hashtag, which constitutes 31.7 percent of the output of this group. It also makes use of the #topprog (Top Progressives) and #votedem (Vote Democratic) hashtags, reaffirming an affinity for liberal politics. This group is strategic in its communication, directing others toward progressive blogs (#p2b) and also using an alternative hashtag, possibly used to avoid hashjacking (#p21, Progressive 2.1), but seldom using any conservative hashtags. Major liberal hashtags represent a sizable proportion of this cluster's expressive behaviors (the top ten hashtags account for almost 63 percent of output and the top thirty hashtags cover 81.5 percent). Retweeting behavior was also

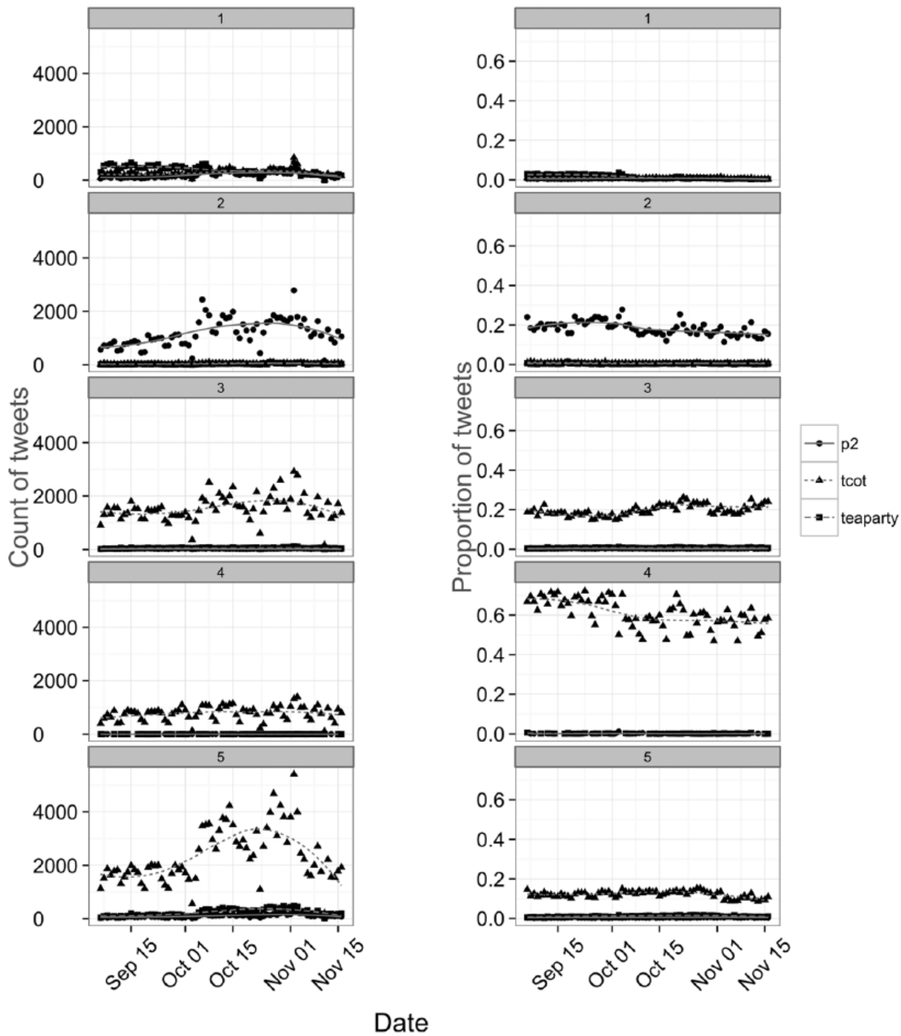
FIGURE 2
All Tweets and Retweets by Cluster



strongly liberal, heavily retweeting tweets from President Obama, Speaker of the House Nancy Pelosi (@SpeakerPelosi), other progressive politicians (notably Alan Grayson, Joe Sestak), and the Democratic Party (@dccc).[6] Although the overall tweet count of this cluster is low, it is most active in retweeting.

Returning to Figure 1, Cluster 1 users are grouped together in the lower left of the map. Directly above this cluster and extending to the top of the plot are

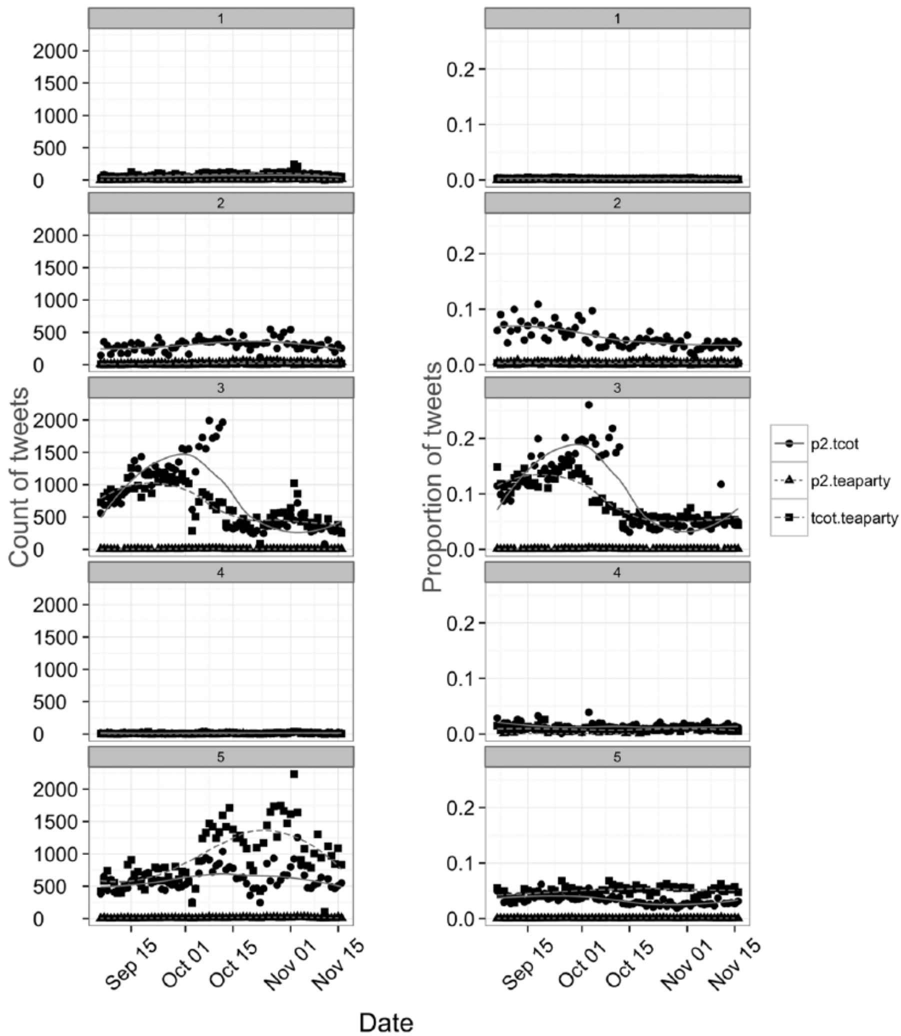
FIGURE 3
Major Hashtags without Hashjacking



the users in Cluster 2. Both of these clusters occupy almost the same width in the plot, suggesting that the vertical axis of Figure 1 represents political partisanship and polarization (as clearly Cluster 2 is more liberal than Cluster 1). However, this still leaves the horizontal axis open to interpretation. For this, we turn to the other three clusters.

Clusters 3 and 4 resemble each other, with differences coming from the size of the community and hashtag use patterns. Cluster 3 is based on 637,073 hashtagged tweets, whereas Cluster 4 is based on considerably fewer (71,823) hashtagged tweets. Both are dominated by the #tcot hashtag, though to differing degrees (34.3

FIGURE 4
Hashjacking of Major Hashtags



percent of Cluster 3 versus 80.9 percent of Cluster 4), and both groups feature consistent use of other conservative hashtags, including #teaparty, #gop, #tlot (Top Libertarians on Twitter), and #orca (Organized Conservative Resistance Alliance). Cluster 3 also includes greater reference to two hashtags connecting conservative women: #sgp (Smart Girl Politics) and #twisters (Twitter Sisters).

Further, what differentiates these two clusters is the degree to which hashjacking behavior is employed (see Figures 3 and 4). While Cluster 3 shows very active hashjacking behavior, Cluster 4 rarely co-opts progressive/liberal hashtags, instead mostly relying on #tcot. The count of #p2-#tcot hashjacking in Cluster 3 often exceeds 1,000 per day, more than 20 percent of its whole tweet count. Closer reading of popular retweets reveals that both Cluster 3 and Cluster 4 heavily retweeted conservative elites, especially, Fred Thompson (@fredthompson), one of the top conservative Twitter users during the 2010 elections.[7]

Cluster 5 is the largest grouping, drawing on 1,132,591 hashtagged tweets (and second largest in total number of tweets). This larger volume of activity also makes it the most diverse in content, though once again, the cluster has a decidedly conservative orientation and seems to be closely connected with Tea Party politicians, including Christine O'Donnell (@ChristineOD) and Sharron Angle (@SharronAngle) through retweeting. The #tcot hashtag represents more than 25 percent of hashtagged tweets from this group (a plurality), with #teaparty second. Other commonly used hashtags include #tlot, #gop, and #orca, along with communication about key races (Delaware, Nevada, and California Senate and Massachusetts 4th District). It also used specialized Tea Party movement groups #tpp (Tea Party Participants) and media voices #hhrs (Hugh Hewitt Radio Show). This cluster also used progressive leaning tags in sizable number, including #dems, #obama, #hcr (Obama's health care reform), and, of course, #p2 and even #p21. The top ten hashtags account for 67.4 percent of this clusters output, and the remaining 33 percent includes sizable amounts of hashjacking of progressive hashtags.

Overall, it seems the conservative side of Twitter was more nuanced and possibly more divided than the liberal side of Twitter during this 2010 election cycle. The horizontal axis of Figure 1 seems to denote differences in strategic communication by different groupings of U.S. conservatives. This may be a reflection of shifts in intraparty politics in 2010, given the rise of the Tea Party and its active use of social media to organize the grassroots movement (Williamson, Skocpol, and Coggin 2011). We explore these differences in strategic expression and adversarial politics more closely below.

Conclusion

Through this project we have developed a method of mapping political networks on Twitter, providing insights into the composition of these networks and their propensity to engage in strategic communication. We found that solely Left-Right distinctions, while useful in some ways, inadequately describe political behavior on this platform in 2010. Rather, we find it much more fruitful to discuss how users employ Twitter for political purposes in more nuanced, often strategic, ways, including how they interact with one another, self-affiliate, and organize online communities using the tools available to them. We think the strategic nature of political action and conversation on Twitter—particularly in terms of organizing tactics (forming alignments around identities, contests, and media rather than general politics) and hashjacking (encroaching on opposition's keywords to inject contrary perspectives into a discourse stream)—is an important contribution to the existing scholarship. Indeed, we find that citizens' political expression on Twitter reflects a multidimensional space, with clusters emphasizing and advancing political movements, media sources, exigent races, gendered identities, and strategic expression. This represents a complicated digital world of multiple public spheres, with specific issues or ideas allowing individuals to coalesce into fluid and ad hoc discursive groupings that exist in addition to the traditional Left-Right continuum.

As such, this study goes beyond the discourses of fragmentation and polarization concerning online political communication to specify the substantive formation of online coalitions via social media during political elections. Consistent with our expectations, we find considerable evidence of multiple subclusters on the Right. In addition, the regularity with which conservative users of Twitter engaged in hashjacking provides support for our expectation that some groups would engage in strategic communication practices of proselytizing and agitating. Notably, this was most prevalent among the cluster representing the Tea Party Movement. This adversarial style of Tea Party proponents may have deeper implications for democratic functioning.

This mapping provides insights into the question of social media, contributing to the pluralization of the public sphere (Dahlgren 2005; Papacharissi 2002; Habermas 2006). In 2010, we see the distinctions within the Republican Party that served to define the emergent Tea Party movement, the continued importance of conservative media, and activism surrounding conservative women. It is worth noting that these distinctions continue to define election cycles in important ways. What is notable about these online clusters of citizens is that they engaged in little hashtagging around specific issues, suggesting limited support for the notion of issue publics dominating online spaces (Kim 2009). Conversely, we also see little evidence of hyperfracturing of the citizenry into multiple isolated clusters.

This analysis focused on the use of hashtags in mapping the candidate networks, with additional evidence provided by retweeting behavior within these clusters. This method can be extrapolated to mapping any bounded space of discourses in the social sphere. We could have employed other entities used within the realm of Twitter, such as URLs, and user mentions, as well as the full text of the tweet and other metadata from within the user profile. For instance, McKelvey, DiGrazia, and Rojas (2014) examine strategic differences in political expression by how candidates are referenced (hashtag, @mention, or free-text). Additionally, with computer-aided content analysis and machine learning methods, researchers can create different sets of features from which to categorize tweets, using political tweeters' own language as data.

While the potential for research within this subfield is enormous, our project represents a step toward understanding the political interactions and connections happening every day on Twitter. The analysis here provides important insights into political realignments, partisan subcommunities, gendered partisan divides, and strategic expression in the form of retweeting and hashjacking. Future research should deepen the analysis of these topics using both computational and conventional methods, while remaining rooted in existing theoretical models and conceptual issues. Such hybrid methods are increasingly common, and require researchers to be conversant in a range of approaches, or work in teams where those capabilities can be tapped. This coming age of computational social science demands this unification.

Appendix

FIGURE A1
Top Eight Hashtags within Each Cluster

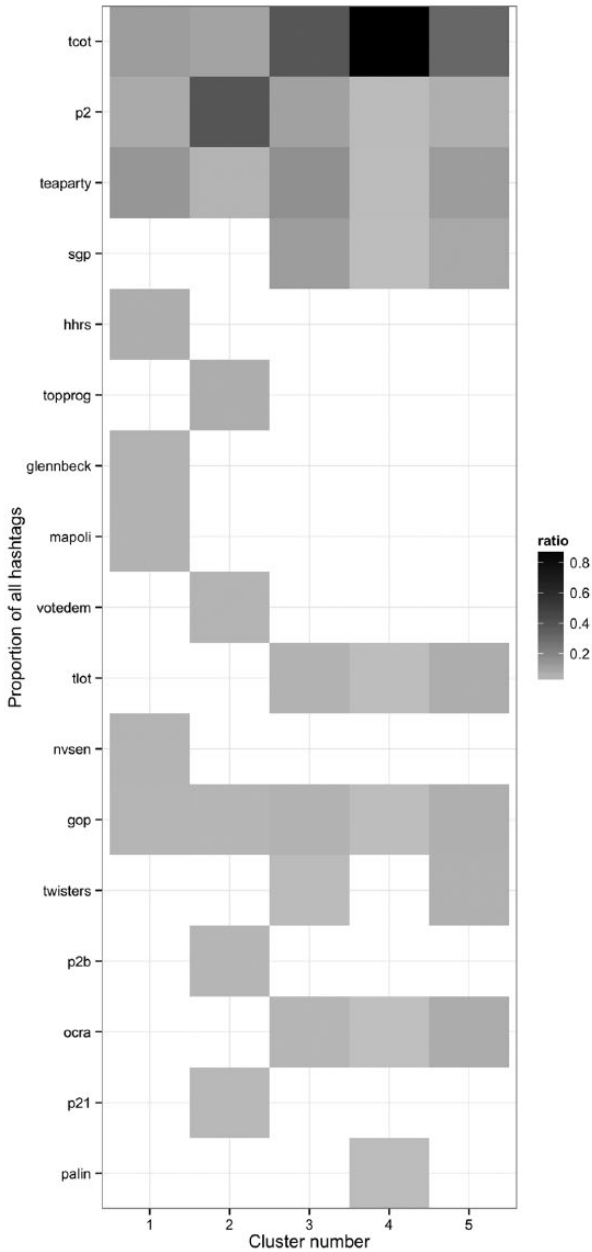
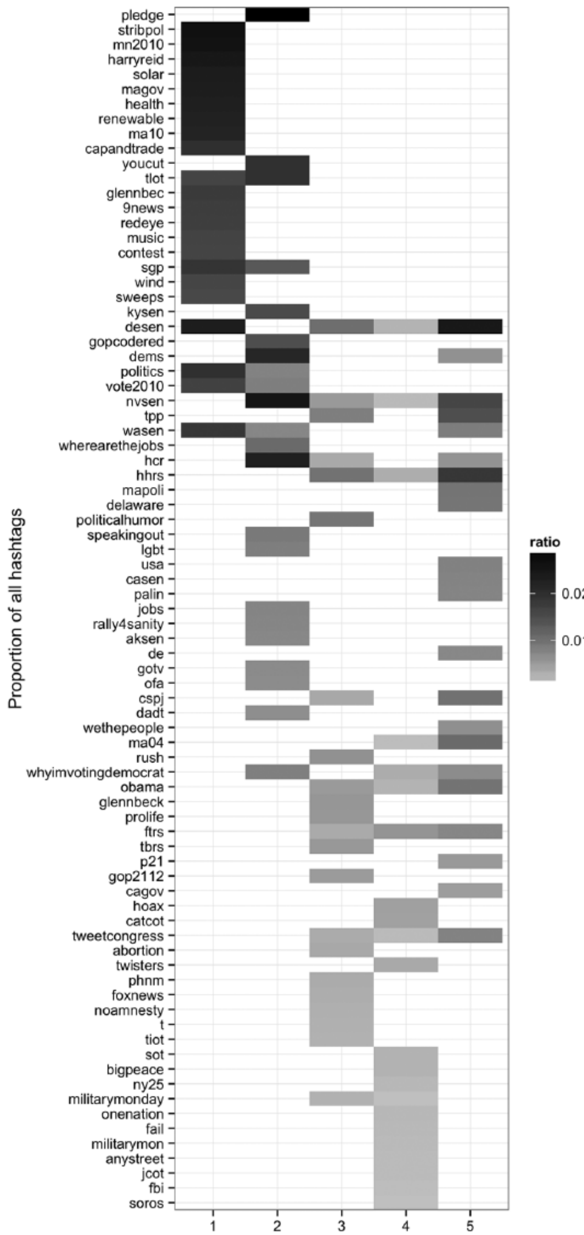


FIGURE A2
Next Twenty-Two Hashtags within Each Cluster



Notes

1. Among thirty-seven races for governor, three included a third-party or independent, and only the two candidates in the Nebraska race had no identifiable Twitter account. Thirty-seven Senate races had four contests with viable third-party candidates. Of 404 identified House candidates, 233 had Twitter accounts, of which 201 represented a major political party.

2. The size of the follower sample per candidate was calculated by the equation

$$n_c = \frac{50}{1 + \frac{(50-1)}{F_c}},$$

in which F_c is the total number of followers for candidate c at the start of measurement. We set an upper limit of 50 based on the total number of followers we could track given our technical limitations.

3. We used the Kruskal's Non-metric Multidimensional Scaling function included in the R MASS package (Venables and Ripley 2002). Input to the MDS was a dissimilarity matrix calculated from Euclidean distance between rows of matrix M in equation 2.

4. The two-mode matrix of users by hashtags was generated with the equation

$$M = \left[\frac{U_{ei}}{U_{e\cdot}} \quad P_{\cdot i} \right],$$

in which entries in the matrix were the number of times each user expressed each hashtag (U_{ei}) normalized by the user's total usage of hashtags (U_e), then weighted by the population's total usage of that hashtag (P_i). We used this weighting as a means of retaining the importance of wider-spread hashtags while also providing enough variation that users could be distinguishable from each other.

5. Using a single dimension did not reduce stress to acceptable levels (13.78). We used a scree plot (not shown) to determine the inflection point in dimensions and determined that two dimensions provide the best solution.

6. The two most popular retweets in Cluster 2 were: @BarackObama: Anybody who wants to serve in our armed forces and make sacrifices on our behalf should be able to. DADT will and & it will end on my watch; and @SpeakerPelosi: Driven by the urgency of creating jobs & protecting #hcr, #wsr, Social Security & Medicare, I am running for Dem Leader.

7. Some examples of heavily retweeted posts in Cluster 3: @fredthompson: Obama: some people in DC "talk about me like a dog". Maybe it's because he keeps treating this country like a fire hydrant; and @ fredthompson: WH rejects "global warming", favors term "global climate disruption". Ya know, I remember back when we used to call it "weather".

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