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Title:

Relationships Among Twitter Conversation Networks, Language Use, and Congressional Voting¹

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Abstract:

As Twitter becomes a more common means for officials to communicate with their constituents, it becomes more important that we understand just how that communication relates to other political activities. Using data from 411 members of Congress' Twitter activity during the summer of 2011, we examine relationships among the resulting conversation networks, language use, and political behavior. The social networks that result from their communications have surprisingly low density and high diameter, indicating a level of independence that is surprising for a group so tightly connected offline. Our findings also indicate that officials frequently use Twitter to advertise their political positions and to provide information but rarely to request political action from their constituents or to recognize the good work of others. Our analysis suggests strong relationships between anti-social behaviors indicated by the loosely connected network and low incidence of pro-social conversations and polarized or extreme Congressional voting records.

Theoretical and/or contextual Keywords:

- Internet/New Technology
- Politicians/Legislatures

Methodological Keywords:

- Quantitative – Network Analysis
- Qualitative – Textual/Discourse Analysis

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Introduction

As of November 2011, members of the U.S. House of Representatives² had 406 active, verifiable Twitter accounts, members of the U.S. Senate³ had 95⁴. Those 501 accounts, and the thousands more who respond to them, generate more than 3000 tweets per day. Given this level of activity, it's fair to ask, what are they tweeting about? And how does tweeting matter?

Twitter has garnered public attention for its use in a number of socio-political events such as social demonstrations (e.g., Gaffney 2010), Presidential debates (Diakopoulos & Shamma, 2010; Shamma, Kennedy, & Churchill, 2009), and campaigning (Livne, Simmons, Adar, & Adamic, 2010). Earlier studies of political communication in social media explored the content of tweets from Congress (Golbeck, Grimes, & Rogers, 2010), connections among political blogs (Adamic & Glance, 2005), and political position among candidates for public office (Livne et al., 2010). Most of this earlier research, though, fails to establish connections between activity on Twitter and activity offline. These studies provide detail about the content of tweets and how tweets by individuals compare, for instance, but do not offer explanations about how behavior on Twitter resembles, impacts, or predicts behavior offline. In this paper, we use data from Twitter to examine the relationships between how members of Congress behave on Twitter, how they relate to one another offline, and how they vote in Congress.

Our findings suggest a number of interesting correlations between Twitter action and polarized voting records. For instance, we find that using Twitter to position one's self in relation to political issues is highly correlated with extreme voting records, but using Twitter to thank or

² <https://twitter.com/#!/CaSMLab/u-s-house-of-reps>

³ <https://twitter.com/#!/CaSMLab/u-s-senate>

⁴ In both the House and Senate, some members maintain more than one Twitter account (“EdMarkeyComm” and “MarkeyMemo”), and some members share an account (e.g., “GOP Conference”), so these numbers do not represent accurate counts of how many members of Congress maintain Twitter accounts. Instead, they are numbers of accounts maintained, officially, on behalf of members of Congress.

congratulate others is highly correlated with centrist voting records. The social networks that results from Congress's Twitter use are remarkably low in density, indicating that they rarely interact with one another or mention each other. The remainder of this paper reviews related literature, describes our data collection and analysis methods, and presents results of our social network and qualitative analysis of Congress's tweets from the summer of 2011.

Related Literature

Using social media as a means of communicating to the larger public effectively replaces communication that was only possible through traditional media outlets (Cook et al. 1983; Edwards III and Wood 1999; Entman 2007; Graber 2000; Lee 2009) or, more recently, websites and blogs that reported statements and speeches of public officials (Gentzkow and Shapiro 2010). We emphasize that Twitter allows public officials to avoid the filters of traditional media and communicate directly to their followers. This can exacerbate the negative effects of the incomplete information held by voters, which already occurs via traditional media outlets. Thus, we expect that public officials' frequent use of "civility," "politeness," and related forms of polarizing language are likely to promote misconceptions about specific political or policy issues.

Analyzing tweets allows us to test the most recent developments of political communication theory, particularly the effects of micro-blogging efforts on party and social group formation. Existing studies have attempted to predict political candidate success in elections (Baum and Groeling 2008) or accurately portray public sentiment about candidates (Wang, Hanna, and Sayre 2011). We adopt the key explanatory variables from network research and social media – e.g., network size and strength of ties (Adamic and Glance 2005; Bakshy, Hofman, Watts, and Mason 2011) – and apply them to the unique case of public officials.

Much research on this topic is overly descriptive in its presentation of Twitter adoption rates by followers of member of Congress (Chi and Yang 2011). In one case, however, Twitter followers have been found to aggregate into politically homogeneous or homophilous groups (Tumasjan, Sprenger, Sandner, and Welppe 2010). Given these findings, we predict that public officials will create homophilous communication networks via Twitter and produce echo chambers in which they speak primarily to one another. Acknowledging the propensity for the public to have preconceived views about the source of information (Boutyline and Willer 2011), we also consider whether officials' networks grow in size and/or strength of support with civil language.

Our approach also provides a methodological innovation: existing research relies on adoption rates and followers, but such measures have been superseded by more appropriate measures (e.g., "mentions," "replies," and TwitterRank) to measure network characteristics (Bakshy, Hofman, Watts, & Mason, 2011, Cha, Haddadi, Benevenuto, & Gummadi, 2010, Weng, Lim, Jiang, Search, & Information, 2010).

Method

We first identified verifiable Twitter accounts for members of Congress, then collected their tweets for a period of time, used the content of those tweets to develop conversation networks, and qualitatively coded a subset of tweets for the action performed within the tweet. We identified Twitter accounts for members of Congress, based on listings at Congress.org.⁵ We hired workers through Mechanical Turk (MTurk) to collect and recheck Twitter screen names for all members of Congress and were able to verify 411 accounts. Mechanical Turk is a marketplace in which requesters hire workers to complete small, self-contained tasks that require

⁵ <http://www.congress.org/congressorg/directory/congdir.tt>

human intelligence. We paid workers on MTurk a set fee (\$0.06) for each Twitter screen name they could find. We hired two or more workers to look up each official and then compared their responses. In cases where the workers disagreed about the screen name, we checked the official by hand on their websites and on Twitter.

Using the Twitter Database Server (Green 2011) and Twitter-collectors (Hemphill, 2011), we gathered 29,684 tweets posted by 411 elected Congressmen between June 14, 2011 and August 23, 2011. Twitter usage generates networks when users establish “follow,” “reply,” and “mention” relationships with one another. Network analysis via UCINET (Borgatti, Everett, & Freeman, 2002) and NodeXL (Smith et al., 2010) enables us to analyze those networks to reveal insights into a group’s dynamics. For instance, we can compare the networks of members of the House and Senate to determine whether the scope or frequency of interactions differs between members of the two branches. Additionally, following someone on Twitter allows a user to view that person’s tweets in a timeline and to be updated every time the followed user tweets. Following enables a passive, peripheral awareness of another users’ contributions. Mentioning, on the other hand, is an active, deliberate communicative act in which one user directs a comment to another or explicitly references another user in his own tweet. We constructed both “follows” and “mentions” networks for the officials we studied.

We also coded a subset of tweets based on the action performed in each tweet. To gather a subset for coding, we collected tweets from the 10 highest and lowest scoring users in three categories: number of followers, number of friends, and number of tweets during the data collection period. By followers, we mean people who have elected to receive the officials’ tweets and by friends we mean those people whose tweets the official has elected to receive. Followers and friends are rough proxies for level of engagement and attention on Twitter (Bakshy, Hofman, Watts, & Mason, 2011). After removing all retweets (posts in which officials merely repeated

something said by someone else) and duplicate tweets (posts in which officials repeated themselves), we were left with 791 unique tweets.

Results and Discussion

Network Analysis

Our network analysis revealed a number of interesting features of the follower/friend and mention networks. First, the Congress mention network, based on a correlation coefficient of 0.138, which represents the correlation between our matrix and the hypothetical ideal pattern matrix were it a core-periphery matrix, does not fit into a core-periphery structure model. Second, fifteen members of Congress who tweet are neither mentioned nor do they mention any other members of Congress.

Third, the transitivity of the Congress mention network, which is a measure of how often an individual's connections are connected to each other, is somewhat lower than we would expect in a social graph. The Congress mention network has higher transitivity (0.229) than a random network of the same size and density (0.012), but transitivity between 0.3 and 0.6 is "normal" for graphs, so this can still be considered low. Transitivity is the measure used to look for "small worlds," or places where relative strangers are linked through common acquaintances, and the Congress mention network does not seem to exhibit them (Faust, 2006; Newman, Strogatz, Watts, 2001). Fourth, the diameter of the graph – the degree of separation between members of Congress – is six, which is surprising in such a small, closed network.

Figures 1 and 2 show respectively the networks resulting from officials mentioning and officials following one another. In both figures, blue solid squares represent Democrats, and red hollow circles represent Republicans. The lone Independent Senator is a yellow solid disc and is visible only in the mentions network (Figure 1), but there is no significant role of third parties in

Twitter communication, confirming Xenos and Foot (2005). The darkness of the lines connecting nodes depends on a measure of the strength of that relationship. In the mentions network, the darkness of a line is determined by the number of times two individuals mention one another. Darker lines indicate more frequent mentioning. In the follows network, gray lines indicate one-way connections (i.e., one official follows another who does not follow him) while black lines represent reciprocal relationships (i.e., both officials follow each other). Edge opacity here indicates the number of mentions, and the dark self-loops on some nodes indicate that officials frequently mention themselves.

[Insert Figure 1 here]

[Insert Figure 2 here]

A division between parties is visible in both graphs. In the mentions graph (Figure 1), we can see that lines connecting Republicans to each other are darker, indicating Republicans mention one another more often than Democrats do. Earlier research that explored similar mentioning behaviors among political bloggers (using links between blogs to indicate connections) found a similar pattern – conservative bloggers also linked to each other more often (Adamic and Glance 2005). The division between parties in the follows graph (Figure 2) is starker. There, we see clear clusters of Democrats and Republicans with fewer links between them. We also see isolates (nodes that do not connect to any others) and two large, disconnected components (subgraphs that are connected to each other but not to the rest of the graph). The smaller component on the left of Figure 2 shows a less clear division between parties. We do not yet know what accounts for the disconnected components in following network. The smaller component could be new House members, accounts very new to Twitter, or a some other explanation may be more appropriate.

Differences in the strength of relationships are visible in both graphs as well. In the mentions graph, the lines connecting Republicans are darker, indicating that they mention each other more often. In the follows network, the large component has more black lines, indicating reciprocal relationships, than does the smaller component. Taken in tandem with our earlier evidence, a lack of transitivity suggests a lack of hierarchy in this network. With no evidence of hierarchy and no evidence of a core-periphery structure, the network does not display any immediately apparent structure.

The follows network is nearly ten times as dense as the mentions network (0.134 vs 0.014, respectively), indicating that officials are passively connected to far more people than the number of people there are actively connected to. This pattern is not surprising – it makes sense that we can only engage with some subset of the people we know or are aware of. What is interesting is that in both cases, the density of the graph is surprisingly low. In a network of actors who are so similar and who, in theory, work together, we would expect to see a much higher density. Instead, we see that, at a maximum, only thirteen percent of the possible connections are made, indicating that even though officials clearly use Twitter, they underutilize the ability to passively monitor one another's communications.

These graphs cannot tell us why officials choose to follow or mention such a small subset of their peers. Other research on Twitter during Congressional campaigns (Livne 2010) suggests that the density of the network correlates to the cohesion of the network's message meaning that we would expect more cohesion among Republicans than among Democrats, enabling Republicans to present a more united front. This could be a function of the campaign process, though, which was not ongoing at the time of our data collection.

Overall, our network analysis of the follower/friends and mentioning networks created by Congress's Twitter behavior in the summer of 2011 suggests that Republican officials are more

likely to use Twitter as a means of communication than Democrats. Yet, conversations among members of Congress are not divided clearly along party lines, unlike political bloggers (Adamic & Glance, 2005), which is a comparable means of political communication. We offer explanations for why this is the case in the sections that follow.

Qualitative Analysis

We used three rounds of coding to develop a robust coding scheme for the action taken in tweets. The resulting scheme used six codes – narrating, positioning, directing to information, requesting action, giving thanks, and other – to categorize the kind of action taken in a tweet. Codes were not mutually exclusive meaning a tweet could be coded as exhibiting more than one action. For example, “With massive debt, why are taxpayers funding wine tasting? Washington's spending addiction continues <http://t.co/2QaYJmo>,” a tweet from Jim DeMint, was coded as both positioning and directing to information. We calculated Cohen's kappa scores for each code and found very strong agreement between coders. The code definitions, examples, and kappas are reported in Table 1. Positioning and directing to information were by far the most common actions exhibited on Twitter.

Our results differ dramatically from earlier results on the content of Congress's tweets. Golbeck and colleagues coded 6000+ of Congress's tweets and found that over half (53%) of all tweets were of the “information” type, meaning they provided “a fact, opinion, link to an article, position on an issue, or resource” (Golbeck et al. 2010, p. 1614). The tweets Golbeck and colleagues analyzed were posted by just 69 users over a few different time periods in 2009. We originally started coding tweets using the scheme they presented but were unable to achieve acceptable intercoder reliability measures. The main problem in applying the Golbeck scheme was the difficulty in determining what tweets did *not* fall in their information category. Nearly all

the tweets we gathered provided a fact, opinion, link or position. After failing to achieve acceptable agreement with the Golbeck scheme after repeated attempts, we used four coders to inductively code a subset of 150 Congressional tweets. We then used three rounds of coding to refine the inductive codes and eventually found very good agreement with our scheme: narrating, positioning, directing to information, requesting action, and thanking. Our scheme differs from Golbeck's in a number of important ways:

- We coded tweets in multiple categories rather than in mutually exclusive categories;
- We distinguish between “positioning” and “information” in order to compare communication on Twitter with communication elsewhere, such as websites (M. A. Xenos & Foot, 2005) because we recognize a difference in providing opinions versus publicizing resources;
- We refined the “requesting action” category to refer to tweets that demanded effortful activities such as signing petitions and participating in community events rather than low-effort activities such as reading a statement;
- We ignored questions of audience (Golbeck's “communication” codes) because we could not reach agreement on the audiences implied in such short posts.

We allowed tweets to fall into more than one category because we noticed that many tweets were explicitly accomplishing more than one communication activity (e.g., pointing to a resource and staking a political position). Such multi-purpose tweeting is not uncommon (Kwak, Lee, Park, & Moon, 2010). Though posts are limited to 140 characters, Twitter users have become remarkably effective at accomplishing multiple communication activities within a single tweet.

Because we are specifically examining politicians, we distinguish between tweets about political positions and tweets about general information. Public officials use Twitter in campaigning (Graf, 2004; G. Gulati & Christine B Williams, 2011; C.B. Williams & G. J. Gulati, 2010; M. A. Xenos & Foot, 2005) and rely on web-based media for a variety of communication activities including “issue dialogue” and “position taking” (M. A. Xenos & Foot, 2005). Distinguishing between positioning and providing information allows us to compare the

tweets to other forms of communication such as candidate websites. We found that, even though they were not engaged in public campaigning activities during our study period, members of Congress used Twitter to publicly position themselves. Our network analysis indicates that this positioning happened not in relation to other politicians but rather in relation to political topics (e.g., debt). According to Xenos and Foot (2005), this kind of public position, a hallmark of traditional offline campaigning, is common in campaign websites. Our results indicate that position taking is common on Twitter as well, suggesting that candidates may be using Twitter to implicitly campaign throughout their tenure. While perhaps not surprising, this finding is interesting because it indicates that public officials do not alter their communication strategies between media but rather use a common strategy across media (e.g., websites, speeches, Twitter). Given the remarkable differences between the audience, length, frequency of updates, and reach among various media, a single strategy for all is somewhat surprising.

We used a stricter definition for “requesting action” in order to differentiate between tweets that pointed to resources (“read here URL”) and those that asked that readers actively engage in some way (“join me at the rally”). In other words, we exclude slacktivism activities from “requested actions” when coding tweets. Slacktivism, a shortening of “slacker activism”, is used to describe activities that require little effort but still provide activists with a sense of accomplishment or engagement (Gaffney, 2010). In our schema, only “active” actions are included in requesting action, allowing us to examine how often public officials encourage their followers to actively engage in the political process or get involved in a social issue. Our results indicate that public officials rarely (only 15 of 791 tweets) request that their followers actively engage. The implications of this result remain to be seen. Earlier research suggests great promise for social media in increasing civic engagement (M. Xenos & Moy, 2007), but our results suggest it is as best underutilized and at worst not used at all.

Regarding questions of audience, Golbeck and colleagues distinguish tweets that are directed at a specific person (those that use the popular @user convention for directing a tweet to a specific user) using the code “direct communication.” Because these tweets can be automatically analyzed using straightforward algorithms, we did not code for direct communication when analyzing tweets by hand. Instead, we have left analysis of direct versus indirect communication for the next phase of our work in which we further examine the content of tweets in order to uncover connections between content and behavior and to devise an automatic coding strategy that enables us to code the whole Congressional tweet corpus quickly and accurately.

Many tweets fell into more than one category. For instance, “Unemployment rate is 9.1%. Democrats promised ‘stimulus’ spending binge would keep it below 8% <http://j.mp/pnaIhs> #wherearethejobs” both positioned the author against the stimulus spending by pointing out a perceived failure and providing additional information by pointing to a URL with additional information. Similarly, “I am on live with Drew Skaggs on WLGC talking about the #debtlimit and our plan to cut spending. Listen in: <http://goo.gl/b62Wi>” narrated the author’s activities (as a guest on a radio show), his position on economic policy (cutting spending) and provided additional information at a URL.

Often, tweets that were providing information were linking to news articles, mainly statistics or a world event:

- 81% say Washington must be forced to balance the budget, including 74% Dems <http://t.co/97usKGO> <http://t.co/E8eKMZb>
- Good news RT @washingtonpost: BREAKING: U.S. to recognize Libyan rebels as legitimate government. - <http://wpo.st/wIX3>

Officials often used narrative tweets to mention a TV or Radio appearance:

- On @FoxNewsLive today 2:15pm EST speaking w/ @ktmcfarland / Watch <http://t.co/ctlwplH> #tcot #tycot #gop #migop #teamTMAC

Many of the position tweets had a very partisan tone placing blame or accusing the other party or president:

- The President is making the wrong move by releasing 30 million barrels of oil from our emergency reserves.<http://tiny.cc/ur6kj>
- Republican leaders have demonstrated that their priorities do not include jobs or a resolution of the mortgage crisis. #debtlimit

We used the qualitative codes to predict an officials' rank on our three criteria (followers, friends, and tweets) as well as DW-NOMINATE (Carroll et al., 2011) measures of polarization in voting. DW-NOMINATE calculates polarization on a scale from negative to positive, and we used the absolute values of DW-NOMINATE scores to indicate how far from center an individual positions him or herself through voting on issues before Congress rather than how far right or left that person votes. Table 2, columns (7) and (8) show the degree to which the action of tweets predict polarizing voting. We found directing to information, positioning, and thanking to be strong predictors of polarization, and these results remained robust when we controlled for sex, party, and branch of Congress.

Table 2, columns (1) – (6), report the results of our ordered probit analyses. Positioning and directing to information were strong predictors of followers (columns (1) and (2)), meaning that officials who spend more of their Twitter time positioning themselves politically or directing their followers to information have more followers than those officials who spend less time positioning themselves. Similarly, officials who spend more time positioning and pointing to information but less time thanking others are more likely to be polarized voters. The greater likelihood that less polarized voters engage in relationship-building behaviors such as thanking and less time engaged in divisive behaviors such as positioning relative to polarizing voters reveals anti-social behavior within the latter group.

Future Work

Our results raise as many questions, if not more, than they answer. For instance, we are not able to discuss what positions public officials take or whether they discuss only a few key issues online. The limited time of our data collection precluded us from making comparisons over time or between campaign season and every day governance. The difficulty in reaching acceptable consensus in qualitative coding suggests it will be difficult but not impossible to devise an algorithm or set of algorithms that will allow us to accurately automatically code tweets for the actions taken within them. Automatically coding tweets for sentiment is increasingly common⁶, but little is known about how to automatically code tweets for the content they contain.

Our results offer clear evidence, however, that polite activities such as thanking are positively related to less polarized political activity, and that there are a number of other activities which correspond with polarized political activity. Public officials use polarizing language – supporting language for one’s self versus pejorative language for others – as a means of establishing clear boundaries on certain issues. This may be intuitive, but ours is the only empirical research that confirms this through tweet analysis. Some previous research has examined the concepts of “civility” and “politeness” in online political discussions (e.g., McClain, 2009, Ng & Detenber, 2006, Papacharissi, 2004), but none puts forward a framework that can be readily applied to our work. Still, our future work must examine officials’ language more closely in order to better understand the relationship between polarizing *language* and polarizing *behavior*. A key challenge of our work is to analyze tweets, which are extremely brief. In linguistic terms, we can describe a tweet as an individual speech act (i.e., a single utterance in

⁶ see, e.g., <http://www.peoplebrowsr.com/>, <http://tweetsentiments.com/>

which the speaker asserts or requests something) rather than a discussion. Therefore, we require a much more fine-grained framework to analyze tweets.

We will base our framework on a well-established sociolinguistic theory of “politeness” (Brown and Levinson 1987). Briefly, the theory proposes how a speaker (or a tweeter) goes about performing a speech act in a way that reduces his or her risk of “losing face.” There are two types of “face” that all adult members of society have according to the theory: one’s negative face represents the desire to act freely, without imposition from others, while one’s positive face represents the desire to be liked and accepted by others.

We will leverage Brown and Levinson’s framework because it has been widely used (e.g., Jansen & Janssen, 2010; Mboudjeke, 2010), explains language use strategies’ effects on social relationships, and can be amended to our needs while remaining accessible to our coders and readers. Our goal is to use the framework to develop quantitative measures of civility at both the level of the tweet and of the tweeter. This framework will characterize the language devices that officials use in interacting with others through their tweets, and will allow us to eventually quantify the extent to which a given tweet (or a given individual) communicates in a civil manner or uses polarizing language. We predict that civil language is a good predictor of political centrism, and we will include this measure in later regressions to test the predictive power of our civility scale.

Republicans clearly communicate to and about one another more frequently than Democrats, and there are also some important differences between the members’ branch of Congress and whether the Congressperson is male or female. Such differences were not unexpected, but the differences in goodness-of-fit between the model which excludes and that which includes party, branch, and sex controls indicate that polarizing voting is likely to be

affected by interactions between these three variables and actions of tweets. Our future work will clarify such interactive effects.

Future study must also deal with the disconnected components in both Figures 1 and 2. Exactly who is not connecting, and why? What is preventing Democrats and Republicans from talking? And is there a pattern to the reciprocal relationships; e.g., are Democrats following Republicans but not getting followed in return? The specific affordances and features of Twitter that make it unique from other media (e.g., rapid update, large reach) may encourage its users to behave differently on Twitter than they would in traditional media or offline. It may be that Twitter is more effectively used as a place for self-promotion than for coalition building and that distinction could explain why we see such low density in its networks. Our analysis suggests a relationship between friendly language (e.g., thanking) and polarizing political behavior, and we will continue to compare uncompromising behavior, (e.g., Congressional voting patterns) with uncompromising language.

Conclusion

As Twitter becomes a more common means for officials to communicate with their constituents, it becomes more important that we understand just how that communication relates to other political activities. Our findings indicate that officials frequently use Twitter to advertise their political positions and to provide information but rarely to request political action from their constituents or to recognize the good work of others. The social networks that result from their communications are surprisingly low density and high diameter, indicating a level of independence that is surprising for a group so tightly connected offline. Their communication networks more closely resemble random networks than other social networks and therefore imply that officials ignore one another online. For the many who fear officials ignore one another even offline, these results are somewhat ominous.

Future work will examine the relationships between these networks and political coalitions, among the language used and the governing behaviors. 2012 offers a unique opportunity to examine campaigning behavior in order to compare campaign communication and social interaction with everyday governance. This will provide an excellent opportunity to apply the theory of electoral incentive to Twitter-based campaigns.

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Figures and Tables

Figure 1 Congressional mentions network

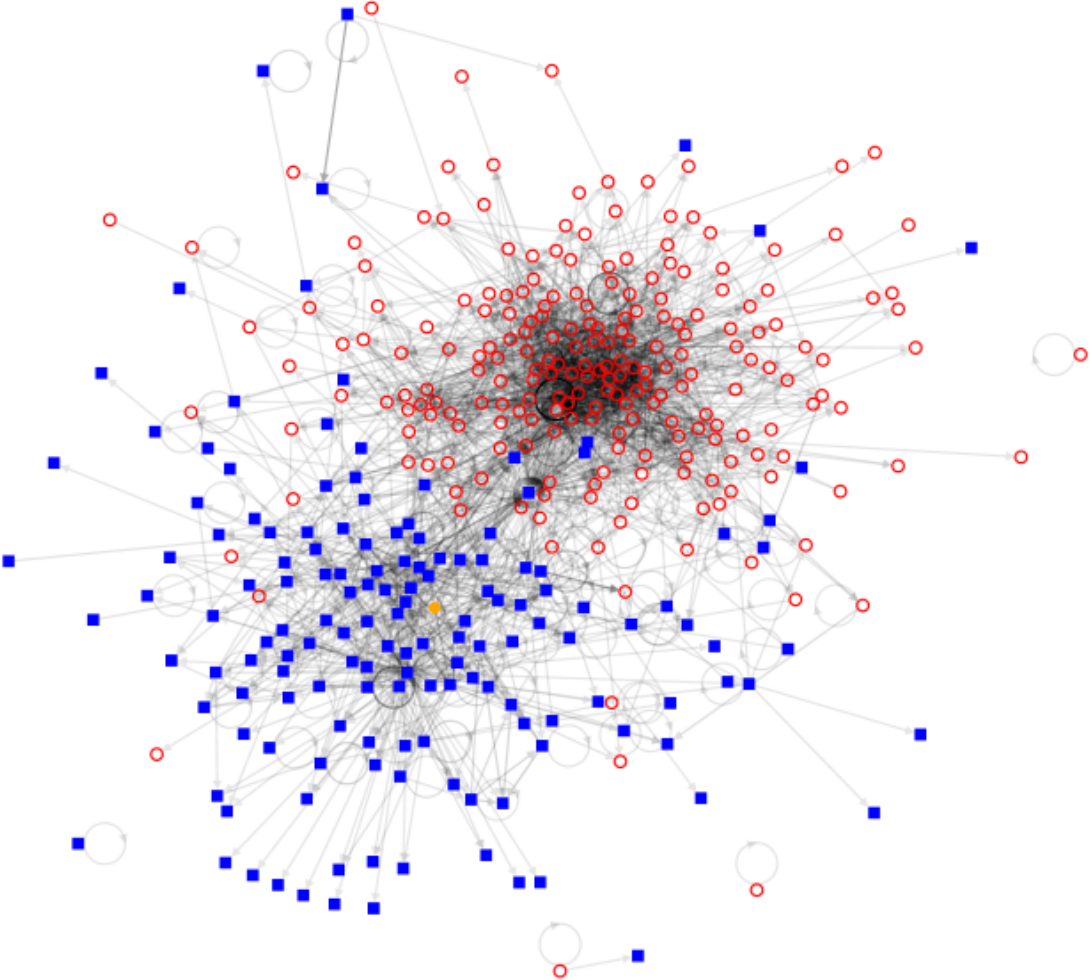


Figure 2 Congressional follows network

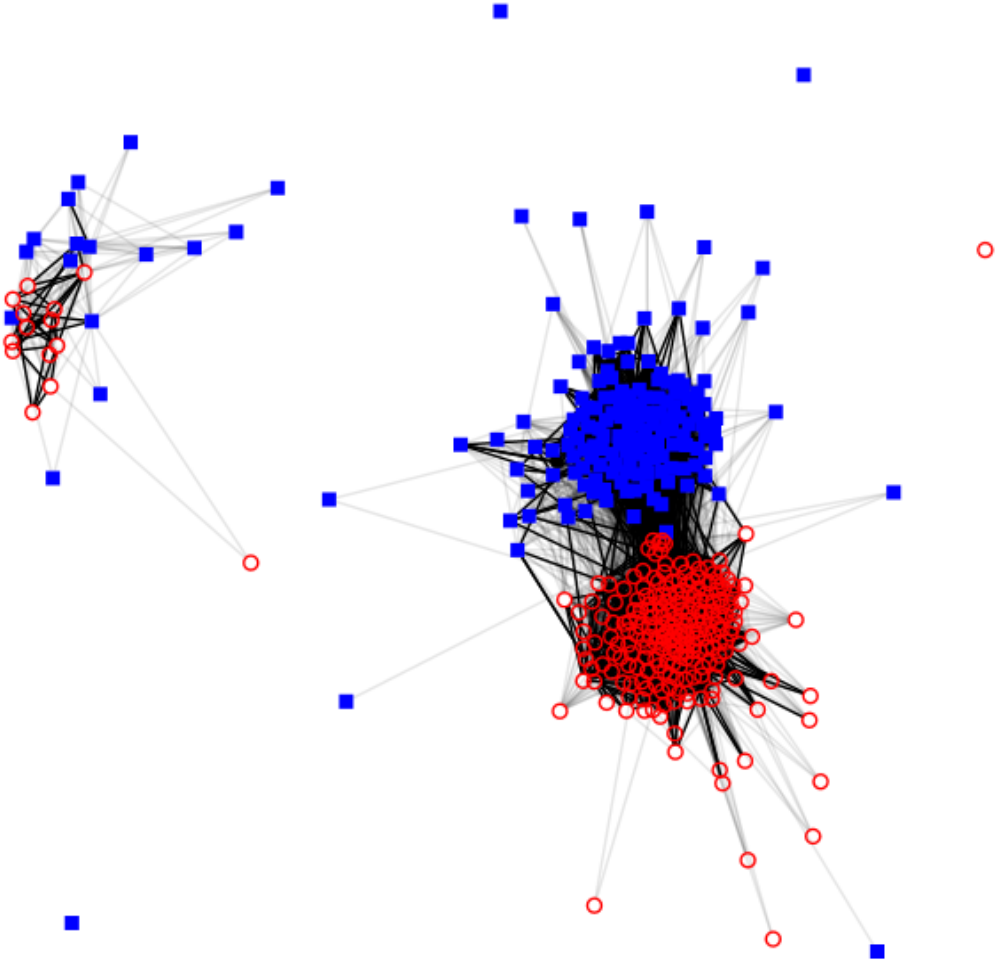


Table 1. Definitions and examples of qualitative action codes

Code	Definition	Example	N	Cohen's kappa
Narrating	Telling a story about their day, describing activities	“headed up to the Fox News camera for an interview” (Ron Paul)	173	0.83
Positioning	Situating one's self in relation to another politician or political issue, may be implied rather than explicit	“A9: Theoretically, not realistically. HC spending is growing 4x inflation and driving our debt. Let's tackle the real threat. #ryanttv” (Paul Ryan)	405	0.87
Directing to information	Pointing to a resource URL, telling you where you can get more info	“Harkin Announces More Than \$300,000 for Housing in Tama County http://1.usa.gov/lf6Aem ” (Tom Harkin)	465	0.70
Requesting action	Explicitly telling followers to go do something online or in person (not just visiting a link but asking them to do something like sign a petition, apply, vote) - look for action verbs	“RSVP to my Immigration Forum with Rep. Luis Gutierrez this Saturday in Brooklyn http://t.co/qTcWugs ” (Yvette Clark)	15	0.70
Thanking	Says nice things about or thanks someone else, e.g. congratulations, compliments	“@rmartindc Thanks. MoC's handwriting is probably on par with M.D.'s. Glad I could make your job easier.” (John Shimkus)	57	0.90
Other	Doesn't fit in any other Action category, or one can't tell what they're doing	“@jfor441 Will do!” (Jason Chaffetz)	20	-

Table 2. Predicting followers, friends, tweets, and polarizing votes

		(1) Ordered probit	(2) Ordered probit	(3) Ordered probit	(4) Ordered probit	(5) Ordered probit	(6) Ordered probit	(7) OLS: DV in logs	(8) OLS: DV in logs
		Followers rank	Followers rank	Friends rank	Friends rank	Tweeting rank	Tweeting rank	Polarizing votes	Polarizing votes
Narrating	Coef.	-0.145	-0.105	-0.221**	-0.175*	-0.340***	-0.336***	-0.050	-0.031
	Std. Err.	0.101	0.107	0.097	0.103	0.114	0.119	0.045	0.038
Positioning	Coef.	0.186**	0.148*	0.140*	0.077	-0.138	-0.112	0.0870**	0.0825***
	Std. Err.	0.086	0.090	0.082	0.088	0.095	0.100	0.038	0.032
Directing to info	Coef.	0.228***	0.293***	-0.441***	-0.440***	-0.348***	-0.336***	0.0696*	0.043
	Std. Err.	0.083	0.087	0.081	0.086	0.092	0.097	0.037	0.031
Requesting action	Coef.	0.228	0.148	0.502*	0.414	0.320	0.406	-0.125	0.049
	Std. Err.	0.284	0.294	0.286	0.300	0.318	0.326	0.127	0.107
Thanking	Coef.	0.084	0.228	-0.057	0.015	-0.255	-0.343*	-0.243***	-0.164***
	Std. Err.	0.161	0.174	0.155	0.169	0.180	0.196	0.073	0.061
Other	Coef.	-0.077	0.015	0.054	0.088	-0.291	-0.337	0.086	0.033
	Std. Err.	0.271	0.278	0.250	0.259	0.281	0.293	0.114	0.096
Male	Coef.	-0.748***	-1.531***	-0.226**	-0.851***	1.094***	1.157***		0.355***
	Std. Err.	0.107	0.132	0.104	0.128	0.156	0.174		0.044
Republican	Coef.	1.202***	1.447***	0.828***	1.201***	0.223**	0.376***		0.345***
	Std. Err.	0.097	0.116	0.091	0.114	0.104	0.119		0.035
Senate	Coef.	1.022***	1.442***	0.238***	0.618***	0.144	0.088		-0.060*
	Std. Err.	0.093	0.105	0.088	0.100	0.103	0.110		0.034
DW Nominate	Coef.		1.348***		0.899***		-0.714***		
	Std. Err.		0.218		0.215		0.249		
N		791	711	791	711	791	711	711	711
Chi2		221.33***	346.09***	122.57***	211.27***	94.69***	93.86***		
F-stat								5.16***	38.86***
Pseudo R2		0.0739	0.1202	0.0360	0.0708	0.0436	0.0485		
R2								0.0421	0.3328

*** p < .001, ** p < .01, * p < .05