Detecting Changes in Congressional Twitter Networks over Time

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Abstract

We apply a new method of temporal network analysis, the varying-coefficient exponential random graph model (VCERGM), to a novel data set using Twitter to measure inter-legislator engagement data in the 114th US Congress. The VCERGM allows us to explore if, when, and how the structure of social media engagement in the House of Representatives evolves over time. Existing methods for temporal networks are limited in their capacity to address inter-temporal shifts in the network topology, which is a limitation that VCERGM improves upon. The VCERGM estimates the evolution of networks and thereby provides useful insights of when political alliances shift in the aggregate network. Applying this new method to congressional network data allows us to estimate how robust intra-party networks are compared to intra-gender or intra-state networks. Additionally, by pinpointing significant topological change points in VCERGM estimates, we can better identify important political events that shift the relationship between legislators. Our results provide insights as to the overall stability of the Congressional Twitter network, as well as some suggestions as to how to assess the substance and real-world impetus of changes in the network.

Keywords: Congressional networks; Twitter data; Varying-Coefficient Exponential Random Graph Models; Change Point Analysis; Text Analysis

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1 Introduction

In the past decade, social media has become embedded into the fabric of U.S. politics (Bennett, 2012). The benefits of social media to legislators is that every engagement is close to real-time and reaches a wide audience. Especially since the advent of Twitter — a low-cost, outward-facing method of communication — more and more members of the United States Congress have begun to adopt Twitter as a way to communicate to their constituents as well as other politicians (Parmelee and Bichard, 2011; Park, 2013). We see an opportunity in using Twitter data as a proxy of inter-legislator relationships, since so far quantitative studies of inter-legislator relationships have largely relied on largely legislative measures such as co-sponsorship or co-voting as proxies of congressional networks.

We construct a novel temporal network data set capturing Twitter engagements between members of the United States House of Representatives for the 114th Congressional session from 2015 to 2017. Ties in the data set represent direct engagements between members, measured as one member 'tagging' another's user name. These engagements are a unique form of publicly-facing but individually-directed communication. Tagging users notifies them that they have been mentioned; any time one member tags another in a tweet the targeted member is made aware of the tweet. Tagged tweets are therefore highly relational, as the origin member makes a conscious choice to engage with another member with the expectation that the receiver will take notice. As a result, we can track inter-legislator relationships (as measured by this form of public communication) between members of Congress by identifying pairs of legislators that tend to often engage with one another. With these unique time-varying data, we can better understand how these relationships change and evolve over the course of a congressional session.

In order to analyze this novel data, we apply a new method of temporal network analysis, varying-coefficient exponential random graph model (VCERGM) to explore how the pattern of inter-legislator engagement has changed over time (Lee et al., 2017). As a temporal extension of a exponential family of random graph models — a widely used modeling strategy for a static, unweighted network — the VCERGM analyzes a gradual evolution of relational data sequentially observed in an interval of time an expresses the fluctuation in topological structures in temporal network as a smooth function of time. We then apply change point (CP) analysis and text analysis to demonstrate the statistical and substantive significance of the inter-temporal shifts in Twitter networks.

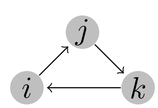
The remainder of this paper is organized as follows. In Section 2, we introduce the VCERGM for analyzing temporal networks, and CV analysis for further investigating the VCERGM estimates. Section 3 describes the process of data acquisition and processing. We present the results of VCERGM and CP analysis in Section 4 and conclude with a discussion of our findings in Section 5.

2 Methods

2.1 Varying-Coefficient Exponential Random Graph Models

The exponential random graph model (ERGM) is a family of probability distributions on unweighted static network. The ERGM has been successfully applied in a wide variety of fields especially in the context of analyzing social networks (Goodreau et al., 2009; Valente et al., 2009; Schaefer et al., 2011; Ellwardt et al., 2012). Let $X \in \{0,1\}^{n\times n}$ denote an unweighted network with n vertices, whose (i,j)th entry X_{ij} indicates a relationship between node i and node j. The ERGM represents the likelihood of X via a function of network statistics $\mathbf{h} : \{0,1\}^{n\times n} \to \mathbb{R}^p$ that describe the topological structure of X. Examples of network statistics for a directed network in ERGM are presented in Table 1.

Table 1: Examples of network statistics for a directed network in ERGM

Network Statistic		Definition
Edge density	$i \longrightarrow j$	$\sum_{i\neq j} x_{ij}$
Reciprocity	$i \longleftrightarrow j$	$\sum_{i<j} x_{ij}\, x_{ji}$
Cyclic triad		$\sum_{i<j<k} x_{ij}\, x_{jk}\, x_{ki}$

Given $\mathbf{h}$, the ERGM posits that X is a binary random matrix generated from the following likelihood

$$\mathbb{P}(X = x \mid \boldsymbol{\phi}) = \frac{\exp\{\boldsymbol{\phi}^T \mathbf{h}(x)\}}{\sum_{z\in\{0,1\}^{n\times n}} \exp\{\boldsymbol{\phi}^T \mathbf{h}(z)\}}, \tag{1}$$

where $\boldsymbol{\phi} \in \mathbb{R}^p$ parameterizes the influence of the network statistics $\mathbf{h}(X)$ on the likelihood of X.

When analyzing dynamic networks, the ERGM framework can be useful to succinctly summarize the evolution of network topology over time. A complication of applying ERGM framework to dynamic networks is that the relational structure of nodes may change over time. For example, it is reasonable to imagine that one characteristic, such as mutual friendship, used to be a dominant property of the network at one point but becomes less important as time goes by. We refer to such evolution as *temporal heterogeneity.* Temporal exponential random graph models (TERGM), proposed by Hanneke et al. (2010), have been widely used for adapting the idea of ERGM to dynamic networks. The TERGM models the difference in topological features between consecutive networks in a similar fashion to the ERGM. However, it ignores the heterogeneity of the differences, and cannot fully capture the time-varying patterns of the network structure.

Varying-coefficient exponential random graph model (VCERGM) proposed an extension of ERGM that accounts for temporal heterogeneity of dynamic networks (Lee et al., 2017). A fundamental proposition of VCERGM is that the contribution of certain network statistic to explain the network topology fluctuates over time. Let $\mathbf{X} = \{X_t : 0 \leq t \leq T\}$ be a sequence of networks observed continuously up to some time $T > 0$. At each time point t, $X_t \in \{0,1\}^{n\times n}$ represents an unweighted, directed or undirected network with n nodes. We first specify a set of functions $\mathbf{h}(x_t) : \{0,1\}^{n\times n} \to \mathbb{R}^p$, which quantify the p topological features of network x_t observed at time t. Given $\mathbf{h}(x_t)$ and the coefficient vector $\boldsymbol{\phi}(t) = (\phi_1(t), \cdots, \phi_p(t))^T \in \mathbb{R}^p$, the marginal likelihood of X_t at time t has an ERGM representation given by

$$\mathbb{P}(X_t = x_t \mid \boldsymbol{\phi}(t)) = \frac{\exp\{\boldsymbol{\phi}(t)^T \mathbf{h}(x_t)\}}{\sum_{z\in\{0,1\}^{n\times n}} \exp\{\boldsymbol{\phi}(t)^T \mathbf{h}(z)\}}, \quad x_t \in \{0,1\}^{n\times n}. \tag{2}$$

The VCERGM supposes that dynamic networks evolve gradually over time and thus represents the coefficients $\boldsymbol{\phi}(t)$ as smooth functions of t with continuous second order derivatives over $[0, T]$. Therefore, by evaluating the smooth coefficients at time point $t \in [0, T]$, one can readily write the marginal distribution of a graph X_t as described in model (2).

The VCERGM provides an intuitive explanation of how a network changes through time. The smooth coefficients $\boldsymbol{\phi}(t)$ in model (2) characterize the influence of the corresponding network statistics on determining the network structure. Namely, the magnitude of coefficients at time t represents the impact of network statistics on the likelihood of network at time t. For example, the increasing coefficient for reciprocity in the House Twitter network indicates the increasing importance of mutual tweets in forming relationships in Twitter. The `R` code for fitting VCERGMs is available on the author's GitHub: `www.github.com/jihuilee/vcergm`.

2.2 Change Point Analysis

A unique advantage of VCERGM is its ability to identify changes in the underlying network generating process. However, it is not immediately clear when and how these changes make a significant impact on the size, density, and tie configuration of the network. We use change point analysis to identify whether and when there are statistically significant shifts in the process of tie formation in the House Twitter network. CP analysis is a method of analyzing time series data to identify shifts in the underlying data-generating process that produced that information (Matteson and James, 2014). This allows the practitioner to divide a given time series into a set of 'regimes' within which data points are drawn from statistically distinct distributions (Szekely and Rizzo, 2005). CP analysis is a useful tool to take a noisy, chaotic set of time series data and extract time points where meaningful shifts occur. By detecting periods in which one or more of the VCERGM coefficients shift, we can identify where and how the social processes that form the House Twitter network change over time.

We use a Bayesian energy-divisive change point analysis (ECP) algorithm, implemented via the `ecp` package in `R` (James and Matteson, 2015). ECP uses non-parametric permutation testing to identify individual time points that are most statistically probable locations for change points (Matteson and James, 2014). This approach has three characteristics that make it well-suited to this task. First, it is entirely inductive: there is no prior information entered into the identification process. Because we do not have strong expectations as to when or how the structure of the Twitter network changes, this is a useful property in exploratory analysis. Second, it allows for a minimum significance threshold to identify a change point. This increases our certainty that the change points detected do in fact identify significant shifts in the underlying data-generating process. Third, the ECP algorithm allows for multivariate change point detection. This is very useful for the VCERGM model, as it allows us to detect simultaneous changes in multiple coefficient estimates.

3 Data

3.1 Collecting Twitter data

We gathered data using Twitter's open-source API, producing a near-complete data set [1] of tweets from the 369 legislators (out of 435 total) who used an official Twitter account during the

[1] We use the term "near-complete" because we found four accounts (Representatives Donald Norcross, Mike Quigly, Joe Wilson, and Steny Hoyer) who use Twitter with such high frequency that the API quota covers their activity for only part of the 114th Congress. For the other 366 Twitter-using members of the 114th Congress, however, we are confident that we have captured all of their Twitter usage during this two-year period.

114th session of the House of Representatives from January 2015 to December 2017 (CLSMD, 2017). The data set includes 587,055 unique tweets. The majority of these tweets are directed to a member's public following, engaging with groups of supporters or discussing day-to-day legislative activities. Out of this corpus of tweets, 14,224 represent direct engagement from one member to another, meaning that a given legislator 'tagged' one or more of their colleagues in the body of a tweet. Henceforth, when we refer to the Twitter network, we only are referring to the set of tweets that include direct engagements.

3.2 Tweets and Inter-Legislator Ties

Surveying the content of the tweets in the Twitter network suggests that most tweets falls within the general categories of social media communication identified by Straus et al. (2013). Personal communication and pleasantries are quite common (e.g. wishing someone happy birthday, discussing social events):

> "Enjoyed participating in my first congressional hotdish competition. *@BettyMcCollum04*'s winning wild rice/turkey dish was quintessentially MN"
>
> — Rep. Tom Emmer, MN-6, 4/22/2016

Members also frequently engaged in professional interaction, discussing conversations or professional events in which they participated with their colleagues:

> "Just met w/ Mayor Cranley & *@RepBradWenstrup*. Productive meeting about coordinating efforts to benefit our city"
>
> — Rep. Steve Chabot, OH-1, 12/12/2013

Another use of Twitter is for members to re-tweet content produced by other members. Because retweets call attention to the user who first produced the tweet they become another avenue for public association with another Representative:

> "RT *@RepGwenMoore*: So much love on these steps tonight. Surrounded by passionate advocates determined to #DisarmHate #LightingTheWay"
>
> — Rep. Kathy Castor, FL-14, 7/15/2016

Finally, other members' legislation was also commonly referenced. Members often discussed a bill's merits, called attention to bills up for vote, and congratulated one another on successful passage:

> “Thanks to fellow Ohioans *@RepSteveStivers* & *@TiberiPress* for co-sponsoring HR 5172,the POW Accountability Act”
>
> — Rep. Bill Johnson, OH-6, 7/25/2014

In isolation, such tweets may not present strong evidence of socializing and relationship-building between legislators. However, thousands of 140-character messages over weeks and months allow us to separate signal from noise and identify underlying relationships between members that would otherwise be difficult to observe.

3.3 Structuring the 114th House Twitter Network

We embed pairwise interactions into a temporal network structure with a rolling one-week time resolution. The tweets we gathered are time- and date-stamped to the second. However, this means that the network data analyzed here — with 14,224 ties over two years between 435 nodes — are potentially very sparse, to the point where they make statistical analysis infeasible. To alleviate the sparsity issue, we aggregate House Twitter activity to the week level, with a rolling overlap of three days. The overlap not only increases the density of the weekly networks, but smooths the evolutionary process of the networks over time. The resulting data set contains 182 rolling weekly observations of the House Twitter network.

For each week in the 114th House session, we generate directed, dyadic ties based on targeted Twitter engagements. Nodes represent legislators who have an official Twitter account, and ties exist between members if one member engaged with another. For each week, there are some isolates (nodes who have no ties) who did not use a Twitter account to engage with their colleagues during that time period.

Figures 1 and 2 illustrate two weekly ‘slices’ of the House Twitter network. In both figures, node shape indicates gender where squares indicate female and circles indicate male, and node color indicates party affiliation where blue denotes Democrats and red denotes Republicans. Figure 1 shows the network in the first week of January 2015, at the beginning of the 114th House session. Visually inspecting these networks shows some immediate differences between time periods. In the first slice, the engagement network is quite sparse, and is characterized by Twitter ties between members of the same party — very rarely do members reach across the aisle. Figure 2 shows the same network in early December of 2016 (near the end of the Congressional session), and looks very different. Not only is the network overall much more dense, but a major ‘hub’ of Twitter engagement has emerged in the Male Republican quadrant that receives ties from all other quadrants. Closer inspection shows this node is Paul Ryan, the leader of the Republican caucus in Congress. The fundamental structure of the network appears much different in this week than in the beginning of the session, and we take this as preliminary evidence that VCERGM is well suited to analysis of this network.

Insert figures 1 and 2 about here.

4 Analysis

4.1 Varying-Coefficient Exponential Random Graph Models

The VCERGM provides a unique opportunity to analyze and understand the temporal network data. Because we have repeated observations over time, the VCERGM allows us to identify changes in the underlying structure of the House Twitter network: what factors contribute to legislators using social media to directly and publicly support, oppose, or call attention to their fellow legislators. Since Representatives who belong to the same political party, have the same gender, or are from the same state are more likely to engage with one another, we suspect that such factors will likely affect changes, or the lack thereof, in the underlying structure of the House Twitter network.

We fit a VCERGM to the 182 rolling weekly observations of the House Twitter network with five network statistics: edges, reciprocity, female-female edges, male-male edges, and intra-party edges. The estimated coefficients for these network statistics are presented in Figure 3. Overall, interactions within same party or same state, or among females are consistently important to understand the relationship of legislators in Twitter. Reversely, interactions among males are not as influential in terms of forming ties.

Insert figure 3 about here.

Visual inspection of these estimated coefficients supports the existence of peaks and dips in each coefficient. The fluctuation observed in the estimated coefficients over time motivates a further analysis of spotting statistically significant change points of the coefficients. In other words, we explore the possibility of politically salient events affecting the evolution of relationships between legislators detected from the VCERGM estimates.

4.2 Change Point Analysis

To identify change points in the multivariate time series, we apply the ECP algorithm to the VCERGM coefficient estimates generated for the 182 rolling weekly observations of the House

Twitter network. We set a statistical threshold of $p <= 0.001$ and set a minimum regime length of 32 weekly observations to minimize sensitivity to short-range noise in the data [2] . The ECP algorithm identifies three change points for the estimated VCERGM coefficients, indicating a set of statistically distinct 'regimes' in the coefficient time series data that are statistically distinguishable from one another. The start and end dates of these regimes are shown below in Table 2.

Table 2: Coefficient regime spans

Regime	Start date	End date
1	2015-01-01*	2015-05-26
2	2015-05-26	2016-02-04
3	2016-02-04	2016-07-19
4	2016-07-19	2017-01-01*

* Regime truncated by sample range.

Figures 4 and 5 visualize the coefficients produced by the VCERGM over the 114th US House of Representatives. Horizontal lines indicate the regime-level means of each coefficient estimate, and vertical lines indicate the dates of change points identified by the multivariate ECP algorithm. Figure 4 shows change points for all coefficient estimates, while Figure 5 'zooms in' to better visualize variation in the coefficients for shared party, state, and male/female gender.

Insert figures 4 and 5 about here.

Upon visual inspection of the change points in figures 4 and 5, we notice a few things. First, although the ECP algorithm identifies points of overall change, the direction and magnitude of change for each individual coefficient estimate is not uniform, either within or across regimes. In other words, the relationships estimated by VCERGM do not necessarily change in tandem with one another. Second, despite significant change over the course of the two-year period, particularly in Regime 3 (between February and July 2016), the coefficient estimates are quite similar in the beginning and ending of the overall period. This suggests that a stable baseline exists, and while variation from this baseline process is possible, longer-term shifts in the fundamental structure of the network are likely not going to arise within this network.

[2] The ECP algorithm allows the user to specify the minimum length any given regime identified by change points in a time series. We tested minimum regime lengths from 8 to 64 weeks, and find that a 32-week regime length seems to capture significant shifts in the time series data while minimizing sensitivity to short-term spikes and dips.

4.2.1 Substantive Impact of Coefficient Changes

Based on visual inspection of the graph, the third regime (between February and July of 2016) shows the greatest change in coefficient values between regimes. During this period, every substantive coefficient estimate (shared party, state, and male/female gender) decreases in magnitude toward zero, as does the structural coefficient estimate on mutual/reciprocal ties between nodes. The baseline edges parameter increases significantly toward zero as well. Taken together, we interpret this variation to indicate a change in the overall structure of the House Twitter network. The overall number of edges does not decrease, but the smaller coefficients on mutuals and node-level covariates indicates that these ties are less driven by reciprocity or shared characteristics between legislators. In other words, the network becomes more difficult to explain using the original model, indicating there may be some set of missing variables that become more important during this time period.

These results are interesting, but beg the question: although we detect *statistically* significant changes in the estimated coefficients over time, do these changes indicate a noticeable shift in the structure of the observed House Twitter network? To answer this question, we compare the structure of the aggregated House Twitter networks for regimes 2 and 3 (May 2015 - February 2016 and February - July 2016).

Insert Figures 6 and 7 about here.

Visually inspecting the the two aggregated regime networks reveals few easily-discernible differences, so instead we compare a set of key network characteristics to identify whether statistically significant differences exist between the two regime networks.

Network density is a network-level measurement indicating how many $i \rightarrow j$ ties exist in the network, relative to the number of possible ties. The House Twitter network is quite sparse in both Regime 2 (0.0141) and Regime 3 (0.0138), but there is very little difference between the two periods. Returning to the coefficient estimates identified by VCERGM, it appears that the increase in the 'edges' covariate (akin to the intercept term in a traditional statistical model) is balanced by the decrease in magnitude of the other coefficients, resulting in little change to the network density.

Degree centrality is a node-level measurement indicating the total number of ties possessed by a given member of the network. Because degree centrality counts the number of ties, it correlates closely with network density, but adds additional information about how these ties are distributed within the network. Calculating nodal degree centrality both regime networks shows that mean degree centrality is very similar for Regime 2 (12.23) and Regime 3 (12.05). Running a t-test on both sets of nodes shows that the difference in mean degree centrality is not statistically significant ($p = 0.877$).

Transitivity, also referred to as the clustering coefficient, can be measured at both the network and node level. At the network level, transitivity indicates how likely any two nodes are i and j are to be connected, given that they they have ties to a common neighbor k. A network with high transitivity suggests a more tightly-knit structure in which mutual neighbors tend to share direct ties as well. The House Twitter network shows an increase in overall transitivity, from 0.14 in Regime 2 to 0.17 in Regime 3. At the node level, transitivity measures the same ratio of open to closed triples for each node separately. Calculating local transitivity for nodes during each regime and comparing them via t-test shows that the increase from Regime 2 to Regime 3 change is statistically significant ($p < 0.001$).

Based on the statistically significant differences in local and network-level transitivity between Regime 2 and Regime 3, we further compare triadic census results between the two regimes [3] . Taking a triadic census of each regimes shows that three triadic classes change markedly from Regime 2 to 3:

- The number of out-stars ($i \leftarrow j \rightarrow k$) increases from 19,615 to 23,631, an increase of about 20%.
- The number of in-stars ($i \rightarrow j \leftarrow k$) increases from 15,784 to 21,436, an increase of about 35%.
- The number of directed lines ($i \rightarrow j \rightarrow k$) decreases from 11,528 to 9,632, a decrease of about 20%.

Taken together, these results suggest that while the overall density of the network may not change significantly from Regime 2 to Regime 3, the configuration of ties - particularly the type and amount of local triadic clustering - does change between these two time periods. In the context of the House Twitter network, this change indicates an increase in the number of Twitter conversations that involve one member engaging, or being engaged by, multiple partners. While we cannot identify the tone of these many-to-one conversations, we suspect that this change in network structure signifies a change in the nature or purpose of Twitter communication among Representatives during this time period.

[3] The triadic census is a system to categorize all observed $i - j - k$ triads in a given network into one of sixteen categories according to the number and direction of ties that exist within each observed triad (Wasserman and Faust, 1994). These categories encompass all potential configurations from the fully disconnected triad $i \quad j \quad k$ to the fully connected $i \leftrightarrow j \leftrightarrow k$ for the focal node j.

4.3 Comparing the Content of Engagement Across Regimes

The VCERGM results, reinforced by change point analysis, show that statistically significant differences exist in how different legislators choose to engage with one another on Twitter. As the previous section shows, these changes seem to have a notable impact: while the overall level of Twitter activity does not show major change between regimes, the local dynamics of the network change significantly between Regimes 2 and 3. These results all point to some underlying shift in the Twitter conversation between members of the 114th House of Representatives. However, the measures identified so far are all somewhat abstract. We cannot make specific claims about why these changes occur, or how they relate to the actual content of what is being said on Twitter. In this section, we now briefly explore what these changes actually mean in terms of *what* is being said, as well as *to whom*.

We suspect that the shift in regime is likely related to the content of the tweets in the Twitter network. By comparing the aggregate frequencies of words and 'hashtags' (phrases that are used after the # symbol to label tweets so that other users can see tweets on the same topic) within each regime, we can explore whether the contents of the Twitter engagements in these regimes show any meaningful differences. Here, we focus on bigrams, or pairs of two consecutive words, as they can contain more complex information that is useful for our analysis.[4] For example, bigrams like 'happy birthday', 'vote yes', or 'gun control' all communicate ideas that could not be identified solely by the individual component words. We identify the most commonly used bigrams in the Twitter engagements of all members in Regime 2 and Regime 3, with a cut-off value of 45 occurrences.

Insert Figures 8 and 9 about here.

Figures 8 and 9 show several notable differences in the most frequent bigrams used across Regimes 2 and 3. First, more bigrams appear frequently in Regime 3 than in the previous regime. Out of all tweets in Regime 2, eleven bigrams appear more than 45 times, whereas 28 bigrams surpass the threshold in Regime 3. This is particularly striking given that, as noted previously, the density of the Twitter network in Regime 2 and Regime 3 changes very little. In other words, it does not imply that the members were simply talking more in Regime 3, leading to more bigrams appearing frequently; rather, the conversation included a broader range of concepts and ideas.

Second, the top bigrams in both Regimes show an interesting trend in the Congressional conversation. While some ideas appear commonly in both time periods – colleagues wishing one another 'happy birthday' is by far the most common bigram in both settings – a new set of bigrams

[4] We also look at the most frequently used words (> 150) and find similar results.

emerges in Regime 3. Phrases related to gun control legislation ('gun violence', 'vote #noflynobuy', '#closetheloophole #gunvote') are unique to Regime 3. This change in the dialogue among Representatives is very likely linked to real-world events: on June 12, 2016 Omar Mateen attacked the Pulse nightclub in Orlando Florida, killing 49 before dying in a police shootout (BBC, 2016). This mass shooting led to a heated debate in Congress about gun control legislation, culminating later that month when Democratic Representatives leading a sit-in on the House floor to force a vote on a "No fly, no buy" bill barring US citizens on the terrorist watch-list from buying firearms (Root, 2016).

It is important to note that this does *not* conclusively link changes in the content of the Twitter conversation to changes in the Twitter network structure; testing this relationship is possible, but doing so is outside the bounds of our current analysis. Instead, our goal is to point out that the time periods identified by both VCERGM and change point analysis as being structurally different also show distinct differences in the topics being discussed, suggesting that such a link likely exists. This is an interesting finding that merits further exploration in future work.

4.4 Summary of Findings

The results of our multi-stage exploratory analysis can be summed up in four parts. First, VCERGM estimation of the House Twitter network during the 114th Congress shows that both substantive and structural factors matter when legislators select partners for engagement on social media. As the literature suggests, legislators are more likely to engage their colleagues on Twitter if they are from the same state or party. Gender matters, but it is different for men versus women: female legislators are more likely to select other women for engagement, while male legislators engage with women and men alike. Furthermore, Twitter conversations are likely to be two-sided, as mutually reciprocal ties are quite common. The VCERGM also shows that these relationships are not necessarily static over time. In both the short and medium-term, the strength of these relationships vary. However, at least for the Congressional network, it appears that this variation is limited. For example, coefficient estimates never reverse direction, although they do change in magnitude over time.

Second, change point analysis shows that there is statistically significant variation in the VCERGM coefficients over this two-year period: the underlying data-generating process does seem to change over time. We identify several distinct 'regimes' over the this period that are characterized by different mean values of each coefficient. Regime 3, between February and July of 2016, shows the greatest differentiation in mean VCERGM coefficient values relative to the rest of the time series.

Third, to assess whether the changes identified by VCERGM and change point analysis represent substantially different data-generation processes, we then compare the structural characteristics of the House Twitter network between Regime 2 and Regime 3. Our results suggest that these two structures are different from one another. While the density and degree of the network does not appreciably change, the distribution of ties shifts. The network becomes more clustered, and there is a distinct increase in the number of in- and out-facing hub structures, indicating more many-to-one conversations during Regime 3.

Finally, we analyze the content of the Twitter conversation between Regime 2 and Regime 3 to identify whether this change in the structure of the Twitter network is also associated with a change in the content of the engagements. By examining the most common bigrams in Regime 2 and Regime 3, we find that that the subject of gun control became a major topic of conversation in Regime 3. We surmise that this change in conversation is at least in part due to the Pulse Nightclub shooting in June of 2016.

Taken together, these findings support the unique benefit that VCERGM provides to the analysis of temporal network data. By allowing the estimated relationships between both substantive and structural factors to vary over time, we were able to identify key time points and periods in the sample where both the structure and the content of social media engagement in the 114th House significantly changed.

5 Conclusions and Discussion

Based on our analysis, we arrive at several conclusions. First, while the structure of the House Twitter network is fairly stable over the two-year session, short- and medium-term variation does exist in how legislators engage with one another on Twitter. Second, it appears that changes in network structure may be linked to broader outside factors that affect legislation: the June mass shooting, and the public discussion of gun violence, co-occur with both an increase in the discussion of gun-control issues in the House, and a change in the underlying structure of the House Twitter network in which legislators were more likely to both send and receive engagements from multiple colleagues. This period may represent the most significant departure from 'business as usual' in the House, as this is also the period in which our key explanatory variables also lose magnitude in explaining the network structure.

This paper also raises several interesting questions and opportunities for future work. First, although we have a large corpus of data, a two-year Congressional session is a relatively short time period to analyze the underlying dynamics of how legislators build and maintain relationships with one another. Using VCERGM to model Congressional interactions on a longer-term data set would help us identify whether the relative stability observed in the 114th Congress is a general trend, or unique to this Congressional session. Given that Twitter was introduced in 2008 and was being widely used in Congress by 2010 (Golbeck et al., 2010), it is theoretically possible to extend this analysis back to the 110th and 111th Congressional sessions, although this would require purchasing older Twitter backlogs that are not available via the public API.

Second, for the Twitter network in particular, future work should expand on our exploratory text analysis to better explain the correlations we find between structure and content in the Congressional conversation. For example, though we find evidence that gun violence was a prominent topic in mid-2016, it was not the only mass shooting in the sample. In December 2015, which falls under Regime 2, an armed man and wife killed 14 and wounded 22 more in San Bernardino, California. However, this attack did not provoke the same level of discussion about gun control as the Pulse Nightclub shooting in June 2016, suggesting that there is not a direct and automatic link between salient political events and discussion of these events among legislators. The rich information contained in Twitter engagements provides us with opportunities to better uncover how the topics of discussion drive the structure of the conversation, and vice-versa. It is also worth exploring the role of internal versus external factors: does Congressional Twitter usage reflect changes in the popular discussion of an issue? Are there certain external factors that drive the Congressional discussion more than others? We argue that VCERGM, coupled with change point analysis, is a great tool for exploring and explaining these potential relationships.

Our analysis shows that although the factors driving Congressional engagement on Twitter are relatively stable, they change in both type and substance even during the two-year period under analysis. We also suggest ways in which future work can expand on this exploratory analysis. Overall, our results demonstrate that the VCERGM approach provides unique and useful insights in modeling temporal network data.

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List of Figures

Figure 1: Twitter engagement ties between Representatives of the 114th Congress: January 1 - 7, 2015.

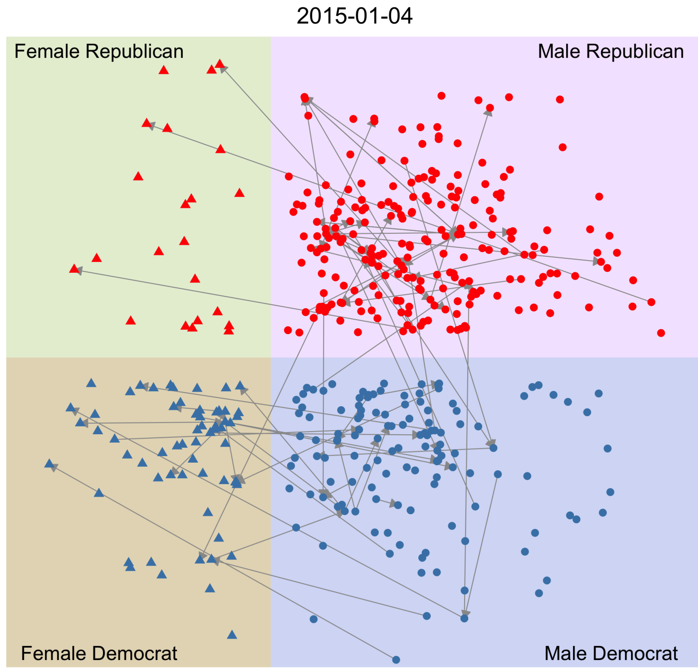
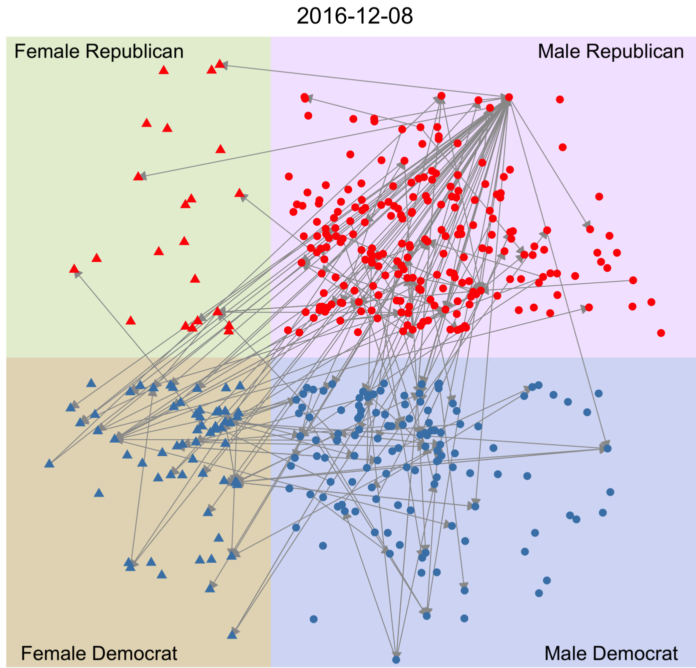


Figure 2: Twitter engagement ties between Representatives of the 114th Congress: December 4 - 11, 2016.



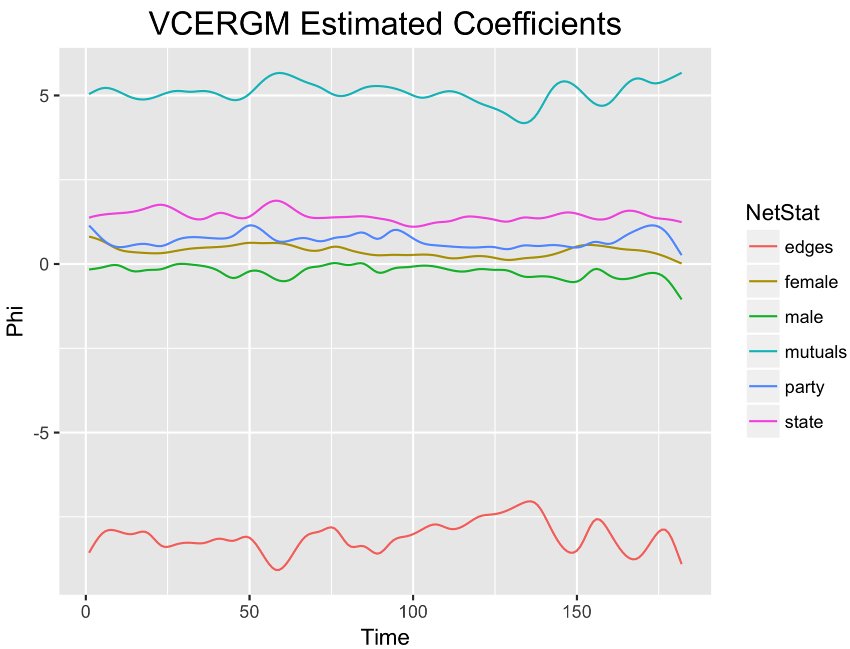


Figure 3: **VCERGM estimated coefficients**

Figure 4: **Multivariate change points for VCERGM coefficient estimates.**

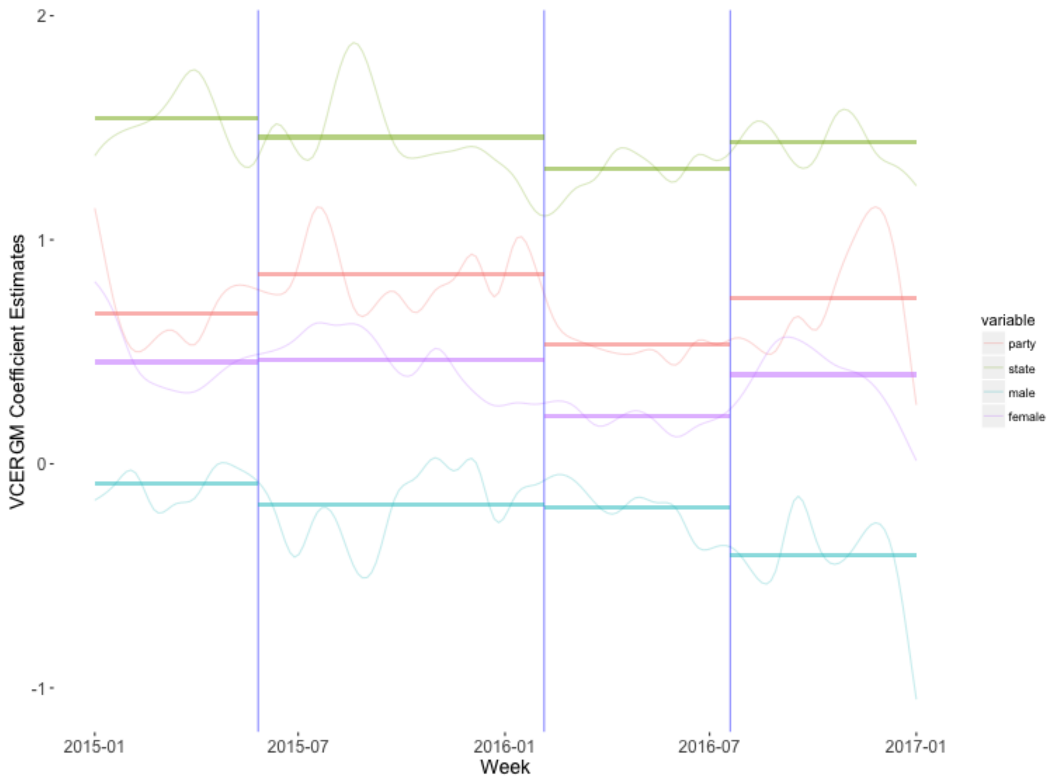


Figure 5: **Change points of selected VCERGM coefficients.**

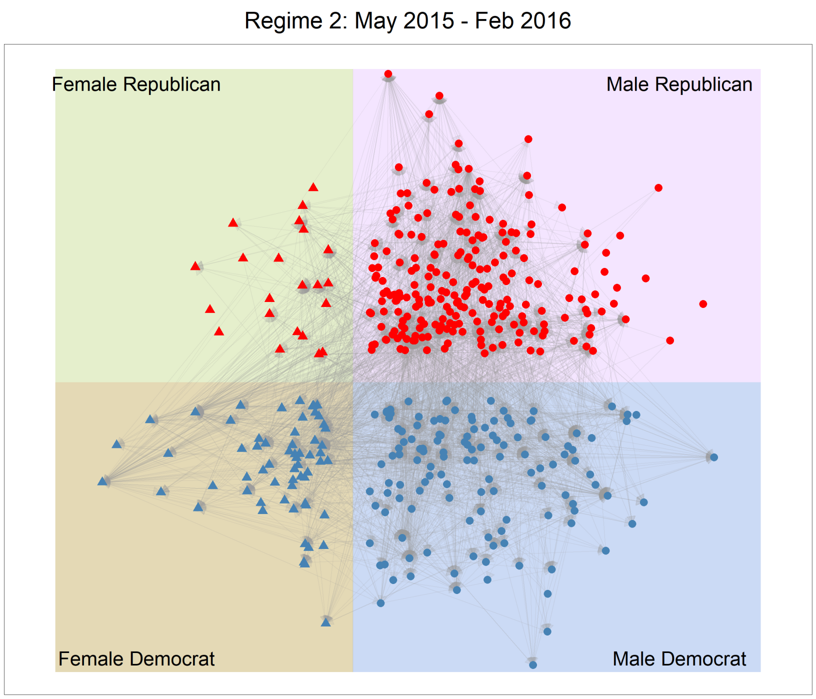


Figure 6: **House Twitter network, Regime 2 (May 2015 - February 2016)**

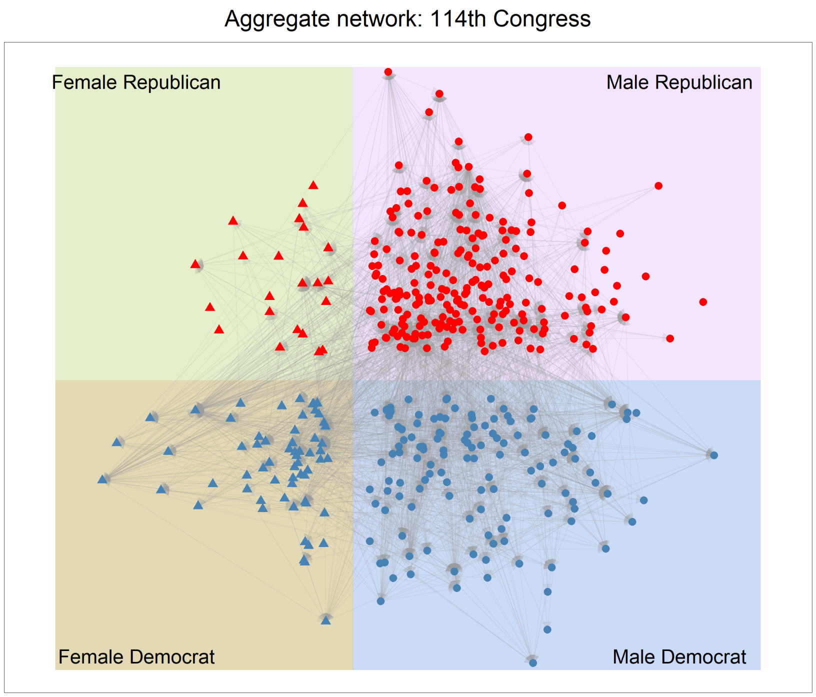


Figure 7: **House Twitter network, Regime 3 (February 2016 - July 2016)**

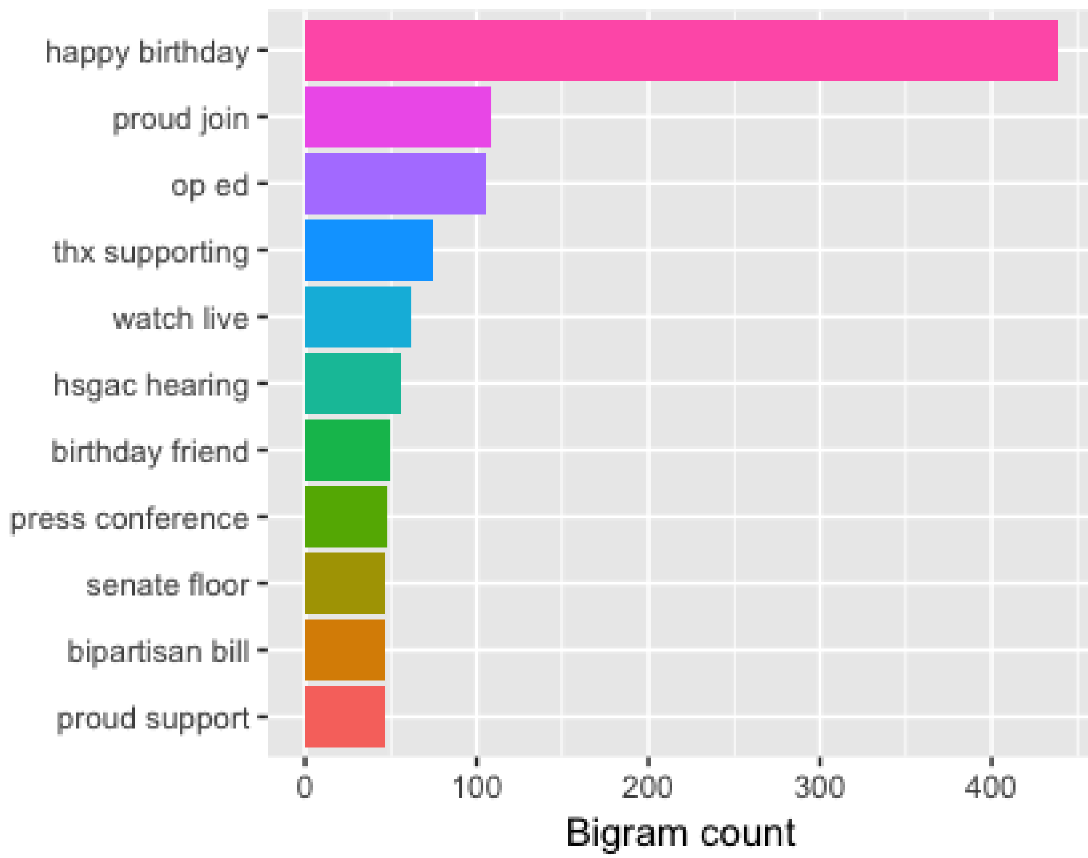


Figure 8: **Most frequent bigrams in regime period 2.**

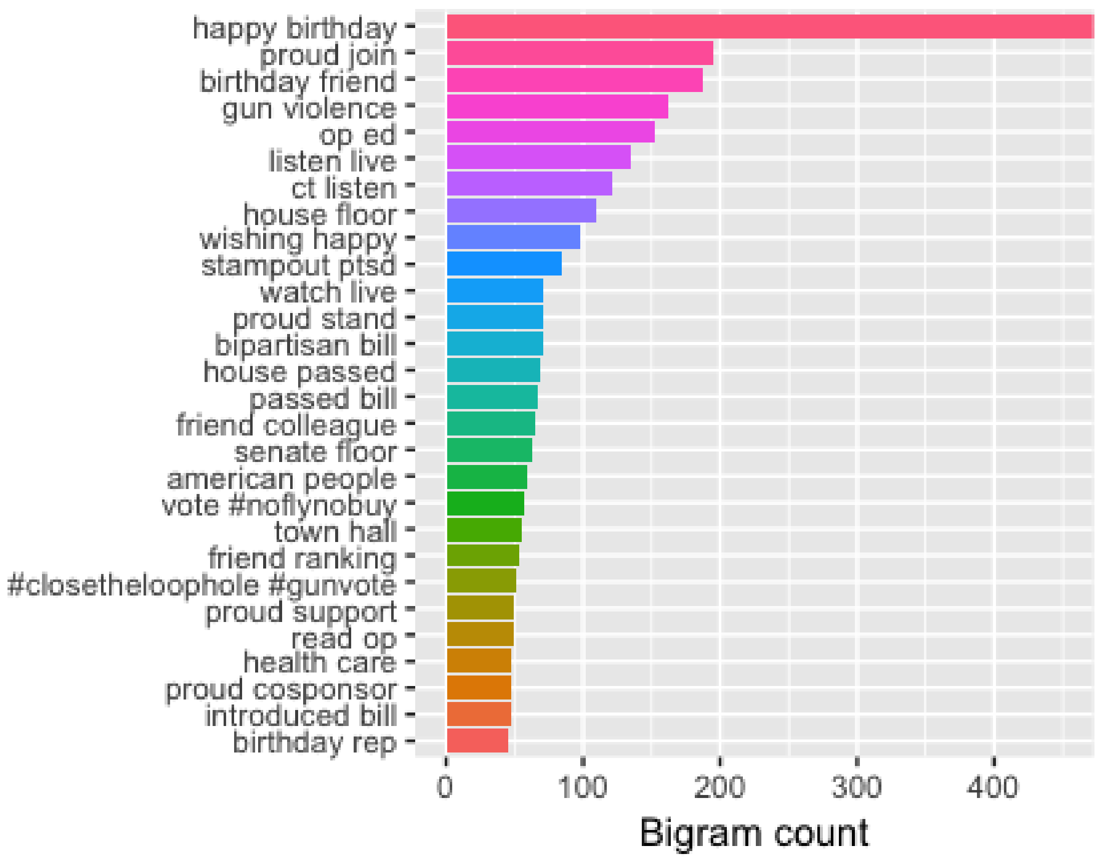


Figure 9: **Most frequent bigrams in regime period 3.**