A Network Analysis of Twitter Interactions by Members of the U.S. Congress

JOSHUA M. CHAMBERLAIN, FRANCESCA SPEZZANO, JACLYN J. KETTLER, and BOGDAN DIT, Boise State University

Usage of Twitter by politicians has become more prevalent in recent years, with a goal of influencing the electorate and public perception. We collect, explore, and analyze over 12 years of public Twitter interactions of U.S. senators and representatives. Using community detection algorithms on these interaction networks, and without considering the content of the tweets, we are able to infer the political affiliation of each member of Congress with up to 98.8% accuracy in the House and 94.1% accuracy in the Senate. In addition, we define two metrics that can determine the political ideology of members of Congress achieving a very high Spearman's rank correlation of 0.86 with the existing DW-NOMINATE score from the field of political science. Finally, we expand our structural analysis to intra-party factions and found evidence that some factions act on Twitter more cohesively than others, suggesting an increasing risk of an echo chamber effect when promoting their political agenda.

CCS Concepts: • **Human-centered computing** → **Social network analysis**; **Empirical studies in collaborative and social computing**; *Social media*;

Additional Key Words and Phrases: Politicians' behavior on social media, community analysis, computational political science

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1 INTRODUCTION

The use of social media by politicians has dramatically increased in recent years, with consequent power of shaping public opinions. According to the Pew Research Center [19], "one-in-five social media users have changed their minds about a political issue or about a candidate for office, because of something they saw on social media."

These days, politicians know very well the importance of having an online presence to interact and disseminate their opinions and positions on certain key issues directly to voters, mainly when

Authors' addresses: J. M. Chamberlain, F. Spezzano (corresponding author), B. Dit, Computer Science Department, Boise State University, 1910 W University Dr, Boise, ID 83725; emails: joshchamberlain@u.boisestate.edu, francescaspezzano@boisestate.edu, bogdandit@boisestate.edu; J. J. Kettler, School of Public Service, Boise State University, 1910 W University Dr, Boise, ID 83725; email: jaclynkettler@boisestate.edu.
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running a political campaign [21]. Twitter[1] is the de facto social media platform for discussing politics online. It is becoming more frequent, especially since the 2016 election cycle, that politicians interact with themselves on Twitter, to support each other or even to directly attack their political opponents.

Previous work has analyzed the political use of Twitter from three different research areas: the use of Twitter by parties and candidates, the use of Twitter by the politically vocal public, and the use of Twitter during, and in reaction to mediated events [32].

In this article, we focus on the first research area and analyze the public Twitter activity of members of the U.S. Congress to study the senator and representative networking ecosystems over a time period spanning 12 years. Politicians use Twitter to achieve electoral goals, share information, and take a position on a specific issue (i.e., position-taking) [24, 29, 46]. Congressional interactions on Twitter, however, likely serve a different purpose than politicians' independent tweets. This raises some interesting questions about how Congress members interact with one another on Twitter and what their interactions can tell us about their political alignments. Political scientists are highly interested in answering such questions and studying the congressional ecosystem [46]. However, they mainly use roll call data, bill-text [10, 22, 23, 42], or news shared on social media [20] and have invested less in the study of the relevance of social interaction networks to political phenomena [2, 34].

To overcome this limitation, we collected a corpus of 12 years of public tweets by U.S. senators and representatives and apply social network analysis techniques to study *longitudinal* Congress Twitter interaction trends. To the best of our knowledge, no such dataset has ever before been analyzed. This work intentionally ignores the contents of the tweets and focuses instead on exploring what can be learned solely from network analysis of user interactions. We start by analyzing the Twitter usage of members of Congress based on their amount and type of tweets, cross-party interactions, and engagement with the public, and then we explore the data to investigate three main research questions. The first research question, *RQ1*, investigates if interactions on Twitter between U.S. members of Congress can be used to determine their political affiliation (e.g., party). The second research question, *RQ2*, investigates the possibilities of defining a quantitative measure from Twitter interaction networks that indicates ideology (i.e., how far left or far right leaning a politician is). It is worth noting that *RQ1* and *RQ2* have been already investigated in the literature but only on snapshots of the data [2, 12, 13]. For instance, Conover et al. [12, 13] showed that, during 2010 midterm elections, the retweet network was more polarized than the @mention network on a dataset mainly including political figures (but not limited to congress members) [11]. Barberá [2] showed that the political ideology of members of the 112th Congress can be inferred from the Twitter network of followers. However, they did not show whether this can be extended to interaction networks as well. Thus, we add to this corpus of research by investigating whether previous findings on snapshot data can be generalized in the long run and provide new insights.

The third research question, *RQ3*, investigates whether or not Twitter interactions are limited to party factions. In the House, many members join a faction (e.g., 76% in the 115th Congress), which are formal ideological organizations within parties, such as the Freedom Caucus or the Blue Dog Democrats [50]. Thus, we want to investigate whether or not these factions affect Twitter interactions among House representatives and if these factions are identifiable in these interaction networks. To the best of our knowledge, we are the first at investigating *RQ3*.

[1] https://twitter.com/.

This article makes the following contributions:

- We collected a new longitudinal dataset spanning 12 years of U.S. Congress members public tweets and derived interaction networks generated from the use of three well-known Twitter features, namely retweets, @mentions, and quotes.[2]
- We investigate U.S. Congress members tweeting behavior according to the volume and type of tweets, cross-party tweets, and engagement with the public. We found that the House and Senate display different levels of partisanship in social media, supporting some of the long-standing views of how the two chambers operate. For instance, @mentions are known to cross party lines more than retweets, but we also observe that cross-party @mentions are more common in the Senate than the House due to the strict hierarchical structure of the House leadership. We also found differences in the engagement with congressional leaders' tweets by members and general users, showing that congressional Twitter interaction networks serve a different purpose than general Twitter users networks.
- We applied community detection algorithms to investigate whether the political affiliation of a congress member can be inferred by their Twitter interactions (*RQ1*). We found that the retweet network is generally more polarized than the corresponding @mention network, consistent with findings in more general domains [12]. Also, the quote network is the least accurate, demonstrating this feature is mainly used to express disagreement. We obtain an accuracy ranging from 59.5% to 94.1% for the Senate (or between 73.6% and 94.1% when discarding the quote network) and between 91.6% and 98.8% for the House. We also observe the Senate increasing its polarization over the time frame while polarization remains high and stable in the House.
- We propose two new metrics, namely the *exclusivity* and *spectral bias*, for computing the legislative ideology of members of Congress from their Twitter network (*RQ2*). We show that there is a high correlation between Twitter interactions and members' DW-NOMINATE scores [42], which describe their legislative ideology (average Spearman's rank of 0.78 in the Senate and 0.87 in the House for Congresses 113th to 115th). We show how to accurately infer a politician's ideology by analyzing an interaction network without analyzing the contents of the tweets. This demonstrates that political truths are encoded in the very structure of the interaction network, which meets the needs of political scientists to be able to measure ideology when voting data are unavailable (e.g., for a new member of congress).
- We extend community detection analysis to search for political factions within Congress (*RQ3*). Certain known political factions [50] such as the Tea Party and Freedom Caucus are easily identified by such algorithmic analyses, providing new insights into the behavior of these factions. Specifically, our findings identify the party leadership communities and the Tea Party/Freedom Caucus to consistently be most insular with their Twitter interactions and increasing their cohesiveness (in terms of density and average clustering coefficient) over time, suggesting an increasing risk of echo chambers.

The data and methods used in this article provide a powerful tool for political scientists to study how and why politicians use Twitter to build a more robust picture of the congressional ecosystem. In fact, the longitudinal analysis of Twitter interaction networks allow us to prove that these networks have been accurately reflecting congressional politics over time in terms of party affiliation, ideology, and known political factions. These data add a new perspective and allows political scientists to better study the public interactions of politicians, going beyond the

[2]The derived network data used in the article are publicly available at https://github.com/fspezzano/poltweet/.

incomplete picture of analyzing a politician's tweets in isolation or studying more traditional data such as that extracted from roll call votes and bill-text.

The article is organized as follows: Section 2 describes related work, Section 3 provides background information on the organization of U.S. Congress, Section 4 explains our data collection process, Section 5 reports on our analysis of politicians' tweeting behavior, Section 6 addresses the problem of using Twitter interactions to infer the party affiliation of a politician, Section 7 defines new metrics to capture politician ideology, Section 8 investigates the relationship between politicians' Twitter interactions and their affiliation to intra-party factions, and, finally, conclusions are drawn in Section 9.

2 RELATED WORK

Members of Congress use Twitter for a variety of purposes. Previous research finds that members tweet to share information with their supporters, self-promotion, influence the coverage of political topics in the media, or talk about their daily activities [21, 24, 29, 30, 32]. This is likely in an attempt to aid their re-election goals. Recent research also finds members regularly use Twitter for position-taking on policy [46], critiquing political opponents [47], or increasing mass political polarization [51]. These findings make sense for individual members' tweeting behavior, but member interactions with each other, like re-tweeting other members, likely serve other purposes. By interacting with other members on Twitter, members may promote policy or ideological positions shared by their colleagues. Consequently, members are likely to mainly interact with members sharing their political orientation (including partisanship, ideological alignment, and party factions) [32].

There has been a variety of prior work that classifies the political orientation of Twitter users. Most of this work is based on classifying users according to several features including user profile, user tweeting behavior, linguistic content of user messages and user social network features [6, 11, 27, 36, 41, 43, 44, 54]. In political science, the task of estimating the political leaning of legislators is referred to as the ideal point estimation problem and it is mainly addressed by analyzing roll call data and bill-text [10, 22, 23, 42]. Among them, DW-NOMINATE [42] is the most frequently used measure and it is based on the historical voting behavior of senators or representatives.

Conover et al. [12, 13] considered both content and structural analysis and explored the possibility of inferring political orientation solely from the structure of various types of interaction networks. They created an *@mention network* where nodes represented individuals and tweet @mentions created edges between nodes. Similarly, they created a *retweet network* where the edges were formed from retweets. In their data (a collection of tweets during the 2010 midterm elections), they observed that the retweet network was more polarized than the @mention network. While they obtained 91% accuracy by evaluating the content of the tweets using SVM, they were able to reach 95% accuracy by evaluating only the structure of their retweet graph [12].

As noticed by Cohen and Ruths [11], while prior work claimed their datasets contained general Twitter users, these datasets (including the ones of Conover et al.) were actually biased toward politicians' accounts. Cohen and Ruths then showed that, by considering the tweet content, classifying typical Twitter users who expressed some political view is not easy (68% of accuracy vs. 91% for political figures) and classifiers do not transfer across types of users.

Golbeck and Hansen [25] proposed a technique for estimating the political preferences of Twitter users by propagating the political orientation of the member of Congress to their followers and media outlet audience.

Regarding the problem of inferring political ideology from Twitter data, Barberá [2] proposed a Bayesian Spatial Following model to infer ideology, as a latent variable, from the Twitter follower network among politics actors. The model is applied to the members of the 112th Congress and shows a high correlation with the DW-NOMINATE scores. The author also proved the method works for other five European countries.

Wong et al. [53] formulated a convex optimization problem to infer political leaning of Twitter users during the 2012 U.S. presidential election campaign by leveraging two main ideas: (i) users are consistent in their actions of tweeting and retweeting about political issues, and (ii) similar users tend to be retweeted by similar audience.

Gu et al. [27] have proposed a method to compute the ideology of Twitter users by considering their heterogeneous links (follow, mention, and retweet) to a selected set of politicians.

Hemphill et al. [28] proposed an algorithm computing a polarization score (#polar score) for both users and hashtags to estimate the political ideology of members of Congress leveraging the use of hashtags on Twitter. They show that the user score highly correlates with DW-NOMINATE scores on a dataset collected between April and September 2012. Preoţiuc-Pietro et al. [43] applied natural language processing techniques to infer political ideology of general users, while Belcastro et al. [4] applied neural networks-based techniques to extract accurate political polarization distributions from tweets' content.

Akoglu [1] proposed a framework based on pairwise Markov random fields to classify politicians' polarity and rank them by the magnitude or extent of their polarity. The author considered a signed bipartite network to represent the opinions of individuals on issues instead of an interaction network between people. The experimental evaluation was performed on the roll call votes for the 111th U.S. Congress and the DW-NOMINATE score was used as ground truth. This method resulted in high rank correlation, which is not surprising as it mimics the way the DW-NOMINATE is computed.

This prior work has been conducted on snapshot data related to particular events such as the 2010 midterm elections [12] or before the 2012 U.S. Presidential Election [2, 11] that provide no insight on whether or not these trends hold in the long run. Also, prior work mainly focuses on general users [25, 27, 43, 53], rather than on congressional networks. Further, all the prior studies have focused on analyzing the polarization of networks derived by Twitter data, without evaluating communities beyond the canonical two parties. Some researchers have analyzed the case of the European and Italian Parliaments [8, 14] and found that the community structure of these retweet networks aligns with existing political groups (e.g., F1 of 0.78 in the European Parliament). Despite some work analyzing the Tea Party candidate Twitter follower subgraph [37], to the best of our knowledge, there is no study analyzing the behavior of all the factions in the U.S. Congress on its Twitter interaction networks.

Thus, this article focuses on studying the interaction networks of U.S. members of Congress, which has considerably less prior work. We investigate the tweeting behavior interactions of Congress members and apply a network-based approach to infer political affiliations and ideology to validate whether Twitter interaction networks accurately reflect congressional politics, and investigate intra-party factions the first time. The temporal dimension of our dataset allows us to derive new insights on member ideology and known political faction and check the validity in the long run of prior work findings on snapshot data.

3 BACKGROUND

This article focuses on the U.S. Congress, which is the branch of government that writes laws. The Congress consists of two houses, the Senate and House of Representatives. The Senate consists of 2 members from each state, for a total of 100 senators. The House is considerably larger, with 441 representatives in the 115th House, including non-voting representatives from non-state U.S. jurisdictions such as Washington, D.C. and Puerto Rico.

We use the term *chamber* to differentiate between the Senate and the House of Representatives. The term *Congress* is used to differentiate between the 2-year election cycles. The most recently concluded Congress we consider is the 115th Senate and House of Representatives, which ended on January 3, 2019.

We focus on the two major U.S. political parties, i.e., Democrats (left) and Republicans (right), and do not consider smaller third parties. Therefore, any politician that was not officially a Democrat or Republican was assigned to one of those parties based on their DW-NOMINATE score. DW-NOMINATE was designed by Poole and Rosenthal [42] and can be used as a metric describing the consistency of a politician for voting left or right in a given Congress. A single politician can have multiple DW-NOMINATE scores if they served in multiple Congresses. A DW-NOMINATE value of -1 indicates a very polarized Democrat (left), while a value of 1 indicates a very polarized Republican (right).

4 DATA COLLECTION

We collected a corpus of 10 GB of tweets authored by members of recent Congresses. Our data collection process is explained in the following subsections.

4.1 Collecting Twitter Accounts

To obtain a list of Twitter accounts of U.S. members of Congress, we collected data from the ProPublica Congress API[3] as a starting point. We downloaded the name, party affiliation, DW-NOMINATE score, and Twitter screen name of all members of Congress in their database. Not every member of Congress had a Twitter screen name, and some of the screen names reported by ProPublica belong to accounts that have been removed or suspended. This resulted in 716 valid Twitter accounts.

We took additional steps to identify Twitter accounts for the remaining 5 Senators and 12 Representatives of the 115th Congress. First, we tried looking for Twitter accounts linked to by the official government websites on `house.gov` and `senate.gov` for each of these politicians, which provided five missing Twitter accounts. Second, we tried looking for Twitter accounts listed on official websites outside of `.gov` domains for each politician, which provided six more Twitter accounts. Finally, we used a search engine to find three more official accounts that do not appear to be linked to by any official website. To ensure the integrity of our data, we confirmed that all Twitter accounts from ProPublica as well as the 15 manually identified accounts are all marked as verified by Twitter. The remaining two politicians without a known Twitter account are the Representatives from Guam and the Northern Mariana Islands. This means our dataset has accounts for all members of the 115th Senate and all voting members of the 115th House of Representatives.

Figure 1 shows the number of Twitter accounts we identified for each chamber of each Congress, starting with the 110th Congress. At any given point, the Senate should consist of 100 senators, two from each of the 50 states. The fluctuations in the number of senators shown above are due to events such as senators leaving office in the middle of Congress. Their seat is then filled by a new senator, which can cause the total number of senators over the course of a Congress to exceed 100. To a less noticeable extent, this type of fluctuation is also present in the House.

4.2 Collecting Tweets

Using the Twitter API,[4] we downloaded most of the tweets from the identified Twitter accounts. The API only guarantees the most recent 3,200 tweets of a user, so we were unable to obtain every

[3] https://www.propublica.org/datastore/api/propublica-congress-api.
[4] https://developer.twitter.com/en/docs/tweets/timelines/api-reference/get-statuses-user_timeline.html.

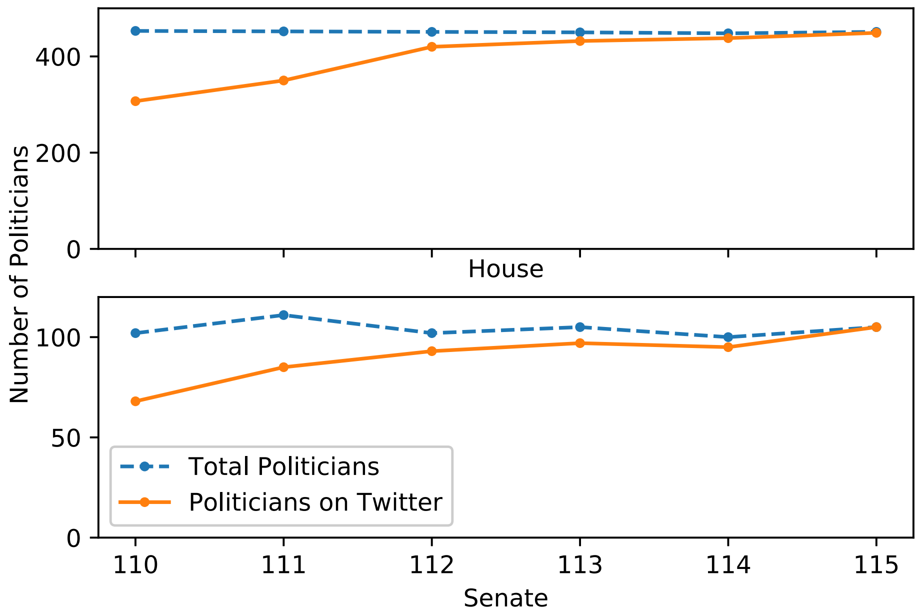


Fig. 1. Collected Twitter accounts for each chamber of each Congress.

Table 1. Start and End Dates of Each Congress for Which We Have Collected Tweets

Congress	Start	End
110	Jan. 04, 2007	Jan. 03, 2009 (House)
		Jan. 02, 2009 (Senate)
111	Jan. 06, 2009	Dec. 22, 2010
112	Jan. 05, 2011	Jan. 03, 2013
113	Jan. 03, 2013	Jan. 02, 2015
114	Jan. 06, 2015	Jan. 03, 2017
115	Jan. 03, 2017	Jan. 03, 2019

tweet from the politicians that have exceeded that number. To mitigate this issue, we downloaded tweets in multiple batches (sessions) between October 2018 and January 2019 and were able to exceed this 3,200 tweet limit and obtain a more complete list of tweets. In our best case, we downloaded 4,204 unique tweets for a single politician.

We divided these tweets into separate datasets for each chamber of each Congress. The oldest tweet was dated July 13, 2007, which was during the 110th Congress, so we did not consider prior Congresses in our study.

The dates of the start and end of each Congress were taken from the `congress.gov` website[5] and are shown in Table 1. Each dataset consists of only tweets that were authored (or retweeted) within the time range of the given Congress. In this article, a *dataset* refers to the portion of the corpus that applies to a specific chamber within a Congress (e.g., the dataset of the House from 110th Congress is different from the dataset of the House from the 111th Congress). *Politician* is

[5]Past Days in Session of the U.S. Congress, https://www.congress.gov/past-days-in-session, retrieved January 12, 2019.

used to refer to a member of Congress within the context of a single dataset, regardless of other datasets that may also contain that member of Congress.

For each politician, we wanted to estimate the completeness of our downloaded Twitter data. Ideally, we would report completeness as the ratio of number of tweets we were able to download per politician per Congress divided by the number of tweets that a politician actually sent within that Congress period (e.g., used as ground truth). Although the Twitter API provides a mechanism to determine the total number of tweets sent by a user, we cannot determine how many of those tweets were sent within the time range of a given dataset, and thus, we were not able to obtain this ground truth. Therefore, we used the following process for approximating the completeness of our downloaded twitter data.

For a given politician p and for a given day day_i, we consider to have been able to download all of p's tweets if there was at least one session of batch twitter downloads in which we downloaded contiguous tweets from days $\ldots, day_{i-1}, day_i, day_{i+1}, \ldots$. For each dataset, for all days for which we were able to download all tweets sent by a given politician, we calculated the average number of daily tweets sent by each politician. In total, of 4,869 politicians across all our datasets (e.g., chamber within a Congress) spanning 12 years, we were able to download all their tweets for 1,612 politicians (33%). However, for the 115th Congress, we were able to download over 99% of their tweets, and, for the 113th and 114th Congresses, we were able to download over 90% of the tweets.

For the remaining cases, in which we could not guarantee that all tweets were downloaded for that politician on that day, we use that politician's average daily tweet rate to approximate the completeness of our downloaded data. This estimation does not account for potential fluctuations in twitter activities.

Many users delete their Twitter accounts after leaving office. Over the course of this work, 23 accounts we were monitoring were made no longer public. For some of these accounts, we were unable to download any tweets. In these cases, we could not compute the average daily tweet rate. To approximate the completeness of our downloaded data, when estimating the number of tweets sent by such a politician, we use an average of all average daily tweet rates within that dataset. In this way, we estimated the number of tweets that should exist for each politician in each dataset.

Based on this estimate, we downloaded 99.4% of the tweets from the 115th House and 99.5% of the tweets from the 115th Senate. Figure 2 shows the estimated number of tweets for each dataset, along with resulting coverage for each dataset.

4.3 Assigning Political Affiliation

As mentioned in Section 4.1, when curating the list of Twitter accounts, we also collected the official political party of all politicians in our datasets. To facilitate the comparisons between Democrats and Republicans, we reassigned the few independents to one of these two parties, based on the DW-NOMINATE score. Specifically, we applied a Democrat label to independents with a negative DW-NOMINATE score and a Republican label to independents with a positive DW-NOMINATE score. There were two independents that did not have DW-NOMINATE score provided by the ProPublica Congress API. In both instances, the politicians caucused with the Democratic party. Therefore, we manually reassigned these two independents to the Democratic party.

In addition to independents, we also needed to account for members of Congress that switched between the Democrat and Republican parties. This only occurred twice over the 12 years covered in this article. Of those, only one had a valid twitter account. This politician switched parties during the 111th Senate and was excluded from analyses related to political affiliation.

After assigning the political affiliations, we observed that our partitions contained approximately the same number of Democrats and Republicans in each dataset.

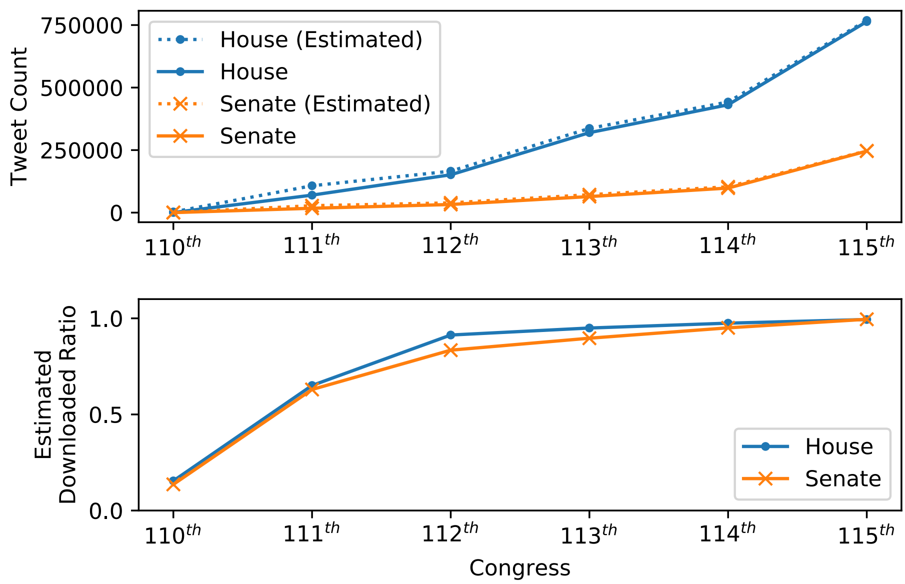


Fig. 2. Number of tweets collected for each dataset per Congress (top); estimated completeness of downloaded tweets (bottom). The x-axis for both figures represents the Congress.

4.4 Building Interaction Networks

For each chamber, we modeled interactions using directed graphs. Each politician is represented by a node. Outbound edges represent an action that was initiated by the node. In our @mention graphs, edges are drawn from the node that authored a tweet to each node that was @mentioned. In our retweet graphs, edges are drawn from the node that sent the retweet to the node that was retweeted. These types of networks have been used in related work, such as Reference [12]. Around 2015 Twitter added the quote feature (also known as "retweet with comment"), after most of the related work has already been published. We apply the concepts of the traditional retweet and @mention networks to this additional tweet type. We construct quote graphs, where edges are drawn from the node that sent the quote to the node that was quoted. Table 2 reports the structural characteristics of the Twitter interaction networks used in the article. We removed nodes without any connection and considered only networks whose resulting number of nodes is at least half of the effective number of chamber members in the corresponding congress.

5 ANALYZING POLITICIANS' TWEETING BEHAVIOR

We now analyze how politicians use Twitter based on their amount and type of tweets (including the amount of cross-party tweets) and their engagement with the public.

5.1 Volume and Types of Tweets

Figure 2 illustrates a clear upward trend in the number of tweets authored by U.S. politicians in more recent Congresses, which is a known trend in Twitter usage [31]. For the chambers for which we downloaded at least 90% of the tweets (Congresses 113th to 115th), we confirm the trend is statistically significant (two-tailed two-sample t-test with $p < 0.05$) between each pair of successive Congresses. We investigated whether there is a Twitter feature (e.g., retweet, @mention, or quote) that politicians prefer to use the most. Figure 3 shows the number of tweets by type written by members of Congress. We see that politicians prefer more to retweet than @mention, while quote

Table 2. Structural Characteristics of the Twitter Interaction Networks Used in the Paper: Number of Nodes, Number of Edges, Average Degree, and Average Clustering Coefficient (CC)

		House				Senate			
Congress	Network Type	Nodes	Edges	Avg. Degree	Avg. CC	Nodes	Edges	Avg. Degree	Avg. CC
112th	retweet	265	870	6.57	0.15	57	92	3.23	0.14
113th	retweet	379	3,324	17.54	0.24	79	244	6.18	0.28
114th	retweet	406	7,853	38.68	0.34	92	568	12.35	0.27
115th	retweet	432	10,496	48.59	0.43	101	1,528	30.26	0.45
112th	@mention	326	2,045	12.55	0.22	69	251	7.23	0.29
113th	@mention	392	6,073	30.98	0.26	92	662	14.39	0.30
114th	@mention	419	11,654	55.63	0.33	94	1,388	29.53	0.39
115th	@mention	439	16,517	75.25	0.36	104	3,415	65.67	0.56
114th	quote	358	1,313	7.34	0.18	82	175	4.27	0.08
115th	quote	420	3,609	17.19	0.29	99	1,021	20.63	0.31

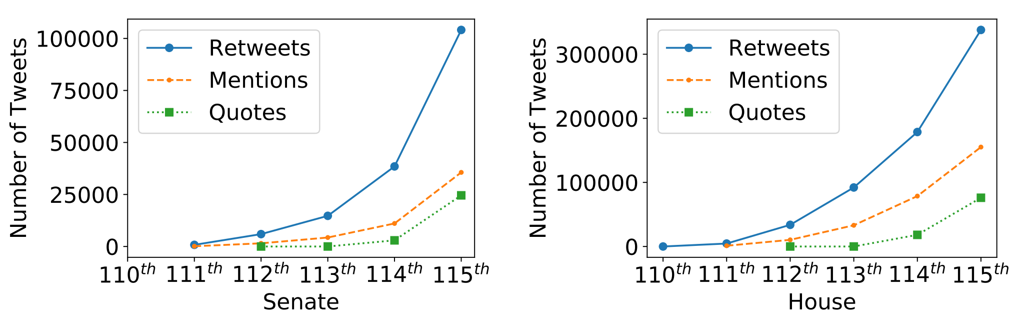
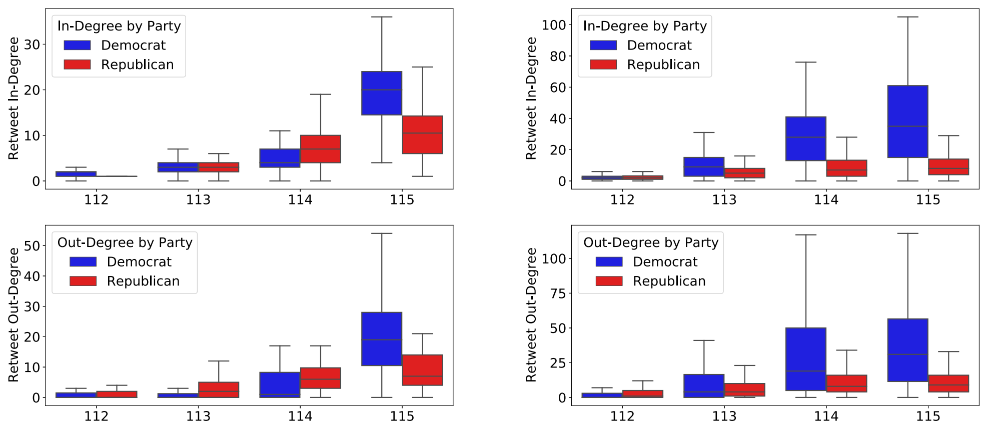


Fig. 3. Types of tweets sent. The number of Mentions is the number of tweets sent that @mention at least one other Twitter user.

is the least used feature. We observe no statistical difference between parties for retweets and @mentions ($p > 0.3$), whereas for quotes, Democrats typically quote more ($p < 0.05$). Retweeting is particularly helpful in amplifying and diffusing messages [30], which may explain its higher usage among politicians. Quote is the least used feature, most likely because, as we show in Section 6, it is mainly used to express disagreement. Democratic members might quote more than Republicans in an effort to respond to or comment on the actions [40] of the Republican majorities in the 114th and 115th Congresses.

The number of tweets from the House is considerably larger than the Senate. This is due to the House consisting of 435 seats, as opposed to only 100 seats in the Senate. However, there is no evidence that individual representatives tweet more than senators. Our null hypothesis is that the mean daily tweet rate is the same for senators and representatives. We used a two-tailed two-sample t-test using the average daily tweet rate of representatives versus senators. For the 110th–114th Congresses, the null hypothesis could not be rejected. However, in the 115th Congress, senators tweeted more ($p < 0.05$) than representatives (3.2 vs. 2.2 tweets per day) and used more @mention ($p < 0.01$). As discussed below, it is Democratic senators that substantially increased their Twitter activity in the 115th Congress, perhaps in response to President Trump's election in 2016. Senators have larger constituencies and more autonomy in office than House members [48], which may motivate Democratic senators to tweet more in response or opposition to the president and the Republican Party.



(a) Senate

(b) House of Representatives

Fig. 4. Comparison of average node in-degree and out-degree in the retweet network by party. The x-axis for all four figures represents the Congress.

5.1.1 Network Degree Analysis. We measured the average node in-degree and out-degree for all the three types of networks described in Section 4.4. Figure 4 reports the average degrees for the retweet network (@mentions and quote networks show similar trends and are not reported for brevity). Using a two-sample two-tailed t-test, we observed a statistically significant difference ($p < 0.05$) for the latest two Congresses between the degrees of nodes in each party for all three types of networks. More specifically, we observe that Democrats in the House retweet more politicians and are retweeted by other politicians more than Republicans. We observe the opposite trend in the Senate up to the 115th Congress, while the retweeting behavior flipped in the latest Congress. After President Trump's election in 2016, Republicans held the presidency and a majority of seats in both chambers of Congress. Senate Democrats may have substantially increased their activity on Twitter in opposition to the Republican majorities and a Republican president (see also Section 5.2).

5.2 Cross-Party Tweets

We observed that politicians frequently cross party lines in public Twitter interactions. We measured the percentage of retweets and quotes that cross party lines. Of the tweets with at least one @mention handle, we measured the ratio that included an @mention of a politician in the opposing party. In the 115th House, 11.3% of @mentions mentioned a politician from the opposite party, and 7.8% of quotes and 4.4% of retweets crossed party lines. When examining our entire corpus of tweets, there is no significant difference of which party is most likely to retweet across party lines. When focusing on the 115th House and Senate, we observed that Democrats @mention the opposing party at a higher rate, 16% vs. 13%, to a statistically significant extent ($p < 0.05$). Conversely, only 10% of retweets by Democrats cross party lines, as opposed to 13% of retweets by Republicans. Using the two-variable two-tailed t-test we confirmed this to be statistically significant ($p < 0.05$), but found no statically significant difference with quotes. Russell [47] found that, during the 113th and 114th Congresses, Republican senators are more likely to name-call their Democratic opponents and use partisan rhetoric on Twitter, particularly when they are the minority party (113th Senate). According to the data provided above, the situation is flipped in the 115th Congress as Democrats (which are the minority party in both House and Senate) mention Republicans more to make opposition and Republicans retweet more Democrats providing some agreement to mitigate

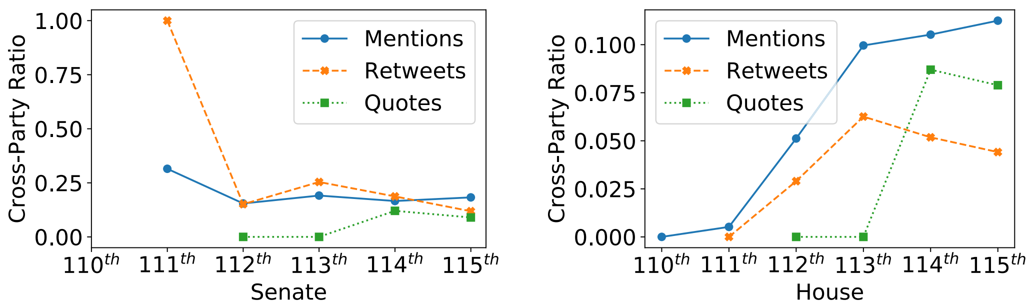


Fig. 5. Percentage of tweets that cross party lines. The 111th Senate contained only two retweets, both of which crossed party lines. Please note the difference in the y-axis scale in for the Senate and House.

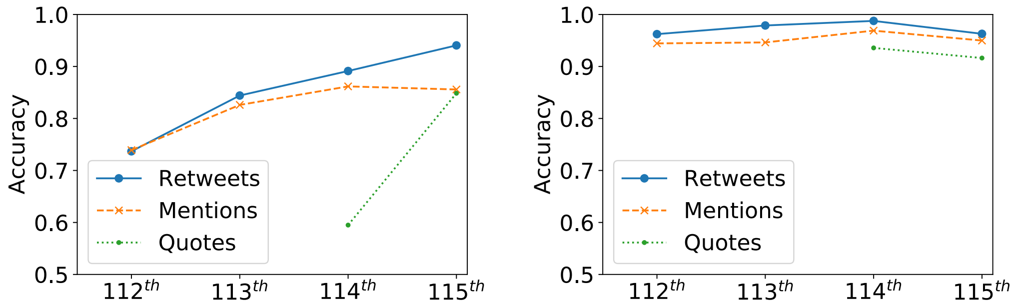
the opposition. This analysis, together with Russell's findings and the observations derived from Figure 4, suggests majority status in a chamber influences politicians' behavior on Twitter.

Figure 5 shows the quantity and type of cross-party tweets for each chamber of each Congress. Conover et al. [12] found in their snapshot data (2010 U.S. midterm elections) that there are more cross-party tweets in the @mention network than in the retweet one. In the long run, we observe from Figure 5 that this trend is true for the House but not for the Senate where cross-party retweets and @mentions have similar ratios. Interestingly, there is also a higher percentage of tweets crossing party lines in the Senate than the House: 25% @mentions or retweets for the Senate in the latest Congresses vs. at most 12% @mentions in the House. These observations align with the traditionally higher levels of bipartisanship in the Senate. The Senate's institutional structure, rules, and norms allow individual members to have more autonomy and requires more bipartisan cooperation [45, 48], motivating more cross-party tweeting among senators.

5.3 Congress Engagement with the Public

We also analyzed the level of engagement the Congress has with the general Twitter audience to some extent. Specifically, we computed, for each Congress and for each member, the number of retweets and the number of likes received by general Twitter users. We found that, for the 114th and 115th Congresses, a Democratic party member is retweeted more by the Twitter audience than a Republican one, in both chambers (all p values < 0.001). Also, the tweets by a representative are liked more by the Twitter audience than the tweets by a senator in the latest two Congresses (both p values < 0.01). Due to the shorter nature of their terms and more frequent elections, representatives may tweet more content related to their campaigns, which may receive more attention. Moreover, Democratic members were in the minority in both chambers, potentially increasing the partisan attacks and calls to actions in their tweets, which tend to be retweeted more frequently than tweets containing messages of advocacy or information [30].

We also investigated whether chamber leaders tend to engage more than other chamber members. The list of leaders has been compiled by one of the authors and includes chamber leadership (e.g., Speaker of the House, Majority Leader, Minority Leader, Caucus Chairs) and committee chairs. Our data reveal that, on one hand, chamber leaders are the ones that chamber members retweet the most as compared to other regular Congress members, in the 114th and 115th House (both p values < 0.001) as well as in the 114th and 115th Senate, but with smaller differences (both p values < 0.05). This indicates that Congress members may use these retweet interactions to help support the party by re-sharing and amplifying their party's messages and positions. On the other hand, general Twitter users liked more leaders' tweets in the 114th and 115th House (both p values < 0.001), but we were not able to prove that chamber leaders are retweeted more than regular



(a) Senate

(b) House of Representatives

Fig. 6. Accuracy of Spectral Clustering for all datasets (left: Senate, right: House). The x-axis for both figures represents the Congress.

chamber members by them. The general Twitter users more active in tweeting about U.S. politics have strong ideological views and preferences [3], so their motivations in retweeting members of Congress may focus more on ideology rather than amplifying party messages. This provides some additional evidence that the congressional Twitter interaction networks serve a different purpose than general Twitter users networks.

6 CLASSIFYING NODES

We used community detection graph algorithms to address our core research question, *RQ1*, of investigating if interactions on Twitter can be used to determine the party affiliation of a politician. Previous work by Conover et al. [12] demonstrated that community detection, specifically label propagation, was more accurate in their retweet network than @mention network. These findings supported their observation that typical users generally only retweet content they agree with.

Several nodes in our dataset explicitly state on their Twitter profile that retweets do not necessarily indicate agreement. Through our familiarity with the data, we believe that it is reasonable to assume retweets generally indicate agreement despite such claims. Additionally, we observed that quotes were used to share content users disagreed with. If this is the dominant use case of the quote feature, then clustering algorithms applied to the quote network should produce less accurate results than the @mention and retweet networks.

For brevity, we only report our findings from the most successful community detection algorithm we tried, namely spectral clustering. Each directed retweet, quote, and mention graph was converted to an undirected graph. Next, we removed all but the largest connected component from the graph. Finally, the unweighted adjacency matrices were processed with spectral clustering. The generated clusters, labeled 0 and 1, are assigned a political party label based on the political party of the majority in the cluster. The accuracy of the clustering is the percentage of nodes that were correctly labeled as Democrat or Republican.

It should be noted that there is a general consensus in binary political classification research that accuracy is a suitable metric. In network clustering, accuracy is more aptly called *purity* and is often discouraged in favor of precision and recall. Purity can be misleadingly high if every node is placed in individual clusters or if the classes are imbalanced. We have shown that our data are balanced and we are only generating two clusters. Therefore, accuracy is a suitable measurement for our analysis.

Figure 6 shows the accuracy achieved for each graph. We achieved a peak accuracy of 98.8% in the 114th House of Representatives on the retweet network. In general, across all the types of networks considered, the accuracy ranges between 59.5% to 94.1% (or between 73.6% and 94.1% when discarding the quote network) in the case of Senate and between 91.6% to 98.8% in the case of the House.[6] The House is more hierarchical with a stronger leadership system than in the Senate. As a result, members are more constrained and partisan in their actions, which may contribute to the higher accuracy for the chamber [33, 45].

We attempted to improve our results by weighting the edges of the network. Some of the techniques we tried could increase the accuracy for a single dataset, but none of them could consistently produce higher accuracy than the unweighted adjacency matrix.

Overall, the analysis performed in this section shows that, across time, the retweet network of each chamber achieves the highest accuracy meaning that it is more polarized than the corresponding @mention network, confirming that previous findings on snapshot data [11, 12] also hold in the long run. Moreover, we find that this trend is more prominent in the Senate than in the House of Representatives for the latest two Congresses considered. Also, while the accuracy of inferring politicians' party in the House is pretty stable over time, it becomes more accurate in the case of the Senate for the latest Congresses, suggesting that the Senate is increasing in polarization over time. Although party polarization in both chambers is now quite high, DW-NOMINATE scores also demonstrate that parties in the House polarized faster with polarization in the Senate continuing to grow in recent Congresses [7, 35, 49]. Moreover, the quote network performed the worst showing less polarization, consistent with our hypothesis that users "retweeting" content they disagree with typically quote the tweet instead of just retweeting it.

Further, the fact that senators cross-party tweet more than House representatives and their @mention networks are less polarized than retweet ones highlights that senators behave more independently on Twitter than House representatives.

Our data consist of only U.S. politicians. In their work, Cohen and Ruths [11] achieved over 90% accuracy on a dataset consisting of only political figures by analyzing the textual content of the tweets and some user network features. Here we show that we are able to uniformly apply a lightweight, unsupervised, and network-based only technique on all of our graphs, to achieve comparable or higher accuracy: The worst accuracy is 96.2% in the House, and we got comparable or higher accuracy for the Senate in the latest two Congresses considered.

7 QUANTIFYING IDEOLOGY

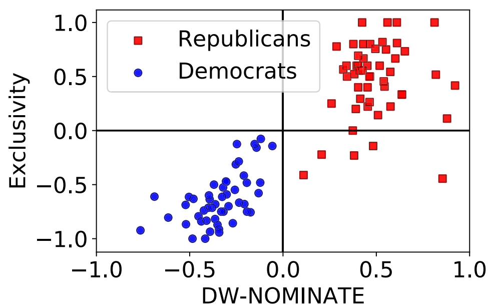
Our second research question, *RQ2*, focuses on defining metrics that can capture the ideology (i.e., how far left or far right leaning a politician is) using our generated interaction networks. We used the DW-NOMINATE score of each politician as ground truth. We ignored nodes for which we were unable to obtain a DW-NOMINATE score. Similarly to Akoglu [1], we evaluate our defined metrics using Spearman's rank correlation, comparing our metric and the DW-NOMINATE score for each node. A correlation of 1 indicates that ranked nodes based on the DW-NOMINATE score would have the same order as ranking by our metric.

Our first metric is the *exclusivity* of a node u. Conceptually, it represents the ratio of a node's edges that are exclusive to its party, and is defined in Formula 1:

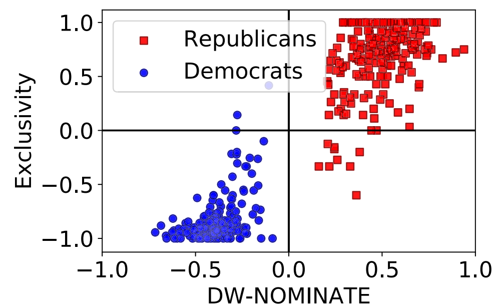
$$\text{exclusivity}(u) = \frac{T_R(u) - T_D(u)}{T_R(u) + T_D(u)}, \tag{1}$$

where $T_R(u)$ represents the number of edges (u, v)[7] where v is a Republican and similarly, $T_D(u)$ represents the number of edges (u, v) where v is a Democrat. We measure exclusivity on the

[6] It is worth noting that a lower accuracy for the 112th Senate may depend on the fact that, in this case, senators' Twitter interactions are not completely captured by our data.
[7] or (v, u) as we consider the graph undirected.



(a) Senate



(b) House of Representatives

Fig. 7. Exclusivity vs. DW-NOMINATE in the 115th Congress using the retweet network.

retweet network where we got the best classification results. In this case, T_R (or T_D respectively) counts the number of retweets of Republicans (or Democrats resp.). Exclusivity matches the same range of values and interpretation of the DW-NOMINATE score in the sense that a node u, for which all retweets are within party lines, has $exclusivity(u) = 1$ if Republican and $exclusivity(u) = -1$ if Democrat.

Figure 7 compares exclusivity and DW-NOMINATE for all nodes in the 115th Congress, as evaluated on the retweet network. As illustrated in Figure 7, the exclusivity metric successfully correlates with the DW-NOMINATE score. The Spearman's rank correlation for exclusivity is 0.845 for the House and 0.826 for the Senate.

The second metric we defined is *spectral bias* and is inspired by spectral clustering.[8] Given a network G, we consider the sub-network G_C given by the largest connected component of G and compute the eigenvector $\mathbf{x}$ corresponding to the second smallest eigenvalue of the Laplacian of G_C (as G_C is connected, the eigenvector corresponding to the smallest eigenvalue is constant [38]). Then, we use the values in $\mathbf{x}$ to score our nodes according to spectral bias.

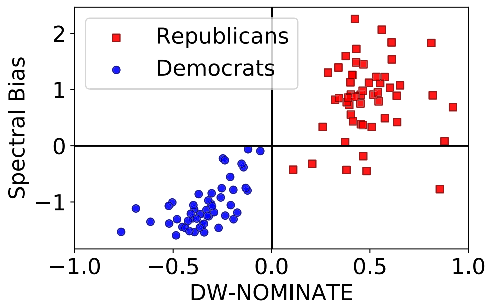
A threshold τ for spectral bias, separating the nodes into two parties (similarly to the 0 threshold for the DW-NOMINATE score), could be determined by (i) running k-means with $K = 2$ on the scores in $\mathbf{x}$, and (ii) computing τ as the middle value of the two centroids. Thus, a node i is considered left-leaning if $\mathbf{x}[i] \leq \tau$ and right-leaning otherwise.

We compare spectral bias and DW-NOMINATE using the retweet network from the 115th Congress in Figure 8. Similarly to Figure 7, in Figure 8, the spectral bias successfully correlates with the DW-NOMINATE score, producing better results than exclusivity. Specifically, the Spearman's rank correlation for spectral bias is 0.864 for the House and 0.826 for the Senate.

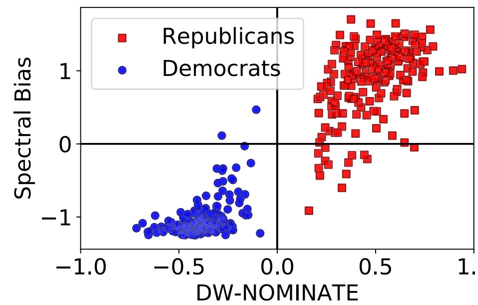
Figure 9 compares the Spearman's rank correlation of exclusivity and spectral bias for all Congresses from the 112th to 115th on the same retweet network. For a fair comparison, we computed exclusivity on the largest connected component only. We observe that spectral bias generally performs better than exclusivity. As spectral clustering is more accurate in classifying nodes in the House than the Senate, we find that spectral bias also performs better in the House, while exclusivity and spectral bias are comparable measures in the case of the Senate.

The results presented in this section show that Congress Twitter interactions highly correlate with the members' legislative ideology, encoded in their DW-NOMINATE score. The DW-NOMINATE score is usually inferred from roll call votes and bill-text [1, 10, 42], and it is interesting

[8]Spectral clustering performs spectral embedding to convert the nodes to coordinates in a lower dimensional space, N=2 in our case, followed by k-means clustering.

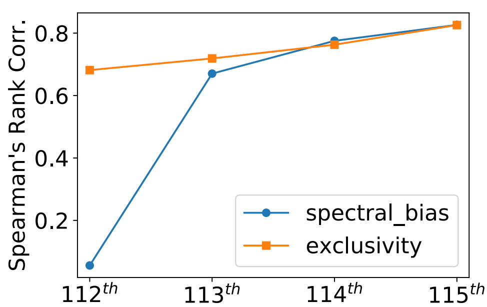


(a) Senate

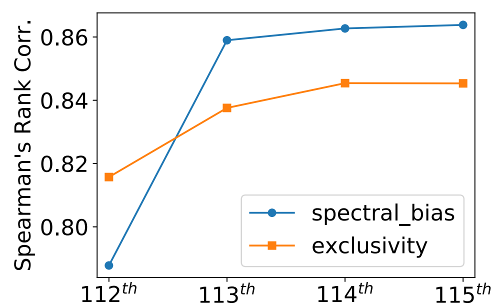


(b) House of Representatives

Fig. 8. Spectral Bias vs. DW-NOMINATE in the 115th Congress using the retweet network.



(a) Senate



(b) House of Representatives

Fig. 9. Spearman's rank correlation (y-axis) comparison of Exclusivity and Spectral Bias across different congresses (x-axis) using the retweet network.

to see that members' legislative ideology is also observed among Congress member interactions on Twitter.

Our defined spectral bias represents an alternative way to compute ideology when voting data are not available or poorly suited for the research question. For example, roll call votes are also only available for incumbents or candidates previously serving in elected office. Using Twitter interactions to evaluate political affiliations provides a way for scholars and political observers to evaluate the political leanings of a broader set of candidates. Additionally, the expression of ideology is more expansive than roll call votes, including candidates' public statements about their beliefs and stated policy goals [5]. By studying candidates' Twitter interactions, we can use their public engagements with each other for additional insights into their ideological alignments.

8 PARTY FACTIONS AND NETWORK COMMUNITIES

Most politicians join party factions in the House of Representatives, which are formal ideological organizations within the parties [17, 50]. Examples of congressional party factions include the Blue Dog Democrats and the Freedom Caucus. These intra-party factions have ideological policy agendas, seeking to push the party closer to their preferred positions. As a result, these factions reflect ideological divisions within the party and can heighten intra-party conflict. For example, the Freedom Caucus organized in the 114th Congress to support a more conservative agenda and push Republican leadership to the right on issues [15].

Table 3. Percentage of Nodes with Faction Membership Affiliation and Normalized Mutual Information and Accuracy (or Purity) Scores to Evaluate Community Detection in the House of Representatives

Congress	**113th**	**114th**	**115th**
Percentage of labeled nodes	78%	80%	80%
Normalized Mutual Information	0.35	0.31	0.43
Accuracy (Purity)	0.58	0.53	0.56

In this section, we investigate our third research question, *RQ3*, focusing on understanding the party faction behavior in Congress interactions on Twitter. Do these Twitter interaction networks also capture party faction membership? Are factions identifiable in these interaction networks?

For our analysis, we consider the 113th to 115th Congresses, because we have 90% data completeness for the corresponding time span. The following factions have been active within the House during these Congresses in order from most liberal to most conservative [9]:

- **Congressional Progressive Caucus**–Liberal Democratic faction.
- **New Democrat Coalition**–Centrist Democratic faction.
- **Blue Dog Coalition**–Centrist Democratic faction.
- **Republican Main St. Partnership**–Centrist Republican faction.
- **Republican Study Committee**–Conservative Republican faction.
- **Tea Party Caucus**–Conservative Republican faction, 111–113th Congresses.
- **House Freedom Caucus**–Conservative Republican faction, 114–115th Congresses.

As the Senate traditionally has less active, formal intra-party factions [52], we focus our study on the House of Representatives only.

A domain expert (one of the authors) retrieved from publicly available data the faction affiliation for each representative in the considered Congresses. For all but the Freedom Caucus, we retrieved membership affiliation from the factions' official membership lists, including archived membership lists accessed using the WayBack Machine.[9] For the Tea Party, some politicians working with the faction were not official members of the caucus. Therefore, we also used other information to create the Tea Party membership lists, including information from the news on politicians endorsed by Tea Party groups. The Freedom Caucus keeps its official membership secret. However, we used the lists by DeSilver [15] and E&E News[10] compiled using public statements, media comments, and communication with representatives' offices. A few Freedom Caucus members were identified by using news coverage. Not all politicians are affiliated with one of six considered factions.

To perform our faction analysis, we run spectral clustering to identify communities on retweet networks. We set the number of communities to six as there are six active party factions in each of the considered Congresses (three within the Democratic Party and three within the Republican Party). Table 3 reports the percentage of labeled nodes in each Congress and Normalized Mutual Information (NMI) and accuracy (or purity)[11] scores for community structure evaluation when we consider the House factions as ground truth. The scores are computed by considering labeled nodes only. An NMI score of 1 indicates perfect correlation. We see that, despite high polarization in the House retweet network, these interactions do not align well with intra-party factions: NMI score

[9] https://web.archive.org.
[10] https://www.eenews.net/stories/1060054645.
[11] We report accuracy (or purity) for the sake of comparison with Figure 6. However, accuracy is not a suitable measure to use here as faction labels are unbalanced.

Table 4. Average Clustering Coefficient and Density of Each Identified Community in the 113th House Retweet Network

113th Congress			
Commun. ID	**Clust. Coeff.**	**Density**	**Description**
3	0.66	0.33	Republican leadership and mainly Rep. Study members
4	0.60	0.31	Democratic leadership and mainly Progressive members
5	0.28	0.12	Mainly Tea Party members
0	0.19	0.09	Mixed with members from both parties
1	0.18	0.08	Mixed with members from both parties
2	0.07	0.03	Mixed with New Dem. and Progressive members

Communities are sorted by density.

Table 5. Average Clustering Coefficient and Density of Each Identified Community in the 114th House Retweet Network

114th Congress			
Commun. ID	**Clust. Coeff.**	**Density**	**Description**
2	1.00	0.67	Republican leadership members
0	0.79	0.48	Democratic leadership and mainly Progressive members
5	0.51	0.25	Mainly Tea Party and Freedom Caucus members
4	0.55	0.18	Mainly Rep. Study members
3	0.25	0.10	Mainly Rep. Study and Main St. members
1	0.05	0.01	Mixed with members from both parties

Communities are sorted by density.

ranges from 0.31 to 0.43 and the accuracy from 0.53 to 0.58. Most communities include politicians from one or more factions, suggesting members communicate across factions.[12]

To further enhance our community analysis, we computed the average clustering coefficient and the density of each retrieved community, for each considered Congress. These values are reported in Tables 4, 5, and 6, where communities are sorted by density. Here we observe that the top-three communities are (1) denser and more tightly knit (higher average clustering coefficient) than the remaining communities, and (2) consistently formed by the same type of members, demonstrating the same patterns hold across time. In both the 114th and 115th Congresses, the top Republican leadership, including the Speaker of the House, exist in their own community (top community in both Tables 5 and 6). The Republican leaders are mainly interacting with each other on Twitter, most likely in an attempt to promote the party's messages and positions. Similarly, in the 113th Congress, the top community in Table 4 contains the Republican leadership members.

The second faction emerging as an active and increasingly dense community in all the considered Congresses includes the Democratic leadership and members of the Congressional Progressive Caucus. As the progressive wing of the Democratic Party has gained strength, this caucus has

[12]We also performed a supervised experiment to further confirm that faction information is not well encoded in the retweet networks. Specifically, we used the spectral clustering embedding features to perform supervised multi-class classification where we used faction membership as labels. We performed fivefold stratified cross-validation, used class weighting to deal with class imbalance, and tried different classifiers, including support vector machine, logistic regression, and random forest. In all the Congresses considered, we reached the best F1 score of 0.50 with random forest.

Table 6. Average Clustering Coefficient and Density of Each Identified Community in the 115th House Retweet Network

115th Congress			
Commun. ID	**Clust. Coeff.**	**Density**	**Description**
1	1.00	0.92	Republican leadership members
2	0.88	0.67	Democratic leadership and mainly Progressive members
3	0.72	0.46	Mainly Freedom Caucus members
0	0.30	0.14	Mixed with members from both parties
5	0.30	0.13	Mixed with members from both parties
4	0.12	0.02	Mixed with New Dem. and Progressive members

Communities are sorted by density.

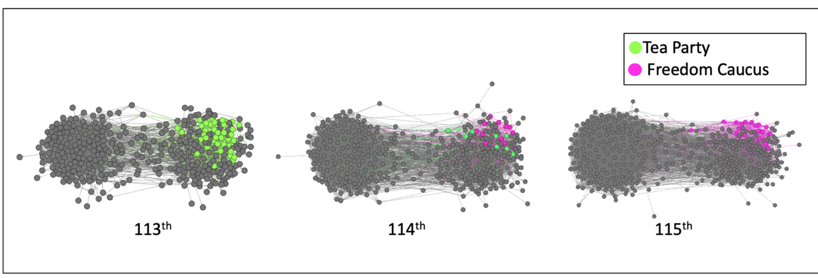


Fig. 10. The evolution of the Tea Party/Freedom Caucus community across Congresses.

exerted more influence in the House Democratic Caucus. Perhaps, as a result, a majority of the House Democratic leadership team are members of the Congressional Progressive Caucus in the 116th Congress [39].

Further, in the 113th Congress, a majority (90%) of one community is comprised of Tea Party Caucus members. Livne et al. [37], in their study of candidates' tweets in the 2010 midterm election, also found the Tea Party candidate Twitter follower subgraph highly cohesive. Moreover, Tea Party candidates shared more homogeneous content, suggesting an organized Twitter campaign. A community including 87% of former Tea Party Caucus and current Freedom Caucus members emerges in the 114th House. Finally, in the 115th House, there is a community composed almost entirely (95%) of Freedom Caucus members. A conservative faction within the Republican Party, the Tea Party Caucus formed in the 112th Congress after the Tea Party movement helped elect dozens of Republicans in the 2010 midterm election. The Tea Party Caucus disbanded after the 2014 midterm election with the Freedom Caucus, its ideological successor, organizing in the 114th Congress. We see this transition in the Twitter interaction communities across sessions (also graphically shown in Figure 10) and the Tea Party/Freedom Caucus community appears as the top-three denser community in all the considered Congresses (cf. Tables 4, 5, and 6).

By acting as a unified block (including voting together) and regularly challenging Republican leadership, the Freedom Caucus has managed to obstruct some bills and impact activity in the House [15, 26]. The insular community of Freedom Caucus members in the retweet interaction network provides more evidence for the unified behavior and strategies of the faction. These interactions on Twitter may be attempts to amplify the faction's policy preferences, most likely in opposition to the other insular community representing the Republican leadership. It also further demonstrates the strength of this faction in recent Congresses.

Given the results and findings presented in this section and Section 7, we observe that representatives' Twitter interactions seem to align more with their voting behavior than with their faction ideology. This extends to 113th and 114th Houses the finding by Clarke et al. on the 115th House that ideological positions of party factions do not matter for their members' legislative effectiveness [9]. However, Twitter interaction networks do provide some useful insights into internal party divisions such as the Tea Party/Freedom Caucus and party leadership communities that seem to act as echo chambers in the House retweet network.

Identifying emerging or active factions can provide important insights into the future directions of the parties [50]. For instance, the data collection and methods used in this article could be used to evaluate factions similar to the Tea Party/Freedom Caucus in future Congresses. For example, are some members in the Congressional Progressive Caucus acting as a similar block against the Democratic leadership in the 116th Congress? Furthermore, the study of political factions within Twitter interaction networks can also be useful to study legislatures outside the U.S., e.g., by investigating the durability of coalition governments in parliamentary systems [16, 18]. In coalition governments, two or more parties join together to reach the majority needed to form a government. Studying the Twitter interaction networks of legislators may help political scientists evaluate the strength of coalitions through the level of engagement between the coalition partners on Twitter. Additionally, these interaction networks may help scholars identify potential splits or threats to the survival of a coalition if members of the coalition parties are segregated in their interactions on Twitter.

9 CONCLUSIONS

We collected and analyzed a corpus of tweets produced by U.S. member of Congress over a period of 12 years. Due to limitations imposed by the Twitter API, we were only able to download *most* of the tweets belonging to U.S. politicians, but not all of them, and particularly not older tweets. For example, we were able to download more than 90% of the tweets belonging to members of Congress from recent Congresses (e.g., 113th through 115th). This raises a concern about the accessibility of political information, especially since more and more politicians are using Twitter for official announcements.

We analyzed our tweet corpus to investigate the tweeting behavior of Congress members. In the scenario of inferring the political party of U.S. politicians, we showed that, by clustering a simple, unweighted, retweet network, we were able to classify politicians' affiliation with at least 96.2% accuracy in the House and 73.7% accuracy in the Senate, with 96.3% and 94.1% accuracy in the latest concluded Congress (i.e., 115th) for the House and Senate, respectively. We proposed two metrics, namely exclusivity and spectral bias, quantifying the ideology of a node in the retweet network and showed that spectral bias generally achieves a high Spearman's rank correlation (up to 0.86) with the DW-NOMINATE score. As a result, it provides political scientists with another useful measure of ideology, one calculated using politicians' interactions on Twitter—not legislative roll call votes. This can be an important alternative measure to use in research when NOMINATE scores, or other measures of ideology calculated using legislative votes, are unavailable.

We have also expanded our structural analysis to intra-party factions and revealed that some factions act on Twitter more cohesively than others, suggesting an increasing risk of echo chambers. By measuring politicians' behavior and public interactions with each other on Twitter, this methodology and resulting measurements provide political scientists (and other social scientists) with a powerful tool to study political alignments. It allows scholars to move beyond labels and voting behavior to examine important topics such as members' ideology and internal party politics, including party factions and governing coalitions in future Congresses and other legislatures.

As future work, we plan to expand our data collection to normal users and compare their characteristics with the ones of politicians we found in this article, perform tweet content analysis, and check how structure and content properties correlate with specific political events.

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