# Polarization and Shared Attention among Influential Amplifiers of 2018 U.S. Primary Candidates


## ABSTRACT

The spread of information on Twitter hinges on a relatively small set of influential accounts that shape the narrative during political events. In this paper, we identify and describe the ecosystem of influencers in the ego networks of candidates from the 2018 U.S. primaries across a large set of governor, house, and senate races. The ecosystem includes both *amplifying influencers,* who shared candidates' tweets, as well as influential accounts regularly promoted by these amplifiers, whom we label *ecosystem influencers*. We describe these accounts with respect to their partisan allegiances and political roles. We find asymmetries across the two major political parties, with Democrats receiving more formal party support than Republicans, whose amplifiers skew more towards 'activist' accounts that feature relatively high levels of bot or bot-like behavior. We also find that the vast majority of amplifying influencers shared tweets from candidates representing a single political party. However, there is substantial overlap in the ecosystem influencers that these amplifiers promoted, who tend to be journalists and news organizations, with over 30% of them being retweeted by amplifiers representing both sides of the political spectrum. We thus find that shared attention exists across these partisan amplifiers – far more than their promotion of campaign messages suggests – and that media accounts serve a central bridging function.

## 1. INTRODUCTION

Digital platforms increasingly shape how politicians reach the public (Kreiss et al. 2018; McGregor 2020). In addition to television (Fowler et al. 2016) and electronic mail (Epstein and Broxmeyer 2020), politicians now regularly draw attention to their campaigns by disseminating messages on social media platforms such as Twitter (Barberá et al. 2019; Golbeck et al. 2010; Hemphill & Shapiro 2019) – or X, as it is now called. During political events, messages on these platforms often do not reach people via formal sources like politicians or the mass media (Hu et al. 2012). Instead, they are often mediated by a dynamic social network of influential accounts that features both traditional figures such as political elites and journalists as well as an emergent set of ‘crowd-sourced elites’ (Papacharissi and de Fatima Oliviera 2012) – who come to harness user attention with minimal formal support from political parties or other institutions. Gaining the attention of these influential accounts can be consequential for political campaigns as an alternative to expensive political advertisements (Shmargad and Sanchez 2020)

The idea that ordinary citizens can play an influential role in the spread of information dates back at least to Lazarsfeld et al. (1944), who documented how so-called opinion leaders helped to spread political messages in the 1940 and 1944 U.S. presidential elections. Katz and Lazarsfeld (1955) label this now well-documented process the *two-step flow of communication*. Indeed, Twitter codifies the two-step flow process by letting people share messages using the standard ‘retweet’ function. Choi (2015) thus explicitly links opinion leadership on Twitter to retweet behavior, showing that those who were regularly mentioned in political discussions were also highly retweeted. Wu et al. (2011) remark on the prescience of this mid-century theory:

> "Given the length of time that has elapsed since the theory of the two-step flow was articulated, and the transformational changes that have taken place in communications technology in the interim—given, in fact, that a service like Twitter was likely unimaginable at the time—it is remarkable how well the theory agrees with our observations." (p.711)

The popularity of Twitter as a political medium coupled with the rise of computational methods for collecting and processing digital trace data have enabled the large-scale analysis of these opinion leaders – what we refer to as "political influencers" in the remainder of this paper (though see Riedl et al. (2023) for a conceptual distinction between these two terms). Shmargad (2018) identified the set of influencers who shared political candidates' tweets in the 2016 U.S. congressional elections, finding that a majority of these users had no formal political affiliations as politicians or members of a political organization. There remain descriptive questions about the partisan allegiances of political influencers and the extent that they facilitate polarization in the amplification of political messages (Conover et al. 2011, Barbera et al. 2015). Because of their gatekeeping function, polarization among political influencers could create information environments in which users are primarily exposed to messages from one side of the political spectrum, the so-called echo chamber effect (Cinelli et al. 2021).

To investigate the extent of polarization among political influencers, we develop a method for identifying influential accounts that shared political candidates' tweets and apply it to a large set of governor, house, and senate candidates who ran in the 2018 U.S. primary elections. The method relies on a novel snowball sampling approach, which starts with candidates' Twitter accounts and collects data about users who amplified their tweets in the months leading up to the election. This approach has two notable advantages. First, it can be used to identify influencers who amplified candidates' messages – whom we call *amplifying influencers* – providing a measure of informal party support to complement formal measures such as elite endorsements (i.e., public announcements of support by party leaders, often made during primary elections). Second, we use the approach to identify accounts whose messages were regularly shared *by* these amplifying influencers – what we call *ecosystem influencers* – to investigate more systematic (i.e., less candidate-specific) polarization among accounts promoted by Democratic and Republican leaning amplifiers.

Our analysis reveals two key insights. First, amplifying influencers who shared tweets by Democrats were more likely to have formal political roles as politicians, political groups, or advocates working for a political organization, compared to their Republican counterparts. On the other hand, amplifiers who shared tweets by Republicans exhibited more informal, "activist" support and were more likely to be fully or partially automated (Davis et al. 2016). Our findings are in line with the asymmetry identified by Grossman and Hopkins' (2016) that the Democratic party is a coalition of interest groups, while the Republican party functions through a shared conservative ideology. Second, we find that amplifying influencers exhibit extreme polarization when promoting candidates. Yet, there was a substantial amount of shared attention in their amplification of ecosystem accounts, which were typically journalists and news organizations, with over 30% of these accounts being promoted by both Democrat and Republican leaning amplifiers. Rather than interacting in echo chambers, these partisan amplifiers were retweeting many of the same accounts, thereby increasing their influence through "cultural bridging" (Bail 2016), with media organizations serving a central bridging role.

The remainder of the paper is organized as follows. In the next section, we discuss some of the nuances in political communication brought about by how and who spreads information on social media. We conceptualize political influencers based on literature distinguishing the roles they play when participating on social media platforms. We then motivate the analysis by framing influencer amplification as an extension of a more standard measure of candidate support during primaries: endorsements by party elites (Cohen et al. 2008). We outline our data collection approach in Section 3, focusing on the affordances and limitations of Twitter's Application Programming Interface (API) for the identification of political influencers. In Section 4, we describe the partisan allegiances and political roles of the influencer ecosystem, which includes both influencers who amplified candidates' messages as well as other accounts that these amplifiers regularly promoted. We conclude in Section 5 with a discussion of our findings and suggestions for future work.

## 2. THEORETICAL DEVELOPMENT

### *2.1 News Information on Social Media*

Although traditional political communication constructs like agenda-setting and gatekeeping are not extinct, they have been expanded to account for new actors who regulate how political information reaches the public and how audiences respond to these messages. Among these new actors are political campaigns and political influencers. Yet, for any of these nuanced forms of information sharing to be effective, audiences must concede credibility to the modality or source of information sharing. Developing a model of "news-ness", Edgerly and Vraga (2020) argue that the hybridization of genres (e.g., entertainment, podcasts, outrage news) has changed audiences' expectations about the value of news information. What is considered news by audiences may not be categorized by the *kind* of news presented but the *degree* of news the content incorporates. This degree of news-ness is subject to the information environments in which audiences frequently interact. For example, among U.S. journalists, those who used Twitter infrequently were less likely to rate headlines produced in a Tweet format as newsworthy as headlines produced in an AP wire format compared to journalists who frequently used Twitter (McGregor & Molyneux, 2020).

There are several reasons for why audiences might prefer receiving news from political elites and influencers on social media. Edgerly and Vraga (2020) speculate that contemporary audiences may be averse to what they believe to be traditional news, maintaining that such news sources are complicit in spreading misinformation and supporting left or right-leaning political agendas. Moreover, audiences may conceptualize news as a function of whether media sources convey congruent partisan cues (Jennings, 2019). For example, Democrats could consider liberal media content as newsworthy while rejecting conservative-leaning messages (see also Edgerly & Vraga, 2019). In theory, political influencers can help to satisfy consumer demands for more sincere, less partisan outlets of political information. The extent to which political influencers hold up to these expectations is an open question that this article seeks to address.

### *2.2 Political Campaigns as News Information*

Social media also provide political elites with a role in establishing what constitutes news information. Past research has discovered that lawmakers are likely to follow rather than lead political discussions on Twitter (Barberá et al., 2019). Auwal et al. (2022), on the other hand, allude to the concept of *agenda-building* (see Lee, 2016), in which news agendas are developed as a matter of media reproducing the pivotal issues determined by elites and politicians, to demonstrate how traditional media outlets rely on Twitter content produced by political elites as "information subsidies" (see Parmelee, 2014). Through a content analysis comparing the most salient issues tweeted by the two major Nigerian presidential candidates in 2019 and the three major English news outlets in Nigeria, Auwal et al. they found that the top three issues for candidates (i.e., security, anti-corruption, economy) were the same top issues discussed by the news media. In this sense, social media may allow political elites a greater influence about what matters to news media, suggesting that social media platforms may be siphoning more power back to the powerful rather than instilling egalitarian dynamics. Perhaps nowhere was this demonstrated more clearly than in Donald Trump's personal Twitter use during the 2016 U.S. presidential electoral season. Wells et al. (2020) confirm that Trump began tweeting more following decreasing advantages in news story coverage over Republican opponent Ted Cruz. The authors' found that Trump's Twitter behavior initiated a cycle of audience engagement that then led to increased news story coverage over a two-day period by both right and left-wing outlets, demonstrating that social media was driving news content and not the other way around.

Indeed, over the last few election cycles, political campaigns have experimented with methods to inform constituents via social media from top-down and bottom-up approaches. Conducting qualitative interviews, McGregor (2020) observed how campaign staffers during the 2016 U.S. presidential election used Twitter engagement data to craft messages congruent with perceived supporter sentiment. For example, after Ted Cruz attacked the media in a 2015 U.S. primary debate, his campaign noticed that social media engagement (i.e., retweets and likes) increased. Cruz's campaign then urged him to continue this kind of aggressive rhetoric to maintain public favor. In a similar study, Kreiss et al. (2018) observed how campaign staffers attempted to convey a sense of authenticity and channel the voice of their candidate by using

Facebook to reach the greatest number of constituents and Twitter to shape the broader news media narratives.

Nevertheless, Kreiss et al. suggested that campaigns' quest for authenticity here is questionable because of their reliance on the performance of the candidate and his or her team. Turning to social media influencers may be a primary method of maintaining authenticity while evading the middleman of traditional news. McGregor (2020) reported that staffers admitted to strategically using social data (i.e., follower counts) to identify supporters who could potentially drive content coming from the campaign during the 2016 U.S. Republican primary cycle. We argue that the function of political influencers is an example of Katz and Lazarsfeld's (1955) two-step flow, circumventing the more typical intervention by journalists or media sources in political communication.

### *2.3 Political Influencers as News Information*

While traditional sources of information are widespread on Twitter, the platform also accommodates a host of less traditional actors that rise to brief or sustained fame by having their messages shared by regular users (Hu et al. 2012). Using a term that echoes the influence that political and media figures have on public discourse, Papacharissi and de Fatima Oliviera (2012) refer to these emergent actors as 'crowd-sourced elites.' Barzilai-Nahon (2008) describes the collective impact that these actors have on information flow as a newly created form of 'network gatekeeping,' and discusses the process by which these actors gain legitimacy and build a large followership. Meraz (2009) documents how the collective power of these networked influencers can become robust enough as to influence how traditional newsrooms report on political events.

While they tend to originate outside of mainstream media organizations, crowd-sourced elites can nevertheless alter their news agendas.

We frame the role of such influential figures in political campaigns as similar to that of partisan activists. In *The Party Decides*, Cohen et al. (2008) conceptualizes political parties as coalitions of groups that, rather than being centered *around* political candidates, exercise power by selecting and working *through* these candidates. While Cohen et al. and others (see also see also Steger 2007, Dominguez 2011) limited their definition of coalition groups to endorsements by party elites, Noel (2018) expanded this definition to include political activists, who he argued had the agency to push back on elite opinion and were the central "labor force for political campaigns" (p. 226). Yet, unlike elite endorsements, there are no established measures of activist support. As Noel (2018) explains, "endorsements are more than just an independent variable. Publicly observable support for a candidate in the form of endorsements is *part of the mechanism*" by which candidates get nominated, "because both voters and party activists need the signal to know what to do" (p. 228, emphasis added). To capture activist support that is observable by the public – both mechanism and measure, in the sense described by Noel (2018) – this study turns to political influencers on Twitter.

To better understand how influencers propel information from political campaigns and traditional media, we first classify different types of influencers using previous research. In their work examining Islamophobia on Twitter, Pintak et al. (2021) categorized a set of specific roles that directed social media discussions: *icons, influencers, and amplifiers*. Whereas icons included celebrities, the media, and political elites who might at some point amplify a message as a result of their large following, Pintak et al. argued that influencers actually play a small part in the dissemination process, merely giving credence to a trending thought or conversation by being tagged or mentioned in a conversation. The bulk of social media messaging is the direct result of amplifiers who do all the work of aggregating, sharing, and posting. Moreover, amplifiers were not relegated to human users alone but also included automated accounts. This inclusion of automated accounts was reflected in the lack of authenticated accounts compared to accounts designated as influencers.

Pintak et al.'s (2021) categorization is appreciated for its precise definitions of the levels of influencers and how each level is performed. The media, while influential, are not necessarily influencers in the sense of working within interpersonal networks as Katz and Lazarsfeld (1955) highlighted. On the other hand, a social media account producing relatively high engagement within their community could be considered an influencer in this sense, even though their overall influence may be smaller than many media accounts. We seek to capture this conceptualization of influencers in our subsequent analysis and adopt the terms *amplifiers* and *influencers* used by Pintak et al., albeit with the slightly different operationalizations that we discuss next.

### *2.4 Identifying Influencers*

To identify the set of influencers who amplified political candidates' messages on Twitter, we adapt a data collection method known as snowball sampling. As Handcock and Gile (2016) argue, snowball sampling has a connection to the identification of political influencers that dates back to some of the earliest research on opinion leadership. Lazarsfeld et al. (1944) first theorized the role that opinion leaders have in the flow of political information, finding that many people discovered political information not through formal sources but rather through their personal connections. To better understand these informal sources of influence, Merton (1949) asked respondents to name the people who influenced them and conducted follow-up interviews with those who were named, inventing the snowball sampling approach in the process.

In a later study, Katz and Lazarsfeld (1955) show that mediation by opinion leaders can explain information diffusion beyond the realm of politics, giving rise to what is now popularly called the 'two-step flow of communication.' While they adapted Merton's (1949) snowball sampling approach to identify opinion leaders, since then the connection between two-step flow and snowball sampling has largely been lost, with the latter becoming a generalized method of identifying hard-to-reach populations (e.g., Trow 1957, Coleman 1958). A notable exception is the work of Wu et al. (2011), who use snowball sampling to crawl Twitter 'lists' to construct their11atasett and analyze the extent that two-step flow explains information diffusion on Twitter. Their method starts with a set of 'seed' nodes (i.e., a set of users), then checks for lists in which these nodes are including to identify additional nodes. The process can then continue indefinitely until a satisfactory number of nodes has been included in the sample.

In this paper, we further re-enliven the canonical connection between two-step flow and snowball sampling by identifying influencers who amplified political candidates' messages, or amplifying influencers, on Twitter. To do so, we do not rely on Twitter lists but rather a feature of Twitter commonly known as a retweet. In simple terms, a retweet reflects one user's decision to share another user's message. We use retweet information in two distinct ways to develop an informal analog to the formal measure of party support, the elite endorsement. First, the number of retweets that a user receives can serve as a measure of their influence on Twitter (Kwak et al. 2010, Cha et al. 2010, Ackland 2013), thus capturing their 'elite' status. Second, since retweets reflect a user's explicit decision to share another user's message, they often serve as an implicit 'endorsement' of that message (Shmargad 2018). Indeed, the popular disclaimer on Twitter, "retweets do not equal endorsements," suggests that there is indeed a connection between the two concepts.

The snowball sampling approach that we describe in this paper makes use of both aspects of the retweet, as a node characteristic and as an edge. Our approach differs from the method in Wu et al. (2011) because they use Twitter lists rather than retweets for snowball sampling. Other research has used follower counts to identify influencers (Alexandre et al., 2022), yet some have argued that retweets are a better measure of influence (Cha et al. 2010) – albeit one that is more cumbersome to construct as it requires collecting a user's tweets (while follower counts are available from a user's profile information). We argue that a focus on retweets specifically lets us identify the *promotional landscape* of the candidate tweets that we collect (Klar et al. 2020). The approach also differs from those of Merton (1949) and Katz and Lazarsfeld (1955), as their bottom-up approach starts with ordinary folks and uses snowball sampling to identify the opinion leaders who informed them. Our top-down approach instead starts with candidates to identify the influencers who amplified their messages. The approach in this paper is thus more informative for understanding digital campaigning than public opinion and might thus be better characterized as 'two-step flow on its head.'

By starting out with candidates, the snowball sampling approach allows us to construct an informal analog of elite endorsements: influential retweets. The approach thus maps digital trace data onto an important social science construct, which is a central goal in the growing field of computational social science (Lazer 2015). The specific construct that we focus on here, elite endorsement, is typically studied in the context of political primary elections because the main activity of primaries, selecting a candidate to run on behalf of the party, provides an opportunity for political elites to make their preferences public. As Hassell (2016) notes, citing Dominguez's

(2011) study of endorsements during congressional primaries, “we need to develop other proxies of this partisan support because previous measures are cumbersome to gather for large numbers of candidates” (p. 80). While hardly effortless, as gathering candidate Twitter handles can take a nontrivial amount of time, our automated snowballing approach nonetheless makes it possible to identify influential retweets for a large set of candidates across hundreds of political races.

Upon identifying amplifying influencers who retweeted political candidates’ messages, we build on the snowball sampling approach to capture polarization among them. If amplifiers are polarized, we would expect them to primarily retweet messages from candidates representing a single party. However, Barbera et al. (2015) find that while polarization exists among Twitter users when they share information about politics, it does not when they share information about non-political topics. We thus check for polarization both when amplifiers retweeted candidate tweets as well as when they retweeted messages from other Twitter accounts. While studies of polarization on Twitter tend to focus on politicians (e.g., Green et al. 2020) or regular users (e.g., Conover et al. 2011), as far as we know, this is a first attempt at capturing what we might call meso-level polarization – among intermediaries that are central to the two-step flow process.

## 3. SNOWBALL SAMPLING USING RETWEETS

### *3.1 Collecting Candidate Handles and Tweets*

Data collection for this project began in August of 2018, closely following the primary elections in Vermont. At the time, the news website Politico maintained a list of primary election results at https://www.politico.com/election-results/2018/.[1] Figure 1 shows a screenshot of this webpage on the day of data collection. The page contained links to the fifty states, and the pages

[1] The contents of this webpage have since been replaced with general election results.

to which these links led included tables of primary results across governor, house, and senate races in that state. We scraped the data in these tables for all available states using the Rcrawler package in R and repeated the procedure a second time one month later to obtain election results for all of the races in 49 states.[2]

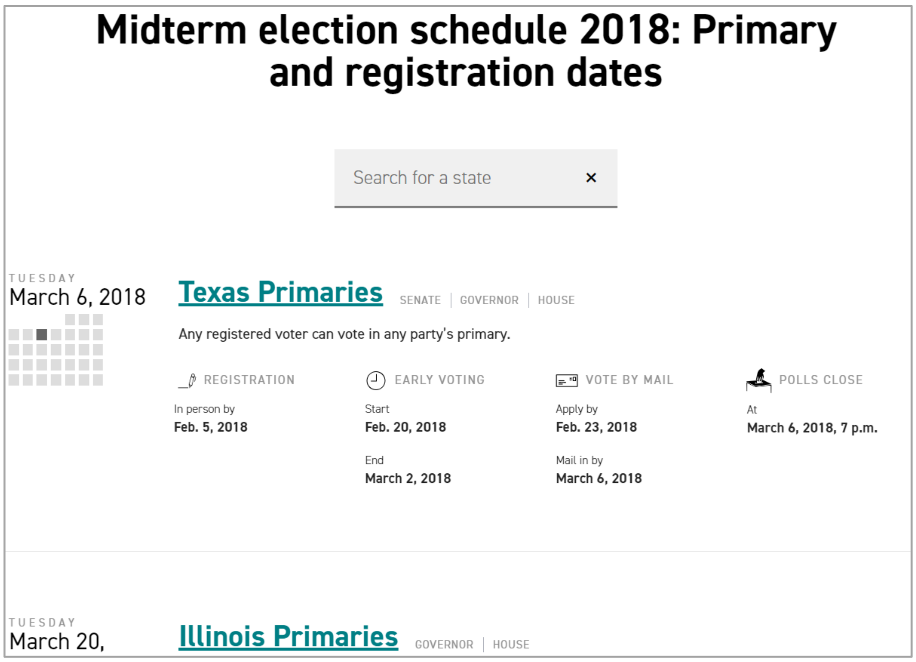


**Figure 1: Politico's website featuring the 2018 U.S. primary election results**

The scraped data include candidate names, the number and percentage of votes they received in their race, and information about the type of race (i.e., governor, house, or senate) and political party for which the primary was held (i.e., Democratic, Republican, or a Jungle primary). Jungle primary elections, also known as nonpartisan blanket primaries, permit candidates from any political party to participate with the goal of mitigating extreme partisanship

[2] Louisiana was excluded because of its unusual timeline, wherein the primary race occurs in November with a possible runoff later in the year.

(Hamlin, 2014). From the list of primary candidates, we kept the winner and first loser in each race – any candidate without a challenger or who came in third or worse was excluded from the analysis. With the help of an undergraduate research assistant, we then collected the Twitter handles of the top two candidates in each race. The assistant was instructed to use Google to search for each candidate's name, state, and district (for House races) to locate the handles, and one of the authors went through the list to assess and improve upon its accuracy.[3] In Figure 2, we provide summary information about the number of candidates and handles that were obtained through this process, as well as their distribution across race type and political party.

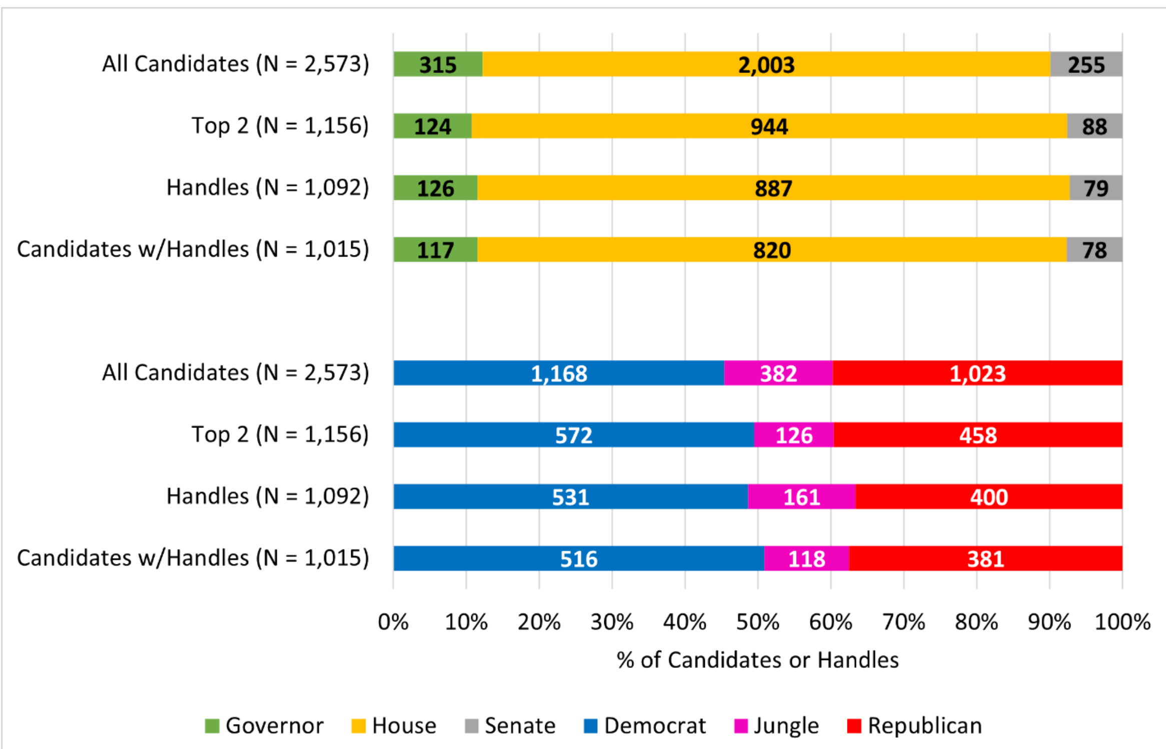


**Figure 2: Summary information of candidates and their Twitter handles**

[3] A complete list of the handles that were collected will be made available in a Github repository that is linked from the article upon acceptance.

Once the candidate handles were obtained, we used the Twitter API to collect data about the posting activity of the candidate accounts. First, we collected the maximum number of tweets that the API allowed at the time, which includes their most recent 3,200 tweets (including replies and retweets of other users' tweets). We then restricted the sample to the original messages by the candidates, including replies but not retweets of tweets by other users. We further restricted the set of tweets to include only those that were posted within 90 days prior to the candidate's primary election date. Finally, we filtered the list of tweets down further to include only those that were retweeted at least once. In Figure 3, we depict summary information of the tweets as they underwent this filtration process. Notably, Democratic candidates tweeted more in the months leading up to the election, even when considering the initial Democratic skew in the number of candidates (see Figure 2).

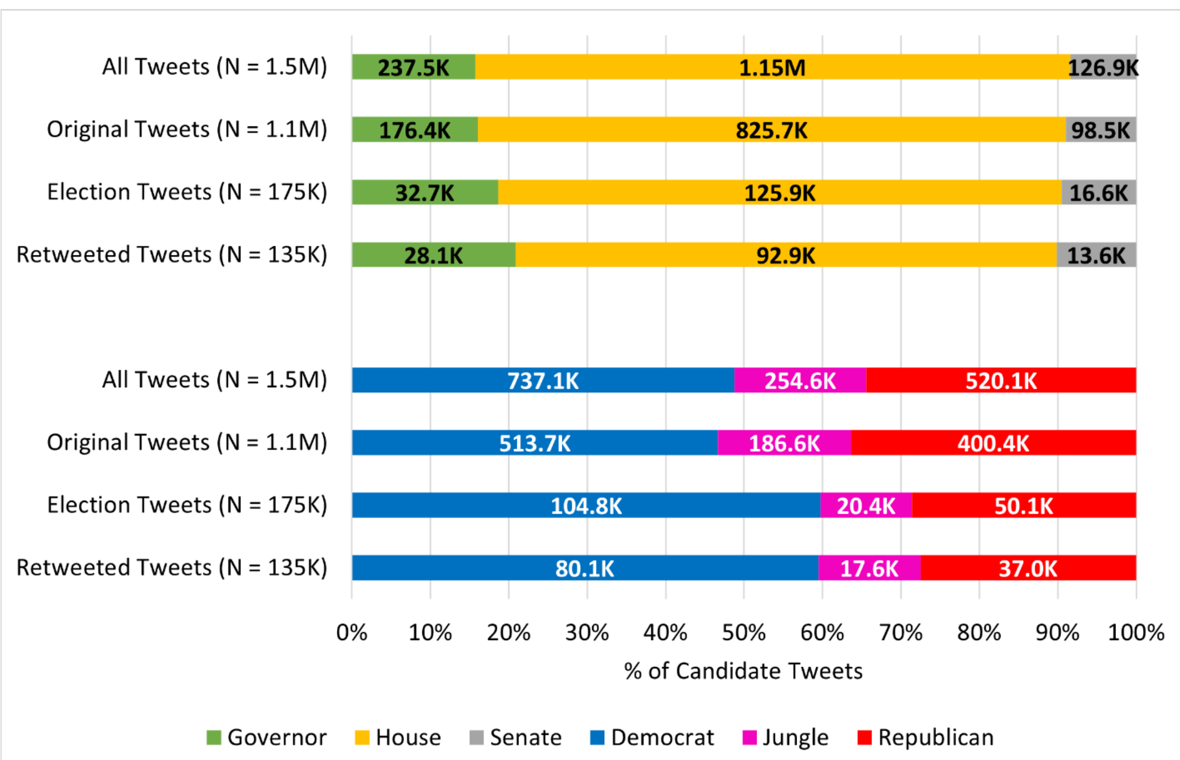


**Figure 3: Summary information of tweets from candidates**

***3.2 Identifying Amplifying Influencers***

The next step of the data collection procedure focused on retrieving the handles of users who retweeted candidates' tweets in the 90 days before their election. The Twitter API restricts the collection of retweeter information to the 100 most recent retweets per tweet. In Figure 4, we depict the retweeter retrieval rate for each candidate, which is calculated as the number of unique retweeter handles retrieved divided by the total number of retweets a tweet received, averaged across a candidate's tweets. The X-axis in Figure 4 depicts the average number of retweets a candidate's tweets received on a log scale. For candidates who received fewer than 100 retweets per tweet, on average, the retrieval rate was about 80%. As we move along the X-axis, getting to popular politicians whose tweets were widely shared, we notice a steady drop in the retweeter retrieval rate, which aligns with the limits of the Twitter API at the time.

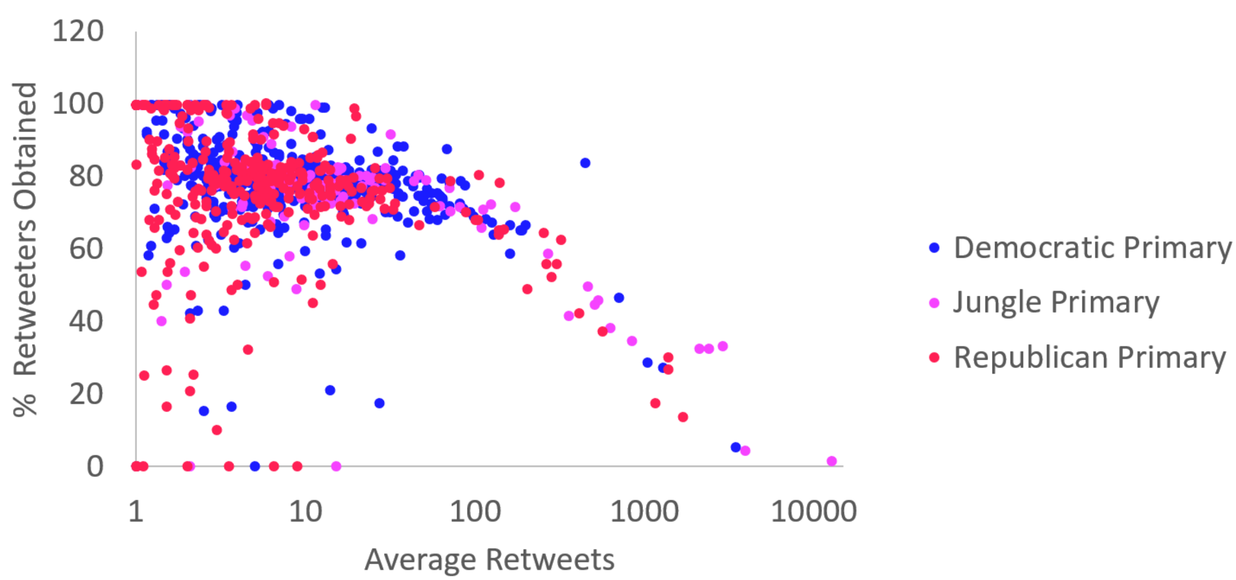


**Figure 4: Retweeter retrieval rate by average number of retweets a candidate received**

In Figure 5, we depict summary information for retweets of candidate tweets, broken down by election type and party. Though Jungle primary candidates produced less than 15% of the tweets, they represent over 50% of the retweets obtained. This is largely due to several California house candidates that make up 5 of the 6 most retweeted accounts (Adam Schiff, ~13K avg. retweets; Devin Nunes, ~4K avg. retweets; Ted Lieu, ~3K avg. retweets; Eric Swalwell, ~2.5K avg. retweets; and Maxine Waters, ~2K avg. retweets). Given the large number of retweets these candidates received, in Figure 5 we see a significant drop in the number of retweeters obtained for Jungle candidates. Incidentally, the number of retweeters obtained for Jungle candidates is more or less proportional to the number of tweets they posted (see Figure 3).

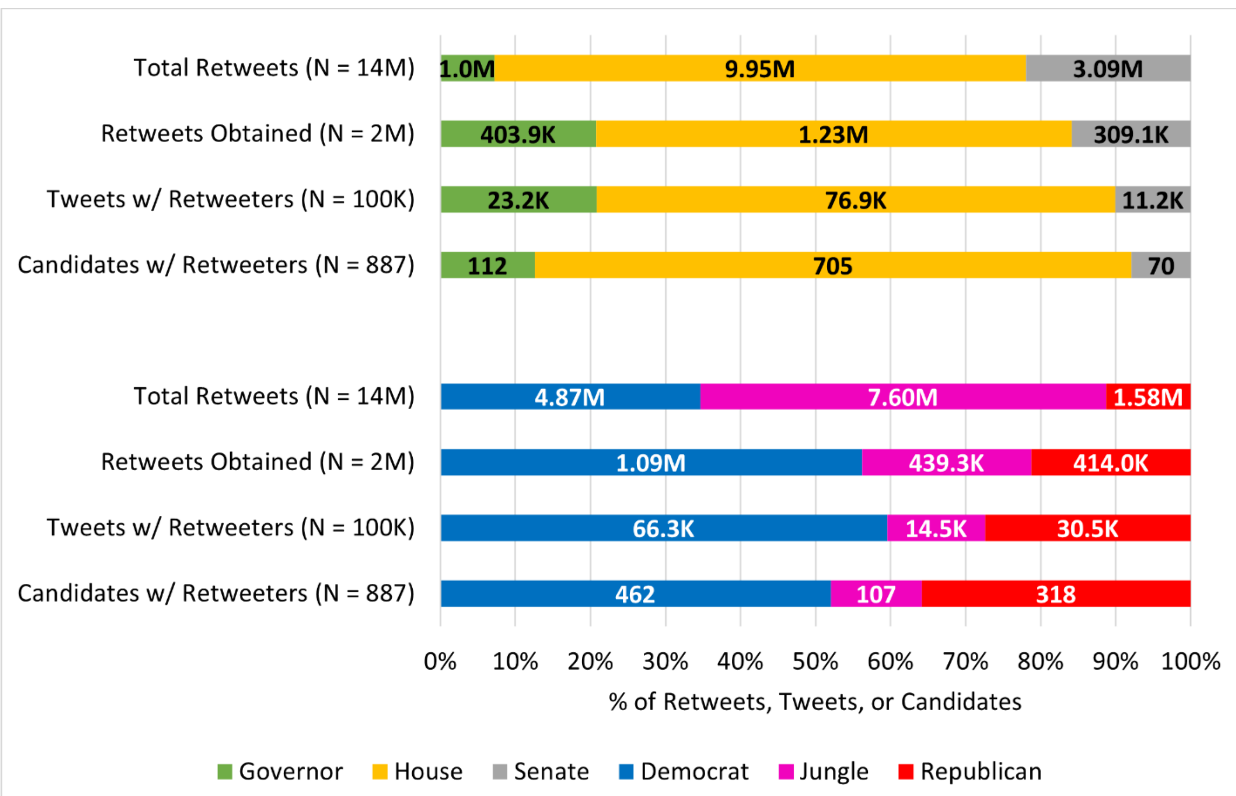


**Figure 5: Summary information of retweets of candidate tweets**

The next step of the data collection procedure was to collect tweets from the retweeter handles. This is an important step as it lets us calculate the relative influence of these accounts by averaging the number of retweets they received on their tweets (Shmargad 2018). In Figure 6, we depict summary information for retweeters of candidate accounts. As is clear from this plot, few shared messages from both Democratic and Republican primary candidates. This is also true for the 943 amplifying influencers – those who received at least ten retweets on their own tweets, on average. In Figure 6, we also classify the amplifying influencers into three distinct groups based on who they retweeted (Badawy et al. 2019): Democratic amplifiers, in blue, retweeted at least one candidate in a Democratic primary but none in a Republican primary. Republican amplifiers, in red, retweeted at least one candidate in a Republican primary but none in a Democratic primary. Jungle amplifiers, in purple, retweeted only candidates in Jungle primaries, candidates across Democratic and Republican primaries, or candidates across all three primary types.

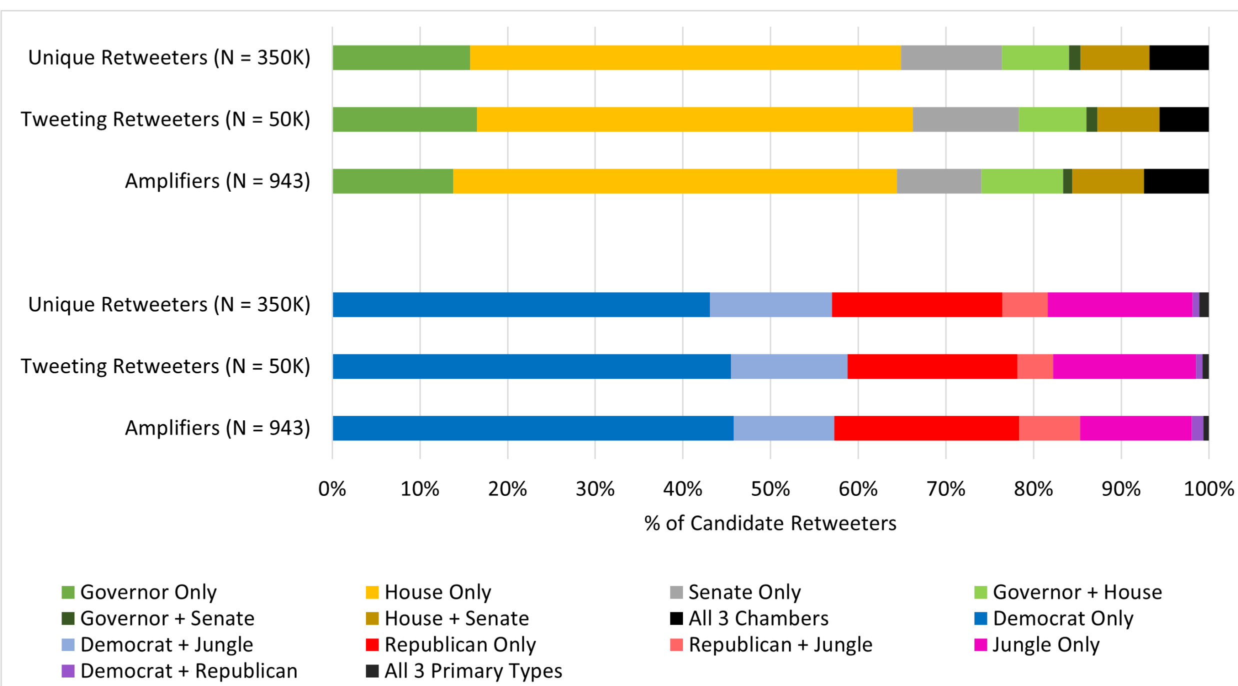


**Figure 6: Summary information and partisan categorization of candidate retweeters**

### *3.3 Identifying Ecosystem Influencers*

The final step of the data collection procedure involved collecting retweets that were made by the amplifying influencers and identifying influential accounts among those that were retweeted. If an account was retweeted by at least ten distinct amplifiers, they were designated as ecosystem influencers. We excluded a handle from the set of ecosystem influencers if it was a candidate or amplifier handle. In total, the influencer ecosystem includes: 1) the 943 amplifiers of candidate tweets who received at least ten retweets, on average, on their original tweets and 2) the 480 accounts whose messages were retweeted by at least ten different amplifiers. In Figure 7, we depict the snowball sampling procedure that we used to construct this influencer ecosystem, which we describe next.

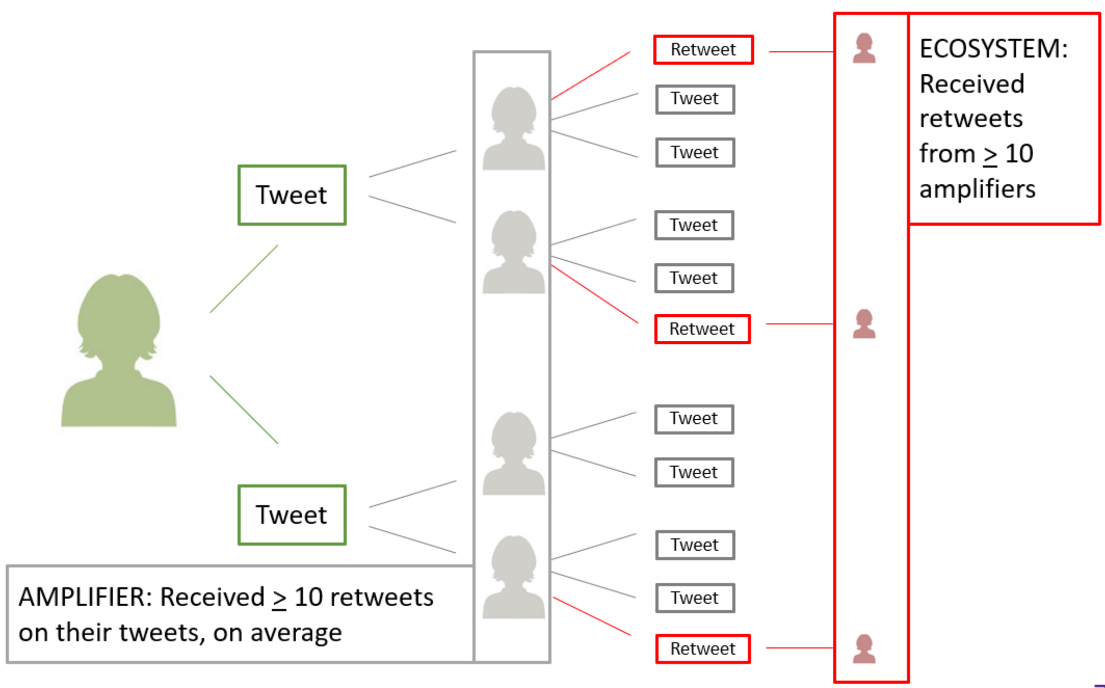


**Figure 7: Snowballing from candidate handles to construct the influencer ecosystem**

## 4. DESCRIBING THE INFLUENCER ECOSYSTEM

In Figure 8, we visualize the social network of candidates and the influencer ecosystem. Candidate nodes are blue, purple, and red, reflecting whether they competed in Democratic, Jungle, or Republican primary races, respectively. Amplifying influencers are depicted with brown nodes, while ecosystem influencer accounts that were retweeted by at least ten of these amplifiers are in yellow. The size of a node captures its overall influence (i.e., the average number of retweets the account received on its original tweets) and is set to zero for ecosystem accounts as data to infer their influence were not obtained. Finally, edges in the social network reflect retweets, with green and yellow edges depicting retweets of candidate and ecosystem accounts, respectively.

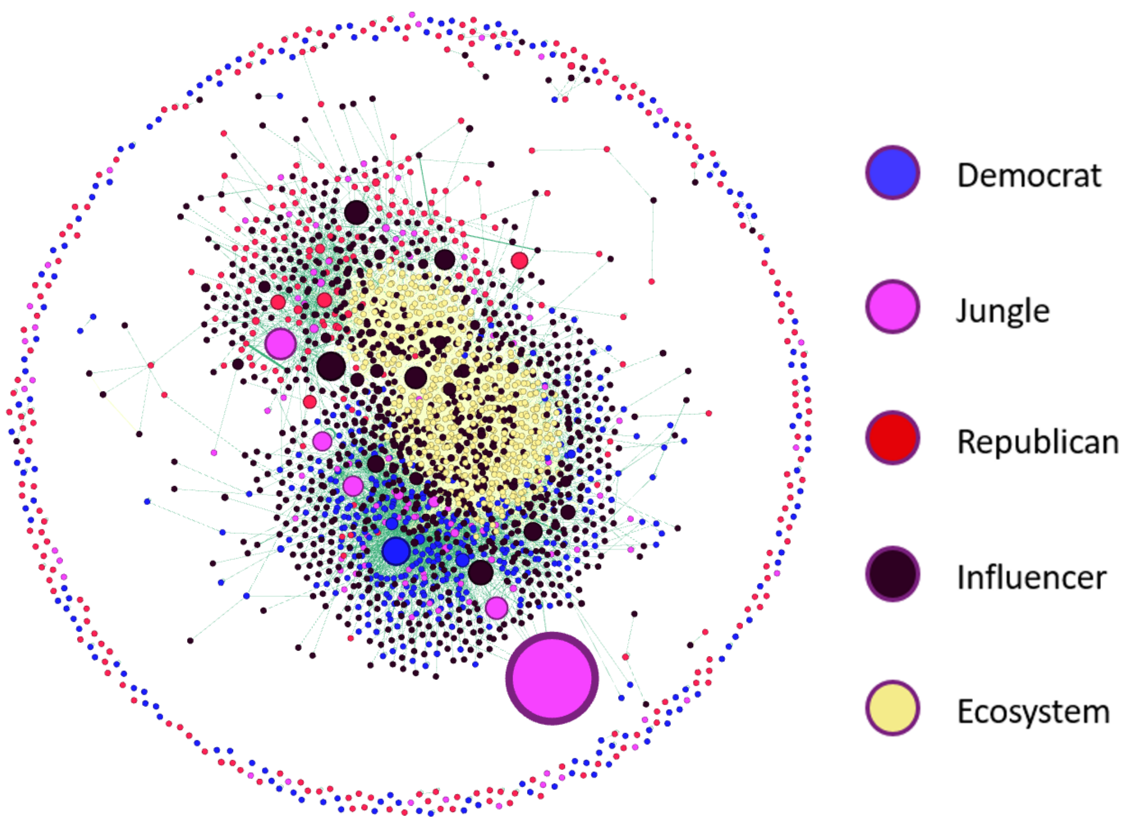


**Figure 8: Social network visualization of the influencer ecosystem**

There are at least two main takeaways from the social network visualization in Figure 8. First, candidates in Democratic and Republican primaries reside in different regions of the social network. Candidates thus rarely shared tweets from the opposing party and, more relevant to the current study, their tweets were rarely shared by the same amplifying influencer. Second, yellow nodes visually "bridge" the two partisan clusters, suggesting overlap in the broader ecosystem in which the partisan amplifiers are embedded. We dig deeper into these features of the network – i.e., polarization among amplifying influencers when retweeting candidates and the bridging role played by ecosystem influencers – below. An interactive visualization of the network can be found on one of the author's website (to preserve author anonymity, the link to the visualization will be included here upon the paper's acceptance).

### *4.1 Describing Amplifying Influencers*

Next, we describe the set of amplifying influencers before turning to the ecosystem influencers that amplifiers retweeted. In Figures 9, 10, and 11, we use the partisan classification discussed with Figure 6. Figure 9 depicts the distribution of amplifiers by how readily their own tweets were retweeted. As was evident in Figure 6, a majority of the amplifiers were classified as Democrat. This could reflect Twitter's demographic skew, which leaned left at the time of data collection (Wojcik and Hughes 2019). Within these accounts, however, Republican amplifiers received more retweets, on average, suggesting that the average Republican amplifier was able to garner more attention than the average Democratic amplifier. Republican amplification was thus more concentrated than Democratic amplification (see also Zhang et al. 2023), with the latter more distributed across smaller 'nano-influencer' accounts (Woolley 2022).

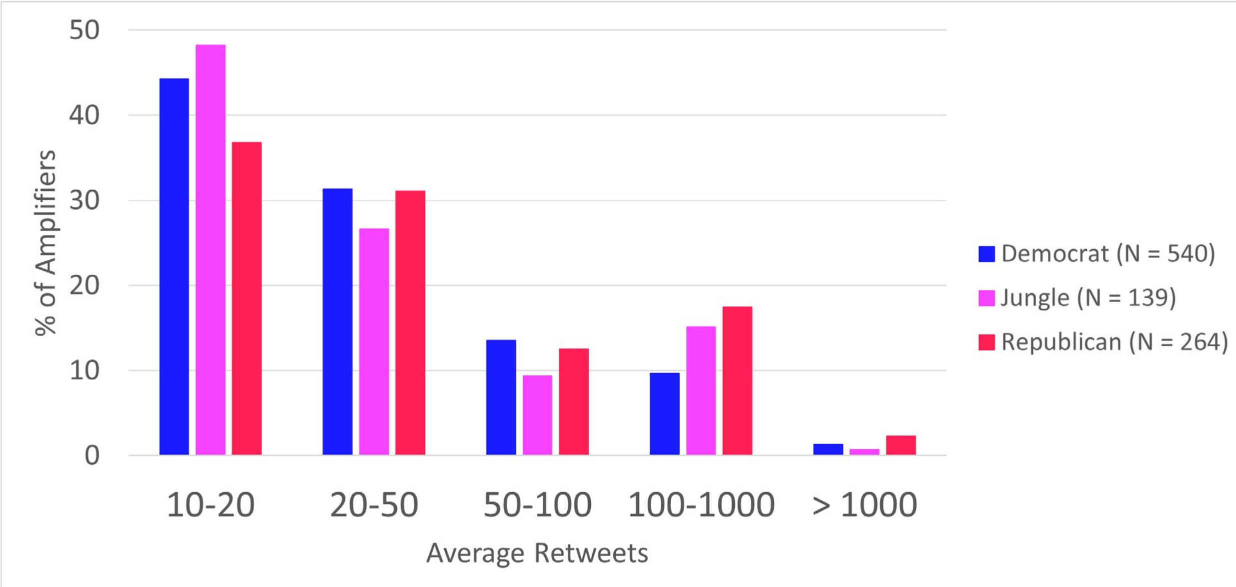


**Figure 9: Influencer distribution by average retweets and partisanship**

Figure 10 depicts a classification of amplifying influencers based on their political role. With the help of six undergraduate research assistants, we classified amplifier handles by visiting their Twitter profiles to infer whether they were Activists, Advocates (working for a political group), Journalists, Artists (including Actors, Musicians, and Athletes), News Organizations, Politicians, Political Groups, Non-Political Groups, Businesspeople, Academics, or Other. The same was done for ecosystem influencer accounts. The students first classified a subset of the accounts, totaling just over 50% of the amplifiers and ecosystem influencers. One of the authors then went through the entire set of handles using student classifications as a baseline.[4]

[4] The list of handles and classification of their political roles will be made available in a Github repository upon acceptance of the paper.

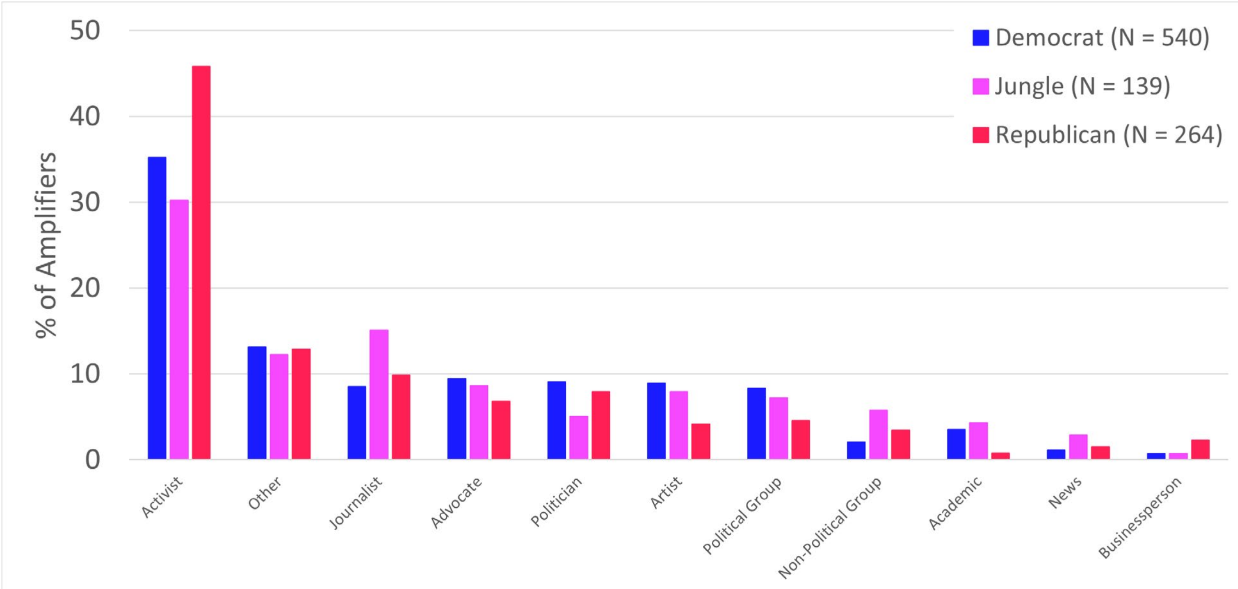


**Figure 10: Influencer distribution by political role and partisanship**

The research assistants largely agreed in their classifications, though there was some divergence between the labels Activist and Other. During the coding process, we thus refined our definition of an Activist as an account that 1) posts political content often, 2) shows a clear partisan bias in their posts, and 3) does not have a detectable political affiliation. When the political affiliation of an account was not detectable from an account's Twitter bio, we used Google to seek out more information. Activists made up a large proportion of the amplifier accounts and was by far the most common label across party. Notably, Republican amplifiers were more likely to be classified as Activists, while Democratic amplifiers were more likely to be classified as Advocates, Politicians, Artists, Political Groups, and Academics.

Figure 11 depicts scores obtained with the Botometer API, which captures the extent that an account's posting behavior is fully or partially automated (Davis et al. 2016). The Botometer API provides two metrics, called English and Universal, and the two were highly correlated for our sample (p = .91). Automation scores range between 0 and 1, with larger scores reflecting a higher likelihood of being automated. The Botometer API failed to generate scores for a small proportion of our sample (just under 6%). Notably, most amplifiers had low automation scores. However, there was a notable partisan difference, with Republican amplifiers having larger automation scores, on average. These differences were larger still when considering Activist accounts (see bottom panel of Figure 11). Still, automation was not widespread among the amplifiers, with fewer than 15% of the amplifiers receiving Botometer scores larger than .5.

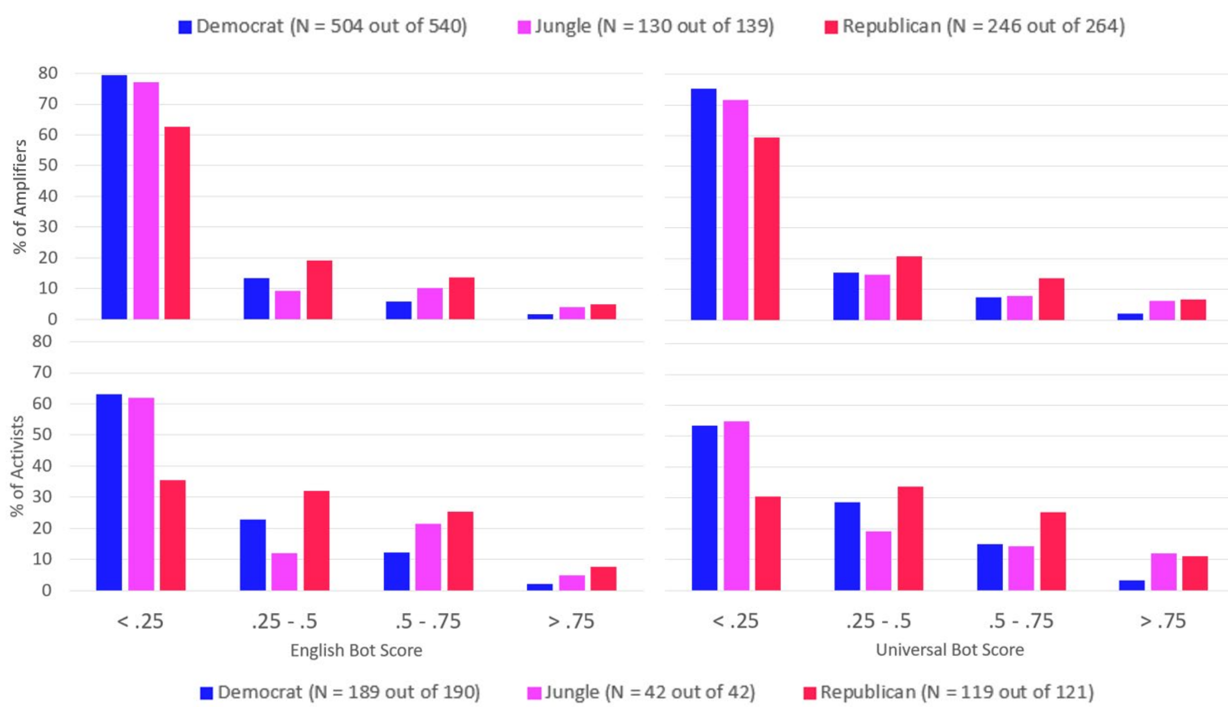


**Figure 11: Amplifier and activist distributions of Botometer scores by partisanship**

In Table 1, we present summary information of the 15 most influential amplifiers of candidate tweets. As before, the influence of an amplifier is captured by the number of retweets they received on their own tweets, on average. The most influential amplifiers were likely to be categorized as either Activist, Journalist, or Politician/Political Group. Given that Journalists and

Politicians each make up about 10% of the entire sample of amplifiers, they are overrepresented in the top echelon of influence. It is also worth noting that the three most influential amplifiers – @kwilli1046, @kevasrobert, and @sweetkatt111 – received Botometer scores larger than .5 (either Universal or English), suggesting that they were likely either partially or fully automated (or, at the very least, exhibited posting behavior that was bot-like). Automation, while typically low in the entire set of amplifiers, was thus also overrepresented in the top echelon of influential amplifiers. Next, we turn to describing the ecosystem accounts that were regularly promoted by amplifying influencers.

**Table 1: Summary Information for Top Amplifying Influencers**

| Amplifying Influencer | Average Retweets per Tweet | Political Role | Bot Score (Universal/English) |
|---|---|---|---|
| @kwilli1046 | 3468 | Journalist | .85 / .38 |
| @kevasrobert | 2894 | Activist | .62 / .67 |
| @sweetkat111 | 2780 | Activist | .72 / .76 |
| @senschumer | 2471 | Politician | .052 / .042 |
| @freedomcaucus | 2204 | Political Group | .16 / .24 |
| @yourlocalemodad | 1919 | Other | .071 / .039 |
| @shaunking | 1717 | Journalist | .071 / .039 |
| @leannewattphd | 1347 | Academic | .17 / .12 |
| @maziehirono | 1161 | Politician | .028 / .042 |
| @thecjpearson | 1160 | Activist | .030 / .030 |
| @katiepavlich* | 1155 | Journalist | - / - |
| @blackcatunloads | 1140 | Activist | .43 / .51 |
| @anncoulter | 1119 | Journalist | .041 / .020 |
| @tomsteyer | 1069 | Advocate | .038 / .033 |
| @clairecmc | 990 | Politician | .024 / .025 |

Note: The Botometer API could not generate scores for @katiepavlich

### *4.2 Describing Ecosystem Influencers*

We now describe the set of influencers that were regularly retweeted by amplifiers of candidate tweets. Figure 12 depicts the breakdown of ecosystem influencers by election type and the partisanship of the amplifiers who retweeted them. Nearly 80% of the ecosystem influencers were retweeted by amplifiers engaged across governor, house, and senate races. Notably, there is also substantial overlap when it comes to amplifier partisanship. In particular, over 30% of the ecosystem influencers were retweeted by all three partisan types of amplifiers, implying that they were retweeted by an amplifier who shared Democratic candidate tweets and an amplifier who shared Republican candidate tweets. Cross-partisan shared attention among amplifiers was thus common and, by appealing to a common center, the amplifiers may have been able to increase engagement with their tweets through a process that Bail (2016) terms cultural bridging.

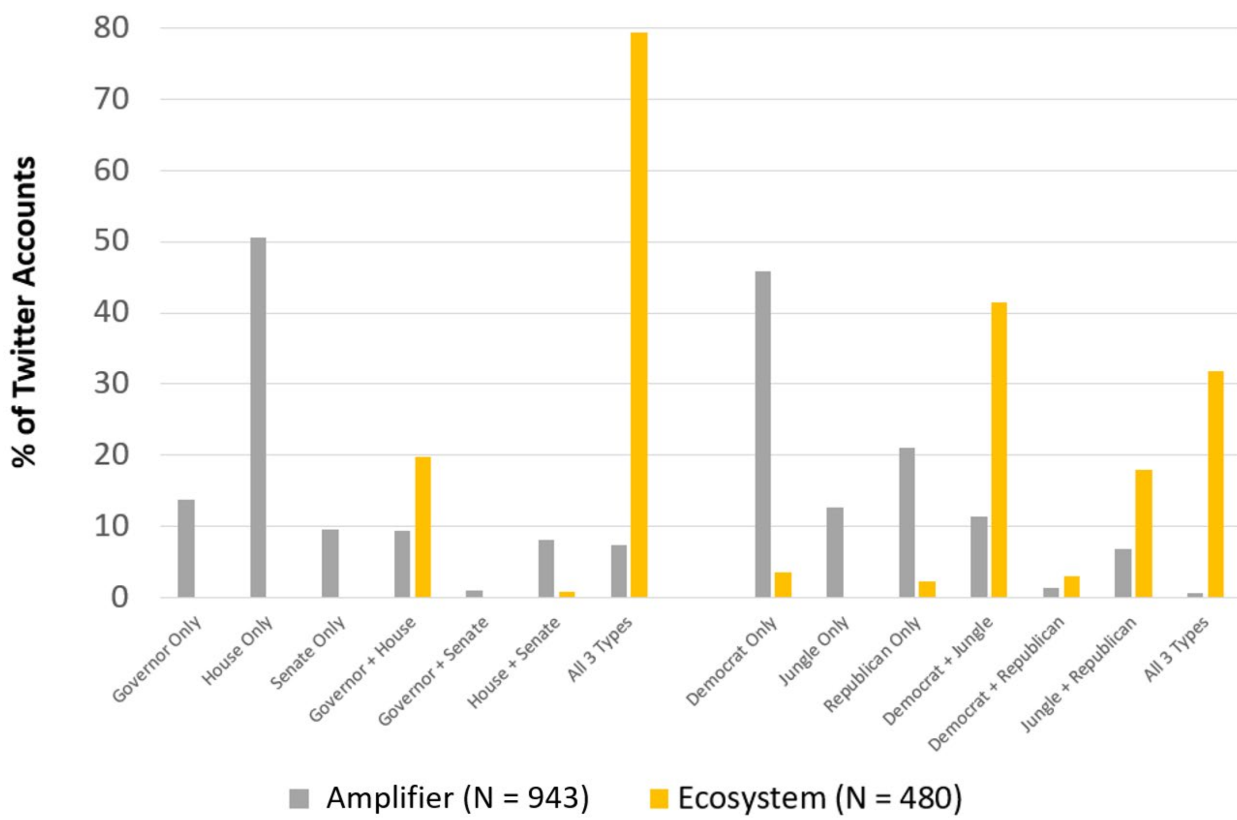


**Figure 12: Distribution of influencers by election type and partisanship**

In Figures 13 and 14, we depict both amplifying and ecosystem influencers by political role and Botometer scores, respectively. In Figure 13, we find that, compared to the amplifying influencers, ecosystem influencers were much less likely to be classified as Activists and much more likely to be classified as Journalists or News Organizations. One implication of this finding is that activists, rather than primarily promoting messages from other Activists in echo chambers, are embedded in the larger, shared media ecosystem. As is evident from Figure 14, Botometer scores of the ecosystem influencers were lower than those of the amplifiers, suggesting a limited role of automation in the broader ecosystem in which amplifiers are embedded.

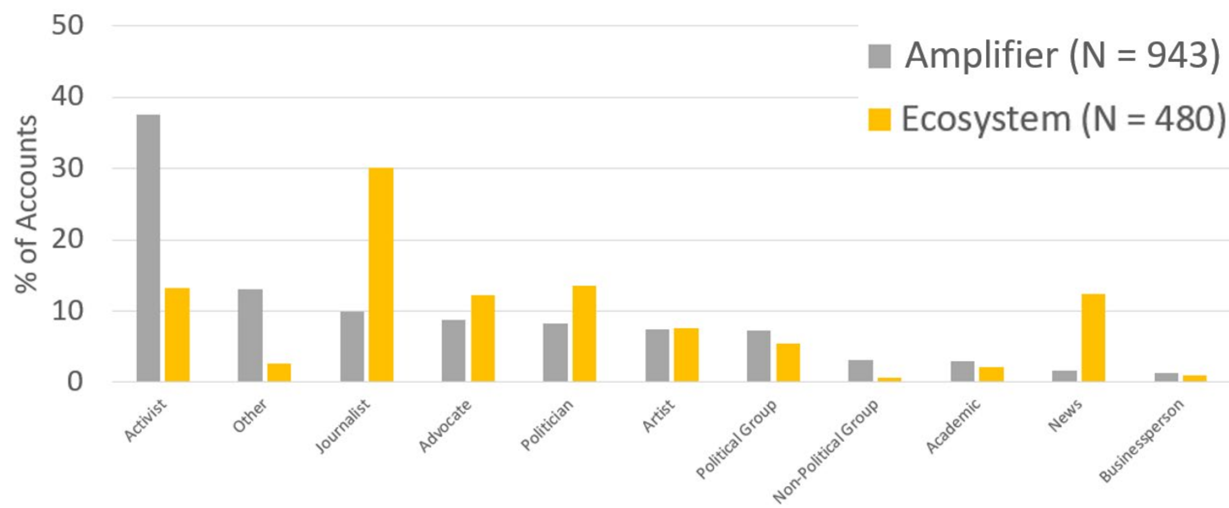


**Figure 13: Distribution of amplifying and ecosystem influencers by political role**

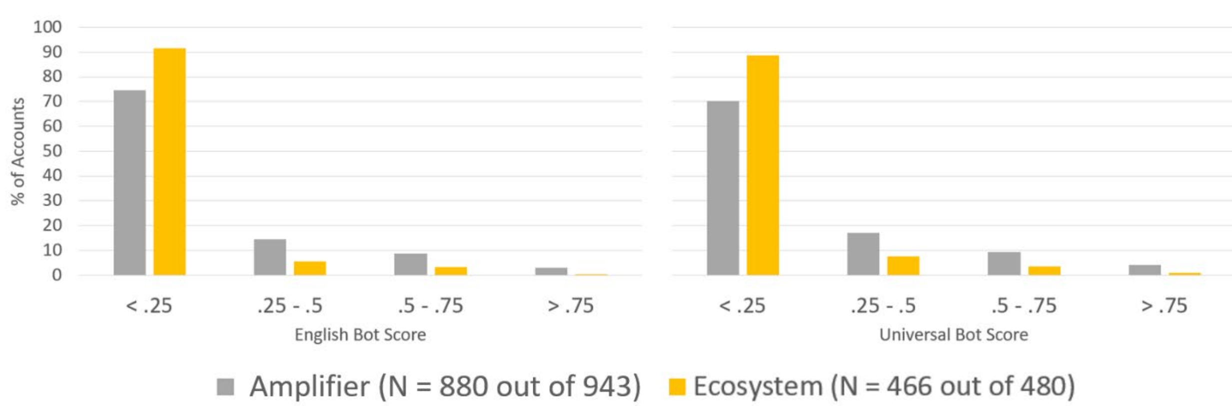


**Figure 14: Distribution of amplifying and ecosystem influencers by Botometer scores**

Next, we present a more nuanced depiction of the overlap in shared attention between amplifying influencers in their retweeting of ecosystem accounts. In Figure 15, we include each of the 480 ecosystem influencers and the number of Democratic, Jungle, and Republican leaning amplifiers who promoted their tweets. There is clear polarization in the retweeting behaviors of these amplifiers, especially at the top and bottom of the figure, which reflects a skew towards Democratic and Republican amplifiers, respectively. However, there is also evidence of shared attention, with many of the ecosystem influencers near the middle of the figure being shared by amplifiers on both sides of the political spectrum. This figure adds support to the claim that amplifiers readily promoted accounts outside of their echo chamber.

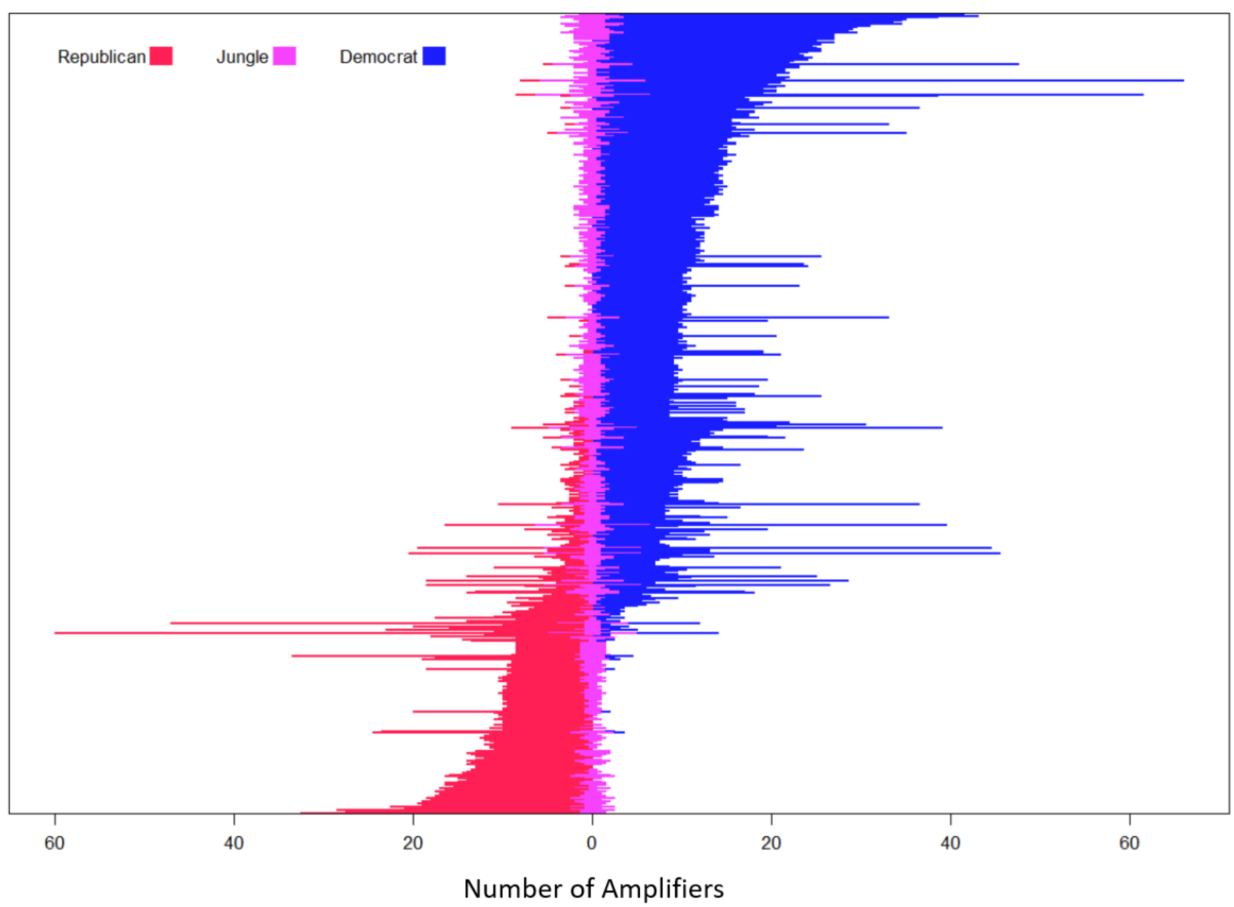


**Figure 15: Distribution of amplifier partisanship by ecosystem account**

We conclude this section with summary information of the 15 most influential ecosystem accounts, which we present in Table 2. Since we did not collect original tweets from ecosystem influencers, we could not calculate the measure of influence used previously – i.e., the average number of retweets one receives on their own tweets. Instead, we report the measure of influence used to identify ecosystem influencers in the first place, which counts the number of amplifiers who retweeted the ecosystem account. The most common political role of ecosystem influencers in the top echelon of influence was News Organization, followed by Politician. Botometer scores were no greater than 10%, suggesting that automation was not common among even the most influential ecosystem accounts. Unlike the amplifying influencers themselves, the accounts that they promoted were often mainstream media outlets, suggesting that amplifying influencers were more partisan in their promotion of candidates than in their general retweeting behavior.

**Table 2: Summary Information for Top Ecosystem Influencers**

| Ecosystem Influencer | # Amplifiers Who Retweeted | Political Role | Bot Score (Universal/English) |
|---|---|---|---|
| @nowthisnews | 74 | News | .044 / .10 |
| @realdonaldtrump | 72 | Politician | .038 / .033 |
| @kylegriffin1 | 68 | Journalist | .071 / .073 |
| @thehill | 64 | News | .056 / .073 |
| @cnn | 62 | News | .071 / .073 |
| @nbcnews | 55 | News | .048 / .068 |
| @foxnews | 55 | News | .030 / .042 |
| @kamalaharris | 53 | Politician | .038 / .033 |
| @abc | 46 | News | .035 / .033 |
| @alyssamilano | 46 | Artist | .056 / .039 |
| @washingtonpost | 45 | News | .048 / .086 |
| @nytimes | 45 | News | .061 / .045 |
| @ap | 44 | News | .061 / .10 |
| @andrewgillum | 43 | Politician | .038 / .028 |
| @betoorourke | 42 | Politician | .032 / .025 |

## 5. DISCUSSION

Political activists are fundamental to the function and success of political campaigns (Noel, 2018). In this paper, we present a novel snowball sampling approach to identifying influential activist accounts on Twitter. The approach allows us to systematically describe the accounts that can help candidates reach the broader public on Twitter via two-step flow (Katz and Lazarsfeld 1955, Wu et al. 2011). We argue that amplifier retweets are an informal analog to elite endorsements because the amplifiers we identify, like elites, have amassed influence among the broader public, and because retweets of candidate accounts are often implicit endorsements of candidate messages. These accounts amplify messages by political candidates, increasing exposure to their campaigns beyond what they would otherwise receive, and are thus not just a measure of activist support but capture the very mechanism by which the public learns and forms opinions about the candidates.

Our analysis reveals partisan differences across the two major parties, with Republican candidates receiving a higher share of their support from activists than Democrats, the latter of whom are more likely to receive support from formal sources – political groups and the people working for them. We find that amplifying influencers are partisan when sharing messages from political candidates, but that there is meaningful overlap in the other accounts that these amplifiers promotes. We refer to the accounts promoted by candidate amplifiers as ecosystem influencers, and show that the ecosystem consists of many journalists and news organizations. These findings suggest that there is shared attention across partisan activists, and that journalists and news organizations are vital for bridging these structural divides. Rather than exacerbating polarization, we find media accounts to be an important source of cross-partisan cohesion.

There are several limitations to this analysis that are worth noting. First, we have chosen an arbitrary cutoff of 10 average retweets to define political amplifiers, as well as 10 retweeting amplifiers to define the ecosystem influencers. These decisions were primarily motivated by the desire to have a feasible set of accounts to classify according to their political role (i.e., Activist, Journalist, etc.). The cutoff was also chose to make it possible to visualize the social network of candidates, amplifiers, and ecosystem influencers (Figure 6) without being overwhelmed by the number of accounts. Still, future research should investigate the robustness of the findings to different thresholds of influence, especially those around the extent of polarization and shared attention that amplifiers exhibit.

At the time the study was conducted, Twitter limited the total number of retrievable tweets and retweets obtained from individual Twitter accounts. We acknowledge that this restriction limited the number of amplifying influencers that we were able to identify. At the same time, we believe this restriction benefitted our analysis by preventing the oversampling of users who engaged with a few prominent political candidates. Figure 4 suggests that candidate influence is distributed as a power law, and that retrieving all of the candidate retweeters would have resulted in most of them having retweeted a single candidate – Adam Schiff – or perhaps a small handful of candidates. Our main objective was to understand those responsible for two-step flow on Twitter during midterm primaries for the median candidate. Our balanced analysis, which also reflects less prominent political races, has produced results that are more reflective of the American political scene writ large.

The political roles of the amplifier accounts, and the Activist label in particular, can often be difficult to infer from Twitter bios and Google searches. There has been an increasing interest in understanding online activism, including activists' use of hashtags (Jackson et al. 2020) and their role in spreading misinformation (Freelon et al. 2020). While this paper does not provide an extensive account of these activist activities, it does support previous research suggesting that political and media elites alone do not explain most of the amplification of campaign messages on Twitter (Pintak et al., 2021). Future research could dig deeper into the identities and activities of activist amplifiers and could illuminate the connections between their engagement with digital campaigns, social movements, and misinformation. We encourage scholars to adopt and adapt our snowball sampling technique to study other political events and digital platforms.

The inclusion of jungle primaries in our analysis could obscure some of the partisan affiliations of the candidates competing in these races. The decision to include jungle primaries was made in order to accurately reflect the nuances of primary election systems throughout the United States. Although some of the results we present may have been affected by this inclusion, our key finding about shared attention through ecosystem accounts does not rest on our decision to include jungle primary candidates. In particular, we find that more than 30% of the ecosystem accounts were promoted by amplifying influencers of all three types – Democratic, Republican, and Jungle. Even if we had classified Jungle primary candidates according to their partisanship, it would still be the case that these ecosystem accounts were promoted by amplifying influencers on both sides of the political spectrum. Indeed, as is clear from Figure 15 above, our analysis included relatively few amplifiers who were only engaged in Jungle primary races.

We recognize that our method of identifying automated accounts has been challenged by some scholars (Rauchfliesh & Kaiser, 2020). We agree that the detection of bots rests on shaky assumptions and that modern tools are probably better suited at capturing semi-automation or bot-like (e.g., repetitive) behaviors than fully automated accounts. Despite these limitations, we believe it was important to account for automation to investigate the extent to which bots played a central role in how two-step flow manifests on Twitter. Prior research reveals that automated accounts have played a meaningful role in recent American elections (Kollanyi et al. 2016), and our findings that they play a limited role in two-step flow helps to better understand the scope of influence of automation. Nevertheless, we encourage the reconceptualization of automation in online spaces and the development of more reliable tools to detect such capabilities.

Finally, the descriptive findings presented here reveal that political and non-political groups make up a relatively small proportion of the amplifier accounts that were identified. In addition to activists and political elites, interest groups make up an important source of influence for political parties (Bawn et al. 2012). The influence of interest groups is likely most prevalent in their donation activity, rather than in their amplification of campaign messages online. To understand these diverse sources of influence that political campaigns draw on to win elections, future research should investigate the financial activity of campaigns in combination with social media and endorsement data (Shmargad and Sanchez 2020). Such linking could shed light on the relationships that exist between donation and social media activity, and the extent that 'organic' content can compete with paid advertising (Kreiss and McGregor 2019). Given the increasingly dominant role that digital platforms play in mediating political content, such questions are central to understanding the promotional landscape in which candidates now find and define themselves.

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