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# Attention and amplification in the hybrid media system: The composition and activity of Donald Trump's Twitter following during the 2016 presidential election

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**Abstract**
Building on studies of the hybrid media system and attention economy, we develop the concept of amplification to explore how the activities of social media–based publics may enlarge the attention paid to a given person or message. We apply the concept to the 2016 US election, asking who constituted Donald Trump's enormous Twitter following and how that following contributed to his success at attracting attention, including from the mainstream press. Using spectral clustering based on social network similarity, we identify key publics that constituted Trump's Twitter following and demonstrate how particular publics amplified his social media presence in different ways. Our discussion raises questions about how algorithms "read" metrics to guide content on social media platforms, how journalists draw on social media metrics in their determinations of news value and worthiness, and how the process of amplification relates to possibilities of citizen action through digital communication.

**Keywords**
Amplification, attention, engagement, algorithm, metrics, power, social media, Twitter

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## Introduction

The contemporary media system is characterized by interaction between a variety of agents: journalists and media companies, social media platforms and publics, algorithms and bots, and more (Chadwick, 2013). These agents produce content, host it, share it, "engage" with it, and—as important as anything else—observe and try to influence the behaviors of others. As Webster (2014) has noted, a defining feature of communication in this new environment is its measurability and the *visibility of those measures* to other actors: news websites track minute by minute the appeal of their stories, advertisers relentlessly count click-through rates, and social media users strive for reactions from friends and contacts (Marwick, 2013).[1]

One concept that is gaining traction for understanding how audiences are stitched together under these conditions is *attention* (Goldhaber, 1997); a number of recent treatments have explored the nature of digital attention from the perspectives of business (Davenport and Beck, 2001), advertising and privacy (Wu, 2016), the challenges of social movements (Tufekci, 2013), the "logic" of social media (Klinger and Svensson, 2016), and the media system as a whole (Webster, 2014). Thinking in terms of attention is appealing because under conditions of information over-abundance, our broadcast-era intuition to think in terms of ability to communicate is analytically rather obsolete (Tufekci, 2013); attention shifts the conversation from who has the power to communicate to who has the power to attract an audience that will pay attention.

Webster (2014) has offered the most comprehensive theoretical account of this "marketplace of attention" and its consequences for media consumption and democratic society. Informed by Giddens' (1984) structuration theory, his treatment considers "users" and elements of the "structure" (chiefly media companies and social media platforms), and he offers a compelling case about how these interact to give shape to content regimes and audience patterns. In broad strokes, structures release offerings, users make choices among available offerings, and structures update future offerings. This "duality" offers some resolution to the perennial opposition of agency and structure.

We take this framework as a starting point for more meso-level theory building. We seek to elaborate in more detail how attention is attracted, aggregated, and expanded in one particular, but politically and socially important, corner of the hybrid media system: how political people, messages, and ideas in social media gain attention and activity that may be "read" by various structures as signals of worthiness. In this, we are partly responding to the "whom" problem posed by Webster (2014): we know too little about the actual constitution of audiences in the digital age (p. 10). Moreover, we know too little about the kinds of actions they take and the consequences of those actions. As Webster makes clear, such publics hold great potential power in that they respond to choices and as a result alter the structures by which new patterns of content are prioritized. We ask how that power is wielded and to what effect.

We build our contribution around the concept of *amplification*, which has become a widely used (e.g. Musgrave, 2017) but so far under-theorized term. We define social media amplification as the contribution of social media publics to the attention paid to a particular object (person, message, idea) by elevating other actors' (citizens, journalists, media platforms) perceptions of the object's worthiness or significance. This lens encourages us to ask how social media publics are constituted and how they act to intentionally (or unintentionally) amplify object around which they are gathered.

We begin by situating our contribution in contemporary conversations about the nature of power in a hybrid media system. After considering the power now wielded by attention in this system, we introduce the concept of amplification as one mechanism by which attention is aggregated and directed. We then apply the concept of amplification to one of the most successful recent cases of the aggregation of public attention: the primary and general election candidacy of Donald Trump. It is already clear that Trump attracted a portion of news coverage that was unprecedented relative to his opponents (Confessore and Yourish, 2016; Patterson, 2016) and that social media buzz played a role in increasing news coverage of him (Wells et al., 2016). But this relationship raises further questions about the constitution and activity of attentive publics in social media: Who was paying such substantial attention to Trump? How did social media publics magnify and extend Trump's message into greater communication influence and ultimately political power? And which publics were most influential in doing so?

## Attention and power in the hybrid media system

In post-industrial information society, media "constitute by and large the space where power is decided" (Castells, 2007: 242). This means that logics of the media system play increasingly central roles in defining the contours of political discourse and through it the "social production of meaning" (Blumler and Kavanagh, 1999; Castells, 2007: 239).

The currency of this media system, in domains from commercial advertising to politics, is no longer the ability to *communicate* to mass audiences but the ability to *attract attention* from them (Davenport and Beck, 2001; Goldhaber, 1997; Webster, 2014). In this "attention economy," media organizations and platforms vie for eyeballs, as do the issues, actors, causes, and factions that make up our civic and political sphere (Lanham, 2006; Webster, 2014).

Scholars of social movements have long been conscious of this problem because attention scarcity is a perennial challenge for those outside the mainstream communication channels—those attempting to access the power inherent in the ability to communicate to publics (Andrews and Caren, 2010; Gitlin, 1980; Snow et al., 1986). However, until recently, this concern has been typically conflated—in both analysis and practice—with the notion of mass media *coverage*. Today, with the categories of public attention and mass media coverage (incompletely) separated, we see the significance of attention more clearly (Tufekci, 2013).

In one example of more recent thinking, Freelon et al. (2016) explicitly recognize the relationship between attention and power in their analysis of the Black Lives Matter movement's social media organizing. They show that it was when Black Lives Matter activists won the attention of the press through coordinated social media messaging that elites started taking seriously the activists' concerns. In this, the problem of attention-getting echoes the more general problem for social movement activists identified by Tilly years ago: achieving perceptions of worthiness, unity, numbers, and commitment (WUNC; Tilly and Wood, 2013).

### Why is attention powerful?

The precise nature of the attention–power relationship has only been sketched in general terms. Here, we might outline four aspects of the power of attention in the contemporary media system. At the most abstract level, attention gives an actor access to the "socialized communication" that lends an audience to an entity's depiction of the world as it is, and as it might, or should be (Castells, 2007: 239). Attention is, thus, a necessary condition for a speaker to change or mobilize the opinions of an audience.

Second, relatedly, attention is powerful because it is a channel by which an actor can ask others to take action: it can be a mechanism for translating communication power into other forms of power. Thus, attention is *potential action*. In the commercial domain, this is the reason advertisers will pay millions to rent brief segments of audience attention from media properties (e.g. Wu, 2016). In the political-civic domain, it is the mechanism by which communication can be converted into civic engagement (Bennett and Segerberg, 2012; Bimber et al., 2005).

A third aspect of the power of attention is that it is usually transferable; it is a form of currency. The holder of attention can choose to direct that attention at some other object (Goldhaber, 1997). Marwick (2013) emphasizes the significance of highly visible celebrities "mentioning" others on Twitter and the consequences of that lease of attention for the mentioned. Moreover, it is this transferability of attention on which the commercial media system is based: media properties want attention, first and foremost, to be able to lease it to advertisers (Webster, 2014). Transferability of attention is significant in the political realm, as well, in that political actors must make choices about where to direct attention that they enjoy: to particular issues, to other political actors, and so on. Here, the press remains powerful—and as a result can significantly shape, and even distort, the actions of activists (e.g. Gitlin, 1980) in their efforts to gain access to that attention.[2]

Finally, attention is powerful because other people think it is powerful. Marwick (2013) has demonstrated the powerful role of status signals—conveyed most of all by audience metrics—in shaping the dynamics of social media communications. This "popularity bias" (e.g. Fu, 2012; Webster, 2014) means that attention tends to beget attention. As Van Dijck (2013) puts it, "the more contacts you have and make, the more valuable you become, because people think you are popular and hence want to connect with you" (p. 13).

## How attention flows

As a major currency of power in the hybrid media system, the critical question of how attention is allocated and how it shifts and flows between entities now occupies a growing research program. A comprehensive review of this literature is beyond the scope of our discussion, but let us note several key observations. First, big media properties still attract gigantic quantities of attention because of the path dependence of their audiences, distribution infrastructure, and network effects (e.g. preferential attachment) that confer growth advantages on nodes that are already well connected (Hindman, 2008; Webster and Ksiazek, 2012).

We also know that our media system is now hybrid, with attention being directed across as well as within sub-systems: older media such as traditional newspaper, TV and cable outlets, and online media, including social media, are in constant competition, cooperation, interpenetration, and adaptation (Chadwick, 2013). Thus, attention to particular issues or topics can be transferred between parts of the media system, as in the examples of the Black Lives Matter movement (Freelon et al., 2016) and Trump himself (Wells et al., 2016) discussed above. This is the reason that questions of intermedia agenda setting are crucial: knowing that mass media continue to command large audiences, it is vital to articulate the conditions under which social media publics may influence their agendas, as well as the reverse (Conway et al., 2015; Guggenheim et al., 2015; Neuman et al., 2014).

## *The logic of audience metrics*

Most pertinent to our case, it is also increasingly clear that attention flow is shaped by actions taken by structures and agents as a result of their *perceptions* of existing attention or attention potential and that these perceptions are largely constructed via audience *metrics* (Karpf, 2016a; Webster, 2014). Click rates, "likes," shares, and other "engagement" measures now play crucial roles in how social media platforms present content to users, how users perceive content, and how the press covers issues. As Webster (2014) puts it,

> Newer forms of digital media are rife with head-counting exercises. Topics "trending" on Twitter are immediately apparent to users and often reported in the press. The same social chatter is harvested by "social listening" firms and translated into metrics that rate engagement. (p. 83)

On the system or platform level where engagement is prized (Gillespie, 2011), attention is directed to what algorithms judge to be popular or potentially popular choices (Webster, 2014). And algorithms have constantly been advanced and perfected in quantifying engagement, such as Netflix's recommendation system (Hallinan and Striphas, 2016) and Facebook's EdgeRank (Bucher, 2012). Nevertheless, this process introduces certain biases to media measures, which as "the result of gathering and reducing data" (Webster and Ksiazek, 2012: 42) tend to equate choices with preferences and popularity with quality (Webster, 2014).

Similarly, for individuals, audience metrics often signify quality, utility, trustworthiness, and status or lack thereof (Fu, 2012; Messing and Westwood, 2014; Metzger et al., 2010; Van Dijck, 2013). Markers of attention have become status signals for important subsets of social media users as they present themselves to social media communities—metrics operate as primary "status affordances," the "technical mechanisms that signal greater social status" (Marwick, 2013: 75). Within the particular platform of Twitter, follower number, retweets, and @replies play critical roles. According to Marwick (2013), they

> imply a level of influence, visibility, and attention [….] the number of followers, shown on each individual profile, displays one's "worth" in terms of quantity, while retweets and @replies

> display one's worth in terms of the number and (implicit) status of users who publically acknowledge one's existence. (p. 95)

The sense of "worthiness" implied in social status also extends to *news*-worthiness (Karpf, 2016b). For journalists and editors, audience metrics enact the concept of "active audience" and come to play an increasingly important role in their news judgment and news-making processes (Anderson, 2011); social media have also been integrated into daily routines and become one of their newsgathering and monitoring channels (Lecheler and Kruikemeier, 2016). Both are results of the changing economic, sociological, and political calculations of the news-making industries (Anderson, 2011; Chadwick, 2013; Gans, 1979). Journalists might feel obliged to cover attention-infused political tweets "either to appear current with their readership or for fear that competing news organizations will scoop them" (Parmelee, 2014: 446). Especially when it comes to making difficult decisions about how to allocate coverage in situations of uncertainty, metrics that quantitatively gauge public interest or public support may be a helpful "objective" indicator (Parmelee, 2014).

The dynamics of attention allocation by these three sets of actors—platforms, users, and journalists—point to the same conclusion: attention flows to objects that succeed in achieving visibility in terms of audience metrics, thus demonstrating that they are already receiving attention and engagement and have the potential to attract more.

## Amplification

Viewing attention as a currency of power in the hybrid media system and its display through visible metrics as a primary mechanism of asserting its influence leads us to our central concern: processes that enhance attention to or visibility of a particular object in social media. Drawing on uses of the phrase in related contexts (e.g. Eilperin, 2016), we propose to call such processes *amplification*. For the purposes of this article, social media amplification consists of actions of individual users that intentionally or unintentionally increase measures of engagement surrounding a person, message, or idea. By measures of engagement, we refer to metrics that may be "read" by other entities as indicators of worthiness for some future action, that is, the provision or distribution of content, the choice to attend to something, or news value.

Seeing amplification in this way concretizes existing understandings of audiences and their behaviors. Although Webster (2014) recognizes the strategic aspect of agency—"The newer way to see users is as members of one or more networks who are aware of each other and may affect each other's behaviors"—embedded in the digital media system, he paints it in broad strokes (p. 26). Amplification, however, demonstrates one specific manifestation of such agency: in political communication settings in which control of message is of central import (Castells, 2013), individuals are not only aware of their ability to choose among offerings but are also increasingly aware of the structure and the fact that the structure makes decisions that affect how others' attention is directed (Phillips, 2015; Webster, 2014). They are therefore capable of taking actions which influence the metrics on which platforms and other media make decisions. A "like" button is not a simple indication of agreement or interest; it may be many things, including a simple vote for other people to pay attention to something, either directly ("hey friends, I liked this so you might too") and also algorithmically ("Twitter, notice that I liked this so that you present it to others").

In this way, the notion of amplification connects to larger conversations about the possibilities of citizen action in the new media environment (e.g. Bennett and Segerberg, 2012; Bimber et al., 2012; Castells, 2013; Jenkins, 2006; Papacharissi, 2015). Especially, this notion helps to develop Webster's project to find agency and free will in the structurational media system. For one thing, amplification heightens the possibility of agency for individual actors because it posits that individuals can recognize, and attempt to influence, the media structures that otherwise define choices. This may offer some rehabilitation for some forms of online "slacktivism" (Morozov, 2009), as Tufekci (2013) notes: "slacktivism, often derided for lack of impact, can also be understood as an intervention in the attention ecology" (p. 851).

## Research questions

We now turn our focus more directly to the case of attention paid to and amplification of Trump and consider the questions raised by the discussion above. Because the extraordinary attention Trump did receive, on Twitter and elsewhere, has been documented (e.g. Patterson, 2016), we do not recite that material here. Instead, we begin by asking about the constitution of the publics that most closely attended to Trump, that is, who was paying attention to Trump. In particular, we wish to examine who followed Trump's messaging most closely by explicitly following him in his own preferred medium of communication—Twitter:

> *RQ1*. Who were Trump's Twitter followers? And how did the constitution of Trump's attentive publics on Twitter evolve over the course of the campaign?

Second, we examine the question of amplification. We know that social media, and especially Twitter, helped to draw attention to Trump from other media sources because of the buzz he generated (Wells et al., 2016); here, we explore where, within Twitter, that buzz came from—in other words, *who* was amplifying Trump's Twitter status and messages. To do so, we examine retweets of Trump, the primary mechanism of amplification within the Twitter platform.

In terms of who was doing the retweeting of Trump, several possibilities present themselves: Was retweeting behavior distributed across the social media audience, as citizens of all stripes reacted to his pronouncements? Or retweets may have been disproportionately the product of small groups of highly active, extreme supporters—perhaps those labeled "deplorables" in Hillary Clinton's memorable phrase; for that matter, liberals may have played a role in inadvertently amplifying his message by retweeting him while criticizing him. These questions have significant implications for how we think about the nature of discourse in social media and its impacts on other media formats:

> *RQ2*. Who amplified Trump's message by retweeting him? How do different groups compare in their contribution to Trump's total retweets?

# Method

## Data

We used Twitter's REST API to download the profile information of all 13 million followers of @realDonaldTrump as of 8 November 2016 and drew a random sample of 377,725 (about 3%) of his followers with probability proportional to their follower counts. This sampling decision was made to ensure a sample of relatively active users and, thus, generally more attentive publics than pure random sampling would yield.[3]

For each sampled handle, we obtained the following data: (1) profile information, including created time, follower count, following count, language, region, and time zone; (2) up to 3200 recent tweets; and (3) the complete list of handles followed by that handle. Aggregating the data in (3) reveals that the 377,725 handles followed more than 150 million unique handles. Of these 150 million, over 5 million were followed by at least 10 handles in our sample.[4] For these 5 million handles, we downloaded (1) above.

Next, we divided our sample according to when each handle began following Trump. This was done to enable comparisons between different stages in his political ascendance. The three periods we identified were as follows: (1) before his candidacy announcement on 16 June 2015, when his follower count was at around 3 million, during which time Trump primarily identified as businessman and entertainer, although he dipped his toes in politics by making birther claims and occasional political commentaries; (2) the primary election (until 19 July 2016), when Trump was fighting more than a dozen competitors for the Republican nomination; and (3) the general election (until 8 November 2016), during which the field narrowed to Trump and his Democratic opponent and the political battle escalated.

## Clustering analysis based on following patterns

To assess who Trump's followers were, we took a "you are who you follow" approach (Latour, 2010; Pennacchiotti and Popescu, 2011) with a cluster analysis that was conducted separately among handles that began following Trump within each of the three time periods. It consists of the following three components.

First, we created a *similarity measure* based on the assumption that the more handles (considered as features for classification) two people follow, the more similar these people are likely to be. A similarity metric based on the weighted common handles was introduced (e.g. Ng et al., 2002; Wu et al., 2008)

$$L_{ij} = d_i^{-0.5} A_{ij} \sqrt{\frac{n_j}{N_j}} \log \frac{n+1}{n_j+1} \quad (1)$$

Here, $d_i$ is following count of a Trump follower $i$. $\mathbf{A}$ is the adjacency matrix representing the follower–following relationship data, with $A_{ij} = 1(0)$ indicating a Trump follower $i$ is (not) following a feature handle $j$. $n_j$ is the number of Trump followers in our sample following feature handle $j$, whereas $N_j$ is the total number of followers on Twitter following feature handle $j$.

Through weighting, we aimed to achieve three goals: (1) down-weighting feature handles such as Kim Kardashian that have large followings but are not relevant to our study; (2) down-weighting feature handles followed by many sampled followers and thus having little discriminant value; and (3) down-weighting sampled Trump followers who followed enormous numbers of feature handles because if a follower follows too many handles, the influence of any individual handle on this follower is low.

After weighting, the similarity between any pair of Trump followers, say $(p,q)$,is the inner product of the two rows in $L$

$$Similarity_{p,q} = \sum_{k=1}^{m} L_{pk} L_{qk} \tag{2}$$

where $m$ is the total number of distinct handles kept in the cluster analysis. This is a weighted version of the number of common handles followed by any two Trump followers $p$ and $q$.

Second, we utilized the similarity relationships among Trump followers and ran our *clustering algorithm* adapted from spectral clustering (e.g. Dhillon, 2001; Von Luxburg, 2007).[5] We set the number of clusters to $k = 50$ after experimenting with $k = 10, 20, \text{and}\, 50$ because it produced highly granular and interpretable clusters that could be easily grouped into larger ones.

Finally, we selected the 40 feature handles followed by handles in each cluster that best distinguish handles in that cluster (adapted from Wang and Rohe, 2016).[6] We then used the profile information (tweets, description, location, language, followers and following counts, etc.) of the 40 distinctive feature handles to organize our 150 clusters (50 clusters in each of three time periods) into nine overarching categories: "Trump supporters," "Far-right conservatives," "Alt-Right," "Conservatives," "Men's interest," "Liberals," "Mainstream politics," "Apolitical," and "Other countries." These categories were derived based on our analysis of the clusters, in combination with our particular interest in how different political sub-publics, especially conservative sub-publics, were responding to Trump.[7]

Briefly, "Trump supporters" consisted of handles that followed Trump family members like @IvankaTrump and @MELANIATRUMP and staunch surrogates such as @KellyannePolls and @RudyGiuliani, as well as lesser known followers who conspicuously proclaimed their loyalty and support to Trump. "Far-right conservatives" included handles that were like "Trump supporters" but also followed high-profile handles on the hard political right, such as @RealAlexJones, @PrisonPlanet, @Cernovich, and @BreitbartNews. We defined "Alt-Right" as clusters that followed White nationalist handles without following handles that professed support of Trump in their profiles. "Mainstream conservatives" were those who followed more mainstream conservative politicians such as @tedcruz, pundits like @AnnCoulter, or mainstream conservative media outlets and journalists like @FoxNews and @BretBaier. Clusters focused on the National Rifle Association or religious figures also fit in this category. "Men's interest" was used to describe clusters that followed sports like baseball and parody handles like @BleacherReport, @MeninistTweet, and @CauseWereGuys. "Liberals" followed liberal politicians, media outlets, pundits, and journalists such as @SenWarren, @TheDailyEdge, and @chrislhayes, as well as lesser known individuals who loudly proclaimed their opposition to Trump. "Mainstream politics" were clusters that followed politicians on both the right and the left and mainstream news outlets and journalists like @CookPolitical and @danbalz. "Apolitical" encompasses clusters that spanned a wide range of interests such as celebrities, TV shows, video games, golf, race cars, parenting, marketing, and financial market, but did *not* prominently include political or news figures. Finally, "Other countries" clusters included handles that followed mostly handles from other countries such as Mexico, Britain, Russia and Kenya.

For illustration, Table 1 presents one cluster from each of the nine cluster categories. It displays the cluster category, the number of handles in each cluster, and the distinctive handles followed by handles in each cluster. To facilitate interpretation and differentiation among more conservative clusters, it also displays what portion of handles in each cluster followed @PrisonPlanet and @BreitbartNews, what portion retweeted at least one Trump's tweet, and the average number of retweets of Trump's tweets per handle in each cluster.[8] Table 1 illustrates that the clustering successfully grouped the handles and even distinguished between subgroups of political conservatives.

## Results

### *The constitution of Trump's attentive publics on Twitter*

To address RQ1, concerning what publics attended to Trump by following him on Twitter, Table 2 indicates what portion of followers added during each of the three time periods belonged to each of the nine cluster categories. For a graphical illustration with more detail, Figure 1 shows the changing numbers of new followers: each data point indicates the number of sampled followers in each category out of every 100,000 new followers of Trump. The two together tell a rich story of the assembly of Trump's Twitter following.

First, Table 2 makes clear that Trump's Twitter followers are a heterogeneous amalgam. All of the cluster types are well represented here. Interestingly, the plurality of followers displays little political interest: aside from following Trump, they follow few other political or news handles, and instead their Twitter streams are filled with information about celebrities, parenting, marketing, financial markets, and so on. It is predictable that such handles should make up a significant portion of Trump's first 3 million followers, who began following him before the 2016 campaign, during which time his primary identity was as real estate mogul and reality show host. But non-political handles continue to make up the largest portion of his growing following during the primaries and general election campaign as well: they are 46% and 42%, respectively, of those who began following him during those periods. Combined with the fact that the second largest category in each period was followers from other countries, this finding speaks to Trump's success at drawing attention from all corners of social media.

As a group, the four categories of conservative clusters make up the next largest set of supporters. Interestingly, as a distinct set of conservatives, handles we labeled Alt-Right were a more prominent portion of new followers *before* Trump's announcement (making

**Table 1.** Nine of the 50 clusters identified among handles that began following Donald Trump during the primary campaign (16 June 2015 to 19 July 2016).

| Cluster category | Size | Top 10 distinctive handles followed by handles in the cluster | % following @ PrisonPlanet | % following @ BreitbartNews | % retweeted Trump's tweets | Average retweets per handle |
|---|---|---|---|---|---|---|
| Trump supporters | 2897 | EricTrump, mike_pence, DonaldJTrumpJr, MELANIATRUMP, TeamTrump, KellyannePolls, IvankaTrump, TiffanyATrump, LaraLeaTrump, MrsVanessaTrump | 3 | 4 | 1 | 7 |
| Far-right conservatives | 1178 | LibertyBell1000, dhotle, conens46, kyliving, nanaboyce, usacsmret, tdtrpnr,_CFJ_, gato_gator, BocaRatonRC | 44 | 51 | 47 | 14 |
| Alt-Right | 2151 | PrisonPlanet, RealAlexJones, infowars, MarkDice, JamesOKeefeIII, RogerJStoneJr, libertytarian, StefanMolyneux, LeeAnnMcAdoo, DRUDGE | 64 | 36 | 8 | 6 |
| Mainstream conservatives | 944 | kimguilfoyle, oreillyfactor, TheFive, greggutfeld, ericbolling, DanaPerino, IngrahamAngle, seanhannity, BretBaier, AndreaTantaros | 6 | 26 | 9 | 4 |
| Men's interest | 3390 | CauseWereGuys, ShitBsbPlyrsSay, RealKentMurphy, drunkamerica, KentMurphy, coachkentmurphy, BrosConfessions, totaldadmoves, BaseballVines, MilitaryUSA, GuyCodes | 0.8 | 0 | 10 | 3 |
| Liberals | 3774 | Sulliview, maggieNYT, romenesko, PostBaron, mattyglesias, jonathanchait, Fahrenthold, daveweigel, ErikWemple, RyanLizza, | 3 | 9 | 3 | 0.5 |
| Mainstream politics | 2122 | TVSpyNews, atompkins, LinseyDavis, CNNNewsource, OHnewsroom, Poynter, NTSB, tv_brendon, tvnewser, NBCNightlyNews | 1 | 5 | 3 | 0.5 |
| Apolitical (interested in NASCAR) | 2057 | KyleLarsonRacin, coleswindell, ericchurch, TonyStewart, austindillon3, ClintBowyer, RandyHouser, DaleJr, mirandalambert, Kenny_Wallace | 0.7 | 1 | 23 | 0.8 |
| Other countries (Britain) | 1931 | MichaelLCrick, GuidoFawkes, LordAshcroft, BorisJohnson, FraserNelson, George_Osborne, faisalislam, IsabelHardman, campbellclaret, DPJHodges | 5 | 5 | 6 | 0.3 |

NASCAR: National Association for Stock Car Auto Racing.

**Table 2.** Distribution of the sampled handles that began following @realDonaldTrump during each time period.

| Cluster category | Pre announcement | Primary election | General election |
|---|---|---|---|
| Trump supporters | 1.51% | 6.73% | 2.77% |
| Far-right conservatives | 1.12% | 3.95% | 3.47% |
| Alt-Right | 6.94% | 2.12% | 2.33% |
| Mainstream conservatives | 4.44% | 8.35% | 5.75% |
| Men's interest | 3.81% | 5.85% | 3.98% |
| Liberals | 0% | 6.65% | 13.83% |
| Mainstream politics | 6.99% | 7.47% | 3.45% |
| Apolitical | 56.72% | 45.68% | 41.87% |
| Other countries | 18.47% | 13.19% | 22.56% |
| Total | 100% | 100% | 100% |

up nearly 7% of his followers at his announcement) than after (about 2% in the later two periods), perhaps because his well-known birther claim resonated with those individuals and indicated an early sense of his potential among them. Trump drew substantially less attention from other conservative clusters until he announced his bid for candidacy: before, the three non-Alt-Right conservative clusters combine to be just over 7% of his following; during the primaries, they made up 20% of his new followers (also demonstrated in Figure 1).

Trump's announcement was a catalyzing event for these groups and also for liberals. We identified no liberal clusters in the pre-primary period; their numbers grew during the primary and again during the general election as attention from both left and right was concentrated on Trump and Clinton (as clearly demonstrated in Figure 1). In fact, liberals made up nearly 14% of the new follower stream during the general election—as many as all four conservative cluster types together. These findings make clear that attention—in the form of following—should not be equated with support, although it often is, implicitly or explicitly. Trump's attentive publics on Twitter were made up of nearly a cross-section of the Twitter publics, with certainly an overrepresentation by those on the hard right.

## *Retweeting amplification in terms of volume*

Having established the contours of Trump's Twitter following, we now turn to RQ2, which concerns the question of who was amplifying Trump and his message. Considering this question through the measure of retweets, we calculated that over 80% of retweets of Trump's tweets came from handles that were following him, which led us to focus on our sample and the groups we identified within it.[9] Table 3 displays the production of retweets of Trump's tweets in terms of the cluster categories, by several measures: the percentage of all retweets of Trump that were produced by handles in each category, the average number of retweets per handle in each category, and the percentage of handles in each category that produced at least one retweet.[10]

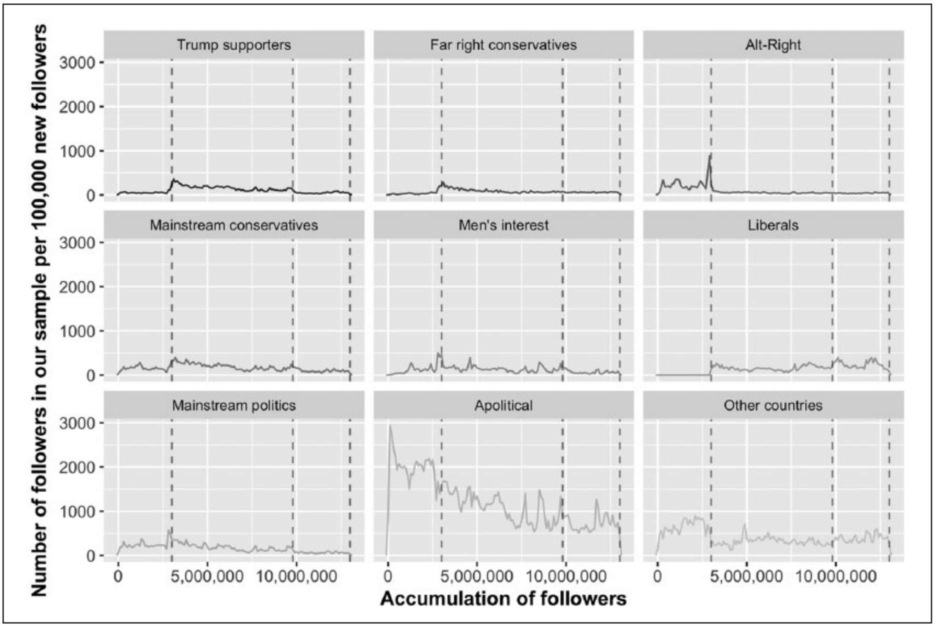


**Figure 1.** Estimation of Trump's new followers. Trump's followers are arrayed on the *x*-axis in order of following, such that Trump's first follower is on the far left and his 13 millionth is on the far right. Therefore, time moves from left to right across the x-axis. However, rather than each data point representing a unit of time directly, every data point represents the number of sampled followers in each category out of every 100,000 new followers of Trump. The three vertical lines represent candidacy announcement, the start of Republican convention, and the general election.

What is clear is that amplifying Trump was a far from equitable phenomenon: handles in the conservative clusters showed much higher amplificatory activity than others, with far-right conservatives having the greatest overall activity. In fact, although the three most extreme conservative categories—the far-right, Trump supporters, and Alt-Right—made up only 11% of our sample, they accounted for a full 60% of all of Trump's retweets and had the broadest engagement, with 46% of far-right conservatives retweeting Trump at least once. By comparison, handles in apolitical clusters, though they made up almost 50% of our sample, produced fewer than one retweet in five. The overall retweet behavior of handles from mainstream political clusters and liberals was similarly low. Interestingly, although handles in the men's interest clusters produced a relatively modest share of retweets, this category had fairly broad engagement, with nearly half retweeting Trump at least once.

In short, unlike the overall attention devoted to Trump, which was diverse and widespread, amplification of his message, in terms of retweets, was largely a conservative, and especially far-right and Alt-Right, activity. This points to the importance of distinguishing analytically those who are *paying attention* from those who are also *engaged in amplification*.

**Table 3.** Relative cluster size and retweet statistics by cluster category, during all three time periods.

| Cluster category | Percentage of all handles in sample from category | Percentage of all retweets of Trump in sample from category | Average number of retweets per handle in category | Percentage of handles within category who retweeted Trump at least once |
|---|---|---|---|---|
| Trump supporters | 4.34% | 20.36% | 11.5 | 35.56% |
| Far-right conservatives | 2.94% | 24.95% | 20.8 | 46.47% |
| Alt-Right | 3.73% | 14.58% | 9.59 | 43.12% |
| Mainstream conservatives | 6.63% | 7.31% | 2.71 | 26.25% |
| Men's interest | 4.86% | 4.88% | 2.46 | 43.01% |
| Liberals | 5.71% | 2.36% | 1.02 | 18.76% |
| Mainstream politics | 6.62% | 3.45% | 1.28 | 22.87% |
| Apolitical | 48.63% | 18.55% | 0.94 | 15.96% |
| Other countries | 16.53% | 3.56% | 0.53 | 11.26% |
| Average for full sample | – | – | 2.45 | 20.56% |
| Total | 100% | 100% | – | – |

Both quoted and unquoted retweets included.

### *Different kinds of retweeting amplification*

Even among those who engaged in retweet amplification, however, there are different varieties of which we must be aware. What we have displayed so far does not distinguish different types of retweets made possible by Twitter's affordances. From our sample of Trump's followers, there are 699,267 *unquoted* retweets (retweets that reproduce Trump's message without adding any text; 88.4%) and 91,995 *quoted* retweets (retweets to which the retweeter has added his or her own comment; 11.6%). Although unquoted retweets are far more common, there are notable differences between who engaged in each type of retweeting (see Figure 2). When it comes to unquoted retweets, the pattern reflects the overall retweeting pattern (Table 3), with far-right conservatives, Trump supporters, and Alt-Right far ahead of all other categories.

However, the pattern of quoted retweets is quite different. There, liberal clusters actually exceed the activity of the Alt-Right and become comparable with far-right conservatives and Trump supporters in this practice. Moreover, liberals and mainstream politics followers are the only groups more likely to add a quote (14% of handles in the liberal clusters) when retweeting than not (8%), as shown in Figure 3. There is no doubt what is happening: when liberals retweet Trump, they are usually reproducing his message specifically to add their own comment—likely critique—to it.

## Discussion

In this article, we have introduced the concept of amplification as a contribution to building theory about how attention is allocated and power accrued in a hybrid media system.

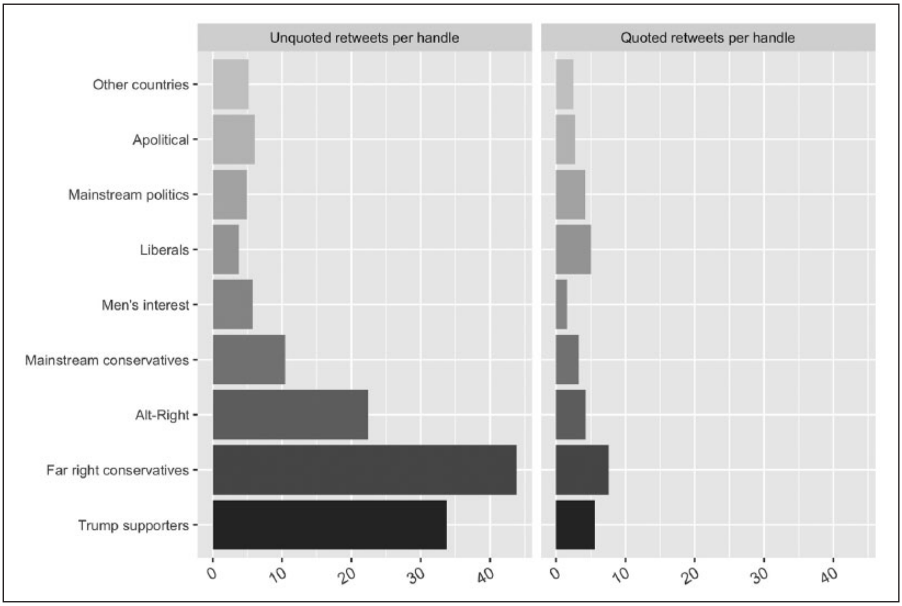


**Figure 2.** Average number of unquoted vs quoted retweets among handles that retweeted Trump's tweets.

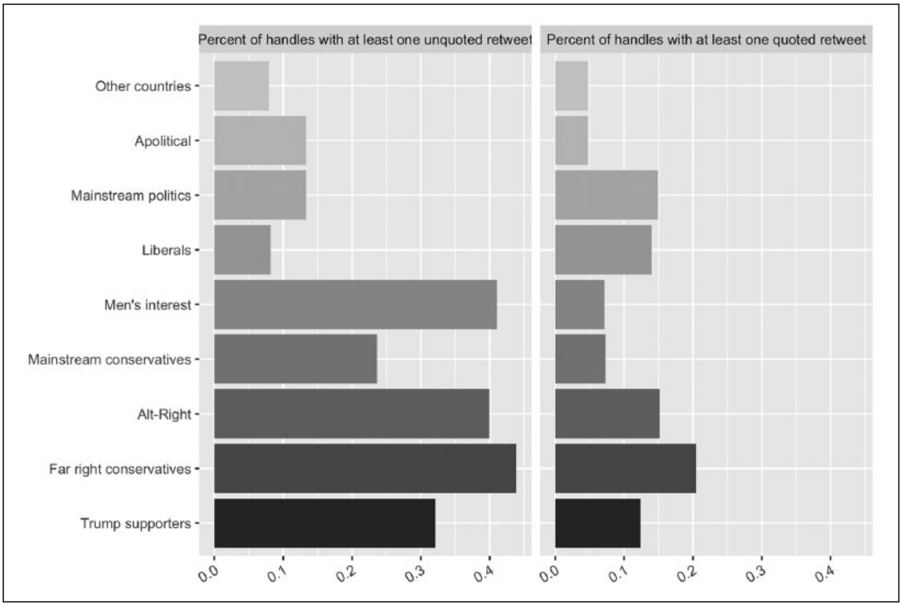


**Figure 3.** Percentage of handles with unquoted vs quoted retweets.

Our focus has been the specific amplification that takes place as social media publics gather around an object of attention and take actions that potentially increase attention to that object, which we have characterized as the currency of power in an attention economy.

We brought a novel application of clustering algorithms to our particular case, demonstrating that Donald Trump's Twitter attentive publics encompassed a variety of individuals from various political and apolitical corners of American society and indeed around the world. This approach offers a more subtle look at Trump's following, enabling us to look beyond the simplistic characterizations of Trump's followers prevalent in the media and discourse—that all or most of Trump's followers are of a particular stripe. Especially for an extremely high-attention object such as Trump, his attention audience defies simplistic characterization.

Just as important, our results demonstrate the utility of considering processes of amplification in the attention economy. While Webster (2014) is rightly concerned with ways in which audiences direct their attention—and rightly notes that the very directing of attention creates metrics that can be read by structures—we show that as an act of support and assistance, amplification is, at least analytically, a distinct phenomenon. While Trump's *following* was composed of a multitude of different groups, including people who displayed little interest in politics and people generally opposed to him, most *amplification* (in the form of retweets) was enacted by members of political society well to the right of even the Republican party and included those with White nationalist and other extreme inclinations.

However, while the hard right core had intentionally amplified Trump, those with little political interest and those opposing Trump might have inadvertently amplified him due to mechanical algorithmic reading by Twitter. Quoted retweeting by liberals and mainstream political clusters as well as retweeting from a diverse amalgam of demographics might have indicated high levels of activeness, reach, and diversity of attention, key factors that Twitter uses in locating what is trending (Gillespie, 2011). Furthermore, apolitical clusters might have amplified Trump not through the sheer volume of their retweets but as a natural result of their relatively broader and more diverse networks.

There are significant implications of this finding, given growing evidence that social media buzz, including retweets, played a substantial role in elevating Trump's news coverage. As Conway et al. (2015) note, the idea of "reverse agenda setting… suggests the public, long seen as a minimal player in agenda setting, may influence news media" (p. 364). Our study of amplification thus provides a cautionary note about reading too blithely levels of "engagement" among "the public" in social media, especially over political people or issues. If indeed retweets or other metrics reach news organizations as signals of newsworthiness, we must ask where those metrics originate and what they can and cannot represent. Retweets are not necessarily neutral or generic indicators of public interest. They can be produced by particular actors, like trolls or bots with particular agendas—even strategies (Graham, 2016; Musgrave, 2017)—including influencing the media structures responsible for a great deal of social communication; they might also be produced by actors in the process of resisting a particular object but eventually serving its interest.

## *Building the amplification research program*

This essay has described the process of amplification within the context of a single case, but the concept could be applied to many other contexts: participants in online social movements clearly participate in amplification as they drive up the visibility of hashtags (Freelon et al., 2016); online marketers clearly aim for amplification when they attempt to seed viral content.

Amplification's connection to the power of activist and grassroots groups and their empowerment in the hybrid media system (Tufekci, 2013) are quite obvious as it implies an avenue for political participation for citizens joining their preferred elites online. Trump-inspired activist, grassroots groups, and bot-makers were weaponizing Twitter to bestow power on him by retweeting his tweets to scale them up quickly to draw wider public and media attention. This phenomenon echoes emergent forms of connective actions and entrepreneurial bottom-up forms of collective actions under the formation of digitally connected interpersonal communication networks (Bennett and Segerberg, 2012; Flanagin et al., 2006). Communication becomes a form of organization as people iteratively share personalized expressions about a personalizable and uniting political idea (Bennett and Segerberg, 2012; Papacharissi, 2016). Such viral communication is essentially a process of amplification, instrumental for the basic goals of social movements—mobilization, validation, and scope enlargement (Gamson and Wolfsfeld, 1993).

Similarly, the concept also has the potential to knit together multiple levels of analysis. Our investigation has taken place at a meso-level, exploring the particular groups of individuals who participated in the amplification of Trump within Twitter. Other studies have taken a more macro-level approach by, for instance, investigating the outcomes of aggregated amplification—as made visible by social media agendas (e.g. Neuman et al., 2014) or engagement metrics (e.g. Wells et al., 2016). Exploration at a more micro-level might examine why individuals participate in amplificatory activities: what motivates them to devote a portion of their attention and their social media voice to amplifying an entity. As a new concept, amplification helps to make clear relations between analyses at these various levels and offers a vocabulary for mapping research across them.

## *The ambiguity of amplification as networked action*

Our findings that liberal followers also retweeted Trump—most often through quoted retweets—raises another set of questions. An important strain of scholarship (e.g. Benkler, 2006; Castells, 2013; Jenkins, 2006; Papacharissi, 2015) celebrates the possibilities opened by digital and social media for individuals to communicate themselves contra large and impersonal mass media. As Papacharissi (2015) puts it, "performing a networked self requires the crafting of polysemic presentations that make sense to diverse audiences and publics without compromising one's own sense of self" (p. 112). In this reading, liberal activists might hope that voicing opposition to Trump on Twitter might help to mute his message while forming action networks of resistance.

Our notion of amplification and our findings trouble this picture. The "engagement" metrics increasingly used to guide media structures are not reliable indicators of simple truths or of the meanings their authors may wish to convey; they are inherently reductive and subject to multiple biases (Webster, 2014). Although few such algorithms are not available to examination, what we know about them is that overall, they privilege content that broad and diverse swaths of users have indicated they will "engage" with—and that will keep them on the site (Gillespie, 2011). Thus, although most liberals did not follow or retweet Trump to draw even more attention to him and his message, the signals left by their actions most likely had that effect: as a group distinct from the hard right core, they signaled to Twitter and other actors such as journalists and media institutions that Trump can generate engagement not only in his base but also outside of it, key evidence of the broader "appeal" and "engagement," thus the value and worthiness of Trump.

In this way, the meaning of the "networked self" (Papacharissi, 2015) such individuals presented was stripped away by structures intent on reading for aggregate engagement; what the structure reads from individuals' expressions might be quite different from what the individuals intended them to mean. This raises significant complications about agency in an attention-based online economy. In the case we examined, amplification likely *enabled* agency for Trump supporters who succeeded in promoting their favored candidate's message, and in fact launching that message into the mainstream press. But what of the agency of those who opposed Trump? Their own attempts to push back, or the slightest display of vigilant attention, may have resulted in the paradoxical reverse of their hopes—the elevation of Trump to ever greater heights of attention. Unfortunately, to the extent that "participatory culture" is increasingly subsumed under structurational interactions between individuals' actions and media structures' interpretations of those actions, individuals' voices in the media system may be distorted beyond recognition (Van Dijck, 2013; Webster, 2014). And the question of individual agency may increasingly be one of how such signals are read and by whom.

Still, our hindsight knowledge of the election's outcome should not mislead us into thinking that criticisms of Trump primarily served to bolster his standing; they also surely served to inform and mobilize opposition publics through amplification of competing views. Thus, it remains for further research to help us understand when individuals or movements are able to channel amplificatory actions to a common end and how those attempts are facilitated or thwarted by the structures under which they increasingly take place. Certain notable examples of organizing that generated spontaneous and effective attention to an issue have received deserved attention (e.g. Freelon et al., 2016; Papacharissi, 2016). Yet, we might also be skeptical about the possibilities of processes that are the result of masses of individuals contributing incrementally to a communication narrative that is also guided by algorithmic hands operating under quite different logics and goals. It may come down to a question of under what conditions amplification is merely a crowd response to an object of momentary fascination and when a concerned group of citizens can direct amplification to the kind of end that scholars of civic action or social movements might recognize—for example, as it appears online public in support of Trump were doing in 2016 (Musgrave, 2017).

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## Supplementary material

Supplementary material is available for this article online.

## Notes

1. The visibility of communicative actions online is, of course, highly uneven. Whereas the actions of citizen publics are typically widely visible, the actions of other agents, such as companies' web traffic and social media algorithms, are almost all proprietary and not visible to users or others.
2. We saw in the 2016 campaign the inversion of the usual attention economics of politicians and the press. Whereas in typical elections news media possess audience attention and may choose how to allocate that attention to candidates (Patterson, 2016), in 2016, once it became evident that Trump was able to capture mass attention, many media outlets were compelled to cover Trump in an effort to borrow *his* ability to build an audience—and sell slices of it to advertisers (Karpf, 2016b).
3. In light of the fact that a preponderance of Twitter handles display little activity, pure random sampling will result in many inactive or marginally active users. Instead, sampling nodes with larger degrees is an efficient method to get active users (Qin, 2015). So our sample is more representative of Trump's active followers than the entirety of his followers. Eventually, 322,461 followers were eligible for clustering analysis. See details of data collection in the Supplementary Methodological Appendix.
4. We only downloaded 5 instead of 150 million handles followed by Trump followers for the purpose of reducing computational cost and noise. We saw handles followed by less than 10 followers as weakly connected features that were the "periphery" of the network. It is an empirical regularity that we have observed elsewhere that these peripheral nodes add more noise than information. Moreover, including them would add immensely to the computational complexity of our procedures.
5. See details of our clustering algorithm in the Supplementary Methodological Appendix.
6. See selection of the 40 handles in the Supplementary Methodological Appendix.
7. The reader may contact the corresponding author for the 150 clusters and their representative features, that is, handles that they follow.
8. The presence of bots within our sample is an important question, but one we are unable to satisfactorily address here. We attempted to adapt the methods of Kollanyi et al. (2016) and Botometer, but obtained conflicting results and do not have great confidence in them. It is possible that our sampling and clustering methods may have reduced the prevalence of bots in our 322,461 categorized Trump followers. First, operating on the assumption that bots have few followers but follow voraciously, sampling Trump followers with probability proportional to their follower counts naturally reduced the number of bots in our final sample. Second, if bots are usually botnets that closely follow each other, our algorithmic decision to only keep the followers who followed at least 10 of the selected feature handles also likely lowered the number of bots in our final sample. This is to say that if botnets are isolated clusters with low out-degrees, they might not be picked up by our algorithm in the first place.
9. We computed the percentage of retweets from Trump followers based on frequency analysis using 1% random Twitter sample archived from the streaming API. That is, we compiled all the retweets and identified those retweets from Trump followers by matching the user ID to the ID of the 13 million Trump followers collected using Twitter's REST API.
10. Both quoted and unquoted retweets. Explored further in the next section.

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