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### Digitally networked grassroots

*Social media and the development of the movement for black lives and immigrant rights movement in the United States*

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# Chapter 6

## **The Swarm versus the Grassroots: Places and Networks of Supporters and Opponents in #blacklivesmatter on Twitter<sup>41</sup>**

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41 This chapter is under review for publication at the time of writing, August 26, 2019.

## Abstract

*While activists have effectively used the #blacklivesmatter hashtag to organize protest against police brutality and racism, this success has also drawn out many who use the hashtag to express their opposition to Black Lives Matter. What can we learn about the network structures of this counter-movement from the way they coordinate activity online? Drawing on a corpus of 18.5 million Twitter posts, this paper compares coordination among supporters and opponents of #blacklivesmatter in terms of relations and spatialities. We show and explain two different models of coordination among opponents and supporters: the swarm and the grassroots respectively. Supporters of #blacklivesmatter are more strongly embedded in local relations and places, suggesting that their online activism builds on grassroots communities. Opponents can be differentiated into two groups. One group consists of conservatives with strong mutual relations, but a geography markedly different than supporters; they are more often located outside of major cities and outside of the coastal states. A second group of digitally networked extreme right opponents coordinates without any such territorial embedding. These findings help to assess the different mobilization capacities of movements and their adversaries.*

## Introduction

Digital networking is crucial for coordinating social movements such as Black Lives Matter. Activists leverage social media to expand movements through personal networks (Bennett and Segerberg, 2012; Tufekci, 2017). One explanation for the rapid and wide-spread rise of digitally networked movements is that social media allow individuals to more easily reach beyond the immediate vicinity of their communities (Castells, 2012; Juris, 2005a; Tarrow and McAdam, 2005).

Meanwhile, antagonism on social media is pervasive and opponents of progressive social movements is on the rise (Colson, 2016; M. Conover et al., 2011; Nagle, 2017). The activity of so-called alt right groups on Twitter, for instance, leverages the same advantages of digital networking (Marwick and Lewis, 2017). Social movement scholars suggest that dynamics with counter-movements are key to the development of social movements (Lind and Stepan-Norris, 2011; Meyer and Staggenborg, 1996), arguing that much 'of the mobilization potential of a movement, its tactics, and its ultimate fate stem from its battles with a countermovement' (Zald, 1979, p. 3). While attention grows for such opposition (see Daniels 2009 for early pioneering work), to our knowledge there has been no empirical analysis of movements and counter-movements dynamics online.

What can we learn about the network structures of such counter-movements from the way they coordinate activity online? Interested in examining and explaining differences in coordination, we propose two models: the grassroots and the swarm. The grassroots model emphasizes networking through local communities: coordination depends on strong local relations between activists. However, this polycentric or distributed network structure makes that synchronization between groups challenging. The swarm model emphasizes interaction cascades (Borge-Holthoefer et al., 2013). In this model, the absence of bottlenecks typical of community structures is beneficial to synchronization because individual interactions freely cascade to produce large-scale effects. We expect varying degrees of both forms of coordination occur among supporters and opponents of Black Lives Matter. Analysis of these coordination models helps to assess the different mobilization capacities of movements and their adversaries.

In what follows, the paper addresses the question of coordination in digitally networked movements and counter-movements. First, we discuss the use of social media in terms of digital networking and the resulting logic of connective action. We then turn to social movements and counter-movements. This sets the stage

for empirical description of differences in coordination among movements and counter-movements. We explain these in terms of two models: the grassroots and the swarm.

## **Conceptualizing coordination at the interface of geography and social media**

This section discusses literature that may help to understand the coordination of digitally networked movements and counter-movements. First, the uses of social media in social movements are outlined in terms of digital networking. Second, counter-movements are considered in order to conceptualize digitally networked opposition. Third, we suggest two ideal typical models of coordination in digitally networked movements: the grassroots and the swarm.

### ***Social media and digitally networked movements***

Social media are key to understanding contemporary social movements (Castells, 2012). Social media provide affordances for activists to network digitally, leading to important questions about *how* such affordances are used in social movements (Evans et al., 2017; Tufekci, 2017). According to Bennett and Segerberg, digital networking facilitates rapid expansion through the sharing of personal action frames (2012). As opposed to collective action (cf. Olson, 1965), the sharing of personal action frames does not necessitate overarching collective identities. Rather, individual views easily traverse personal networks through social media. These are frames ‘inclusive of different personal reasons for contesting a situation that needs to be changed’ (*ibid.*: 744). The inclusive nature of frames (e.g. We are the 99%; #metoo; March for Our Lives) allows a wide range of people to recognize the frame as meaningful and adapt it to make sense of personal experiences (Benford and Snow, 2000; Melucci, 1996). These individualized frames potentially have broader reach and appeal to generate action that resembles that of the more monolithic frames typical of traditional collective action. The resulting ‘logic of connective action’ has become particularly salient in a social context of individualization and social fragmentation (Bennett and Segerberg, 2012; Della Porta and Tarrow, 2005; Juris, 2012). If overarching identity markers such as ideology, religion, class, or nationalism form the foundation of collective action frames, social media

enable people to create and share personal action frames that relate to more individualized aspects of identity.

For instance, the death of Michael Brown at the hands of police officers in Ferguson was amplified from a local tragedy to national attention through social media (Bonilla and Rosa, 2015; Jackson and Foucault Welles, 2015). The fast and wide diffusion of protests quickly garnered national attention, spurring thousands of people to fill the streets not only of Ferguson but of cities across the United States to protest police brutality. The hashtag #blacklivesmatter enabled activists to relate specific and local conflicts to broader questions of racial and social justice.

### *Digitally networked counter-movements*

At the same time, attention for events in Ferguson generated a backlash on social media (Gallagher, Reagan, Danforth, and Dodds, 2016; Ray, Brown, Fraistat, and Summers, 2017). A considerable proportion of social media activity associated with protest hashtags is hostile to social movements. Like activists, their adversaries can take advantage of the affordances of digital networking to oppose movements. Such opposition ranges from arguments to slander and defamation, outright racism, flagrant hatred and physical threats. The backlash against historically marginalized groups is especially virulent (Crenshaw, 1991; Gray, 2012; Sobieraj, 2017).

While scholars have argued that the 'emergence of mass self-communication offers an extraordinary medium for social movements and rebellious individuals to build their autonomy and confront the institutions of society in their own terms and around their own projects' (Castells, 2007, p. 248) realization grows that many of these 'rebels' are reactionaries who mobilize a backlash through social media (Nagle, 2017). Although a number of authors have shown how white supremacists mobilize online (Daniels, 2009, 2016), most scholars have focused attention on progressive movements whose egalitarian ethos was said to align with horizontal and open social media networks. Given widespread agreement that social media are important platforms and incubators of resurgent online extreme-right counter-movements, including the so-called alt right, we need to account for such adversaries. Instead of an unequivocal progressive revival, we are observing the proliferation of mediatized conflicts in which different sides seek to valorize the affordances of social media to shape public debate. Do these progressive movements and counter-movements take on the same network structures? An answer contributes to assessment of the different mobilization capacities of movements and their adversaries.

*Two models of engagement: the Grassroots and the Swarm*

To explain how supporters and opponents coordinate online, we contrast two models: the grassroots and the swarm. First, notion of grassroots is elementary to the social movement literature, both as a normative ideal and as empirical focus historically (Chong, 1991; Della Porta and Tarrow, 2005; McAdam et al., 2001). A key question is how local communities form large movements while retaining degrees of autonomy. That interest carries forward in studies of digitally networked social movements. It aligns well with the logic of connective action as formulated by Bennett and Segerberg, who emphasize personal action frames as ‘transmission units across trusted social networks’ (2012, p. 755). Thus, local interactions allow for large-scale forms of collective behavior to arise, as frames branch outwards, bridging communities through personal networks without central coordination (Benkler, 2006). As a drawback, synchronization is difficult to achieve because individuals are oriented to group rather than movement goals. In fact, connective action breaks down if transmission fails through personal networks (Bennett and Segerberg, 2012, p. 754). A key challenge for grassroots movements is thus to synchronize action, for example in reaching consensus between groups, or communications between local chapters (Khan-Cullors, 2016).

We reason that stronger relations are more conducive to sharing personal action frames, and that relations are strongest with those close to us (Baldassarri and Bearman, 2007; Feld, 1981). While digital technology ostensibly diminishes geographical constraints on interactions, place structures the networks underlying online interactions so that social movements remain territorially rooted (Routledge, 2017; van Haperen et al., 2018). Activists continue to derive advantages from local relations, as these provide material and intangible resources such as trust and commitment. Cities especially can form incubation spaces for marginalized groups to find and connect with each other (Nicholls and Uitermark, 2017, 2018). This suggests that coordination remains embedded in local grassroots communities (Castells, 1983). The grassroots model of coordination, in short, relies on networked local communities.

Second, a model of swarm coordination is adopted from engineering and robotics. The question is similar to our interest in social movements: how large-scale collective behavior arises from the interactions of locally embedded autonomous actors. In engineering, swarms are defined as ‘large numbers of relatively simple physically embodied agents [...] designed such that a desired collective behavior emerges from the local interactions among agents and between the agents and

the environment' (Şahin, 2005, p. 12). It emphasizes that interactions between autonomous agents allow for system-wide synchronization, not only in the absence of centralized control, but without reliance on group relations (Bonabeau, Dorigo, and Theraulaz, 1999; Kennedy, Eberhart, and Shi, 2001). For example, a simple rule guiding local interactions might be to maintain a minimal distance from other agents. As these interactions cascade through the system, overall synchronization can be achieved without the structural bottlenecks typical of polycentric networks (Burt, 2004; Granovetter, 1973). System robustness is achieved through redundancy so that individual malfunctions does not drastically affect performance. Typically, a level of flexibility allows swarms to operate regardless of environmental context (Camazine et al., 2001, p. 36; Dorigo and Stutzle, 2004). In short, in a swarm, isolated interactions can generate large-scale synchronization without reliance on relational structures or territorial embedding.

In many instances of digital networking, local relationships are not prerequisites for being exposed to personal action frames. Affordances of social media such as visibility and accessibility allow for the engagement with activists far away. Such interactions may be based more on interest than proximity (Rheingold, 2000). As such, the swarm model fits well with what Jeffrey Juris calls a cultural logic of aggregation: 'the viral flow of information and subsequent aggregations of large numbers of individuals' (2012, p. 266). In our understanding, the notion of aggregation emphasizes that synchronization can be achieved without necessitating trust.

To summarize, the key difference between the grassroots and swarm models is the place of the individual in the collective. This is a matter of relations and, by extension, place. The grassroots model refers to engagement with movements through personal networks, suggesting individuals are strongly embedded in local communities. While this benefits the sharing of personal action frames, it makes overall synchronization between communities difficult. The swarm model refers to engagement with movements through the aggregation of autonomous agents in the absence of local embeddedness. While less conducive to the sharing of personal action frames, overall synchronization is more feasible because it does not rely on relational structures.

### *Expectations*

Following from the discussion, we expect different forms of coordination models depend on how individuals are embedded in local relations and places. Both models

outlined above are ideal-typical and we should not expect movements to operate fully according to grassroots or swarm models; movements will typically combine elements from both. We do hypothesize that, in general, supporters of social movements are more strongly embedded in local communities than opponents. Public activism takes courage, particularly for marginalized groups, necessitating solidarity and comradery. Direct actions are inherently local and typically require strong ties. We think such activism is more likely among supporters of Black Lives Matter. Opponents appear more focused on online disruption and tactics such as ‘tweet storms’ rather than direct actions (Tufekci, 2017). Resource needs would be relatively low and as a result, opponents may be less reliant on local communities and display more swarm-like coordination.

## Data and methods

We suggested that digitally networked social movements and counter-movements coordinate according to different models: as grassroots characterized by strong local embeddedness but little overall synchronization, or as a swarm characterized by limited local embeddedness but strong synchronization. To compare the online coordination of supporters and opponents of Black Lives Matter, we draw on data collected from Twitter. Tweets were collected from the streaming API, constructing a sample of tweets with the hashtag #blacklivesmatter<sup>42</sup> in the 30 months between June 15<sup>th</sup> 2015 and December 15<sup>th</sup> 2017. Content analysis was employed to differentiate between the movement and its opponents and infer geographical locations on the basis of self-reported information. Subsequently, the relational structures of opponents and supporters were examined using measures from network analysis.

### *Identifying opponents and supporters*

To identify opponents and supporters of #blacklivesmatter, we develop a three-tiered, semi-supervised method for content analysis. First, we drew and coded a training sample from all tweets in the dataset. To ensure representativeness despite variable traffic volumes over time, this sample was constructed by randomly selecting 1% of the daily volume for each day in the data set. We then coded this

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42 Including variations: #blacklivesmatters, #blacklivematter, #blacklivematters, #blacklifematters, #blacklifematter.

training set manually. Tweets were coded as positive or negative towards Black Lives Matter. Only unambiguous sentiments were assigned either category.

Second, the training sample informed classification of the full dataset. From the two subsets of positive and negative tweets we derived a lexicon of n-grams, i.e., combinations of characters typical for positive or negative tweets. Cross-referencing these n-grams, all tweets in the dataset were coded as positive, negative, or residual. This procedure yields 5.6 % positive tweets (n= 1,027,554) and 1.9% negative tweets (n= 360,473). Given the stringent criteria for assigning a positive or negative codes, many tweets in the dataset were assigned to the residual category (n=17,113,758 or 92.5%). Our analysis is focused on the sizeable sample of unambiguous tweets.

Third, these tweets informed classification of opponents and supporters. Accounts were assigned either category when at least two thirds of their coded tweets are negative or positive. Only accounts with three or more coded tweets were considered in order to minimize misclassification from an incidental tweet (41,527 out of 4,240,861 unique users or 1%). Following this procedure, we identify 31,271 users as supporters and 4,791 users as opponents. The self-reported biographies of opponents were examined manually to validate the procedure.

Since we used several stringent filters (users who employ the #blacklivesmatter hashtag; users who have sent at least three unambiguously supportive or antagonistic tweets), this sample is a small subset of the people talking about #blacklivesmatter on Twitter. However, since we focus on comparing movements and counter-movements, for our purposes it is more important to have reasonably reliable data on users' disposition than to cover all Twitter activity relevant to Black Lives Matter.

### ***Ethical concerns and validity***

Data was collected as per the Twitter terms of service, stipulating uses of data and user consent. Addressing concerns about risk of harm to users, particularly in the context of individuals engaged in contentious actions, we subscribe to more rigorous research principles (Moreno et al., 2013). All identifiable personal information was anonymized and aggregated to reduce risk of harm.

We assess the presence and activity of accounts that are operated through bots or by malfeasant actors (Varol, Ferrara, Davis, Menczer, and Flammini, 2017). Recent reports have specifically addressed the role of Twitter accounts operated or directed by Russian intelligence to steer and escalate political conflicts. We

cross-referenced our dataset with the list of accounts released by Twitter in relation to investigations of campaign meddling used in official hearings (United States House of Representatives, 2018). Of the 3,841 accounts in that release, 55 appear in our data (of 4,240,861 unique accounts originating tweets in our data). Together, these 55 accounts sent 2,993 of the tweets in our dataset (of 18,501,785 tweets)<sup>43</sup>. We note that bots and trolls are an integral part of activity faced by activists on Twitter, so rather than filtering out these accounts we opted for inclusion in our analysis.

### ***Examining the local embeddedness of opponents and supporters***

We suggested different levels of local embeddedness between grassroots and swarm models. We examine the local embeddedness on the basis of users' geographical referencing. Twitter offers the option to geotag posts, but users rarely do this (Jurgens, Finnethy, McCorriston, Xu, and Ruths, 2015). We therefore also extract self-reported information from Twitter bios to estimate locations. This biographical data comes with limitations. It is self-reported, not always accurate, and non-uniform. To deal with this, results were manually examined and aggregated: colloquial toponyms and boroughs to cities, (e.g. 'Big Apple' and Brooklyn to New York City, Long Beach to Los Angeles). Territorial embeddedness is measured by comparing the frequency of locations for both opponents and proponents of Black Lives Matter. Self-reporting a location signals that the location is significant to the user. In addition, we test the degree to which geographical proximity predicts relations among both supporters and opponents of Black Lives Matter. When a shared geographical location predicts a tie, we interpret this as an indication of geographical embeddedness.

### ***Examining the relational structures of supporters and opponents***

We examine the relations of supporters and opponents in terms of network structure by drawing on mentions and retweets. We consider users to have a relation when they reciprocate interactions, i.e. when both users have mentioned or retweeted each other at least once. When they do they not just talking about

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43 It is not unlikely that additional accounts or tweets in our data originate from inauthentic sources, but remain as of yet unidentified. In addition to the accounts identified in the release, we identified another 1,039 suspect accounts. To do so, we flagged accounts with ties to the original seed accounts and checked high tweet volumes. Interestingly, of the 55 accounts reported in the official documents, our procedure yielded 11 supporters, reflecting disinformation strategies to influence multiple sides of public debates (Stewart, Arif, Nied, Spiro, and Starbird, 2017).

each other but with each other. Drawing on these reciprocated ties we determine the network structures among both supporters and opponents.<sup>44</sup>

We measure how strongly users are embedded relationally with density scores (empirical ties divided by realizable ties), mean degree, and power law exponents. Comparing graph cohesion is a non-trivial task because density interacts in complex ways with graph size due to non-isomorphic local structures (Anderson, Butts, and Carley, 1999; Schieber et al., 2017). We adopt a simple density measure, normalized by graph size: mean degree / (n-1). Since this measure is sensitive to group size, we also report mean degree as an indicator of the propensity of individuals to interact with others in their camp.<sup>45</sup> We further report power law exponents to give insight into the structure of interactions within groups: higher exponents indicate more unequal degree distributions (Csardi and Nepusz, 2006). Exponents are calculated for both in- and outdegree. This allows for comparison of how (un)evenly individuals are embedded relationally.

### ***Examining synchronization among opponents and supporters***

We suggested a difference in synchronization between the grassroots and the swarm models. The level of synchronization among users is measured in two ways: as simultaneous activity and as a mutual focus of attention. We study synchronization of *activity* among groups by comparing the peak times of post volumes on Twitter. A high level of simultaneous tweeting activity suggests a stronger level of synchronization in a group. We study the synchronization of a *shared focus of attention* by examining whether many users focus on the same target simultaneously (cf. Collins 2004). More specifically, we count the daily number of supporters and opponents as well as the targets they focus on, and then divide these numbers. This gives the average number of users from groups who simultaneously focus their attention on the same targets.

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44 While we discuss these groups separately, our data also includes reciprocated ties between opponents and opponents (a rare occurrence) and reciprocated ties between these groups and users who are not categorized as supporters or critics (a frequent occurrence).

45 More advanced measures of cohesion, such as vertex connectivity calculated as k-cores, do not lend themselves well for our weakly connected Twitter networks (Csardi and Nepusz, 2006; Moody and White, 2003; D. R. White and Harary, 2001). While our density measure does not account for non-isomorphic substructures, it does allow us to compare the overall connectedness between the networks.

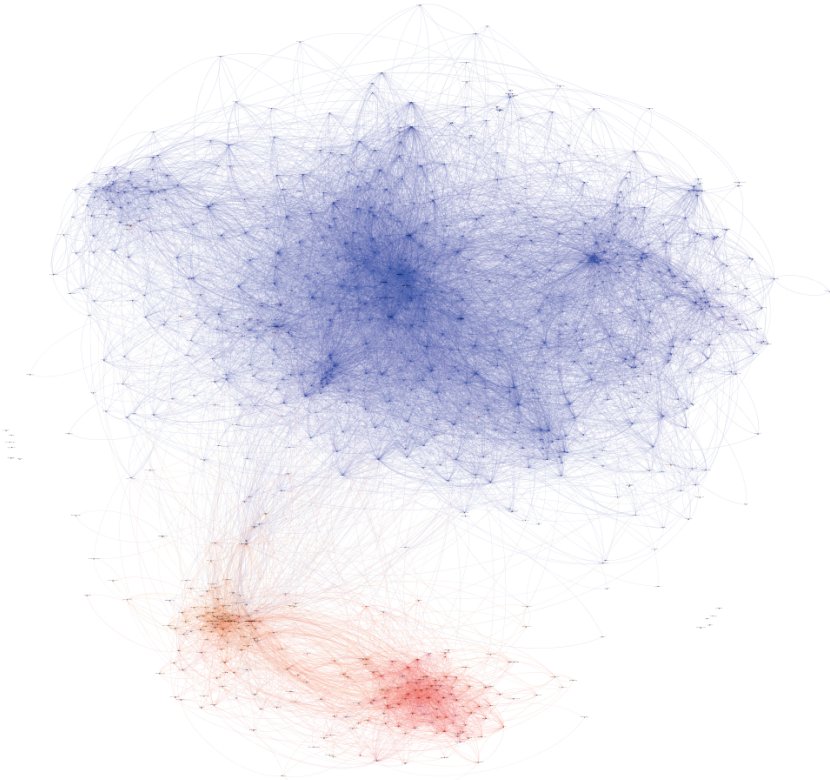
## Results

In the period between June 15<sup>th</sup> 2015 and December 15<sup>th</sup> 2017, we collected 18,501,785 tweets from 4,240,861 unique users. We first present the overall network. Next we compare the local embeddedness of supporters and opponents. Then, levels of synchronization are compared.

### *Overall network of supporters and opponents*

The interactions on Twitter result in a network structure of both supporters and opponents. Figure 6.1 shows how these networks are organized.

*Figure 6.1. Interactions between supporters and opponents.*



*Note: Colors represent how strongly someone supports (blue,  $n=31,271$ ) or opposes (red,  $n=4,791$ ); the darker red nodes are accounts with more negative content. To aid visualization, users with fewer than five relations are omitted.*

Groupings in the network are based on interactions, and result from particular interests shared with others<sup>46</sup>. Among supporters, there are many different such groups. For example, supporters in one group are avid hip-hop fans and artists, who mostly tweet about music and occasionally retweet news about Black Lives Matter. Among opponents, there are roughly two groups, which we identified using content analysis: the first (left in Figure 6.2) can be characterized as conservative, the second as alt-right<sup>47</sup>.

The first group of opponents is composed of individuals with conservative political views. Oftentimes, these accounts are not anonymous. Descriptions that stand out in user biographies in this group are related to family, veteran affairs, the second amendment, Christianity, and Trump. Although not unconditionally uncritical of the 45<sup>th</sup> president, slogans such as ‘Make America Great Again’ are prevalent. Subgroups interact on Twitter daily about all sorts of topics, often to criticize mainstream media viewpoints and sharing links to alternative sources. One day, the topic may be Hillary Clinton, unemployment among veterans the next. They engage with the hashtag #blacklivesmatter in the same way: something triggers attention, which leads to the group focusing an intense gaze, for example by sharing a meme about crime statistics among several compatriots, reinforcing group membership and ideological views.

The second group of opponents can be characterized as alt right, a source of extreme content. 55 accounts in this group show signs of automation. We assessed the scope of this activity as per our methodology and include these in our analysis as forces that movements have to contend with online. The thematic scope in this group is narrower, less news-driven, and more extreme than among the conservative group. Content and images can be disturbing; examples include images of KKK lynch mobs and idealizations of Nazism. Most accounts do not disclose pertinent information. Manual verification of user names and tweeting activity brought up slight name variations, pointing to similar malicious accounts. Many of the accounts in this group have since been suspended by Twitter or deleted for violating terms of service.

46 The layout algorithm used for the visualization in Gephi was ForceAtlas2, in which groupings are force-directed based primarily on degree (Jacomy, Venturini, Heymann, and Bastian, 2014). The striking alignment between spatiality and measure of support was not adjusted manually.

47 For reference we compared this topology with a random walk-trap algorithm (Pons and Latapy, 2005) and confirmed a strong overlap between group membership and cluster membership, that is: 76% of users that were identified independent of community structure as opponent or supporter turned out to share the same cluster algorithmically.

### *Local embeddedness of supporters and opponents*

We hypothesized that in a grassroots model people would be more geographically embedded than in a swarm model. We examine how strongly people relate to specific places. First, we compare self-reported locations for supporters and opponents (Table 6.1). Supporters tend to more often disclose geographical information than opponents. Moreover, their information tends to be more specific: geotagging is more common and city-level information more frequently disclosed. State and country names are more likely among opponents, conservatives are more likely to display pride for their country and home state. Localization of the alt right accounts is more difficult. Few provide specific locations in comparison to those among conservatives. Instead, non-descript locations such as ‘USA’ or ‘Reality’ are used. In this sense, among this group there is little identification with specific localities. These findings suggest that supporters are more open about the specifics of their location.

*Table 6.1. Supporters are more likely than opponents to provide pertinent location information*

	Group		Location <sup>47</sup>	Geo opt in <sup>48</sup>	State	City	Non-pertinent <sup>49</sup>
Supporters	All	89,203	67.35 %	0.06 %	14.5 %	55 %	27 %
Opponents	Conservative	8,703	62.14 %	0.01 %	23.5 %	35.5 %	36 %
	Alt-right	8,477	58.05 %	0.00 %	36 %	33.5 %	26 %

*Note: Counted are the number of supporters or opponents who disclose self-reported locations. Group membership is determined by the estimated measure of support on the basis of at least three unambiguously coded tweets.*

Second, we test how strongly groups are locally embedded. Are interactions more likely with nearby others? We compare geographical proximity and tie formation among both supporters and opponents. The relations among supporters are more strongly embedded in places than relations among opponents (Table 6.2). Supporters are more than six times more likely to connect online with other supporters in the same city than might be expected at random. By contrast, interaction among proximate opponents is about as likely as might be expected from randomness. For supporters, a large share of interactions is with others in the same city. Among supporters in New York City, for example, ten times as many tweets are exchanged with other supporters in the same city than among opponents in that city. Among opponents, it is not uncommon to identify with

48 User has entered more than 1 character in self-reported location field

49 User has used geotagging coordinates opt-in for at least one tweet

50 Examples of non-pertinent locations are: “earth”, “woke”, “a galaxy far far away”.

particular places, for example as proud Nevadans and Arizonans, but they are not more likely to interact with others in those localities.

*Table 6.2. Supporters are more likely than opponents to interact with others in the same location*

	Empirical same city	Random same city
Supporters	563 of 8,431 (6.68%)	86 of 8,431 (1.02%)
Conservative	8 of 580 (1.38%)	7 of 580 (1.21%)
Alt-right	8 of 418 (1.91%)	6 of 418 (1.46%)

*Note: Counted are the number of network ties where both the source and target share a location<sup>51</sup>. A baseline for comparison is provided by randomly reassigning locations among the same number of nodes in an identical network configuration.*

### ***Relational structures of supporters and opponents***

We suggested different *relational structures* in the swarm and grassroots models. First, we examining different levels of cohesion among groups (Table 6.3). Among supporters, there is a lower overall level of cohesion. While comparable among conservative and alt-right opponents, the lower density score for supporters indicates a sparser network. At the same time, while also comparable for conservative and alt-right opponents, the mean degree is higher for supporters. The higher density score and comparable mean degree suggest that differences in cohesion result not from the propensity to interact but from group size: since the groups of opponents are smaller, it is comparatively easier to achieve cohesion. The power law exponent confirms that opponents' networks are more unevenly distributed than those of supporters, suggesting that relatively few opponents account for a large share of activity. Although the measures for relational structures do not give a uniform picture of cohesion, it is clear that opponents are at least as cohesive as supporters. This is remarkable considering that the cohesion of supporters derives in part from geographical proximity; apparently the cohesion of opponents has different origins.

<sup>51</sup> Opting for accuracy over quantity, the following conditions were applied, explaining the relatively small numbers. Only ties are included of users unambiguously classified as supporter or opponent, which includes having sent at least three tweets. Only ties are included of users with unambiguous, pertinent locations. Ties are included only if the target also occurs in the dataset as a source, because otherwise a location could not be determined.

**Table 6.3 Cohesion among supporters and opponents**

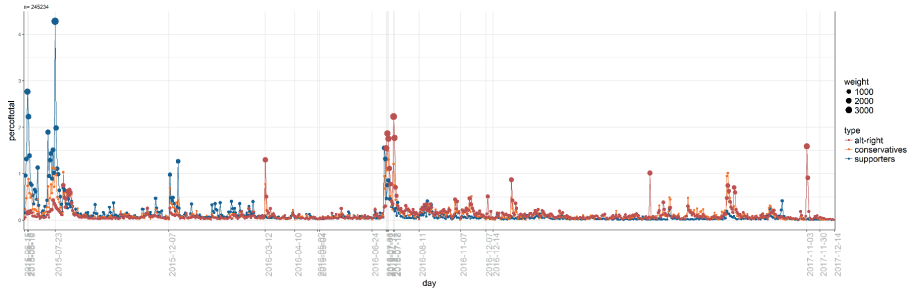
	Group	Nodes	Edges	Density	Mean degree	Power law exponent
Supporters	All	105,818	89,203	0.00001593289	1.69	2.14
Opponents	Conservative	12,702	8,703	0.00010789190	1.37	2.57
	Alt-right	10,916	8,477	0.00014229350	1.55	2.25

Note: Density is calculated on undirected graphs (mean degree / (n-1)). Note that while normalized, density interacts in complex ways with graph size, as discussed in the methodology section. The power law exponent is calculated for the discrete cumulative distributions, with the following Kolmogorov-Smirnov statistics for goodness-of-fit: supporters (KS.p = 0.67, xmin = 6), conservatives (KS.p = 0.95, xmin = 4), alt-right (KS.p = 0.73, xmin = 5).

**Synchronization among supporters and opponents**

We suggested that there would be more synchronization in a swarm model than in a grassroots model. Synchronization is examined in two ways: as tweeting activity and as a shared focus of attention. We study synchronization of activity among groups by comparing time series of tweet volumes. More simultaneous tweeting activity indicates a more synchronization (Figure 6.2).

**Figure 6.2: Synchronized activity among supporters and opponents of #blacklivesmatter**



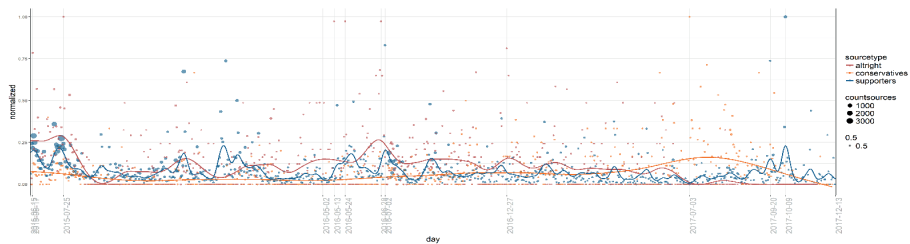
Note: daily volume of tweets sent, by day, from opponents alt-right (red), conservatives (orange) and supporters (blue). Point size indicates the number of tweets.

Overall, both supporters and opponents are synchronized only at certain times. Such coordinated activity in large numbers occurs more often among opponents than among supporters. Among supporters, the range lies between 1 and 3786 tweets, the mean is 113.2, the median 49 and the standard deviation is 254.3. Among conservatives, the range is between 1 and 177 tweets, the mean is 15.4, the median is 9, and the standard deviation is 20.7. Among alt-right, the range is between 7 and 3233 tweets, the mean is 183.3, the median is 109, and the standard deviation is 284.2. We note the non-normal distributions.

Different dynamics are at the root of synchronized moments. The graph depicts proportions of overall activity, showing how evenly activity is spread out over the period in the different groups. Supporters tend to engage ongoing conversations in small groups, generating a baseline of daily activity. Because of this, as the grassroots model suggests, synchronization among large numbers of supporters is rare. It occurs when many groups converge around the same topic. For instance, this happens in July 2015, with the tragic death and funeral of Sandra Bland, instances of police brutality, or events like the Academy Awards ceremony. For opponents, synchronization occurs, for instance, by the circulation of links to alternative news sources. Among the alt-right, there is little activity related to #blacklivesmatter in between such moments of synchronization.

We suggested different degrees of *synchronized attention* in the swarm and grassroots models. Whether many people synchronize their attention is measured as the average number of users from each group focusing on the same target simultaneously (Figure 6.3). Intuitively, a high average value suggests a large group of users directs attention on a relatively small number of targets.

Figure 6.3: Synchronized attention among supporters and opponents of #blacklivesmatter



Note: Average number of users from group focusing on targets, by day, from conservatives (orange), alt-right (red) and supporters (blue). Values are normalized for each group to membership as  $y = (x - x_{min}) / (x_{max} - x_{min})$ , the absolute sum of which is shown as point size.

Synchronization of attention is generally limited. This is illustrated by the low values throughout the period, ranging roughly between 0 and 0.25, with outliers during brief periods. The mean normalized scores are 0.08 for supporters, 0.06 for conservatives, and 0.11 for the alt right. For instance, on October 9<sup>th</sup> 2017, various groups of supporters (369) align in support of Kaepernick. The level of focused attention is particularly low among conservative opponents. There is a relatively high level of focused attention among the alt-right. Moments

of synchronized attention are more frequent among supporters than among opponents.

## Discussion

Activists have often seen in technology a promise that the power to represent the world will be more evenly distributed. For example, the wide diffusion of video cameras provided a crucial tool for activists speaking out against police violence. It was a landmark event in the history of mediatized conflict when a passerby, George Holliday, witnessed the brutal beating of Rodney King at the hands of officers from the Los Angeles Police Department. The recording of the beating and the subsequent failure to convict the police officers triggered massive riots in 1992. Since that time, recording devices have become lighter, smaller, better, and cheaper. Recent years have seen the proliferation of recordings of police confrontations. For example, vigilant observers and their cameras made us witness to Oscar Grant's death at the Oakland Fruitvale BART station in 2009, and to Eric Garner's death at the hands of the New York Police in 2014. The words 'I can't breathe' were shared time and time again, the clips recorded by eyewitnesses contradicting the testimonies of authorities. Digital networking is often analyzed as a means to organize progressive egalitarian movements (Bennett and Segerberg, 2012; Castells, 2007; Della Porta and Tarrow, 2005; Juris, 2005a). Against a backdrop of increasing individualization, people today can easily and rapidly share personal action frames to coordinate the struggle for a more just world.

While digital tools provide activists with powerful ways to coordinate against injustice, social media also serve as a vehicle for backlash. In this context, social media are not just a channel of communication for spreading information but also a way to coordinate among movements and counter-movements alike. This means that we may have to change the way we understand digitally networked action.

To explain different forms of coordination among movements and counter-movements, we suggested two models: a grassroots and a swarm model. At the heart of the grassroots model are community relations, based on the notion that the fabric of movements consists of many interwoven local groups. Relationships within groups are strong (kinship, friendships, comrades, affinity groups, etc.) while tools like social media facilitate coordination between such groups (Bennett and Segerberg, 2012; Tarrow and McAdam, 2005). Key to the swarm model is that

individual actions generate large-scale collective behaviors that can resemble the coordinated action of social movements. This is facilitated by social media, through which individual actors can observe and adjust their behavior to other individuals in the absence of or isolation from community relations. Both supporters and opponents might benefit from these digitally networked forms of coordination, and although ideal-typical, we expected to find more of the grassroots model among supporters, and more swarm-like features among opponents.

Findings confirm our expectations. With regard to local communities, supporters are strongly embedded in place: supporters are more forthcoming and specific about their home base in their Twitter bios and geographical proximity drastically increases the probability of a relationship. However, we find different spatialities among opponents, and their interactions less bound to specific locations. Considering that researchers consistently find that social movements networks are rooted in places (Borge-Holthoefer et al., 2014; Conover, Davis, et al., 2013; van Haperen et al., 2018), it is striking that geographical proximity does not increase the probability of ties among opponents. The counter-movement is more deterritorialized. Together, these findings indicate that supporters are more strongly embedded in local geographies, confirming expectations of the grassroots model. The alt right group is not rooted in specific localities, as suggested by the swarm model.

While our coarse measure of cohesion suggests a lower overall embeddedness among supporters, we interpret the networks measures in concert as evidence of a polycentric structure among supporters, as expected from the grassroots model. Research honing more specified measures might provide further insight; modularity-based methods provide promising avenues, if non-isomorphic substructures can be accounted for adequately. We interpret the current findings as evidence of the grassroots model among supporters and the swarm model among opponents, particularly for the alt-right.

In terms of synchronized activity, supporters are less coordinated overall, as expected from the grassroots model. Ongoing interactions within a wide range of communities provide a baseline activity. When synchronization is achieved between communities, it is the result of impactful tragedies or events. The activity of conservatives is similarly community-based, with ongoing interactions at times veering towards #blacklivesmatter. Synchronization among the alt-right is more frequent and concentrated, corroborating swarm model expectations. There is a degree of sequencing between opponents and supporters. Peak activity among

alt-right opponents follows after, never precedes, supporter activity. While no expectations were formulated about coordination between opposing groups, this suggests more reactionary activity among swarm opponents, and perhaps less than spontaneous emergent synchronization than the swarm model suggests.

With regard to the synchronization of attention, interpretation of opponents' results is not straightforward. The grassroots model suggests multiple groups each sharing a focus of attention among themselves, while not necessarily synchronizing attention between groups. Indeed, in combination with the evenly distributed activity, the higher frequency of moments of focused attention among supporters suggests a polycentric structure. Among conservative opponents, there is a baseline focus among groups, but few moments of synchronized attention between groups. Our interpretation is that both supporters and conservatives focus attention among subgroups, as the grassroots model suggests. However, supporters achieve synchronized attention between groups more often. Among the alt-right opponents, there is a baseline of more focused and less frequent moments of attention. When a group of these accounts retweets content from each other, moments of strong focus arise, as is the case in mid-June 2016 for a fabricated, supposedly hacked e-mail that is tweeted by others not in this group. Such instances were not anticipated in our measure. Strictly isolating only tweets directed at targets might produce less noisy results, but does not accurately represent how Twitter is leveraged by users, particularly the alt-right opponents. These findings align with the swarm model: individualized attention with emergent moments of highly synchronized attention as focus cascades through the system (Centola, Eguíluz, and Macy, 2007; Seguin, 2017).

## Conclusions

The advent of social media provides affordances for the coordination of social movements. In recent years, the movement for Black lives has powerfully demonstrated the potential of digital networking. Simultaneously, a resurgence of online rightwing extremism has benefited from the same digital networking tools. What can we learn about the network structures of such counter-movements from the way they coordinate activity online?

To describe how digitally networked movements and counter-movements coordinate, we draw on a dataset of 18.5 million tweets, comparing supporters and

opponents of #blacklivesmatter in terms of relations and spatialities. To explain these differences we suggest and test two ideal-typical models of coordination: the grassroots and the swarm. In short, the difference between the grassroots and swarm models is relational: how strongly individuals are rooted in communities and places. The grassroots model refers to engagement with movements through personal networks, suggesting individuals are strongly embedded in local communities and places. Key to the swarm model is that individual actions generate large-scale collective coordination without reliance on local relations or embeddedness. We measured synchronization and embeddedness in communities in terms of cohesion and geographic reference. Synchronization was measured in terms of synchronized activity and a mutual focus of attention.

We find that supporters of #blacklivesmatter are more strongly embedded in local relations and places, suggesting their online activism builds on local community relations, often rooted in specific cities. Opponents have very different relations and geographies. One group is, to a degree, rooted in localities but with a different geography than supporters, typically based in red states. We describe this group as conservative opponents. A second group of opponents is described as extreme right and is the source of the most extreme content. This group is highly synchronized but its members do not rely on being embedded in local communities.

We conclude with contributions to the literature. The examination of counter-movement dynamics may be of interest to activists and scholars for being the first to do so on a large scale in digitally networked movements, and Black Lives Matter specifically. Theoretically, we specify a further understanding of online movement and counter-movement dynamics. This helps to assess the different mobilization capacities of activists and their adversaries. The models of coordination suggests different pathways for scaling up digitally networked movements. Paradoxically, pervasive individualization can be conducive to coordination, allowing activity to cascade through aggregated crowds without the structural bottlenecks typical of polycentric community structures. While the affordances of digital networking are leveraged by progressive movements and their adversaries alike, they operate according to different kinds of connective action: that of the grassroots and that of the swarm.