Drawing the Lines of Contention: Networked Frame Contests Within #BlackLivesMatter Discourse

LEO G. STEWART, Human Centered Design & Engineering, University of Washington
AHMER ARIF, Human Centered Design & Engineering, University of Washington
A. CONRAD NIED, Computer Science and Engineering, University of Washington
EMMA S. SPIRO, Information School and Sociology, University of Washington
KATE STARBIRD, Human Centered Design & Engineering, University of Washington

This research examines Twitter discourse related to #BlackLivesMatter and police-related shooting events in 2016 through a mixed-method, interpretative approach. We construct a "shared audience graph", revealing structural and ideological disparities between two groups of participants (one on the political left, the other on the political right). We utilize an integrated networked gatekeeping and framing lens to examine how #BlackLivesMatter frames were produced—and how they were *contested*—by separate communities of supporters and critics. Among other empirical findings, this work demonstrates hashtags being used in diverse ways—e.g. to mark participation, assert individual identity, promote group identity, and support or challenge a frame. Considered from a networked gatekeeping perspective, we illustrate how hashtags can serve as channeling mechanisms, shaping trajectories of information flow. This analysis also reveals a right-leaning community of BlackLivesMatter critics to have a more well-defined group of crowdsourced elite who largely define their side's counter-frame.

CCS Concepts: **• Human-centered computing~Empirical studies in collaborative and social computing • *Human-centered computing~Social media***

Additional Key Words and Phrases: Social media; online activism; Black Lives Matter; Twitter; networked gatekeeping; networked framing

ACM Reference format:

Leo G. Stewart, Ahmer Arif, A. Conrad Nied, Emma S. Spiro, and Kate Starbird. 2017. Drawing the Lines of Contention: Networked Frame Contests Within #BlackLivesMatter Discourse. *PACMHCI*. 1, 2, Article 122 (November), 20 pages.
https://doi.org/10.1145/3134920

1 INTRODUCTION

On a fundamental level, protests and social movements give voice to a division between society and some of its members regarding the interpretation or meaning assigned to some aspect of reality [6]. Scholars of social movements and communications often study the dynamics of these divergences using the concept of frames, which are the "schemata of interpretation" [28], [32] that allow individuals and groups to bracket off and highlight some aspects of the problem to emphasize certain causal links and possible solutions. For social movements, these framings come to motivate and sustain collective action, promote identity formation and set the cultural opportunities and constraints [8]. These collective framings are socially constructed and negotiated through "a politics of signification" [36] that can involve

This research is a collaboration between the emCOMP lab and DataLab at the University of Washington and was supported by National Science Foundation Grant 1420255. We also wish to thank the UW SoMe Lab for providing infrastructure support.
Author's addresses: lgs17@uw.edu, ahmer@uw.edu, anied@cs.washington.edu, espiro@uw.edu, kstarbi@uw.edu

https://doi.org/10.1145/3134920

counter-framing, which are attempts "to rebut, or neutralize a person's or group's myths, versions of reality, or interpretive work" [7].

Social media have repeatedly been utilized by political activists to do this kind of framing work—e.g. by Iran election protesters in 2009 [33], Arab Spring revolutionaries in 2011 [37], and Gezi Park activists in 2013 [67]. For these and other movements, social media have served as an extension of the public sphere that facilitates organizers and more peripheral participants of social movements to symbiotically construct their frames and share them with a broad audience, circumventing traditional media gatekeepers. Understanding how social media users are crowdsourcing their own gatekeepers and framings to prominence has captured the attention of scholars from several diverse fields (e.g. [9], [23], [40], [43], [55]). However, due to the relative youth of social media and their rapid evolution in terms of both platform affordances and the associated evolving practices and norms, there is much we do not yet know about how these platforms facilitate political activism.

For example, from research on political activism in the offline context, we know that frames are both negotiated within groups and contested between groups (e.g. [8], [21], [24], [58]). While previous studies explore practices around counter-framing within online social movements or from the perspective of a single networked public (e.g. [27], [51], [65]), our work examines frame contests between distinct, competing online communities. Specifically, we examine the networked framings and counter-framings that manifested on Twitter around Black Lives Matter (BLM), a political movement that emerged in online and offline contexts to confront the use of deadly force by law enforcement against African Americans. In response to this movement, as well as several shootings that targeted police officers, counter-movements (with related framings) began to develop.

In this work, we compare the structure, networked affordance-based actions, and discursive acts of these groups while following Meraz and Papacharissi [51] in applying “networked gatekeeping” and “networked framing” as a lens to guide our analysis. Our findings highlight structural distinctions between the left-leaning and right-leaning communities, and demonstrate how users from both “sides” used similar discursive techniques—facilitated by specific affordances on Twitter—to produce and amplify their own narrative and challenge/confront the other side’s narrative. Specifically, we demonstrate how hashtags are used in tweets and profile descriptions to organize digital activism. This work also contributes to the articulation of an emerging method for conducting mixed-method, interpretative research on digital trace data, and demonstrates the value of using a “shared audience network graph” to guide that analysis.

2 LITERATURE REVIEW

2.1 Competing #BlackLivesMatter Frames Online

The BLM movement began in 2013 after community organizers Alicia Garza and Patrice Cullors used #BlackLivesMatter in Facebook posts in response to the acquittal of George Zimmerman in the death of Trayvon Martin [11], [34]. The term spread virally on social media soon after. The BLM movement asserts that African-Americans are uniquely and disproportionately targeted by systematic racism [11], arguing that the deaths of African-American men involving police officers are not isolated incidents, but rather support a greater pattern of police brutality and violence in the U.S.

Anderson and Hitlin [2] studied BLM’s Twitter presence under the broader theme of online conversations about race, finding that offline events had significant impacts on the dynamics of online discourse. Until 2016, Twitter activity linked to #BlackLivesMatter was primarily supportive of the BLM movement [2]. The shootings of police officers in Dallas, Texas and Baton Rouge, Louisiana prompted an increase in tweets critical of the movement with the #BlackLivesMatter hashtag as well as a spike in volume of tweets with #BlueLivesMatter and #AllLivesMatter [2], which represent counter-narratives to #BlackLivesMatter. Where #AllLivesMatter supporters argue that the focus on African-American lives comes at the cost of deprioritizing other lives, #BlueLivesMatter offers a more direct challenge to BLM, asserting that police are heroes who are the true victims of violence between officers and civilians [2], [12].

Other researchers have studied the actors and mechanisms related to the BLM movement’s digital presence. Twyman et al. identified prominent processes involved in Wikipedia documentation of BLM, noting how editors collaborated across articles to document the significance of past events in relation to the overarching BLM framing portrayed on Wikipedia [65]. However, the dynamics of Wikipedia are quite distinct from those of Twitter, as neutrality and notability criteria on Wikipedia constrain divergence and competition of frames. For this reason, Twitter’s platform perhaps facilitates more authentic manifestations of competing frames. Olteanu et al. explored the demographics—age, race, gender—of those discussing BLM on Twitter between 2012 and 2015 as a heuristic for understanding whose voices dominated the discourse [53]. We share a similar goal of understanding the power structures ingrained in the contestation of divergent frames. Our work expands on that of Olteanu et al. by using structural homophily to identify distinct groups of participants and examine the organizing tactics used to promote and proliferate their frames. De Choudhury et al. studied BLM engagement on Twitter in the context of four events significant to the BLM movement [25]. They use linguistic indicators to determine that those engaging with BLM on Twitter developed a stronger collective identity over time. Moreover, more new users engaged during significant offline events and the proportion of continuing users engaging increased over time. We similarly explore the temporal dimension of online participation in BLM; however, our shared audience graph presents a structural lens to online activism and engagement, allowing us to study the bifurcated nature of the conversation.

2.2 Networked Framing within Social Movements

2.2.1 Frames as Dynamic, Negotiated Schemes of Interpretation. We utilize the networked framing approach to understand the processes—i.e. the aggregations of online actions—that functioned to frame (and counter-frame) the BlackLivesMatter discourse. The concept of "framing" has been repeatedly applied to both political discourse generally [28] and social movements [6], [8], [27], [51] to describe how groups of people achieve a shared sense of reality. This research typically draws on Goffman's [32] work, where he defined frames as "schemata of interpretation" that help us make sense of the world—giving us the conceptual structures for interpreting what we see, hear, and otherwise experience. Frames help people to organize experience and guide action [8].

Framing is a process for constructing schemata that can be shared, to some extent, across multiple people. Within social movements, framing functions to define the problem or problems that a group cares about, diagnose causes, make moral judgments, and suggest remedies [28]. In this context, framing is a negotiated process and frames are dynamic, "continuously being constituted, contested, reproduced, transformed and/or replaced during the course of social movement activity" [8].

The process of framing occurs through various discursive actions. In Entman's view, this process has two complementary components, selection and salience, where a frame calls attention to some aspects of reality and directs attention away from other aspects [28].

2.2.2 Networked Framing Within Social Movements. Meraz and Papacharissi [51] adapt Entman's definition of framing to apply it to online, networked, crowdsourced actions—specifically looking at the use of Twitter re: the 2011 political revolution in Egypt. That work extends the definition of "text" to the ongoing activity of the networked, interacting crowd and looks specifically at the role of conversational markers on Twitter (e.g. RTs and @mentions) as tools of these practices, a methodological technique that we utilize here as well (though focusing on different markers).

2.2.3 Contested- and Counter-Frames. Frames are negotiated from within, but they can also be contested by those outside a movement. Benford and colleagues define counterframes as efforts to "rebut, undermine, or neutralize" another person's or group's narratives or interpretative framework [7], [8], and describe how, faced with direct confrontation of their frames, a social movement may adapt and revise their own frames in response [8]. These back and forth challenges and responses can be thought of as "framing contests" [58].

While existing work on networked [51] and crowd-sourced [27] framing examine contested frames from the perspective of a single collective, our research in this space explores contested and (specifically) counterframing activities within and between two structurally distinct online communities.

2.3 Networked Gatekeeping in Online Social Movements

Following Meraz and Papacharissi [51], we utilize theories of "networked gatekeeping" [4] to better understand how various actors within the online crowd worked to produce and amplify their frames—collectively establishing both the preferred message and the preferred messengers of the movements. Gatekeeping is a theory of information control that attempts to explain how information is filtered, curated, and disseminated [61]. Initially, this theory focused on how mass media and other elites controlled information flow—defining the available frames. Barzilai-Nahon extended gatekeeping theories to online interaction [4]. Using the information control perspective, she described networked gatekeeping as having three goals: "(a) a 'locking in' of gated inside the gatekeeper's network; (b) protecting norms, information, gated and communities from unwanted entry from outside; and (c) maintaining ongoing activities within network boundaries without disturbances" [4]. This conceptualization speaks both to the structure and the structuring of online interaction.

While other researchers challenged the utility of the gatekeeping metaphor in the networked age—such as Bruns' argument that online gatekeepers have been replaced by gatewatchers [16]—Barzilai-Nahon instead posited a shift in who the gatekeepers are—i.e. from "elites" in media and government to others who have to power to operate "gates" within the network structure. Relating this power shift to online social movements, downstream researchers have argued that the Internet, and specifically social media, allow non-elites within social movements to tell their own stories without the gatekeeping of mainstream media [15], [31], [38], [44] and to participate in frame production, including by challenging traditional (broadcast and press) media framings [19]. Meraz and Papacharissi [51] describe specifically how Twitter provides a platform for alternative voices through social structures involving "crowdsourced elite." These elite—who may represent perspectives that do not align with mainstream cultural narratives—gain their status from producing content that resonates with their audience [17]. Our research explores some of the activities on Twitter that serve to establish the crowdsourced elite as well as the shaping function of these new elites on the #BlackLivesMatter discourse.

2.3.1 The Role of Hashtags in Examining Counter-Frames. This research examines the practices and resulting structure of networked framing and networked gatekeeping within two distinct, connected, and competing online movements. To do this, we focus on the varied use of hashtags (in combination with a shared audience metric described below) as an analytical lens for observing contested frames between the BlackLivesMatter movement and a significant countermovement present on Twitter in 2016.

Hashtags are a dynamic and flexible convention that were initially introduced as a tool for organizing tweets into topics. As a gatekeeping tool, hashtag phrases can amplify messages far beyond their original audience. They can also serve as a framing tool and facilitate contestation [51]. Exploring the changing meanings of hashtags in the BLM movement, Booten [13] noted that the meaning of hashtags may broaden or otherwise evolve as a movement's needs and identities shift, dubbing this phenomenon "hashtag drift." Exemplifying this varied use, #BlackLivesMatter specifically can be used to indicate that a tweet is about race, intentionally engage with a conversation about race, or make commentary on the BLM movement [2]. Tweets tagged with *LM hashtags also include "calls to action", disagreement, debate, or appropriation of a narrative [2], [18]. These findings suggest that who is using the hashtag says as much about its associated narrative or frame as the word or phrase within the hashtag itself. Conversely, hashtag use also appears to be a marker of identity and a tool of networked gatekeeping, an idea we explore in this paper.

3 METHODS

We approach the *LM conversation on Twitter as a large-scale online environment, adapting tools and methods from [3], [14], [41], [42], [47], [57], in order for us to 'hear' certain collective narratives and 'see' the attendant practices that seek to articulate them. The basis of this approach is to consolidate observations from different groups and entry-points, paying attention to both ties and content, and letting comparisons between groups emerge out of the findings [57]. In keeping with this perspective, our high-level process involved harnessing structural data (articulated network ties) to cluster social media users based on a similarity metric of shared audiences. We then use the products from this analysis as a component of a qualitative inquiry by drilling down and sampling individually distinctive data from these clusters (such as tweets and profile content) for discursive and organization-related patterns and themes.

3.1 Data Collection

We collected data using the Twitter Streaming API to capture public conversations that contained the keywords "shooting", "shooter", "gun shot", and "gun man", as well as the plural and contracted forms of each keyword. This collection ran for roughly nine months, between December 31st 2015 and October 5th 2016, during which we captured 58,812,322 tweets. From this larger set, we created a subset of 248,719 tweets by selecting tweets that contained any of the following terms: "blacklivesmatter," "bluelivesmatter," and "alllivesmatter". Tweets in this dataset therefore contain both a shooting-related keyword term and a *livesmatter term. Within this paper, we use *LM to designate use of any or all of: "BlackLivesMatter," "BlueLivesMatter," and "AllLivesMatter."

Our sampling method—i.e. limited to *LM tweets with shooting terms—enables us to explore the relationship between significant and provocative offline events and related digital narratives and framing processes. However it is not necessarily representative of the broader *LM discourse. Specifically, our sample has likely biased our analysis towards discursive acts that connect *LM narratives with violence. We take care to report our findings within the limitations of this sample.

After the tweet collection, we began the process of retrieving social network information for accounts associated with the tweets in this subset, using the Twitter REST API. To make this tractable, we focused on accounts that demonstrated a relatively high volume of engagement in this conversation—specifically, accounts that shared more than three tweets in our dataset. This subset contains 8,524 accounts responsible for 66,357 tweets. For each account, we attempted to gather the account's follower list. Due to limitations of the Twitter REST API and our need to quickly capture information from a large number of profiles, we capped the number of followers retrieved for any given user at the 100,000 most recent followers[2]. This cap affected 77 (<1%) high followers accounts—primarily high-profile journalists, commentators, activists, and organizations. We also note that we were unable to collect follower data for accounts that were protected or suspended. This affected 336 (3.9%) accounts in our dataset. Followers were collected between November 15th, 2016 and January 17th, 2017.

Fig. 1 graphs the temporal distribution of the resulting dataset (66,357 tweets from 8,524 accounts) along with captions for a number of tragic events that correlated with spikes of activity in the conversations we are studying. We attribute the largest spike in our data set to shootings in Dallas and Baton Rouge that targeted police officers.

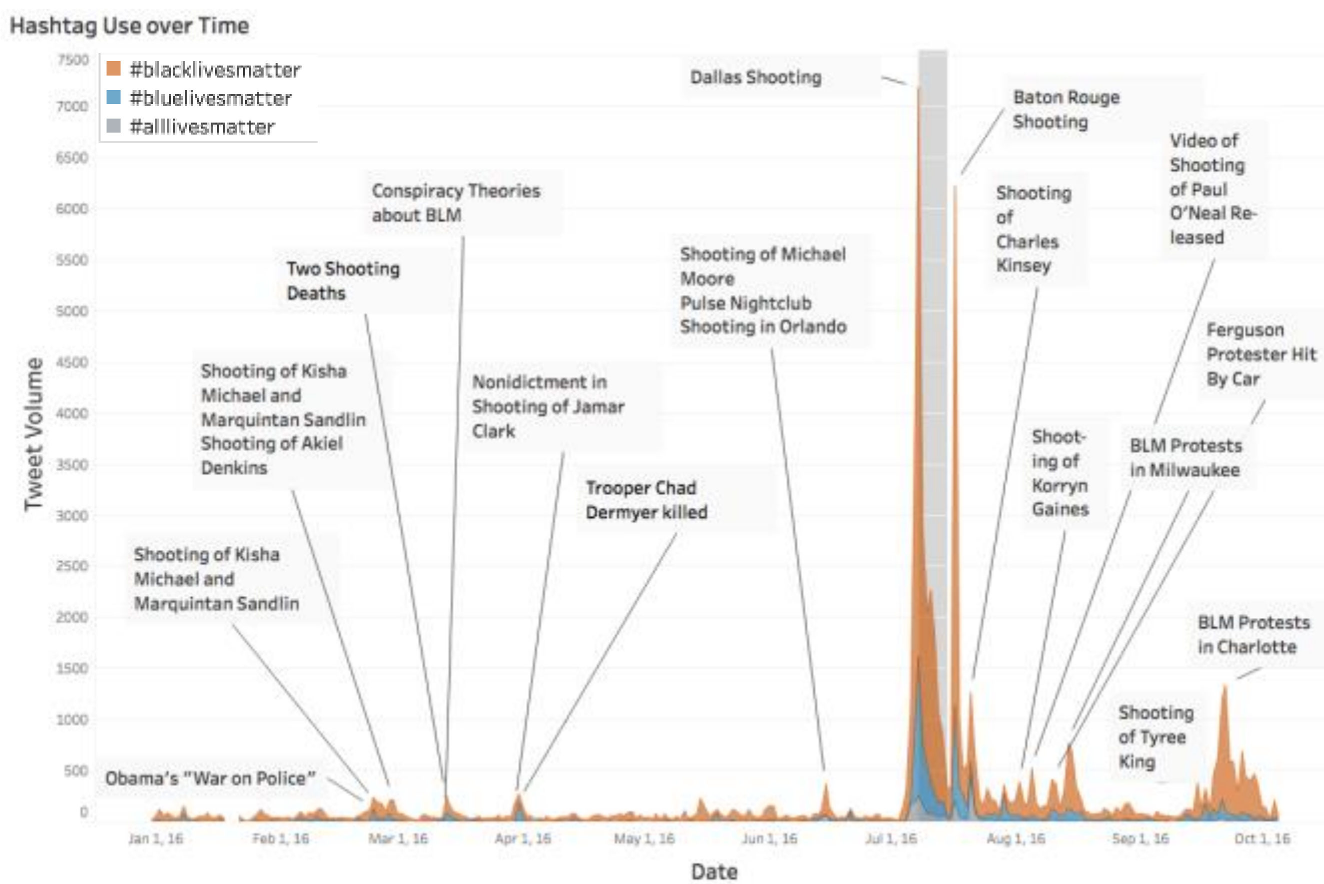

Fig. 1. Temporal Signature of Shooting-Related Tweets with #BlackLivesMatter, #BlueLivesMatter and #AllLivesMatter

3.2 The "Shared Audience" Measure

[2] Our understanding is that the Twitter REST API returns the most recent followers with each call, and we assume that the follower lists for these accounts are biased towards the most recent.

On Twitter, one of the primary mechanisms for automated information exchange is follower ties. A user's followers will be shown that user's messages in their "home timeline" which appears in their default Twitter view. To understand how groups of users are similar to each other—in terms of which accounts are following them and therefore receive their messages in their home timelines—we compute a shared audience metric for every pair of users in our set. The shared audience metric between any two users (A, B) is calculated using the Jaccard similarity of their follower lists as seen in Equation 1.

$$J(A,B) = \frac{|A_{followers}| \cap |B_{followers}|}{|A_{followers}| \cup |B_{followers}|}$$

This metric is calculated between every user pairwise regardless of whether they have an existing following relation between them. The resulting graph provides an alternative to networks generated from friend-following ties (e.g. [45], [46]) or retweet-mention ties (e.g. [54], [68]). Instead, it demonstrates similarities in audience and potentially in influence—i.e. accounts are clustered together with other accounts with whom they share common followers.

3.3 Graphing and Clustering By Shared Audience

Defining users as nodes and the shared audience metric between any two nodes as their edge-weight, we use Gephi [5] to build a graph. Calculating shared audience edges between each pair of accounts yields 25M nonzero edges. As we wish to display strongly overlapping audiences while preserving the nuances afforded by smaller edge weights, we select the 20th percentile of edges (by weight), or roughly 5M edges. After constructing this graph of users, we cluster them by Louvain modularity [10]. This clustering algorithm iteratively seeks to maximize modularity by assigning nodes to communities, where each community initially consists of only one node and modularity measures the intracommunity edge weights compared to the intercommunity edge weights. The resolution parameter in the clustering algorithm controls the granularity of the community detection algorithm. Though we investigated the effects of varying the resolution value, we chose to use the default value of 1, as the resulting clusters were the most structurally distinct.

3.4 Qualitative Analysis of Clusters

Treating the shared audience and retweet graphs as both an anchor and point of departure, we utilized a grounded approach [20] to interpret and explore four different units of analysis: hashtags, tweets, account profiles, and websites being cited within these clusters. Our analytical approach was iterative and consisted of two sets of interrelated activities that helped us follow the people, objects, stories and conflicts [48], [57] in this setting. The first involved conducting visual explorations and coding exercises along various cuts of our data, such as the top-25 most retweeted tweets from each of the clusters for a given *livesmatter hashtag or the most quoted users across different clusters. A key research product that resulted from these activities was a qualitative frame analysis of how the most circulated tweets from different clusters collectively frame [42] and give meaning to #BlackLivesMatter and #BlueLivesMatter.

These activities also recursively moved us from a general focus on patterns and anomalies in the data to a deeper examination of the activities that specific users engaged in to help generate and elaborate on these frames. To this end, our second set of activities focused on closely studying and following specific groups of accounts both through their Twitter data and into other online spaces to see some of the tools and practices that are being employed by these groups to help elevate what they considered to be newsworthy.

3.5 Note Regarding the Anonymization of Twitter Accounts

We attempt to obscure identities by withholding identifying information and paraphrasing tweets with the exception of prominent, high-follower accounts. The identities of these prominent users, which include journalists, are crucial for communicating our findings.

4 FINDINGS

4.1 Characterizing the Shared Audience Clusters

The shared audience graph (Fig. 2) reveals structurally distinct communities within the *LM discourse. The graph shows two large groups of accounts (superclusters) in the center of the graph, one on the left (green) and another on the right (multi-colored). The accounts in these clusters are linked to other accounts that have similar shared audiences. They are surrounded by a ring of accounts (grey) that are minimally connected—i.e. either they do not have a significant shared audience with any other account in the set or they are part of a small cluster of accounts that only have a significant shared audience with each other. Characteristics of the most prominent (numbered) clusters are summarized in Table and Table 1.

We categorized the clusters by identifying common attributes of accounts within them. We first looked at the frequently used hashtags within account descriptions. Roughly one-third (37.6%) of accounts in the central (numbered) clusters of shared audience graph had one or more hashtags in their profile description. Recall that the graph consists of users who sent more than three tweets about *LM within a larger collection of tweets about shooting events. Within that larger collection, only 10.8% of accounts have hashtags in their profiles. So, high volume and socially integrated *LM tweeters are more likely to have hashtags within their profile descriptions than other users who tweet about shooting events. This suggests that hashtags within profiles are performing a network gatekeeping function—i.e. both marking participation in an ongoing conversation and perhaps also facilitating the development of social network ties around specific topics, perhaps similar to the use of the location field to express community identity as explored by Hecht et al. [39].

We looked to these markers of participation and self-identification to better understand the common identity or identities within each cluster. For this analysis, to include changes to profiles over time, we included for each account any hashtag that appeared in their profile description at the time of posting a *LM tweet in our data. Each hashtag was counted only once for each user.

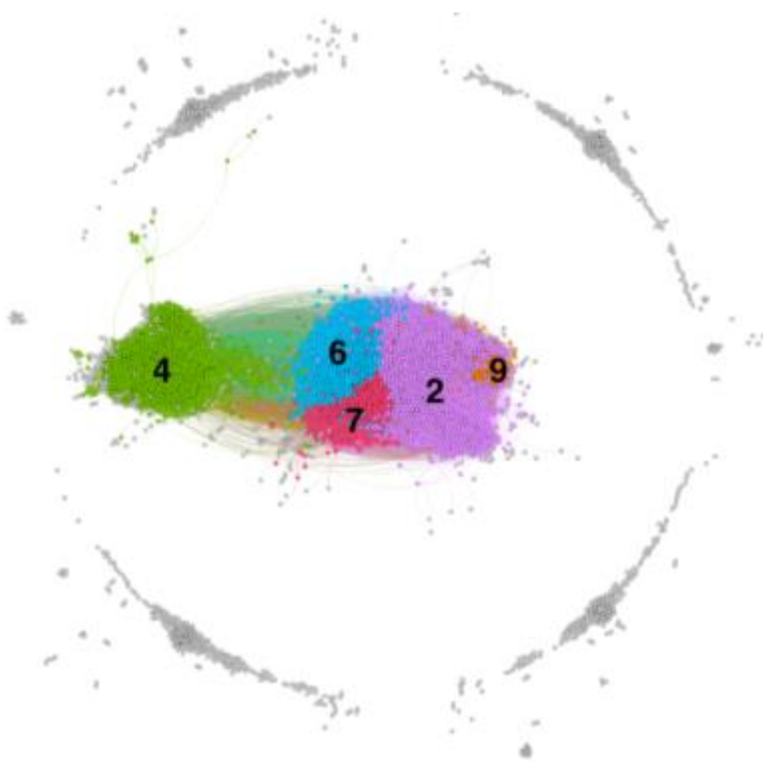

Fig. 2. Shared Audience Network Graph

We also qualitatively analyzed frequently cited domains within tweets from accounts in each cluster as well as characteristics of the most highly retweeted accounts. Additionally, we looked at quantitative measures of participation and influence for the accounts in each cluster, including the percentage of accounts that are verified, the number of retweets per tweet, and the log number of followers for each account.

4.1.1 A Left-Leaning Supercluster: A Common Cause, Underlying Political Division. For the green cluster (#4), the most common hashtag by far is #BlackLivesMatter. 12.2% of accounts in that cluster had that hashtag in their profile description, specifically identifying themselves as participants in that conversation and/or supporters of that movement. Other salient hashtags related to political views, specifically in the context of the 2016 U.S. presidential election. Interestingly, though most of these could be characterized as left-leaning, they encompassed a diverse array of political opinions—e.g. #ImWithHer, #BernieOrBust, and #NeverHillary were all used by significant portions of the green cluster. Structurally, in terms of overlapping shared audiences, these accounts were relatively similar, but their stated political identities as communicated through hashtags within their profile descriptions were not completely convergent.

4.1.2 A Right-Leaning Collection of Clusters: Uniting Around a Counter Narrative. The supercluster on the right (see Fig. 2) contains four smaller clusters—purple (2), blue (6), pink (7), and orange (9). We determined this supercluster to be politically right-leaning. The most frequently used hashtags in the profile descriptions, the most frequently cited domains, and the accounts that were most retweeted by accounts in these clusters all reflected a right-leaning political orientation. Unlike the Left-Leaning Supercluster, accounts in the Right-Leaning Supercluster were generally consistent in their support of their candidate in the 2016 election—#MAGA (an abbreviation of a slogan from the Donald Trump campaign) was among the top ten hashtags for each of the four clusters.

The three larger clusters (purple, blue, and pink) look very similar in terms of their profile descriptions and the content of their tweets. Breitbart news—a media outlet that has embraced the “alt-right” label—is among the top-cited domains in their tweets. Accounts in these clusters retweet the same five accounts (among their top ten) more than any others—@PrisonPlanet, @PlayDangerously (now @Cernovich), @DrMartyFox, @MarkDice and @LindaSuhler. Many of the same hashtags—e.g. #Trump2016, #2A and #NRA—are among the top hashtags in each of these clusters, though their ranking varies.

Table 1A. Features of the Central Clusters in the Shared Audience Network Graph

ID	Top 10 Hashtags in Account Profile Descriptions
4	#blacklivesmatter (262), #uniteblue (70), #imwithher (65), #feelthebern (50), #blm (45), #bernieorbust (39), #neverhillary (36), #nevertrump (32), #ourrevolution (25), #freepalestine (22)
2	#maga (157), #trump2016 (151), #2a (99), #bluelivesmatter (60), #trump (54), #neverhillary (53), #trumptrain (52), #makeamericagreatagain (50), #alllivesmatter (41), #nra (40)
6	#2a (146), #tcot (114), #nra (77), #pjnet (77), #maga (65), #trump2016 (62), #ccot (54), #neverhillary (50), #conservative (48), #bluelivesmatter (47)
7	#trump2016 (175), #maga (154), #2a (104), #trump (82), #makeamericagreatagain (71), #neverhillary (53), #americafirst (49), #trumptrain (49), #1a (44), #bluelivesmatter (44)
9	#gamergate (20), #opskynet (4), #maga (3), #notyourshield (3), #altright (2), #atheist (2), #blacklivesmatter (2), #gamer (2), #bringbackhanging (1), #teamvalor (1)

Table 1B. Features of the Central Clusters in the Shared Audience Network Graph

ID	Label	Number of *LM Tweets	Cluster Size	% Accts. w/ >= 1 Hashtag in Acct. Descript.	Avg. RTs per Tweet	% Verified	% Accts. with edges crossing superclusters
4	Composite Left	18213	2153	39.9	0.302	1.11	45.1
2	Broader Public of Right-Leaning *LM Tweeters (Right)	17095	2432	29.8	0.025	0	53.7
6	Conservative Tweeters and Organizers (Right)	10549	1268	49.8	0.212	0.473	71.7
7	Alt-Right Elite: Influencers & Content Producers (Right)	7200	844	60.5	1.66	1.66	90.5
9	Gamergate (Right)	984	145	28.3	0.120	0	17.9

Distinctions between these clusters are more subtle, but interesting. The purple cluster (#2) is by far the largest in terms of number of accounts. The most highly used hashtags in profiles are related to support of Donald Trump, gun rights, and #BlueLivesMatter. The most highly cited domains in tweets from these accounts include mainstream and right-leaning media—Breitbart and Fox News are both in the top five. Though content-wise this cluster looks similar, compared to the other right-leaning clusters, accounts in the purple cluster are not as highly retweeted, and have lower numbers of followers. There are no verified accounts in this cluster. We categorized this cluster as the broader public of right-leaning *LM participants.

4.2 Characterizing Cluster Interactions

To better understand the relationship between the structure of the communities and the underlying practices of framing and counterframing, we examined the dynamics of interactions, such as retweets, quotes, and replies, as they took place across the shared audience graph.

Through this lens, we can see how the "shared audience" property reflects political homophily, apparent in both the social structure of the graph and in the dynamics of information flow across it. Of the 5,026,316 edges in the graph, only 32,571 (0.648%) cross the two distinct superclusters shown in Fig. 2. This shows the relatively insular nature of each supercluster and, considering what we learned (above) about the kinds of accounts in each, demonstrates the concept of political homophily [1], [22], [62]. However, more than half of the accounts in each supercluster do have a shared audience edge (of at least 2%) with at least one account in the opposite supercluster, suggesting the existence of some bridge accounts that follow accounts in both superclusters.

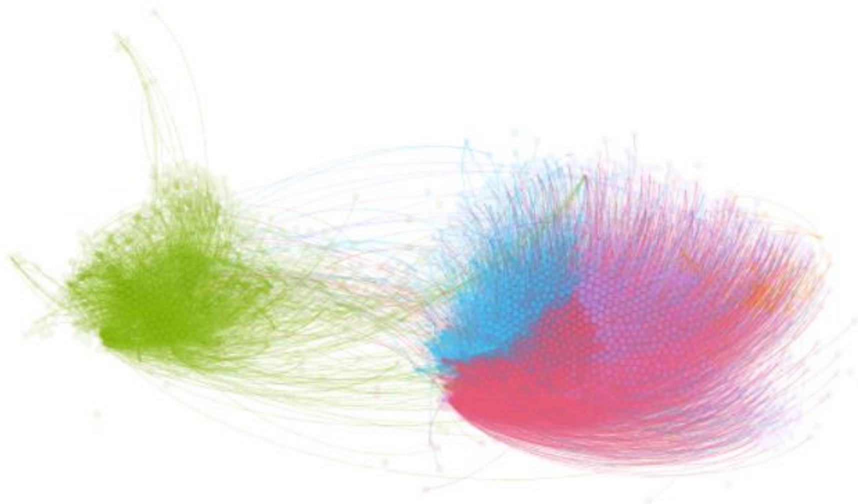

Fig. 3. Retweet Trajectories on the Shared Audience Graph

Fig. 3 overlays retweet dynamics on top of the shared audience network. Edges reflect a retweet of one account by another and are colored by source cluster (the cluster of the original tweeter). This graph shows very few retweets crossing the Right- and Left-Leaning Superclusters. Of the 18,414 times when an account in one supercluster retweeted another account in a supercluster, only 204 (1.11%) crossed superclusters. In other words, for tweets related to *LM conversations, accounts within each structurally (and ideologically) distinct supercluster primarily amplify messages from other accounts within their supercluster. These dynamics reflect networked gatekeeping practices to establish a "gated" community of sorts, where the preferred messages are coming from inside the group.

This graph also shows that accounts within the pink cluster (#7, the Alt-Right Influencers) are much more highly retweeted than others (see Table 1B as well). Content originating in this cluster is often passed along by accounts in the other right-leaning clusters, especially the purple cluster. As noted before, the pink cluster contains several of the "crowdsourced elite" on the right. These dynamics demonstrate how these new elites are performing as gatekeepers for the crowd that has helped to establish them, selecting the messages that are propagated there.

4.3 Framing in #BlackLivesMatter Discourse

Having investigated their structure and dynamics of information flow, we examine how members of the two superclusters engaged in the production, elaboration and contestation of their preferred frames through their use of *LM hashtags in tweets. From a network framing perspective [28], [51], we perceived qualitative differences (and similarities) with respect to how the two sides made attributions around police related shootings, what counts as newsworthy, and what needs to be done. To illustrate these variances, we draw on examples from the top 25 most retweeted *LM tweets from each super cluster as a window into what crowdsourced frames rose to prominence.

4.3.1 #BlackLivesMatter Framing on the Left. Accounts from the left-leaning cluster used #BlackLivesMatter primarily to develop and project what Gamson and others refer to as 'injustice frames' [30], [43], [69]. This type of framing centers on calling attention to victims of perceived injustice at the hands of authorities as a way to generate collective non-compliance and/or protest to realize political change. Highly retweeted #BlackLivesMatter tweets from this cluster produce this type of framing by 1) highlighting individual and structural instances of police misconduct; 2) spotlighting and remembering victims; and 3) positioning non-violent resistance as a proposed solution:

```
(Tweet 1): Cops called elderly Black man the n-word before shooting him to death
#KillerCops #BlackLivesMatter
```

(Tweet 2): Recent acquittals of multiple officers involved in shootings makes Economic Boycott perfect for #BlackLivesMatter

(Tweet 3): Anyone blaming this Dallas shooting on the #BlackLivesMatter movement is sick. Those protestors were peaceful. This terrorized them too.

4.3.2 #BlackLivesMatter Framing on the Right. In comparison to this, highly retweeted #BlackLivesMatter content from the politically right-aligned clusters demonstrated an effort to reframe that movement as being detrimental to social order and being anti-law (protestors vs. police). This counter-framing was constructed by 1) defining the problem around shootings that targeted police (as opposed to the left supercluster's focus on police shootings of African Americans); 2) attributing these shootings to BlackLivesMatter protestors and linking the movement to violent criminal acts; and 3) morally evaluating police retaliation as justifiable. Again, these discursive trends can be captured using examples from the top 25 most retweeted tweets from the right-leaning clusters:

(Tweet 4): Nothing Says #BlackLivesMatter like mass looting convenience stores & shooting ppl over the death of an armed thug.

(Tweet 5): 3 cops shot dead in Baton Rouge. Shooter is black. Another #BlackLivesMatter-inspired attack, no doubt.

(Tweet 6): What is this world coming to when you can't aim a gun at some cops without them shooting you? #BlackLivesMatter

4.3.3 Framing Contests between Competing Social Movements. Tweets 4-6 demonstrate how Twitter users within the Right Leaning Supercluster appropriated the #BlackLivesMatter hashtag to promote a counter-frame to the one produced and promoted by the Left Leaning Supercluster. This counter-frame represents a challenge to the original BlackLivesMatter frame, and several highly retweeted tweets from the left side of the graph demonstrate the left reacting to that challenge by defending and revising their frames. For example, the tweet below, which circulated within the left side of the graph, represents a challenge to the argument that African Americans are more dangerous to police than White men and that police violence is necessary and justified:

(Tweet 7 – Left Leaning): Question of the day to #BlueLivesMatter~ Does the police shooting of #CharlesKinsey hurt your cause?

In some cases, we see evidence from both sides of direct, explicit challenges to the other side's framings—i.e. the facts and events they chose to promote and those they chose to ignore:

(Tweet 8 – Left Leaning): WHERE'S ALL THE #BlueLivesMatter PEOPLE?? 2 POLICE OFFICERS SHOT BY 2 WHITE MEN, BOTH SHOOTERS IN CUSTODY NOT DEAD.

(Tweet 9 – Right Leaning): A 2-year-old girl was shot in the head Friday in a drive-by shooting in Cleveland - #BlackLivesMatter DO YOU CARE???

These tweets make the move of equating the online silence (real or imagined) of Twitter users with ambivalence and double standards. This is interesting because they suggest a false either/or dichotomy that positions users as only caring about certain causes based on what they don't share. Considered from a networked framing perspective, these tweets directly challenge the other side's framing practices for what they choose not to select and make salient.

The tweet record shows the two sides continually challenging the other side's framings as well as defending and adjusting their own in response. This activity—a 'framing contest' [8], [58]—can help sustain and drive the network framing process (even becoming preemptive in some instances), and some of these square offs can potentially add to the prominence of crowdsourced elites within the community. For instance, the following highly retweeted tweets were made by crowdsourced elites in the context of their group's collective frames being contested:

(Tweet 10 – Left Leaning): The identity of this new shooter in Baton Rouge has not even been released and folk already blaming me or #BlackLivesMatter. Foolishness.

(Tweet 11 – Right Leaning): How is shooting cops in Dallas justice for whatever may have happened elsewhere? It is not. #BlueLivesMatter

Though the two sides are clearly promoting oppositional frames, there is a remarkable amount of interdependence and symbiosis at work as well. Essentially, their frames are being co-produced through interaction with and reaction to the frames produced on the other side. Additionally, the two sides share high level framing strategies and demonstrate similar interaction techniques.

4.3.4 Explicitly Contesting Media Framings. Another point of convergence comes from how users from both superclusters accuse traditional mainstream media of being biased:

```
(Tweet 12 – Right Leaning): MSNBC ignores rioting, assaults, looting, claims
#BlackLivesMatter is peaceful because they cleaned up some trash.
```

```
(Tweet 13 – Left Leaning): So @cnnbrk Where's the background report on Billy
Jones' Associates? Where's the Outrage or do #BlueLivesMatter when the shooter
is Black?
```

Here silence on an issue is used as evidence that traditional media outlets are carrying and reproducing the cultural codes of other groups. These arguments form the rationale for these online communities to have their own gatekeepers.

4.3.5 Hashtags as Tools of Framing Contests. Within the 'framing contests' around BlackLivesMatter, different *LM hashtags came to be used, appropriated and re-appropriated to promote in-group and challenge out-group frames. Table 2 summarizes the use of *LM hashtags in tweets by supercluster, demonstrating significant differences across superclusters regarding the use of the three hashtags. #BlackLivesMatter was employed by Twitter users on both sides of the graph (and the political spectrum)—99.5% of left-leaning accounts and 96.4% of right-leaning accounts posted at least one tweet with #BlackLivesMatter. This shows that people engaging in these conversations from different political perspectives are utilizing a common hashtag to mark their participation—making it visible (and searchable) to other conversation participants from both sides of the political spectrum. In stark contrast, #BlueLivesMatter was used much less frequently by left-leaning accounts (only 15.5%) than by right-leaning accounts (65.3%). This is perhaps not surprising, as #BlueLivesMatter was employed explicitly to promote a counter-narrative to the #BlackLivesMatter movement, reframing it as one that was explicitly anti-police [12]. Finally, #AllLivesMatter was used by only 26.6% of left-leaning accounts and 17.3% of right-leaning accounts. Though #AllLivesMatter elicited comparable levels of activity from each supercluster, the hashtag was not associated with the same levels of overall engagement.

Table 2. Number of accounts that posted a *LM tweet

Hashtag	Left-Leaning Supercluster	Right-Leaning Supercluster
#BlackLivesMatter	16,742	25,372
#BlueLivesMatter	581	9,277
#AllLivesMatter	964	1,357

While users from the Right-Leaning Supercluster appropriated #BlackLivesMatter to directly confront and challenge the left side's frames, they employed #BlueLivesMatter and #AllLivesMatter hashtags to promote an alternative, adversarial framing [30] that sketched 'good protagonists' versus 'evil antagonists'. This was done by expressing solidarity with police forces that were framed as victims in a battle against domestic terrorism, hatred, and cultural decay:

```
(Tweet 14): Shooting of Dallas officers spurs acts of kindness to police
#Trump2016 #bluelivesmatter
```

```
(Tweet 15): Breaking: Racist Black Shooter has Islamic ties & attended Mosque!
#BlueLivesMatter#WhiteLivesMatter #MuslimBan
```

```
(Tweet 16): THIS CULTURE IS MORTALLY ILL Microsoft Panders To Progressives
Following Dallas Shootings #BlueLivesMatter
```

(Tweet 17): Tennessee gunman who shot postal carrier dead 'targeted white people' #AllLivesMatter #StopSpreadingTheHate

Conversely, highly retweeted #BlueLivesMatter and #AllLivesMatter tweets from accounts in the left-leaning supercluster employed those tags as a mechanism to frame the #BlueLivesMatter and #AllLivesMatter movements as being against racial equality. This was primarily done by defining perceived silence around certain issues as an indication of double standards (as seen in Tweets 7 and 8).

4.3.6 Quoted Tweets as Tools of Framing Contests. Table 3 summarizes "crossover" interactions. Though the retweet patterns across the graph demonstrate limited interaction between the two "sides" of the *LM conversation (see Fig. 3, above), the quoted tweets and replies reveal a slightly different story. In 2015, Twitter added a quote tweet feature that allowed users to retweet another tweet with a comment [52] and tinkered with the reply feature to better support threaded conversations. These features were still gaining traction during our data collection period in 2016. We examined quoted tweets and replies where the downstream tweet (the comment or reply) contained a *LM hashtag. Though separation between groups is still evident here, considering interactions between users in our dataset, quoted tweets (8.68%) and replies (21.0%) are much more likely to cross superclusters than retweets (1.11%).

Table 3. Tweet Interactions across Superclusters

	RTs	Quotes	Replies
Interactions between accounts in superclusters	18414	2649	267
Crossovers	204	230	56
Left-to-Right Crossovers	108	164	34
Right-to-Left Crossovers	96	66	22

Examining the content of quoted tweets that crossed superclusters, we see these features being used to directly challenge the other side's narrative or frame. For example, in the quote tweet exchange below, the original tweet was posted by an account in the Right-Leaning Supercluster and the comment tweet was posted by an account in the Left-Leaning Supercluster:

Original Tweet: Multiple gunmen in #BatonRouge, two still on the loose. #BlackLivesMatter got the race war it wanted.

Comment Tweet: Shut the entire fuck up you dumb son of a bitch. Nobody in #BlackLivesMatter wants a fukin race war. Go diaf https://t.co/f24xFQZB29

This re-framing of the Black Lives Matter Movement as a race war, and response with a personal attack and defense of the original narrative, demonstrates how quote tweets are used within framing contests to explicitly and directly challenge and contest the opposing side's frame—as well as those who promote those frames.

The quote tweet exchange below demonstrates a slightly different approach:

Original Tweet: People are already trying to link the Baton Rouge shooting to #blacklivesmatter, you people are why this country needs the movement

Comment Tweet: #ViolentFelonLivesMatter #blacklivesmatter @<username>

In this exchange, the original tweet from an account in the Left-Leaning Supercluster expresses a defense of the #BlackLivesMatter movement against claims that it is connected to anti-police violence. The comment from an account in the Right-Leaning Supercluster uses sarcasm to mock the original tweet and affirm the counter-narrative that frames #BlackLivesMatter as supporting violence and implicitly equates black people with violent felons.

A relatively large percentage of cross-supercluster quoted tweets and replies were of left-leaning activists with high follower counts—e.g. 23.0% of quoted tweets were of @ShaunKing and 14.3% were of @deray. This explicit interaction with high status accounts in the other supercluster shows users employing these mechanisms intentionally to confront "leaders" of the other side. These are likely not acts of attempted persuasion, but are perhaps intended instead to utilize the visibility of the challenged account to draw attention to the counter-narrative. They may also serve to highlight the targeted accounts status within the other group, strengthening their gatekeeper role.

4.4 Organizing Political Activism Through Twitter Hashtags

4.4.1 PJNET: Patriotic Journalists Network. During our content analysis of the clusters, we noted the presence of an unfamiliar hashtag within the blue cluster: #PJNET. This hashtag was the third-most common hashtag in profile descriptions within the blue (grassroots organizing) cluster, appearing in 77 account profiles. It also appeared in the profile descriptions of 20 other accounts within the right-learning supercluster. Accounts with the #PJNET hashtag posted *LM tweets in ways that align with typical use from the Right-Leaning Supercluster. These accounts also often included #PJNET in their tweets as well. Together, these accounts posted 168 original tweets with the #PJNET hashtag, and these tweets were retweeted 182 times (36 by other #PJNET accounts in the graph and 146 by others).

To better understand the meaning of the #PJNET hashtag—including how and why it was used—we first looked to see where it appeared within the tweets in our data set. Fig. 4 shows the temporal signature of original tweets (not retweets) containing the #PJNET hashtag.

Prior to the Dallas shootings, the temporal signature of #PJNET tweets aligns with the signature of the broader dataset. However, high volumes of #PJNET activity that come after that event, particularly the activity that begins on August 10, do not line up with the broader conversation. In particular, there are several spikes reaching more than 15 tweets in a day. Examining these spikes, we note that tweets constituting this volume are almost all exact copies of the same tweet—i.e. not retweets, but copies of the same content sent out as original tweets by different accounts. The following tweet was selected from that time period:

```
MT @Boazziz: If U Point A Gun At A Cop & Get Shot, Who's Stupid #BlueLivesMatter
#BlueLivesMatter #PJNET <image>
```

This tweet contains a graphical meme of the type that were popular among the alt-right Twittersphere in 2016 [49]—in this case an image of a hooded individual pointing a gun, overlaid with the text that says "If you point a gun at the police and get shot you're not the victim of anything but your own stupidity" and "Bearing Arms Guns & Patriots". Memes can function as networked framing devices, using repetition and connection to other culturally familiar symbols to render certain ideas more salient [28]. This meme tweet was shared (as an original tweet with the exact content as above) by 29 accounts that had #PJNET within their profile descriptions and 16 others. It constitutes 80% of all original tweets that contain #PJNET. Tweets with this content were retweeted a total of 222 times. 43 of these came from other #PJNET accounts and 179 were from accounts that did not have #PJNET in their descriptions.

The presence of this copied tweet across multiple #PJNET accounts suggested some kind of coordination across this group. Content analysis of #PJNET accounts revealed users who identify as conservative and Christian, often include patriotic imagery in their profiles, and are affiliated with pro-gun, pro-life, pro-Israel, and anti-Islam political stances. Further investigation of the #PJNET hashtag (using online search techniques) led us to the partner website, patriotjournalist.com [56] and revealed a community platform designed to mobilize and organize a grassroots conservative movement. The website contains several important components. The first is an online forum that is publicly accessible through their website. A survey of forum activity suggests the existence of a core group of members who are active on a daily basis and who use the forums both to communicate about organizing efforts as well as to build community and interpersonal ties.

The website also contains a selection of "featured" template tweets, like the one we identified in our data, with instructions for PJNET members to tweet them. Users can nominate an existing tweet—that they create themselves or find elsewhere on Twitter—to be a featured tweet. Most of the #PJNET tweets in our data, especially the tweets shared after August 10, are copies of a featured tweet. Featured tweets must have an image, likely because images make Twitter content more visible and are more likely to be retweeted [26]. In most cases, "MT @", an abbreviation for "modified tweet," is appended to the beginning of the tweet, allowing the downstream user to modify the original tweet while crediting the upstream author. This convention was more common in the early days of Twitter when retweets were manually created and had to conform to character limits. Its use here suggests an effort to garner more visibility for the downstream authors who get "credit" for the retweets of this modified original.

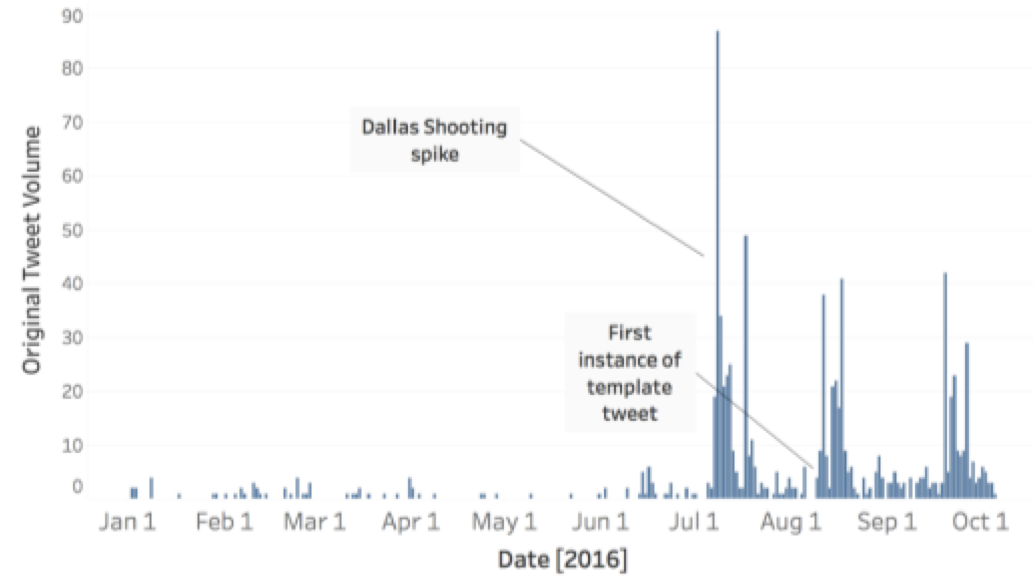

Fig. 4. Temporal Signature of #PJNET Original Tweets (by Day)

Group members can encounter and engage with featured tweets through various mechanisms. On the forum page, there is a list of featured tweets with buttons for tweeting or retweeting the content. PJNET also allows users to schedule their activity through a feature available on their website—which results in many of their accounts appearing to be "cyborgs", at least partially operated by machines.

In the user forum PJNET users regularly discuss scheduling their tweets and retweets. What appears to be a core group of experienced users welcomes new users and help them learn the platform. They also exchange comments that suggest coordination of their activity—for example around "hashtag rallies" and "twitter choirs".

From reviewing PJNET's website, we glean that the primary objective of the PJNET platform is grassroots mobilization of politically conservative Twitter users. The goal of this mobilization is to generate visibility for specific conservative issues (#BlueLivesMatter, #UnbornLives-Matter). Recent research shows PJNET users participating in similar ways within online discourse about "common core" education policies [63].

4.4.2 TGDN and UniteBlue: Orchestrating Social Connections. We found evidence of two similar groups in our data: Twitter Gulag Defense Network (TGDN) and UniteBlue. Both surfaced in 2013 in direct opposition to each other, respectively right-leaning and left-leaning. In both groups, members signified their participation in the network by adding #TGDN or #UniteBlue to their account profile description. While both networks were created with the goal of increasing social connections between members to shield them from Twitter's suspension algorithms [64], [66], the UniteBlue platform also includes organizational affordances reminiscent of PJNET, including local organizing, a "UniteBlue chat," a "LibCrib lounge," and various Twitter integrations. Though UniteBlue, TGDN, and PJNET differ in ideology and purpose, all three used hashtags in their account descriptions and tweets, suggesting that this practice is not restricted to one movement or organizing tactic.

5 DISCUSSION

5.1 Networked Gatekeeping and Frame Contestation in Online Movements

In this paper, extending Meraz and Papacharissi's work, we apply networked gatekeeping and networked framing to examine the underlying structure and dynamics of two competing online social movements. The shared audience network graph allowed us to identify and observe activities within and across two structurally distinct and politically homophilic communities of participation in *LM conversations on Twitter. Integrating network and content analysis revealed a politically left-leaning community of Twitter users who participated in developing and propagating messages aligned with the original meaning of the #BlackLivesMatter hashtag (problematizing violence by police officers against African American citizens), and a politically right-leaning community that produced and disseminated messaging reflecting a counter-frame (problematizing violence from African American citizens).

From a networked gatekeeping perspective, we can conceive of these highly retweeted accounts within the alt-right influencers cluster as the "crowdsourced elite" [17], [51] and observe them performing a gatekeeping function for the larger right-leaning supercluster by largely defining the frames produced and propagated there. From this perspective, the Right Leaning Supercluster appears to have more organization than the Left Leaning Supercluster—with a structurally more well-defined gatekeeper class.

Interestingly and perhaps reflective of the 2016 U.S. Presidential campaign and election that occurred contemporaneously with data collection, our analysis shows the Left-Leaning Supercluster to be more politically fragmented as well. While right-leaning accounts across the distinct communities could be seen to "close ranks" behind their preferred candidate (Donald Trump), left-leaning accounts, though consistent in their support for BLM, expressed divided sentiments about the Democratic candidate (Hillary Clinton). These findings, which suggest more structural cohesion and implicit coordination among right-identified online actors, align with contemporaneous work [29], [49]. More broadly, the audience's construction and selection of frames at the core of networked gatekeeping and networked framing echoes other research on social movements [60].

5.2 The Roles of Hashtags as Gatekeeping Mechanisms

Hashtags, more traditionally embedded in tweets, are notable for crystallizing frame negotiations "on the front stage" [51]. This is especially apparent with the highly contested frames linked to *LM hashtags. While our discourse analysis shows that *LM hashtags serve multiple purposes within each side, perhaps suggestive of "hashtag drift" [13], more prominent are the directly conflicting frames from Right and Left, where "hashtag hijacking" [35] becomes a mechanism to contest the original frame.

Beyond analyzing the discursive frames attached to hashtags in tweets, this paper explores the emergent use of political hashtags in user profiles. Similar to what Bonilla and Rosa described [14], our findings show that hashtags serve diverse purposes within "Twitter activism"—e.g. to mark participation in the conversation, to assert an individual identity, to establish and promote a group identity, to support or challenge a frame, and as a tool for coordinating action. Initially we utilized hashtags within Twitter profiles as an interpretive device to understand individual and group identities. Yet, the relative proliferation of hashtags in profiles within the main clusters—far greater percentages of *LM participants within the superclusters had hashtags in their profiles than *LM participants outside those superclusters (around the periphery of the graph)—suggests that the use of hashtags in profiles may be playing a functional role in organizing those communities as well.

This emerging practice denotes a shift away from having an ambient affiliation with hashtags (through tweets) to a more permanent one (through profiles). This type of self-documentation and disclosure bears similarities to how armbands are sometimes worn to display political allegiances or to identify the wearer to fellow members in a social movement. At the individual level, this way of leveraging political hashtags—a kind of virtual 'armbanding'—can serve to communicate the identities and political or ideological allegiances of their users. At the collective level, this practice can become a powerful way of structuring communities instead of just conversations, as hashtags become a manifestation of group identities and enable group ties and organization by making members visible to others, internally and externally. And in the context of explicit framing contests, it could reflect a strategy for garnering support during users' forays into the conversation spaces of the 'opposing side'.

Considered from the perspective of networked gatekeeping, hashtag use within account profiles can be seen as a "channeling" mechanism, which Barzilai-Nahon defines as using "gateway stations designed to attract the attention of gated and convey or direct them into or through their channels" [4]. This spreading norm therefore functions to establish and protect the boundaries of the gated community, signaling to potential members and non-members about the kinds of topics (and frames) that are present and conversely those that are off-limits within the networked group.

5.3 "Grassroots" Activism as Networked Gatekeeping and Framing

Explicit network gatekeeping practices, including channeling, are also apparent in the activities of the Patriotic Journalist Network (PJNET). PJNET is an online community with a stated goal of grassroots mobilization of politically conservative Twitter users. Members are encouraged to add #PJNET to their Twitter profile descriptions to signal their membership to current members within the group and promote the group to potential members outside of it. The organization provides resources for the "gated" to help construct and disseminate specific messages, to some extent collectively chosen, but inherently aligned with the gatekeepers (the forum administrators') preferred frames.

The use of graphical memes by PJNET (and online social movements more broadly) can also be viewed through the lens of networked framing [51]. Entman argues that framing occurs through selection and salience—whereby a preferred message is chosen and promoted [28]. Speaking to the selection aspect, the PJNET community employs a crowdsourced process—members nominate and submit memes through an online forum, community leaders select the preferred memes, and members then distribute these messages through their individual accounts. Through this process, the group collectively decides what the preferred message is and amplifies that message—with community leaders performing the gatekeeping-framing function of selection. Graphical memes are particularly well-suited (and perhaps intentionally designed) for the salience aspect of framing, which Entman describes as "making a piece of information more noticeable, meaningful, or memorable to audiences," which can be done through "placement or repetition, or by associating [it] with culturally familiar symbols" [28]. The meme promoted by #PJNET accounts within our dataset was rendered meaningful within the context of the #BlackLivesMatter discourse and functioned both to directly contest the original #BlackLivesMatter frame and to promote a counter-frame of #BlueLivesMatter. Memes become relevant and perform their salience function through propagation and amplification, which can occur when a message goes viral. PJNET accelerates that process utilizing coordinated and automated tweeting practices that serve to simulate and/or to trigger virality. The use of memes in this way—and PJNET's broader range of online tactics—demonstrate "grassroots" activism groups utilizing intentional tactics of networked gatekeeping and networked framing to shape online discourse.

6 CONCLUSION

This research applies an integrated networked gatekeeping and networked framing lens to explore frame production and contestation in the context of the BlackLivesMatter movement. Utilizing a shared audience graph to identify structurally and ideologically distinct groups of participants, we examine framing practices within and between competing social movements—revealing the mechanisms of networked frame contests on Twitter. This research makes three kinds of contributions. Conceptually, it further articulates an approach for integrating networked gatekeeping and networked framing to understand the production and maintenance of online social movements. Methodologically, it demonstrates the utility of using a shared audience graph as an interpretative artifact to guide the investigation of contested frames. And empirically, it reveals the underlying structure of the BlackLivesMatter discourse, as well as the use of specific strategies (e.g. hashtags in profiles) that help to shape that structure, and tactics for contesting narratives (e.g. quoted tweets) between distinct structural groups.

ACKNOWLEDGMENTS

This research is a collaboration between the emCOMP lab and DataLab at the University of Washington and was supported by National Science Foundation Grant 1420255. We also wish to thank the UW SoMe Lab for providing infrastructure support.

REFERENCES

[1] Lada A. Adamic and Natalie Glance. 2005. The Political Blogosphere and the 2004 U.S. Election: Divided They Blog. In *Proceedings of the 3rd international workshop on Link discovery*, 36-43. DOI: 10.1145/1134271.1134277

[2] Monica Anderson and Paul Hitlin. 2016. Social Media Conversations About Race: How social media users see, share, and discuss race and the rise of hashtags like #BlackLivesMatter. August 15, 2016. Retrieved April 23, 2017 from http://www.pewinternet.org/2016/08/15/social-media-conversations-about-race/

[3] Ahmer Arif, Kelley Shanahan, Fang-Ju Chou, Yoanna Dosouto, Kate Starbird, Emma Spiro. 2016. How Information Snowballs: Exploring the Role of Exposure in Online Rumor Propagation. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing*, 446-477. DOI: 10.1145/2818048.2819964

[4] Karine Barzilai-Nahon. 2008. Toward a theory of network gatekeeping: A framework for exploring information control. *Journal of the American society for information science and technology*. 59, 9 (2008), 1493-1512. DOI: 10.1002/asi.20857

[5] Mathieu Bastian, Sebastien Heymann and Mathieu Jacomy. 2009. Gephi: An Open Source Software for Exploring and Manipulating Networks. In *Proceedings of the International AAAI Conference on Weblogs and Social Media*. DOI: 10.13140/2.1.1341.1520

[6] Robert D. Benford. 1993. Frame disputes within the nuclear disarmament movement. *Social forces*. 71, no. 3 (1993), 677-701. DOI: 10.2307/2579890

[7] Robert D. Benford. 1987. Framing activity, meaning, and social-movement participation: the nuclear-disarmament movement. Univ. of Texas, Austin (USA).

[8] Robert D. Benford and David A. Snow. 2000. Framing processes and social movements: An overview and assessment. *Annual Review of Sociology*, 26, 1 (2000), 611-639. DOI: 10.1146/annurev.soc.26.1.611

[9] W. Lance Bennett, Alexandra Segerberg and Shawn Walker. 2014. Organization in the crowd: peer production in large-scale networked protests. *Information, Communication & Society*, 17, 2, 232-260. DOI: 10.1080/1369118X.2013.870379

[10] Vincent D Blondel, Jean-Loup Guillaume, Renaud Lambiotte and Etienne Lefebvre. 2008. Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment*. DOI: 10.1088/1742-5468/2008/10/P10008

[11] Black Lives Matter. 2017. About. Retrieved July 8th, 2017 from http://blacklivesmatter.com/about/

[12] Blue Lives Matter. 2017. About Us – Blue Lives Matter. Retrieved April 23, 2017 from https://bluelivesmatter.blue/organization/

[13] Kyle Booten. 2016. Tracing the Evolving Use of Political Hashtags Over Time. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems,* 2401-2405. DOI: 10.1145/2858036.2858398

[14] Yarimar Bonilla and Jonathan Rosa. 2015. #Ferguson: Digital protest, hashtag ethnography, and the racial politics of social media in the United States. *American Ethnologist*, 42, 1 (February 2015), 4-17. DOI: 10.1111/amet.12112

[15] Rachel K. Brickner. 2016. Tweeting Care: Educators' Dissent through Social Media in the US and Canada. *Labour/Le Travail*, 77 (Spring 2016), 11-36. DOI: 10.1353/llt.2016.0022

[16] Axel Bruns. 2003. Gatewatching, not gatekeeping: Collaborative online news. *Media International Australia Incorporating Culture and Policy*. 107, 1 (2003), 31-44. DOI: 0.1177/1329878X0310700106

[17] Candis Callison and Alfred Hermida. 2015. Dissent and Resonance: #IdleNoMore as an Emergent Middle Ground. *Canadian Journal of Communication*, 40 (2015), 695-716. DOI: 10.22230/cjc.2015v40n4a2958

[18] Nikita Carney. 2016. All Lives Matter, but so Does Race. *Humanity & Society*, 40, 2, 180-199. DOI: 10.1177/0160597616643868

[19] Andrew Chadwick. 2011. The political information cycle in a hybrid news system: The British prime minister and the "Bullygate" affair. *The International Journal of Press/Politics*. 16, 1 (2011), 3-29. DOI: 10.1177/1940161210384730

[20] Kathy Charmaz. 2006. *Constructing Grounded Theory: A Practical Guide Through Qualitative Analysis*. Sage Publications Ltd, London, UK. DOI: 10.1016/j.lisr.2007.11.003

[21] Roberta L. Coles. 1998. Peaceniks and warmongers' framing fracas on the home front: dominant and opposition discourse interaction during the Persian Gulf crisis. *The sociological quarterly,* 39, 3 (1998), 369-391. DOI: 10.1111/j.1533-8525.1998.tb00509.x

[22] Elanor Colleoni, Alessandro Rozza and Adam Arvidson. 2014. Echo Chamber or Public Sphere? Predicting Political Orientation and Measuring Political Homophily in Twitter Using Big Data. *Journal of Communication*, 64, 2 (April 2014), 317-332. DOI: 10.1111/jcom.12084

[23] Dharma Dailey and Kate Starbird. 2014. Journalists as crowdsourcerers: Responding to crisis by reporting with a crowd. *Computer Supported Cooperative Work*. 23, 4-6 (2014), 445-481. DOI: 10.1007/s10606-014-9208-z

[24] Scott Davies. 1999. From moral duty to cultural rights: A case study of political framing in education. *Sociology of Education.* (1999), 1-21. DOI: 10.2307/2673183

[25] Munmun De Choudhury, Shagun Jhaver, Benjamin Sugar and Ingmar Weber. 2016. Social Media Participation in an Activist Movement for Racial Equality. In *Proceedings of the Tenth International AAAI Conference on Web and Social Media*. Retrieved August 19th, 2017

[26] F. J. Ruiz del Olmo and J. Bustos Díaz. 2016. From tweet to photography, the evolution of political communication on Twitter to images. The case of the debate on the State of the Nation in Spain. 2015. *Revista Latina de Comunicación Social*, 71 (2016), 108-123. DOI: 10.4185/RLCS-2016-1086en

[27] Jill P. Dimond, Michaelanne Dye, Daphne LaRose and Amy S. Bruckman. 2013. Hollaback!: the role of storytelling online in a social movement organization. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work*, 477-490. DOI: 10.1145/2441776.2441831

[28] Robert M. Entman. 1993. Framing: Toward clarification of a fractured paradigm. *Journal of Communication*. 43, 4 (1993), 51-58. DOI: 10.1111/j.1460-2466.1993.tb01304.x

[29] Robert M. Faris, Hal Roberts, Bruce Etling, Nikki Bourassa, Ethan Zuckerman and Yochai Benkler. 2017. Partisanship, Propaganda, and Disinformation: Online Media and the 2016 U.S. Presidential Election. Berkman Klein Center for Internet & Society. http://nrs.harvard.edu/urn-3:HUL.InstRepos:33759251

[30] William A. Gamson. 1995. Constructing social protest. In *Social movements and culture,* Hank Johnston and Bert Klandermans (eds.), University of Minnesota Press, Minneapolis, Minnesota, US, 85-106. DOI: 10.4324/9781315072562

[31] R. Kelly Garrett. 2006. Protest in an information society: A review of literature on social movements and new ICTs. *Information, Communication & Society*, 9, 2 (2006), 202-224. DOI: 10.1080/13691180600630773

[32] Erving Goffman. 1974. *Frame analysis: An essay on the organization of experience*. Harvard University Press, Cambridge, Massachusetts, US

[33] Lev Grossman. 2009. Iran Protests: Twitter, the Medium of the Movement. (June 17, 2009). Retrieved April 25, 2017 from http://content.time.com/time/ world/article/0,8599,1905125,00.html

[34] Jessica Guynn. 2015. Meet the woman who coined #BlackLivesMatter. (March 4, 2015). Retrieved April 23, 2017 from https://www.usatoday.com/story/tech/2015/03/04/alicia-garza-black-lives-matter/24341593/#

[35] Asmelash Teka Hagdu, Kiran Garimella and Ingmar Weber. 2013. Political hashtag hijacking in the U.S. In Proceedings of the 22nd International Conference on World Wide Web, 55-56. DOI: 10.1145/2487788.2487809

[36] Stuart Hall. 1982. The rediscovery of 'ideology': Return of the repressed in media studies. In *Cultural, Society, and the Media*, Michael Gurevitch, Tony Bennet, James Curran and Janet Woollacott (eds.), 52-86, Routledge, London, UK. ISBN: 0-203-97809-9

[37] Karim Hamza. 2014. Social media as a tool for social movements in Arab spring countries. In *Proceedings of the 8th International Conference on Theory and Practive of Electronic Governance*, 71-74. DOI: 10.1145/2691195.2691241

[38] Summer Harlow and Thomas J. Johnson. 2011. Overthrowing the Protest Paradigm? How *The New York Times*, Global Voices and Twitter Covered the Egyptian Revolution. *International Journal of Communication*, 5, 1359-1374. Available at <http://ijoc.org/index.php/ijoc/article/view/1239>

[39] Brent Hecht, Lichan Hong, Bongwon Suh and Ed H. Chi. 2011. Tweets from Justin Bieber's Heart: The Dynamics of the "Location" Field in User Profiles. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 237-246. DOI: 10.1145/1978942.1978976

[40] Alfred Hermida. 2013. #Journalism: Reconfiguring journalism research about Twitter, one tweet at a time. Digital Journalism, 1, 3, 295-313. DOI: 10.1080/21670811.2013.808456

[41] Sarah J. Jackson and Brooke Foucault Welles. 2015. Hijacking #myNYPD: Social Media Dissent and Networked Counterpublics. *Journal of Communication*, 65, 6 (December 2015), 932-952. DOI: 10.1111/jcom.12185

[42] Hank Johnston. 2002. A methodology for frame analysis: From discourse to cognitive schemata. In *Methods of Social Movement Research*, Bert Klandermans and Suzanne Staggenbord (eds.), University of Minnesota Press, Minneapolis, Minnesota, US, 2l7-246. ISBN: 978-0816635948

[43] Brian Keegan and Darren Gergle. 2010. Egalitarians at the gate: One-sided gatekeeping practices in social media. In *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work*, 131-134, DOI: 10.1145/1718918.1718943

[44] Sherry Lowrance. 2016. Was the Revolution Tweeted? Social Media and the Jasmine Revolution in Tunisia. *Digest of Middle East Studies*, 25, 1 (Spring 2016), 155-176. DOI: 10.1111/dome.12076

[45] Kwan Hui Lum and Amitava Datta. 2012. Finding twitter communities with common interests using following links of celebrities. In *Proceedings of the 3rd international workshop on Modeling social media*, 25-32. DOI: 10.1145/2310057.2310064

[46] Kwan Hui Lum and Amitava Datta. 2012. Tweets Beget Propinquity: Detecting Highly Interactive Communities on Twitter using Tweeting Links. In *Proceedings of the The 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology*, 214-221. DOI: 10.1109/WI-IAT.2012.53

[47] Jim Maddock, Kate Starbird, Haneen J. Al-Hassani, David E. Sandoval, Mania Orand, Robert M. Mason. 2015. Characterizing Online Rumoring Behavior Using Multi-Dimensional Signatures. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 228-241. DOI: 10.1145/2675133.2675280

[48] George E. Marcus. 1995. Ethnography in/of the World System: The Emergence of Multi-Sited Ethnography. *Annual Review of Anthropology*, 24 (October 1995), 95-117. DOI: 10.1146/annurev.an.24.100195.000523

[49] Alice Marwick and Rebecca Lewis. 2017. Media Manipulation and Disinformation Online. *Data & Society* (2017). Retrieved August 19th, 2017 from https://datasociety.net/pubs/oh/DataAndSociety_MediaManipulationAndDisinformationOnline.pdf

[50] Adrienne Massanari. 2017. #Gamergate and The Fappening: How Reddit's algorithm, governance, and culture support toxic technocultures. *New Media & Society*, 19, 3 (March 1, 2017), 329-346. DOI: 10.1177/1461444815608807

[51] Sharon Meraz and Zizi Papacharissi. 2013. Networked Gatekeeping and Networked Framing on #Egypt. *The International Journal of Press/Politics*, 18, 2 (April 2013), 138-166. DOI: 10.1177/1940161212474472

[52] Jared Newman. 2015. Twitter's 'Quote Tweet' revamp leaves more room for your thoughts. (April 7, 2015). Retreived April 24, 2017 from http://www.pcworld.com/article/2906764/twitters-quote-tweet-revamp-leaves-more-room-for-your-thoughts.html

[53] Alexandra Olteanu, Ingmar Weber and Daniel Gatica-Perez. 2016. Characterizing the Demographics Behind the #BlackLivesMatter Movement. In *AAAI Spring Symposia on Observational Studies through Social Media and Other Human-Generated Content*, 310-313, AAAI Press, Palo Alto, California, US.Retrieved August 19th, 2017 from https://www.aaai.org/ocs/index.php/SSS/SSS16/paper/view/12720/11945

[54] Yusuke Ota, Kazutaka Maruyama and Minoru Terada. 2012. Discovery of Interesting Users in Twitter by Overlapping Propagation Paths of Retweets. In *Proceedings of the The 2012 IEEE/WIC/ACM International Joint Conferences on Web Intelligence and Intelligent Agent Technology*, 274-279. DOI: 10.1109/WI-IAT.2012.110

[55] Zizi Papacharissi. 2015. *Affective publics: Sentiment, technology, and politics*. Oxford University Press, New York, New York, US. DOI: 10.1093/acprof:oso/9780199999736.001.0001

[56] Patriot Journalist Network. Retrieved July 9th, 2017 from http://www.patriotjournalist.com

[57] Dana Rotman, Jennifer Preece, Yuron He, and Allison Druin. 2012. Extreme ethnography: Challenges for research in large scale online environments. In *Proceedings of the 2012 iConference*, 207-214. DOI: 10.1145/2132176.2132203

[58] Charlotte Ryan. 1991. *Prime time activism: Media strategies for grassroots organizing*. South End Press, Boston, Massachusetts, US.

[59] Julian Sanchez. 2016. Keep calling the alt-right 'the alt-right.' Soon, it won't be a euphemism anymore. (November 28, 2016). Retrieved April 24, 2017 from https://www.washingtonpost.com/posteverything/wp/2016/11/28/keep-calling-the-alt-right-the-alt-right-soon-it-wont-be-a-euphemism-anymore/.

[60] Saiph Savage and Andrés Monroy-Hernandez. 2015. Participatory Militias: An Analysis of an Armed Movement's Online Audience. In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing. 724-733. DOI: 10.1145/2675133.2675295

[61] Pamela J. Shoemaker and Timothy Vos. 2009. *Gatekeeping theory*. Routledge, New York, New York, US. DOI: 10.4324/9780203931653

[62] Cass Sunstein. 2001. *Republic.com*. Princeton University Press, Princeton, New Jersey, US. ISBN: 978-0691070254

[63] Jonathan Supovitz, Alan J. Daly, Miguel del Fresno, Christian Kolouch. 2017. #commoncore Project. Retrieved April 26, 2017 from www.hashtagcommoncore.com

[64] Twitter Gulag Defense Network. 2013. Twitter Gulag Defense Network. (April 16, 2013 via the Wayback Machine). Retrieved April 24, 2017 from https://web.archive.org/web/20130416134130/tgdn.org

[65] Marlon Twyman, Brian C. Keegan and Aaron Shaw. 2016. Black Lives Matter in Wikipedia: Collaboration and Collective Memory around Online Social movements. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*, 1400-1412. DOI: 10.1145/2998181.2998232

[66] UniteBlue. 2013. UniteBlue. (October 11, 2013 via the Wayback Machine). Retrieved April 24, 2017 from https://web.archive.org/web/20131011234824/uniteblue.org

[67] Onur Varol, Emilio Ferrara, Christine L. Ogan, Filippo Menczer and Alessandro Flammini. 2014. Evolution of online user behavior during a social upheaval. In *Proceedings of the 2014 ACM Conference on Web Science*, 81-90. DOI: 10.1145/2615569.2615699

[68] Beidou Wang, Can Wang, Jiajun Bu, Xiaofei He. 2013. Whom to Mention: Expand the Diffusion of Tweets by @ Recommendation on Micro-blogging Systems. In *Proceedings of the 22nd International Conference on World Wide Web*, 1331-1340. DOI: 10.1145/2488388.2488505

[69] Aaronette M. White. Talking feminist, talking Black: Micromobilization Processes in a Collective Protest against Rape. *Gender & Society,* 13, 1 (1999), 77-100. DOI: 10.1177/089124399013001005

Received April 2017, revised June 2017, accepted August 2017