Activist and Counter-Protest Movements in Tandem: A Longitudinal Analysis of #BlackLivesMatter

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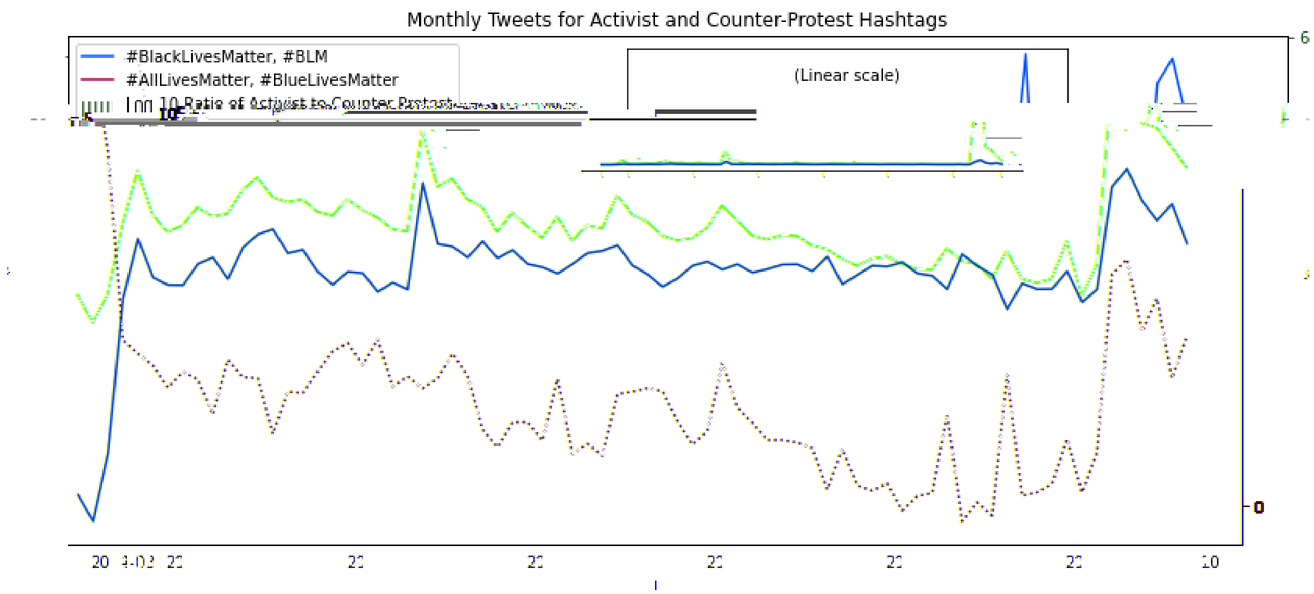

Figure 1: #BlackLivesMatter hashtag activism is characterized by peaks, downturns, and vigorous counter-protest

ABSTRACT

The #BlackLivesMatter movement is one of the most successful and enduring examples of hashtag activism. Yet its history includes significant downturns and the challenge of a robust counter-protest movement organized around opposing hashtags such as #AllLivesMatter and #BlueLivesMatter. Analysis focused on peak-period tweets of #BlackLivesMatter will therefore overlook important dynamics of hashtag activism. The movements do not evolve in isolation; rather, a dynamic interplay through distinct phases is observed.

In this paper, we conduct a longitudinal study of Twitter datasets from two periods through phases of struggle, surge and consolidation. After segmenting the data into activist and counter-protest communities in each phase, we apply measures of Twitter activity, sentiment polarity, emotion detection, social awareness, and diffusion to understand the evolution of the two opposing movements along several dimensions:

- *Framing Strategies*: The two movements have used hashtag framing to contest the definition of victimhood. The counter-protest movement has also engaged in an aggressive campaign of hashtag hijacking.
- *Language Expression*: Activists' measures of sentiment polarity and social awareness have generally been higher than counter-protesters', while counter-protest tweets have generally contained higher shares of fear words. Frequency of activist anger expressions shifted according to phase.
- *Network Analysis*: The #BlackLivesMatter movement has been distributed across a loose coalition of communities organized around attributes such as locality or profession. The coalition has grown as new communities organized around related concerns have joined the fold. The counter-protest movement, by contrast, has been concentrated in one or two communities per language, and has grown by adding members to existing communities. #BlackLivesMatter activism

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has long traversed language barriers, while significant foreign language counter-protest communities did not appear until the last half of 2020.

CCS CONCEPTS

• **Applied computing** → **Sociology**; • **Human-centered computing** → Social media; Social network analysis; • **Computing methodologies** → Natural language processing.

KEYWORDS

social media, activist movement, counter-protest movement, social networks, sentiment analysis, emotion recognition, lexical semantics

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1 INTRODUCTION

According to Parham [15], #BlackLivesMatter hashtag activism traces its roots back to the Black Twitter movement. Black Twitter was a real-time forum on Twitter for millenial blacks to share jokes, inside cultural references ("#uknowurblackwhen u cancel plans when its raining"), and real-time conversation about the latest episode of *Scandal*. When news of Trayvon Martin's death hit the news wire, though, conversations on Black Twitter began to take an activist turn.

The protest conversation on Black Twitter became more prominent when white police officer Darren Wilson shot and killed Michael Brown in Ferguson, Missouri on August 9, 2014 [16]. Before the major news networks even picked up the story, the Black Twitter community began rapidly retweeting reports from the streets by Ferguson residents. Initially, the #Ferguson hashtag was the focus of hashtag activism, but it was soon overtaken by the more thematic #BlackLivesMatter. Black Twitter had ushered in an activist movement that would take on a life of its own.

As seen in hashtag counts downloaded from [2] and visualized in Figure 1, the #BlackLivesMatter online movement has experienced three major peaks in activity:

(1) In November and December of 2014, in the wake of the shooting death of Cleveland youth Tamir Rice;
(2) In the 2016 NFL season, when Colin Kaepernick first took a knee during the playing of the National Anthem; and
(3) In the summer of 2020, in the wake of George Floyd's murder by Minneapolis police officer Derek Chauvin.

However, the movement has not experienced consistent growth. Between the second and third peaks, #BlackLivesMatter hashtag activism dropped precipitously until, in early 2020, it was far lower than it had been at any point since October 2014.

Figure 1 also shows that #BlackLivesMatter cannot be fully understood without also studying the corresponding counter-protest movement, characterized by the hashtags #AllLivesMatter and #BlueLivesMatter. The counter-protest movement largely tracked the activist movement at some distance through the first two years, but during the first three years of the Trump presidency its hashtag volume gradually drew equal with that of the activist movement.

In this paper we address the following research questions about #BlackLivesMatter activist and counter-protest movements during the periods under study:

- *RQ 1: How can statistical techniques be used to identify phases of struggle, surge, and consolidation in an activist movement?*
- *RQ 2: How did measures of activity, sentiment polarity, emotion recognition, and social awareness evolve in the activist and counter-protest movements?*
- *RQ 3: How did the activist and counter-protest movements use hashtags to promote their contesting narratives?*
- *RQ 4: How did the activist and counter-protest movements diffuse across geographical, linguistic, political, and professional categories?*

While there is a network of legally incorporated Black Lives Matter advocacy groups, the subject of this paper is the much broader, online activist movement that uses the #BlackLivesMatter hashtag. We will occasionally use the abbreviation BLM as a reference to this broader #BlackLivesMatter activist movement.

2 BACKGROUND AND PRIOR WORK

Many papers have studied #BlackLivesMatter hashtag activism in the context of short periods: either a single, short period [4, 12, 17] or a series of event-focused episodes [6, 8]. Some papers have analyzed a dataset gathered over 6 - 12 months but have treated the dataset as coming from a single undifferentiated period rather than multiple phases [7, 18]. A notable exception to this trend is Wu et al. [25], which tracked the mention of the names of Black victims over periods of waxing and waning interest across 12 years.

Retweet edges are commonly used to detect homophilous communities in a network of Twitter accounts. Hadgu et al. [9] labeled political homophily according to retweets of well-known politicians, and Darius and Stephany [5] used retweet edges as input to the Louvain community detection algorithm for a Twitter dataset focused on German political debate. In 2016, only 1.11% of retweets crossed the boundary between liberal and conservative superclusters [18], providing confidence that retweet edges do in fact signal homophily in BLM Twitter data.

Several studies have noted the use of hashtags as means of framing the rationale and strategies of Twitter activism. According to Stewart et al. [18], #BlackLivesMatter activists have used hashtags to highlight police misconduct, to memorialize victims, and to call for protest. In response, counter-protest influencers have used hashtags to frame the activists as opposed to law and order and to justify law enforcement actions against protesters.

As movements debate one another, they can engage in a framing contest by attempting to hijack opposing hashtags. Hashtag hijacking, defined by Darius and Stephany [5] as "the use of someone else's hashtag in order to promote one's own social media agenda," is a debate tactic available to both sides of an online argument [9]. Counter-protest influencers in 2016 used hashtag hijacking as a means of reframing the BLM movement as violent and felonious [18], for example.

According to protest theoretician Sidney Tarrow [20], loyalty, anger, and optimism are among emotions that can mobilize a protest movement. De Choudhury, et al. [6] found that usage of anger words and usage of first person singular pronouns in tweets were negatively correlated with offline BLM protest, but usage of first person plural and second person pronouns were positively correlated with offline protest.

3 DATA AND METHODS

3.1 Twitter Data

We collected two corpora of Black Lives Matter tweets in November 2020. The first is a set of tweets corresponding to #BlackLivesMatter status IDs that we downloaded from the CrisisLex online database[14]. This set includes all #BlackLivesMatter tweets published in the period August 9, 2014 to May 8, 2015 that could still be accessed via the Twitter API. The second contains tweets with the hashtags *#BlackLivesMatter* and *#BLM* included in the Twitter Decahose API during the period January 1, 2020 to October 31, 2020. The tweets were collected from the Indiana University Observatory on Social Media, which maintains a database of Decahose tweets dating back three years for researchers associated with Indiana University.

Throughout, we adopt the convention of [2] in classifying each tweet as either an *original tweet* or a *retweet*.

Due to the confounding effect of hashtag hijacking, simple hashtag volume cannot be treated as an indicator of activist or counter-protest Twitter activity. Instead, we used community and stance detection techniques (described in Section 3.3.1 below) to infer Twitter activity of the competing movements from the tweet corpora.

3.2 Identification of Movement Phases

To establish the volume of activity in the primary activist hashtags (#BlackLivesMatter, #BLM) and counter-protest hashtags (#AllLivesMatter, #BlueLivesMatter) from August 2014 to October 2020, we queried [2].

In our qualitative analysis of the daily tweet frequencies, we saw that each period started with a relatively flat phase of activity, followed by a surge phase in which activity increased by 2 to 3 orders of magnitude, and then a period of a few months in which activity decreased by approximately an order of magnitude. We labeled the three chronological phases as "Struggle," "Surge," and "Consolidation," respectively.

To identify the boundaries of the phases, we used the bottom-up change point detection method implemented in the Python `ruptures` library[22]. This method begins with a segment for each observation, then continuous segments are merged according to their similarity as measured by the `L2` loss function. We set the number of breakpoints to 2 to demarcate the 3 phases.

3.3 Social Network Analysis

3.3.1 Community Identification. We built a network of Twitter account nodes and directed retweet edges for each of the six chronological phases. The weight of each edge was the number number of times an account retweeted the linked account. We used the `leidenalg` Python library, an implementation of the Leiden algorithm [21], to detect homophilous communities in the network. For each phase, we excluded communities from analysis which did not meet a threshold number of original tweets. The thresholds, depicted by dashed lines in Figure 3, were set to maximize the inclusion of original tweets in community analysis while minimizing the inclusion of insignificant communities.

We identified the stance (activist or counter-protest) of the communities in each phase by the following steps:

(1) We assigned a stance label to the 40 largest communities by qualitative examination of their top retweets and memes.
(2) We trained a phase-specific Naive Bayes model on leading retweets of those communities.
(3) The model predicted the stance label for the remaining communities using the weighted average of their most popular retweets. We assigned the label *Unknown* to communities without a strong lean toward one of the opposing stances.

3.3.2 Twitter Activity. Because the phases under study vary in length, we used *per diem* measures of activity.

- *Original tweets per day* - An original tweet is a status post not having previously appeared.
- *Retweets per day* - A retweet repeats another account's status to a new set of followers. It typically signifies a desire to amplify the retweeted status; in modern slang, *retweet* means "I agree" [23].

3.4 Diffusion

We observed the diffusion of the activist and counter-protest movements on social media along several dimensions:

- *Linguistic*: We used Google Translate to detect the language of non-English tweets.
- *Geographic*: We identified hashtags with geographic connotations, such as the name of a city (e.g., *#millionsmarchnyc*)
- *Profession*: We identified hashtags with connotations of profession (e.g., *#lawyerdiein*).
- *Argumentation*: We identified hashtags connoting forms of strategic framing such as reminders of victims' names (e.g, *#tamirrice*) or citations of perceived injustices ignored by the opposing movement (e.g., *#abortion*).

3.5 Sentiment Polarity, Emotion Recognition, and Social Awareness

We used natural language processing techniques to measure the sentiment polarity, emotions, and social awareness expressed in tweets.

- *Sentiment polarity*: We used the NLTK implementation of VADER (Valence Aware Dictionary and sEntiment Reasoner)[10] to measure the sentiment polarity of each tweet on a scale from completely positive (1.0) to completely negative (-1.0).
- *Emotion Recognition*: We used the Python `nrclex` library to identify the count of words associated with eight emotions (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust) according to the National Research Council Canada Word-Emotion Association Lexicon[13]. For each tweet, we divided the emotion word counts by the total of lexicon words to derive the percentage of each emotion. We assigned a percentage of zero for all emotions to tweets with no lexicon words.

- *Social Awareness*: We used the Python open-source `textblob` library[1] to tokenize each tweet, then used a list of standard English pronouns classified by their person and number to derive the percent usage of each of four classes (first person singular (1s), first person plural (1p), second person singular and plural (2d), and third person singular and plural (3d)). Tweets with no pronouns were assigned a percent usage of zero for all classes.

4 RESULTS

4.1 RQ 1: Identification of Movement Phases

In figure 2, the Y-axis is scaled logarithmically because of the explosion in #BlackLivesMatter/#BLM hashtag use during the surge phases. The green and red dotted lines demarcate the surge boundaries identified by change point analysis.

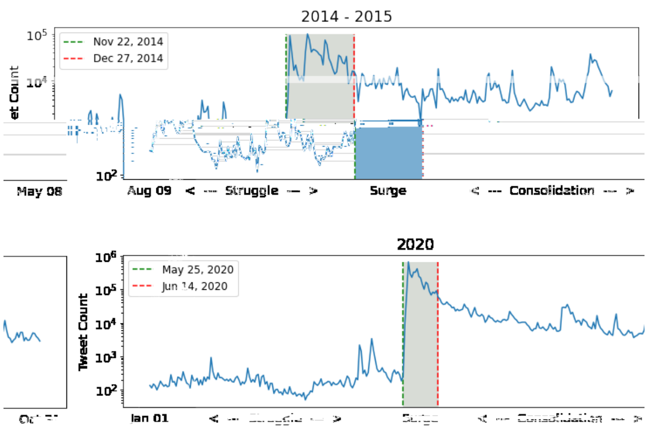

Figure 2: Identification of BLM Online Activism Phases

In the 2014-2015 period, change point analysis identified November 22, 2014 and December 26, 2014 as the first and last days of the surge in #BlackLivesMatter tweets. In the 2020 period, change point analysis identified May 25 and June 13 as the first and last days of the surge in #BlackLivesMatter tweets.

4.2 RQ 2: Activity, Sentiment Polarity, Emotion Recognition, and Social Awareness by Stance

4.2.1 Stance Identification. As seen in Figure 3, the relationship of original tweets per community (y axis) to number of communities having that number of original tweets (x axis) exhibits a power-law distribution in the long tail. The per-phase activity threshold filtered out 98.7% of communities from analysis due to their low activity; the remaining communities exhibited 91.1% of the activity, as measured by original tweets.

4.2.2 Activity by Stance. As seen in Table 1, the number of accounts supporting #BlackLivesMatter activism increased dramatically during both surge phases, then decreased modestly in subsequent consolidation phases to a level about an order of magnitude higher

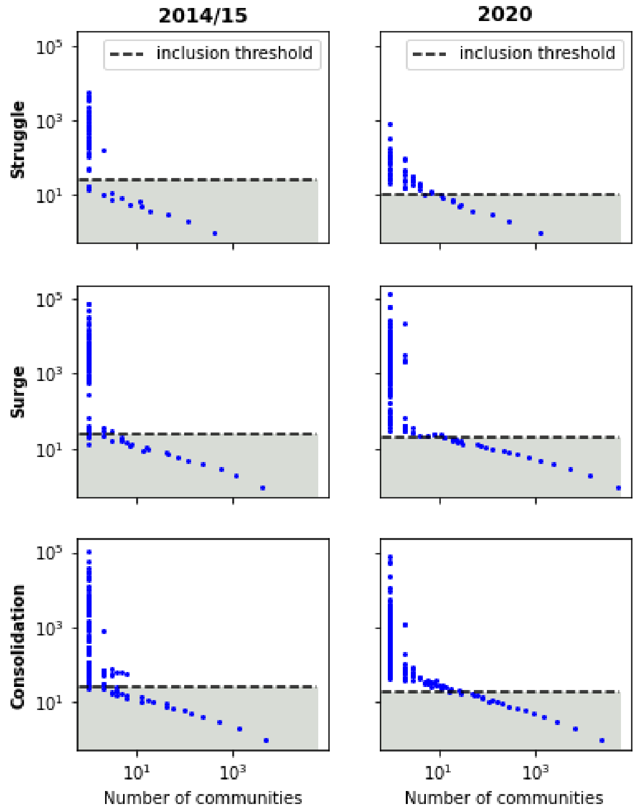

Figure 3: Original Tweet Count by Community Count

Table 1: Number of Accounts By Stance

Period	Phase	Activist	Counter-Protest
2014 - 2015	Struggle	24,675	606
"	Surge	248,173	9,565
"	Consolidation	199,286	14,492
2020	Struggle	7,963	45
"	Surge	1,471,656	65,414
"	Consolidation	403,632	171,240

than in the previous struggle phase. Counter-protest accounts likewise increased sharply during the surge phase, albeit from a lower base. However, counter-protest participation continued to grow while activist participation was ebbing during the consolidation phase.

Table 2 shows the average total Twitter activity (both original tweets and retweets) across the phases. In both periods, individual activist Twitter activity increased strongly during the surge phase and continued to increase by a small increment during the consolidation phase. Twitter activity by counter-protest accounts grew quite strongly during the consolidation phase.

As shown in Table 3, activist and counter-protest accounts exhibited almost indistinguishable ratios of retweets to original tweets

Table 2: Average Tweets/Day By Stance

Period	Phase	Activist	Counter-Protest
2014 - 2015	Struggle	3.23	2.49
"	Surge	3.86	2.72
"	Consolidation	4.11	3.38
2020	Struggle	1.31	1.87
"	Surge	1.72	1.75
"	Consolidation	1.76	2.58

Table 3: Ratio of Retweets to Original Tweets

	2014-2015		2020	
Phase	Activist	Counter-Protest	Activist	Counter-Protest
Struggle	0.97	0.98	3.45	1.41
Surge	0.98	0.94	2.56	2.63
Consolidation	0.70	0.71	2.00	1.79

(hereafter, retweet ratio) during the 2014-2015 period. While [3] estimates the overall English retweet ratio as approximately 0.6 during the 2014-2015 period, retweet activity around #BlackLivesMatter was approximately 60% higher during the struggle and surge phases. However, retweet activity fell to a level roughly equal to the overall English language retweet ratio during the consolidation phase.

During the 2020 period, the retweet ratios of both communities during the surge phase (2.56 and 2.63) once again vastly exceeded the overall English language ratio (approximately 1.4) and fell during the consolidation phase to 2.00 (activist) and 1.79 (counter-protest).

Table 4: Sentiment Polarity of All Tweets

	2014-2015		2020	
Phase	Activist	Counter-Protest	Activist	Counter-Protest
Struggle	0.00	-0.31	-0.21	0.28
Surge	-0.04	-0.16	0.03	-0.18
Consolidation	-0.04	-0.23	-0.05	-0.16

4.2.3 Sentiment Polarity, Emotions, and Social Awareness. The difference in average sentiment polarity between activist and counter-protest movements (Table 4) is significant at $p < .000001$ (Welch's unequal variances t-test).

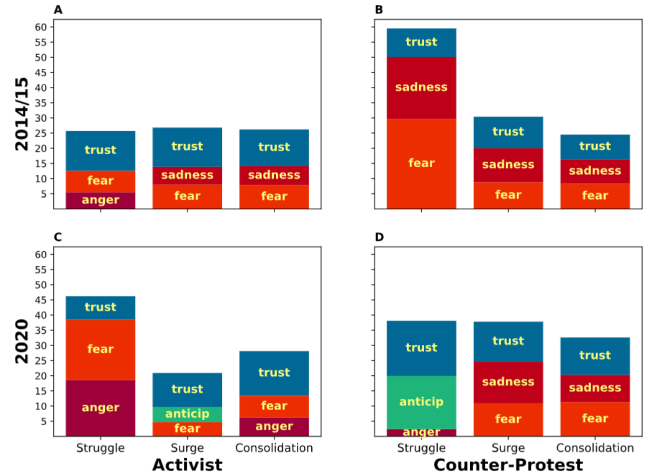

Figure 4: Top 3 Emotions Detected

The most prominent emotions detected in both activist and counter-protest movements were trust and fear (Figure 4). Notable observations include:

- While fear was most prevalent for the activist movement in the struggle phase of 2020 (Figure 4C), the counter-protest movement expressed its greatest fear at the inception of the #BlackLivesMatter movement in 2014-2015 (Figure 4B). Fear remained more prominent in counter-protest tweets throughout all phases except the 2020 activist struggle phase (Figure 4B and 4D).
- Anger was strongly present in activist tweets during the struggle phase of 2014 and the struggle and consolidation phases of the 2020 period (Figure 4A and 4C).
- Anticipation was most visible in activist tweets during the surge of 2020 (Figure 4C). It was most visible in the counter-protest movement during the activist struggle phase of 2020, but disappeared quickly during the 2020 surge (Figure 4D).

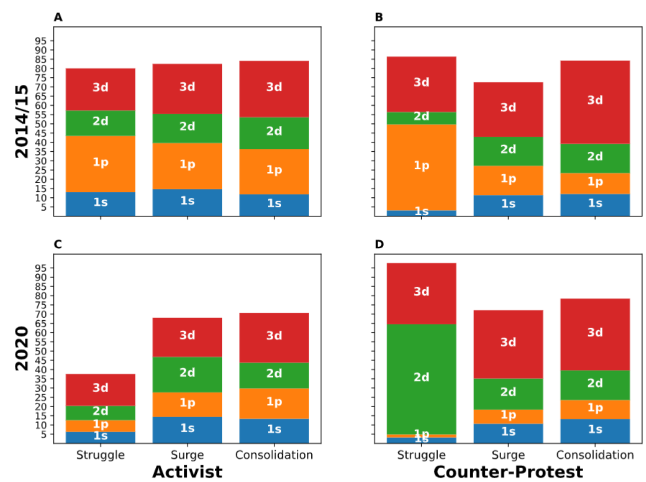

Figure 5: Pronoun Usage, a Proxy for Social Awareness

Social awareness as measured by the proxy of second person plural pronoun usage was consistently higher in activist tweets than in counter-protest tweets, except during 2014-2015 struggle phase (Figure 5).

4.3 RQ3: Hashtags and Contested Narratives

Table 5: 2014-15 Illustrative Hashtags: Memorialization and Grassroots Organization vs. Centralization and Redefinition of Victimhood

Phase	Activist	Counter-Protest
Struggle	#ferguson #mikebrown #johncrawford #chicago #handsupla	#hiphop #obamacare
Surge, Consolidation	#millionsmarchnyc #tamirrice #berkeley #lawyerdiein #baltimore #oscarssowhite	#tcot #alllivesmatter #whitelivesmatter #policelivesmatter #baltimoreriots #prolife

The #BlackLivesMatter activist movement used hashtags to memorialize victims of law enforcement killings such as Tamir Rice, Walter Scott, and Freddie Gray in the 2014-2015 period (Table 5). The activist narrative on victims likely served both to promote identification of Black community members with the activist movement ("it could have been me") and to arouse sympathy beyond Black communities. The activist movement also used hashtags to facilitate grassroots sentiment and organization both in the struggle phase (*#handsupla, #chicago*) and later phases (*#millionsmarchnyc, #baltimore*).

The counter-protest movement, by contrast, focused on key themes commonly articulated by conservative commentators known as *#tcot* ("Top Conservatives on Twitter"[19]). The#tcot hashtag became the counter-protest's most important as it centralized around well-known influencers. Other counter-protest hashtags attempted to reframe the narrative by calling attention to those considered true victims of violence:

- *The unborn victim:* #prolife, #abortion
- *The just cop victim:* #policelivesmatter
- *The non-black victim of protest:* #alllivesmatter, #whitelivesmatter

Opposing victimhood assertions can be seen in hashtags related to the unrest in Baltimore following the death of Freddie Gray in police custody. The main activist hashtags were *#baltimore* and *#baltimoreuprising*, which emphasized the activation of protest in the local community. The most popular counter-protest hashtag, *#baltimoreriots*, brought attention to community considered victim of the protest.

Table 6: Usage of Activist Hashtags by Stance

Period	Phase	Activist	Counter-Protest
2014 - 2015	Struggle	98.2	1.8
"	Surge	97.4	2.6
"	Consolidation	94.4	5.6
2020	Struggle	99.2	0.8
"	Surge	95.7	4.3
"	Consolidation	61.6	38.4

Table 6 shows that the counter-protest movement also attempted to reframe the BLM narrative by hijacking the #BlackLivesMatter and #BLM hashtags. This hijacking campaign grew during consolidation phases even as activist usage of the hashtags diminished. In the 2020 consolidation phase, counter-protest usage of the hashtags approached that of activists (Table 6).

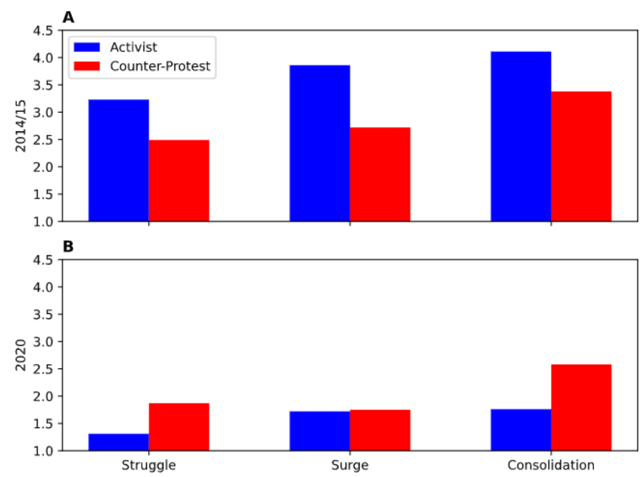

Figure 6: Average Tweets/Day by Stance

During the 2014-2015 period, counter-protest accounts used the hashtags substantially less than activist accounts (Figure 6). However, in the 2020 period, counter-protest accounts used the hashtags far more actively than activist accounts during the struggle and consolidation periods (Figure 6).

4.4 RQ4: Diffusion

Table 7: Number of Homophilous Communities Detected

Period	Phase	Activist	Counter-Protest
2014 - 2015	Struggle	45	1
"	Surge	61	2
"	Consolidation	72	1
2020	Struggle	37	1
"	Surge	172	1
"	Consolidation	125	7

The activist movement's innately local focus on specific victims and specific communities was accompanied by a plethora of activist retweet communities (Table 7).

As the #BlackLivesMatter activist movement grew in the 2014-2015 period, it diversified its base of participants/allies and widened the scope of injustices addressed. These trends are seen in the hashtags appearing among the largest activist retweet communities in the surge and consolidation phases:

- *Locations:* #baltimore, #seattle, #tokyo4ferguson, #palestine, #westpapua, #nigeria
- *Universities:* #berkeley, #princetonu, #uncwalkout
- *Professions:* #lawyerdiein, #whitecoats4blacklives
- *Scope of injustices:* #oscarssowhite, #blacktranslivesmatter

During this early period, the movement also diffused across languages as Spanish and French tweets appeared among the largest activist Twitter communities.

Table 8: 2020 Linguistic Diffusion

Phase	Activist	Counter-Protest
Surge	Korean Brazilian Portuguese Thai French Spanish Japanese Indonesian German	N/A
Consolidation	French Dutch Thai Japanese Spanish German	Japanese French Spanish Dutch German

During the 2020 surge and consolidation, the activist and counter-protest movements continued their strategies of memorializing victims and promoting an alternative victimhood frame, respectively. However, the counter-protest movement joined the activist movement in diffusing across national and linguistic boundaries (Table 8).

During the 2020 surge, English language international activist tweets appeared in England and Belgium (*#londonprotest, #antwerp, #brussels, #manchester*). During the consolidation phase, they appeared in England, Nigeria, and Zimbabwe (*#fosburygardens, #endsars* (End Special Anti-Robbery Squad, a Nigerian police unit), *#zimbabweanlivesmatter*).

During the 2014-2015 period, the activist movement was focused simply on the desired outcome of ending police violence against Blacks. During the 2020 surge and consolidation periods, however, the activist movement began to adopt policy strategies (*#defundthepolice*) and political strategies (*#bidenharris2020tosaveamerica*) to achieve the desired outcome.

5 DISCUSSION

5.1 Longitudinal Analysis of Activist Communities

In both periods, Twitter activity supporting #BlackLivesMatter remained an order of magnitude higher in the consolidation phase than in the preceding struggle phase, indicating that much of the surge momentum had been conserved several months later. However, the extended decline of the activist movement between late 2017 and early 2020 shows that a successful movement must be prepared to continue striving over periods much longer than a few months. By early 2020, activist tweets seemed to have become much more pessimistic, angry and fearful, perhaps due to a broader shift in liberal political discourse away from #BlackLivesMatter toward opposition toward whatever the 45th president had most recently tweeted. The activist movement exhibited lower measures of collective social awareness and higher levels of negative sentiment and negative emotions (fear, anger).

The 2020 surge was accompanied by important changes. Collective social awareness rebounded and continued to increase in the consolidation phase. Moreover, years of experience and collaboration provided the activist movement with new strategies (in particular, *#defundthepolice*) that it had previously lacked. However, when the surge did not yield lasting policy or political change in the ensuing consolidation period, activists' anger reappeared, and collective social awareness waned.

5.2 Longitudinal Analysis of Counter-Protest Communities

In an era of great political polarization, it is not surprising that coalition-building, diffusion, and spikes in activity would occur on both sides of a contentious issue. We have shown that counter-protest tweets coalesced around key hashtags (*#tcot*), built bridges to other conservative movements (*#prolife*), and worked hard to hijack activist hashtags.

By the beginning of 2020, counter-protest hashtags had become a significant hub of conservative Twitter activity. Usage of counter-protest hashtags was on par with usage of activist hashtags (Figure 1), and the counter-protest community apparently felt little need to contend with the activist community by hijacking activist hashtags (Table 6).

The activist movement demonstrated huge activity gains in the 2020 surge, but its dominance could not be sustained. As activist Twitter activity receded during the ensuing consolidation phase, counter-protesters' hashtag hijacking surged forward and even crossed linguistic and international borders.

5.3 The Importance of Community Detection and Stance Detection in the Study of Social Media Activism

We have shown that much of the Twitter activity associated with #BlackLivesMatter represented attempts by the counter-protest movement to hijack activist hashtags. In fact, during the consolidation phase of the 2020 period, counter-protest Twitter volume in the primary activist hashtags was nearly level with the activist Twitter volume.

The presence of strong counter-protest hashtag hijacking has important implications for social media research. In a highly polarized political environment, studies of activist movements should first segment social media data by stance before performing an analysis of activity, sentiment, emotion, social awareness, or other attributes of activist movements.

5.4 Change Point Analysis as a Tool for Identifying Phases of Activist and Counter-Protest Movements

Research on activist Twitter movements has typically anchored periods of analysis to known historical events. This approach introduces the risk that the researcher's intuition of significant turning points may not reflect the actual activity being observed. Change point analysis, by contrast, offers a bias-free method of identifying significant turning points. In our Twitter datasets, bottom-up change point analysis of Twitter activity harmonized quite remarkably with well-known historical events:

- November 22, 2014, the first change point in the early dataset, was the day that Tamir Rice, a 12 year-old black boy playing with a BB gun, was shot and killed by police officers just moments after they responded to a 9-1-1 call about a juvenile with a "probably toy" gun in a Cleveland park [11].
- May 25, 2020, the start of the 2020 surge, was the day that Minneapolis police officer Derek Chauvin murdered George Floyd by kneeling on his neck and back for over 9 minutes during an arrest [24].

This confluence between change point analysis and external historical events indicates that change point analysis successfully identified key inflection points in #BlackLivesMatter Twitter activity. We therefore advocate the use of this promising technique to analyze other periods in the #BlackLivesMatter movement (such as the 2016-2017 #taketheknee movement). It should also be possible to profitably apply change point analysis to other social media activist movements such as #MeToo and #lgbtq.

5.5 Limitations and Future Work

In this study, we analyzed several trends in Twitter data and suggested interpretations consonant with the sociology of activist movements. However, we are unable to make causal claims based on these data. In addition, our differing methods of data collection in the two periods caused us to restrict our longitudinal analysis to relationships and ratios that have no dependency on absolute Tweet volume (e.g., retweet to original tweet ratio, ratio of activist tweets to counter-protest tweets).

Further study of the data in this study can yield insights on the role of previous movement experience to participation in the activist and counter-protest movements. Questions that can be answered include:

- How does previous experience correlate to activity, influence, sentiment, emotions, and social awareness?
- How stable are retweet communities across time?
- To what extent does a movement grow by addition (i.e., new participants joining existing communities) vs. multiplication (i.e., entirely new communities joining the movement)?
- During consolidation, to what extent does participation decrease by community shrinkage vs. departure of entire communities?

We believe that the techniques of community identification and stance detection could be broadly employed to the longitudinal study of other Twitter datasets, including Twitter data from the period surrounding the the 2016-2017#taketheknee surge and datasets connected to other activist movements such as #MeToo and #lgbtq.

6 CONCLUSION

We provided some of the first empirical insights into the evolution of #BlackLivesMatter discourse across distinct phases of struggle, surge, and consolidation. We introduced a combination of several techniques (change point analysis, community detection, and stance detection) that facilitate more accurate longitudinal analysis of both activist and counter-protest movements.

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