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Completed Research

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Abstract

Online social networks (OSN's) have shaped collective action into a new form of organizing and engagement known as connective action. Protests, demonstrations, and social movements have largely relied on social media as their primary organizational process for resource mobilization. These platforms also provide a method to coordinate and influence behavior. Most social science research on connective action has taken a qualitative approach. There are some quantitative studies, but most focus on statistical validation of the qualitative approach (e.g., survey's) or focus on only one aspect of connective action. Computational analysis as a complement to existing survey methods offer in-depth insights about the role of identity and provide insights into the underlying behaviors we see as catalysts for these online movements. This paper presents an interdisciplinary computational approach to analyze connective action by exploring the key features of collective identity, network organization, and mobilization in connective action movements.

Keywords

Connective Action, Collective Action, Social Network Analysis, Protests, Computational Social Science

Introduction

Digital media has disrupted and revolutionized citizen participation in political and social movements. Low costs, immediacy, decentralization, greater exposure, and reach all contribute to the way social media provides affordances for users to participate in these movements. Individual micro-actions, such as likes, mentions, and re-tweets, can contribute to collective action by making social information visible to personal networks, thereby creating circumstances for conditional cooperation (Spann, et al., 2020). When collective action is coordinated using digital technologies it is referred to as connective action. Connective action is a form of collective action where users form more individualized and more technologically organized actions around a protest, demonstration, or social movement using online social networks. One of the key principles of a connective action movement compared to a collective action movement is the absence of formally organized groups. Connective action networks tend to have more loosely based organizational properties of communities within a network (Bennett & Segerberg, 2012). Narrative framing also tends to take a more personalized approach to action framing in connective action. Social media enables these types of networks to organize and emerge quickly, but often lack the leadership and direction needed to ensure long-term policy change (Margetts, et al., 2015). In this paper, we advance the social sciences by providing a computational framework to measure connective action. We examine digitally enabled protests from a computational perspective to measure connective action within COVID-19 anti-quarantine protests in Michigan using social network analysis techniques. This multidisciplinary approach helps to address gaps in social science research by applying a socio-technical approach to measure the collective identity, network organization, and network mobilization features surrounding collective and connective action movements.

In recent years, many robust quantitative approaches have been applied to analyze user metrics in complex social networks. The most common methods are centrality methods such as degree, betweenness, closeness, and eigenvector centrality methods at the individual level (Zafarani, et al., 2014). Also, methods such as modularity help to characterize the cohesiveness and community structure at the network or group level (Zafarani, et al., 2014). We leverage these methods to look at the emergence of a collective network, however, both of these methods lack a method for identifying active hidden groups *within* a complex network as explained below (Sen, et al., 2016). Therefore, we use an integrated model, called focal-structure analysis (FSA) to consider the individual-level measure of the users' betweenness centrality value, and the group-level measure utilizing the spectral modularity method employed to measure the groups' influence in the entire network.

We further extend these techniques to consider the role of the network in connective action. In this analysis, we evaluate the temporally evolving communities participating in the social media COVID-19 anti-quarantine protests by measuring modularity over time. By performing entity resolution and a categorization of users, then graphing the communication network between these users, we can see a polarization of communities emerge over time. We hypothesize that as the protest hashtags gain more users, we will initially see modularity increase as users with different protest objectives or social interests join the protest. However, by examining the individual communities we expect to see more loosely based organizational groups become more tightly knit as modularity decreases. This could suggest that connective action groups are becoming more cohesive. The fundamental goals of this paper are to explore the following research objectives:

RO1: Explore the use of quantitative social network analysis methods to detect the network structure of collective or connective action groups in anti-quarantine protests related to COVID-19.

RO2: After identifying polarization around this protest topic at the macro level, we hypothesize a method to infer connective action using modularity and centrality techniques.

Literature Review

The traditional collective action problem is a scenario in which there is conflict between the individual interest and the group interest. In the context of our case study using anti-quarantine protests, the conflict has multiple consequences to consider. Physical protesters individually risk catching COVID-19 and risk possible arrest by law enforcement. Successful protesters would like to collectively have the quarantine, or stay at home orders, lifted. The protests at the Michigan state Capitol involved protestors that went to the Capitol with firearms primarily to demand the quarantine orders be lifted. By showing up with firearms, this was meant as an expression of constitutional rights (for anti-quarantine) but also a display of second amendment rights. These expressions also represent the protestors social identities.

Social identity theory can be described as the perception of an individual's own views of themselves in association with others; both on an individual level (interpersonal) and as a member of a group (intergroup) (Tajfel & Turner, 1986). In a connective action network, the online discourse and narratives are shaped through personal or individual action framing when compared to collective actions for a group that may be brokered through more formal organization. As group members become increasingly aligned with "group norms and expectations" their own attributes are suppressed and individuals "behave according to how they believe other people from the same social category will behave" (Chan, 2010, p. 1315). This research explores these effects through computational social network analysis.

The analytical model in this paper embraces the theories of collective action (Olson, 1965) and collective identity formation (Melucci, 1996). Extensive quantitative research has been conducted within social media over the past several years, however research in the areas of digitally enabled collective action is relatively new. The field of computational social science has also grown tremendously. Online Social Networks (OSNs) afford users greater opportunities to participate in collective action. These platforms also provide a method to coordinate and influence behavior. The type of collective action coordinated using digital technologies is referred to as connective action. Connective action is a term first defined by

Bennett and Segerburg (Bennett & Segerberg, 2012) as separate from collective action in that they are more individualized and more technologically organized actions. Communication can serve to exchange information, but in digital communication, the structure of crowd-enabled networks can also serve as the organizational component to achieve coherent organizations. This type of organization results in actions without the need for collective identity framing and without the need of organizational resources. This allows world-wide protests to be successfully organized and can reach smaller individualized populations that may be hard to convince to join if they must personally identify with an organization's goals. Connective action is a result of changes to the information environment that affect the way that citizens seek and find political information. OSNs impact the nature of the information that users receive and reduce the costs of interacting with each other. Digital technologies are not, however, the only property of connective action. The coordination must be either self-organized or lack formal organizational structure. In this study we assess the formation of these cyber collective communities and analyze interactions between actors and identify how they influence their communities.

In analyzing collective actions, social networks can be presented as networks of individuals. Social networks thus contribute significantly to individual participation. Personal friends, relatives, colleagues, and neighbors may all affect individual decisions to become involved in the act. Individuals may also be linked through indirect ties generated by their joint involvement in specific activities and/or events. Most studies in this area look at how the involvement in networks affects individual behavior. The overall structure of networks linking individuals is rarely assessed to evaluate the potential for collective action in a given collectivity, which is the very nature of the research.

Al-khateeb and Agarwal (Al-khateeb, Agarwal, 2014) used the concepts of collective action and collective identity to model the factors of successful and unsuccessful deviant cyber flash mob (DCFM). This work proposed a conceptual framework for predicting outcomes of DCFMs that is primarily based on the calculation of the basic collective action concepts of power, control, utility, and interest. Al-khateeb et al. (Al-khateeb, Agarwal, 2014) expanded upon their work to focus on the parameters of interest and control to develop a conceptual framework for predicting collective action in the form of cyber flash mobs. They subsequently applied their model to the social media activities of the terrorist group ISIL to illustrate the model's real-world applicability (Al-khateeb, Agarwal, 2015). Ahuja et al. (Ahuja, et al., 2018) examined the context of digital activism from the perspective of collective action concepts. Their work primarily focused on the concepts of affordance, network building, and synthesis. Alassad et al. (Alassad, et al., 2019) applied the DCFM model to the context of cyber-attacks on "smart city networks". With the addition of focal structure analysis (FSA), their work illustrated a model for how communities can be identified in online social networks (OSNs) based on the ability to identify "hidden influential sets of aggressors in the network." Alassad et al. (Alassad, et al., 2020) expanded upon their work based on the integration of the DCFM and FSA models to examine multiple datasets and to illustrate how the identification and removal of "malicious sets of coordinated users" can help to curb the spread of negative information on OSNs.

Data Collection and Research Methodology

To capture the COVID-19 protest data from Twitter, a Python script was used to collect a co-hashtag network using #MichiganProtest, #MiLeg, #Endthelockdown, and #LetMiPeopleGo hashtags over the time period of April 01, 2020 to May 20, 2020. During this timeframe state and local stay-at-home orders were issued due to the novel coronavirus Pandemic. The data collected resulted in a network of 16,383 Tweets, with 9,985 unique User Ids. Modularity of the network was calculated, and the nodes were clustered by community. The graph revealed 3,632 nodes with 382 communities. However, for this analysis we chose to focus on the top 5 communities, as these were the communities with the highest number of users, with the remaining communities quickly falling under a long-tail distribution. Subsequent Focal Structure Analysis (FSA) revealed a network of 273 users and 1,244 nodes with 55 Focal Structures. We also derived user-generated topics for each community through topic stream analysis using natural language processing (NLP). The twitter data corpus was used as input data and was manually cleaned with common stopwords being identified and removed. This remaining Twitter corpus was then used to train a Latent-Dirichlet Allocation (LDA) topic model to generate topic streams, which allowed us to highlight both shared social interests among communities and polarizing themes across each community as they emerged. Digitally enabled protests need to have three key features to form a successful collective action: they should have a collective identity, they should produce organization, and they should mobilize participants (either online or physically). The type of organization largely determines whether the movement is a collective action or connective action network. Next, we discuss the techniques used to measure these features and how our quantitative analysis addresses each of these key components.

Analysis and Results

We first analyzed users with traditional Social Network Analysis (SNA) methods measuring degree centrality and modularity. Users that show up as having high out-degree measures and as having a lot of interactions may not be identified as being influential using traditional methods of network analysis. We used a novel method to calculate power as used in deviant cyber flash mob (DCFM) detection and focal structure analysis (FSA) as mentioned in the literature review section, to find influential sets of small network structures capable of spreading information throughout the network. The focal structures with high power may be hidden without this type of extended analysis. Additionally, we looked at in-degree and out-degree centrality measures. Those with high out-degree measures were communicating the most, and those with high in-degree measures received the most attention. Based on modularity, we identified several communities and key information brokers based on this analysis that showed close connections and ad-hoc coordination. These were primarily the discussion leaders in these communities and linked to different sets of influential people that are found at the center of each cluster. The overall key finding was that Information Brokers/Influential users had the following features: high out-degree, high betweenness, and are members of focal structures with high power.

Collective Identity

One of the first features that define collective action is a shared collective identity. To measure collective identity, we first performed a qualitative content analysis on the tweets, then used an NLP-LDA model to perform a topic analysis for each community. Since the network was collected using a set of seed hashtags, we use this method as a proxy for collective awareness by the group. We further strengthen the sense for collective identity by showing that the group has a strong sense of shared social interests through the topic analysis used on the text corpus extracted from the tweets. We use these two methods to infer that the groups have formed a collective identity. We see a polarization of support emerge in the network graphs shown in Figure 2 in the Mobilization section of this paper. Prominent conservative party views are seen in the top three communities and liberal party views primarily were seen in the fourth and fifth ranked communities. To further analyze the range of themes for the protesters, the top hashtags were extracted from the 16,383 tweets and ranked by frequency for each community. We then performed a manual content analysis to remove the highest cross-community hashtags, as these were generally the common seed hashtags, we originally collected in our initial Twitter search. After removing the cross-community hashtags and common stop words, we used the remaining Twitter corpus in an LDA model and generated the semantic themes showing in Table 1 below. We present these results as a method for measuring the collective identity of a collective or connective action group. In the next section we examine the organizational component of these groups.

Community	Manual Classification	Semantic Themes from Topic Analysis
Largest Community	Right, Anti-Gov Whitmer, Calls for Protests	a call to action to vote and recall whitmer; convince that the quarantine is excessive; focus on rights, such as freedom; pointing out the prison problem; and directing attention to @joshuabhoe (former UofM debate director)
Second Community	Primarily Far Right (includes QAnon); However, includes some Trump	the terms "white", "black", and "whiteprivilege" are also prevalent within this community. we also see a focus on bluelivesmatter, while also having a focus on "facts" and "science". this community also seems interested in discussing

	Resistance	"testing" and masks. "rights" related to guns are discussed, as well as issues relating to the "economy", "jobs" and "businesses" and the need to be "free". the "nra" and "dnc" are also discussed. "breitbartnews" is referred to, as well as the "police" and seatemajldr (a misspelled reference to senate majority leader mitch mcconnell)
Third Community	Far Right, Trump /Law Enforcement Support	a mixture of referring to "terrorists", trump, the terms "racist" and "morons"; convincing that the quarantine is excessive. this community also seems to be a call to action to "vote", focus on "election", "patriots", "rally" and "openamericanow"; this community also brings up "black" and "white" and "whiteprivilege", and mentions high-profile figures such as trump, donaldtrumpjr, and ivankatrump. additionally, this community discusses the term "veryfinepeople", which is a term that president trump used back in aug 2017 when discussing the charlottesville protest that resulted in the murder of heather hayer.
Fourth Community	Far Left - Calls for Release of Prisoners	major focus on high-profile figures such as heidiwashington (MI dept of corrections director), @joshuahoe (again), AFSCMICJProgram, chrisgautz (MI public information officer), and ltgovgilchrist (MI lt gov); the prison topic is VERY dominant within this community; and references to sawarimi (an org that promotes "building community between people in prison, their families, and future advocates" is prominent.
Fifth Community	Far Left - Gov. Whitmer Support	focus on high-profile figures such as senmikeshirkey (senator, majority leader in MI senate), leechatfield (MI senator and speaker of MI house of reps), and senpolehanki (MI senator); a focus on rights, guns, unemployment, nursing and health care and a sense of emergency, republican lawmakers, and gongwer (a news service focusing on politics)

Table 1 – Collective Identity Themes for each of the Top 5 Topic based communities based on NLP-LDA

Network Organization

To measure the organizational component of the connective action network, we examine how the information is spread between nodes and communities. If the organizational logic follows a pattern of diffusion and not mutual exchanges, the information flow should be rather one-directional than reciprocal (Theocharis, et al., 2017). We can measure the information flow in the communication network by calculating the degree centrality of the network structures, where we measure the in-degree and out-degree centrality for each node. There are multiple inferences that may be drawn from the data shown in Table 2 below. Communities with a low degree of centrality suggest more asynchronous communication. The largest community detected in the Michigan protest data also has the lowest weighted average centrality, consistent with the tweets that were mostly tweeting to Governor Whitmer. Interestingly, Governor Whitmer, had zero out-degree linked, or zero tweets to others. It is important to note that orchestrating actors may not be actively coordinating the action but could be passively contributing to the overall organization of the issue. For example, many users may be posting @mention tweets to the Governor of Michigan, and even though she may not respond, protests could rally around this echo chamber of tweets. Within the top 5 communities, 3 have conservative party properties and 2 have liberal party properties. We also see there are more users in the top three communities than the fourth and fifth communities. The topic themes described in table 1 from the collective identity section above also reveal organizing properties. First, the derived topics suggest that the Michigan anti-quarantine protests were primarily driven by conservative party interests. This is consistent with the physical protest demonstrators that showed up at the Michigan State Capitol claiming the lockdown protest to be a 2nd amendment rally. We also see diverse polarization in topics and responses to each category around the protests. The conservative communities appear to have more densely connected communities than the liberal communities. We infer from this data that connective action from these communities is more cohesive and thus more successful in their protest efforts. Media reports validate that armed protesters physically protested at the capital resulting in a shutdown of the State Capitol.

Communities	Political Category	No. of Nodes	No. of Edges	Modularity	Avg. Weighted Degree	Avg. Betweenness Centrality	DCFM Power
Largest Community	Right	459	526	0.294	1.457	0	90.88
Second Community	Right	152	419	0.578	2.771	0	77.12
Third Community	Right	212	322	0.468	1.792	0	280.98
Fourth Community	Left	78	491	0.422	9.779	24.26	10.36
Fifth Community	Left	115	339	0.608	7.683	0.16	28.94

Table 2 – Network measurements for Top 5 Largest Modularity-Based Communities

Additional steps using social network analysis were taken to identify key features and key orchestrating connective action networks. Two novel methods were used to determine the organization and computational density of the network. The previously discussed DCFM method was used to calculate powerful actors within the protest network, and the communication network was extracted from this dataset. Next, Focal Structure Analysis was performed to identify highly influential groups of nodes with the ability to spread information through the network. The Deviant Cyber Flash Mob (DCFM) phenomenon can be considered a form of a cyber-collective action that is defined as an action aiming to improve a group's conditions (such as, status or power). If we can identify those strong influential groups within a network that are organizing, we can provide policymakers or anlaysts with data to to design countermeasures or support for these information campaigns. Previous work by Al-khateeb and Agarwal (Al-khateeb, Agarwal, 2014a) developed a collective action based theoretical model which identified factors to predict success or failure of a DCFM.

Control (C)	*In-degree Centrality*	*(1)*
Interest (I)	*Number of retweets+mentionsTotal number of tweets*	*(2)*
Power(P)	*Control C× Interest (I)*	*(3)*

In their model, the identified factors are – Utility (U) (the benefits an individual gains if the DCFM succeeds or fails), Interest (I) (how much interest a user has based on the utility gained), Control (C) (how much control the aggressor has on the outcome of the DCFM), and Power (P) (how powerful a user is in the group). In this study, we calculate the structural characteristics of our sample DCFM network and assess the impact of these collective action measurements (i.e., I, C, and P) using our Focal Structure Analysis (FSA) model. Using these detailed insights into the connective action structure provides additional details into the influence and positional roles of coordinating actors.

Network Mobilization

Connective action networks must display some level of collective action and citizen engagement and if they are to be successful. They often rely on resource mobilization theory by users sharing campaigns in local, national, and transnational arenas. A connective action network must also have the ability to draw in outside users. As such, our Michigan protest network represents a good case for assessing the use of digital technologies and different action frames (from personalized to collective) to engage and mobilize citizens, and to examine various related capacities and effects of those engagement efforts (Blei & Laerty, 2009). In our case study we analyze the mobilization effect by examining network modularity over time. We see that as the protest movement gains users (Fig.1), we also see the network begin to separate into homogenous communities (Fig.2) as they shared similar social constructs. The cumulative user count curve shown in figure 1 also shows that as users adopt into this information campaign, the campaign trajectory takes on an s-curve diffusion model. Spann et al. (Spann, et al., 2022) discussed how digital technologies create new affordances and interdependencies between users that create this s-shaped function similar to the diffusion of innovations theory (Rogers, 1962). We can use this approach to help understand whether the campaign is accelerating, decelerating, or has reached critical mass.

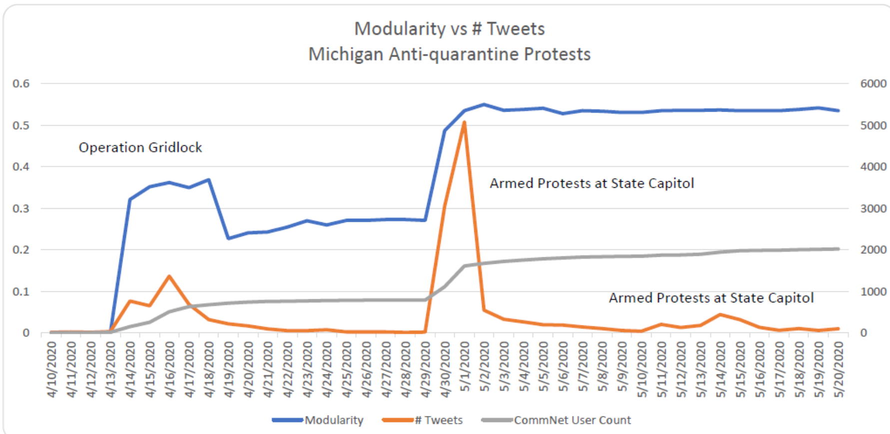

Figure 1 - Frequency of Tweets, cumulative protestors, and modularity over time

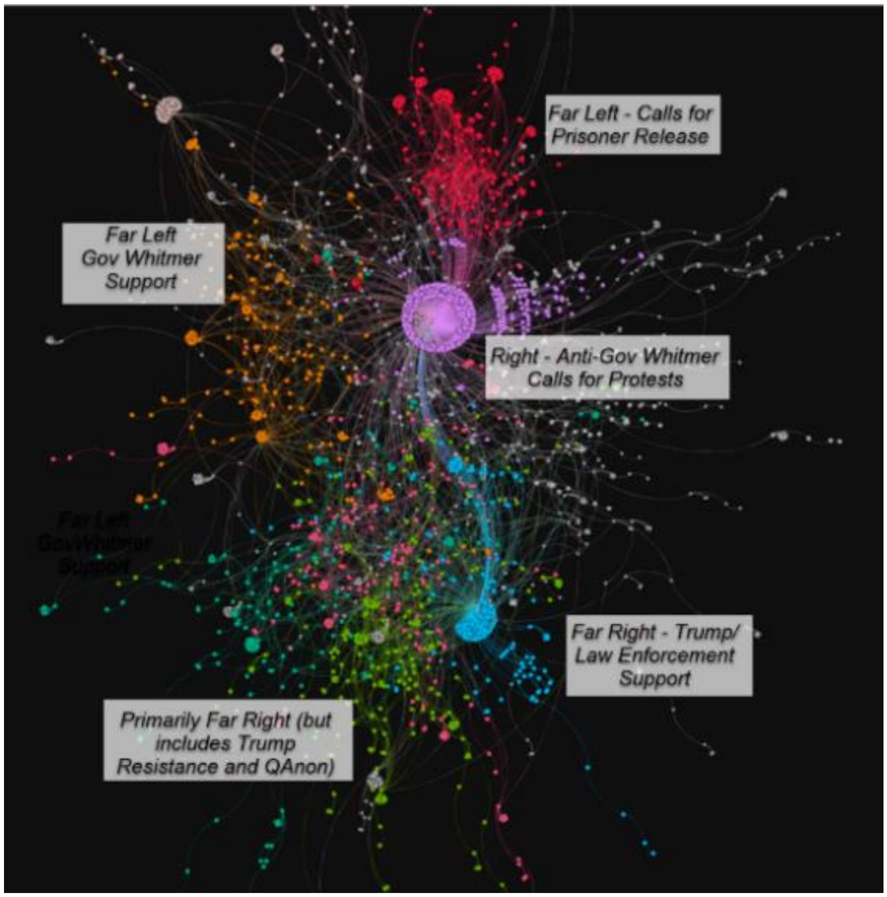

Figure 2 – Separation of Anti-quarantine communication network by modularity communities

Conclusions and Future Work

In this paper we performed a quantitative and exploratory analysis of the COVID-19 anti-quarantine or lockdown protests in the State of Michigan examining the impact of collective and connective action on the protest network. Social network analysis and topic modeling was used to computationally identify connective action groups within the protestor communication networks on Twitter. We identified several methods to support a future model to identify connective and collection action. We infer from connective action theory that groups that exhibit connective action may be leaderless and display self-organizing properties. High betweenness centrality suggests a more centralized organizational component, and low betweenness centrality is an indicator of more self-organizing networks. We also used modularity and topic modeling to identify cohesiveness and polarizing themes within the protestor communities. One of the conclusions we derive from this study is that the largest community has the lowest modularity and lowest average weighted degree. Therefore, none of the nodes have a structural advantage for disseminating protest information. The top 3 communities have zero betweenness, but communities 4 and 5 have higher centrality, suggesting a slightly more organizational component as indicated by the prisoner led organizations and members of the senate engaging in the protest conversations on twitter. Focal structure analysis also revealed that the top ranked communities did not contain any focal structures. Interestingly communities 4 and 5 were part of the most influential focal structure sets that also had the highest DCFM power. Since the top three communities did not have any members in the highest ranked focal structures, this also supports a connective action model of leaderless organization. The contribution of this analysis provides a foundation for mathematical characterization of connective action signatures, and further, offers policymakers insights about campaigns as they evolve. This gives policymakers, analysts, and other researchers a deeper assessment of these type of information campaigns and the behaviors involved. The affordance approach along with social network analysis will help us to understand the social and organizational components. The topic modeling approach provides insights into the collective identity emerging from each of the communities involved. Our next steps are to parameterize a mathematical equation so that we can more accurately model campaign dynamics and identify additional features for predictive modeling of the emergence of connective action campaigns. Establishing this theoretical framework will help researchers develop predictive models to more accurately model campaign dynamics.

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