Beyond the Eye-Catchers: a Large-Scale Study of Social Movement Organizations’ Involvement in Online Protests

Proponents of Internet activism postulate that social media affordances drastically reduce education, coordination and participation costs, and thus render social movement organizations (SMOs) nonessential. Yet, such claims currently lack sufficient evidence due to the difficulty of identifying SMOs at scale. This paper aims to fill that gap and characterize the role SMOs play in online protest movements.

We use large-scale crowdsourcing platforms in combination with nested supervised learning models and identify more than 50 thousand SMOs participating in 2 distinct Twitter movements. Our results reveal that beyond the few high profile eye-catcher SMOs, the rest vary significantly in terms of role and importance, and that an average SMO behaves surprisingly similar to an average individual. We set out to unearth the reasons behind this finding. By assigning each SMO to its respective social movement industry (SMI) according to its primary objectives using unsupervised methods, we show that an extensive number of SMOs from peripheral SMIs participated, alongside SMOs from the core SMI, most commonly in solidarity with lower commitment. Finally, we propose a predictive model of SMOs mobilization volume. Our analysis shows that structural embeddedness of SMOs within the SMO network is the biggest indicator of success—SMOs that have more bi-directional ties (or, alliances) with other SMOs have higher mobilization volume. Lastly, SMOs that have higher network brokerage or access to more varied information also possess higher mobilization volume.

ACM Reference Format:

1 INTRODUCTION

The importance of highly professionalized and respected social movement organizations (SMOs) have been extensively documented in prior studies. Indeed, SMOs advanced the recruitment of participants in high risk activism [25]. SMOs provide the structure and leadership needed to coordinate different groups of participants for swift offline actions [63]. Finally, SMOs sustained movements and kept their members’ ideologies alive in times of public apathy or hostility [68].

Yet, Internet activism slowly replacing traditional civic engagements has brought into question the significance of SMOs in the era of Web 2.0. Some scholars argue that the decentralized structure of the Web and social media affordances have drastically lowered the associated costs, rendering SMOs less important [7, 8, 22, 23, 40, 61]. Earl and Kimport show that many online protests such as petitions and boycotts are organized by individuals [23]. Bennett and Segerberg, studying Arab Spring and Occupy Wall Street, make similar observations [7]. This conclusion is, however, not uniformly accepted. For instance, Fetner and Key [27], by analyzing the role of teapartypatriots.org in the Tea Party movement, credit the movement’s success to the well financed interest groups behind it. Spiro et al. [62] show that SMOs eventually supersede any one individual activist as movements progress and become the center for broadcasting information and organizing events. In other words, they play a crucial role without which the success of a movement would be short-lived [68].

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XXXX-XXXX/2018/4-ART $15.00
https://doi.org/0000001.0000001
There is a growing academic interest in Internet activism. [5, 15, 20, 30, 64, 69, 72]. Given SMOs’ importance in past social movements and the incongruent hypotheses on their role in the new era, it’s surprising that only few distinguish SMOs’ participation from individuals and other organizations. The ones that do make the distinction [34, 45, 56] often times require substantial manual labor and only focus on the eye-catchers—a limit set of exceptionally successful and popular SMOs.

Unlike the aforementioned studies, we move beyond focusing on selected few high profile SMOs and provide the first automated method in identifying SMOs at scale. Using this approach, we identify and study the behavior of more than 50 thousand SMOs in 2 distinct online social media protests—the BlackLivesMatter movement and gender-related advocacies broadly categorized as Women’s rights movement. We provide the following contributions:

1. Consistent with prior studies [27, 62], eye-catcher SMOs are indeed more committed to protests; they partake in more knowledge sharing and community building efforts, and draw significant fraction of endorsements and acknowledgments. For instance, the top 5% quantile SMOs received $\geq 135$ retweets, while the number is 5 and 15 for the top 5% quantile individuals and other organizations respectively.

2. More interestingly, however, we observe that an average SMO is very similar to an average individual both in terms of commitment and importance. For instance, over half of all SMOs in BlackLivesMatter only contributed 1 or 2 protest tweets and had 0 recruitment. The similarity is even stronger for individuals that are structurally close to SMOs. This demonstrates the existence of a long tail of SMOs beyond the eye-catchers studies traditionally concentrated on.

3. Focusing on the observed variance, we first show that it is partially due to differences in social movement industries (SMI). Indeed, an SMO with the goal of defending women’s reproductive rights can easily show solidarity to an online movement of another cause, while spending the majority of its efforts on Women’s Rights movement. We identify SMIs using automated unsupervised methods and show that SMOs from an extensive set of peripheral SMIs, including LGBTQ, Women&Health and 9 others, protested in solidarity in BlackLivesMatter alongside the SMOs from the core African American SMI. Further, we observe that some of the “peripheral” SMIs with established networks and resources played a vital role in the development of the BlackLivesMatter movement despite having other primary objectives. Additionally, we also see a significantly lower level of solidarity for Women’s Rights: only 2 other SMIs protested alongside the core Women SMI.

4. Finally, we build predictive models of SMOs mobilization volume operationalized using the following metrics: i) the number of times when an activist’s first protest tweet is a retweet of or mentions an SMO, and ii) the number of an SMO’s followers that participated in a movement after the first protest tweet contributed by the SMO. We identify variables including account characteristics, network attributes, strategies, and participation patterns that are indicative of how well an SMO can successfully induce its followers and others to protest. Our models have moderate to substantial predictive power for both metrics: adjusted $R^2$ of 0.52 and 0.92 respectively with cross validation.

In sum, this study presents the first large-scale analysis of SMOs for online movements; it exposes a long tail of SMOs, substantial in number, beyond the eye-catchers. We illustrate characteristics and behaviors of these SMOs and highlight the various important implications of this tail.

2 BACKGROUND & RELATED WORK
We draw from numerous classic theories and studies addressing SMOs within traditional participation media [25, 48, 51, 54, 68, 73, 74]. We adopt the definition of social movement organization from
the Resource Mobilization Theory proposed by McCarthy and Zald [51, 73]. In addition, we observe and adhere to the coding schemes published by McAdam [49]. We define the following:

Social Movement Organizations (SMO): An SMO “is an entity consisting an assembly of people that deliberately attempts to change individuals, established cultural norms, statu quo, institutions and structures, and/or to redistribute wealth.” SMOs are distinct from other organizations in two ways. First, SMOs do not provide regular goods or services. Second, SMOs’ incentives are primarily purposive. In this work we categorize advancement and progress based non-profit, community, and student organizations, advocacy groups, interest groups, lobby groups, unions and employee associations, non-established political melioristic political groups, and proselytisic (conversion-seeking) religious entities as SMOs [73]. Examples of SMOs are shown in table 1.

Social Movement Industries (SMI): An SMI is a group of SMOs that share broad preferences or goals of a social movement [50]. Examples of SMIs include Christianity and Environment.

Other Organizations (OTHOs): Service-based nonprofit, community, and student organizations, established political entities, structures and systems, for-profit organizations (e.g. retailers) and nonproselytisic religious groups are OTHOs.

Individuals: Twitter accounts that are neither SMOs nor OTHOs will be coded as individuals.

Table 1. Organization Categorization and Examples

<table>
<thead>
<tr>
<th>Categories</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>SMOs</td>
<td></td>
</tr>
<tr>
<td>Subcategories</td>
<td></td>
</tr>
<tr>
<td>Advancement and Progress Based Non-profit, Community, and Student Organizations</td>
<td>Artist of Color; PRIDE Radio; Communities for a Better Environment in California; Graduate Student Employees Union</td>
</tr>
<tr>
<td>Advocacy Groups, Interest Groups, Lobby Groups</td>
<td>The American Civil Liberties Union; Ku Klux Klan; National Smokers Alliance</td>
</tr>
<tr>
<td>Labor Unions and Employee Associations</td>
<td>American Medical Association; United Automobile Workers</td>
</tr>
<tr>
<td>Proselytisic Religious Groups</td>
<td>Christianity; Islam</td>
</tr>
<tr>
<td>Non-established Political Organizations</td>
<td>Green Party; Socialist Party of America; the Tea Party</td>
</tr>
<tr>
<td>Non-SMOs</td>
<td></td>
</tr>
<tr>
<td>Subcategories</td>
<td></td>
</tr>
<tr>
<td>Relief and Service Based Non-profit, Community, and Student Organizations</td>
<td>Student Accounts Services; Creative and Performing Arts; Social and Recreational Clubs; Neighborhood Watch; Doctors Without Borders</td>
</tr>
<tr>
<td>For-profit Organizations</td>
<td>Business and Finance; Corporate Media; Law Firms</td>
</tr>
<tr>
<td>Non-proselytisic Religious Groups</td>
<td>Buddhism; Modern era Judaism</td>
</tr>
<tr>
<td>Established Political Organizations, Societal Institutions and Structures</td>
<td>the Democratic Party; the Department of Labor; State Funded Public Educational Institutions</td>
</tr>
</tbody>
</table>

There are several recent papers on SMOs [17, 22, 27, 34, 45, 53, 56, 62] that are worth noting here. Spiro et al. [62] examine the distinctions between zealots and SMOs in initializing and sustaining online social movements. Conversely, research conducted by Lovejoy et al. [45] suggests that SMOs fell short of employing social media optimally. Furthermore, analyses done by Earl [23], Karpf [40], and Shirky [61] suggest the waning importance of SMOs due to social media affordances and personalized political participation. Unlike the aforementioned studies, our research is based on a more comprehensive set of SMOs.

3 DATA ACQUISITION & ANNOTATION

Our dataset consists of over 80 hashtag protests that are categorized into 2 broad topics: the BlackLivesMatter movement and Women’s Rights movement. There are over 50 raced-related hashtag movements including #ferguson, #blacklivesmatter, #polic Brutality, et cetera, spanning 36.6 million

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1 Some organizations both provide services and engage in advocacy. We label these accounts by their primary objectives and functionalities, or as SMOs if primaries are unclear.

2 All branches of Christianity, Islam, and Hinduism are classified as proselytisic religions, while modern era Judaism and Buddhism are considered nonproselytisic.

3 For instance, Greenpeace and Sierra Club belong to this SMI.
tweets and involving 4.3 million Twitter participants. Gender-related hashtags summate to 7.3 million tweets and 2.4 million advocates, covering issues including sexual violence, women’s healthcare, women empowerment, wage equality, et cetera. The dataset includes all tweets with the corresponding hashtags between 02-2014 and 05-2015.

Given Twitter does not supply account categories, we use crowdsourcing and supervised learning to classify all users into 3 distinct groups: SMOs, OTHOs, and individuals.

3.1 Crowdsourcing Task
We recruit MTurk workers to label a subset of Twitter accounts into SMOs, OTHOs, and individuals. **Sample Selection:** A quick inspection of a random sample of Twitter accounts in our dataset reveals that SMOs (and organizations in general) are a rare class—there were 4 SMOs and 12 OTHOs in a random sample of 200 users. To ensure a balanced sample for labeling, we stratify our dataset using 3 attributes organizations are likely to have: (1) having an URL listed under Twitter profile; (2) having more than 3 thousand followers; and (3) being included on the homepage of any web domain listed under the Society and News categories on Alexa or DMOZ. We divide accounts into 6 strata: accounts that possess all 3 attributes, any 2 of the 3 attributes, any one of the 3 attribute, accounts that posted at least 2 tweets across all movements, accounts not included in previous strata, and finally, accounts selected completely at random. We stratify and randomly select over 1600 accounts. This way, we are able to provide a wider coverage of the rare classes (SMOs and OTHOs) while still sampling randomly from the broader distribution for testing purposes. In addition, we also obtain the dataset from Olteanu et al. [57] which contain over 300 labeled organization accounts. Our final selected set has approximately 2000 accounts. **Instructions:** We take screenshots of these accounts’ Twitter page, randomly assign each screenshot into sets of 25, and export each set as an individual Mechanical Turk “human intelligence task” (HIT). Each HIT is assigned to three workers in order to assess label quality. Upon accepting a HIT, we first provide workers the definitions of SMOs, examples, and instructions for inclusions, exclusions, and exceptions. Next, we take them through a training task before finally starting on the actual task.

**Qualifications and Monitoring:** Success of a crowdsourcing task relies heavily on the right mechanisms to ensure worker qualifications [47]. We require that workers: 1) reside in the U.S. 2) have successfully completed at least 1,000 HITs; and 3) have an approval rate of at least 98%. We first provide workers with instructions on how to identify SMOs, we then take them through a training process including 10 pre-labeled accounts. Furthermore, we allow workers to skip cases they are unsure about while still providing compensation. Such choices are shown to improve label quality [75]. Finally, we inject a number pre-labeled Twitter accounts as a gold standard, monitor worker accuracy for such cases and block workers whose accuracy fall below 60%.

**Evaluation:** Despite the complexity of the task, the workers provide high quality and reliable labels with sufficient training and quality checks. We apply Krippendorff’s alpha separately to assess inter-rater reliability. Our labels have a scores of 0.72 indicating a substantial agreement [60]. In addition, we also calculate Turkers’ Gold set (pre-labeled by the researchers) accuracy at 82%.

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4Threshold is informed by related work on Twitter accounts [13] as the 99 percentile in terms of followers.
5We crawl the homepages of all the websites listed under Society and News for both Alexa and DMOZ, and gather all the Twitter users contained within these homepages. Our crawler obtain over 500K website URLs and our dataset has 300K Twitter users listed under the homepages of these websites.
6A random sample is used as test set to reflect classifiers’ performance against real-world distribution of accounts.
7We will include links to such screenshots in the final version of the paper. We omit the links here in order not to jeopardize the double-blind process.
8In only 3.7% of tasks did the workers choose this option.
3.2 Supervised Classification Task

There are several existing methods that focus on categorizing Twitter accounts [19, 42, 52, 58], many of which are binary classifications (organizations v.s. individuals). Unlike these related work, we seek to further classify organizations into SMOs and OTHOs. For that, we utilize a two-step classification process. We first build a binary classifier to label accounts into individuals and organizations, then for the accounts that are labeled as organizations, we apply a second classifier to further label them as an SMO or an OTHO. Such a nested classification approach has been shown to work well in the case of imbalanced classes [14]. This approach also allows us to identify the optimal combinations of featuresets, preprocessing steps and classifier types, which yield better results than a regular multiclass classification method.

Table 2. Feature Selection

<table>
<thead>
<tr>
<th>Feature-set</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>User Name&amp; User Handle</td>
<td>(i) Whether field contains an actual person’s name (python NLTK Name Corpus); (ii) whether user handle is included within any hyperlinks in the homepages of websites listed under Alexa and Dmoz’s News and Society categories.</td>
</tr>
<tr>
<td>User Profile</td>
<td>Whether field contains (i) an URL, (ii) an occupation (Kazemi’s Occupation Corpus[41]), (iii) numbers, (iv) nonascii characters (e.g. emojis); (v) whether URLs, if present, belong to a social media website; (vi) readability (Flesch–Kincaid Grade), (vii) word semantic vectors in the dimensions of 10, 25, and 50 using Fasttext’s Skipgram method [21, 39], (viii) word dimensions, such as pronom, using LIWC [59].</td>
</tr>
<tr>
<td>User Motive</td>
<td>(i) Total tweet count, (ii) protest tweet count, (iii) protest retweet count, (iv) protest mention count, (v) ratio between (i) and (ii), (vi) number of days between users’ first and last protest tweets, (vii) number of distinct protest hashtags, (viii) the timestamp of users’ first protest tweet</td>
</tr>
<tr>
<td>User Influence</td>
<td>(i) Friend count, (ii) follower count, (iii) ratio between (i) and (ii), (iv) number of retweets and mentions users received from others. All in log-scale.</td>
</tr>
<tr>
<td>Tweets</td>
<td>(i) Number of original protest tweets (i.e. not a retweet), (ii) url count, (iii) hashtag count, (iv) non-ascii characters count, (v) readability, (vi) word semantic vectors using Fasttext’s Skipgram, (vii) word dimensions using LIWC.</td>
</tr>
</tbody>
</table>

Featureset Selection: In Table 2, we list our feature selections with the intent to discriminate individuals from organizations and/or SMOs from OTHOs.

Classifier Selection: We select 5 commonly used single classifiers: Linear Regression, Linear Support Vector Machine (SVM), Random Forest, Extra Trees, and K-Nearest Neighbor as implemented by Python’s Scikit-learn library to compute baseline performance. We generate 5C3 (5 choose 3) combinations of classifiers from the single classifier list and assign the selected 3 as base estimators to a voting ensembler as implemented by Scikit-learn. We apply another ensemble classification technique called Stacking [66] from the MLxtend library. This method combines multiple classification models via a 2nd level meta-classifier where the prediction outputs by the level-1 classifiers are used as inputs to the meta-classifier.

Classification Performance: We assess classification performance based on (1) testset including datapoints from all the strata and (2) testset only including the random stratum. For the former, we apply a stratified ten-fold cross validation; for the latter, all non-random strata accounts are assigned to trainingset, we then utilize a three-fold cross validation on the random strata accounts to estimate performance. We assess the best performing classification pipeline using the sum of the minority class’s precision and recall.

Individual and Organization Classification: Detailed evaluation statistics are summarized in Table 3. All our classifiers for both test-set types have AUC above 0.9 which is considered excellent for an unbalanced datasets [11]. Our best classifier is the stacking classifier with Linear SVM, Random Forest, and Extra Trees as level-1 classifiers, and Linear Regression as the meta classifier with 0.93

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9 We apply Platt’s scaling to derive the prediction probability.
10 Due to space limitations, we only present results for the best preforming classifier from each category for the minority class.
precision and 0.68 recall for classifying organizations. Using this classifier, we categorize 312K accounts in our dataset as organizations. We also inspect the features with the highest weights to gain insights about the classifier. Unsurprisingly, having an actual person’s name or an occupation in the profiles strongly indicate accounts as individuals.

**SMO and OTHO Classification:** For our second classification step, we only use accounts classified as organizations from the previous classification step. Table 3 summarizes our best classifiers’ performance. When testing against all strata, our classifier achieves an accuracy of 0.87 and an AUC score of 0.83; when testing against random stratum, our classifier has an AUC score of 0.77 with SMO precision and recall are both approximately 0.7. Furthermore, an inspection of feature weights reveal that the ratio between total protest tweets and all tweets posted by accounts, and being retweeted more by other participants suggest accounts as SMOs instead of OTHOs. We apply the best performing classifier to the set of 312K accounts classified as organization and identify more 50 thousand accounts as SMOs.

Table 3. Classification Summary

<table>
<thead>
<tr>
<th>strata type</th>
<th>Individual/Organization</th>
<th>SMOs/OTHOs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>accuracy</td>
<td>precision</td>
</tr>
<tr>
<td>all stack</td>
<td>0.97</td>
<td>0.98</td>
</tr>
<tr>
<td>all voting</td>
<td>0.92</td>
<td>0.94</td>
</tr>
<tr>
<td>all single</td>
<td>0.91</td>
<td>0.93</td>
</tr>
<tr>
<td>random stack</td>
<td>0.98</td>
<td>0.93</td>
</tr>
<tr>
<td>random voting</td>
<td>0.98</td>
<td>1.00</td>
</tr>
<tr>
<td>random single</td>
<td>0.98</td>
<td>0.92</td>
</tr>
</tbody>
</table>

4 ANALYSIS

We first conduct additional quality assessment by addressing Twitter bots, Countermovement SMOs, and robustness check. We then explore the importance of SMOs in comparison to individuals and OTHOs in Section 4.2. We see a substantial variance in SMOs role in online protests. Next, we provide a partial explanation of the variance observed by examining SMOs within the context of SMIs in Section 4.3. Finally, we operationalize SMOs mobilization volume using 2 metrics and propose models robust and predictive of their mobilization performance in Section 4.4.

4.1 Quality Assessment

**Automated v.s Genuine Accounts:** There is a growing body of research addressing how interest groups use bot farms to both support and interfere with social movements. To measure the “genuineness” of the SMO accounts, we first select the subset of SMO accounts that belong to the top 5 percentiles in terms of protest tweet contribution. We then use the Botometer API to assign each account a bot score. However, scores for organization accounts—often operated by multiple individuals, or combinations of users and automatic tools—are commonly

11 We qualitatively examine organization accounts that were incorrectly classified as individuals; we observe that 42.8% left their user profile description field blank.

12 To ensure a more accurate assessment of SMOs’ role in social media activism, we also examine the most active (>99.99 percentile in number of protest tweets contributed), or most influential (>99.99 percentile in both number of retweets and mentions received) participants within our dataset. We found over 700 highest value participants within our labeled organizations dataset and manually reassign them into correct categories as SMOs, OTHOs, or individuals. Accuracy measures for this sample is comparable to the findings in the test set. For instance, approximately 78% of SMOs are correctly identified by our classifier.
inaccurate. This shortcoming is indeed acknowledged by [71]. Consequently, we choose to include all SMOs for analyses regardless of bot score. Nevertheless, as a robustness check, when comparing SMOs’ direct tweet contribution to OTHOs and individuals, we repeat the analysis excluding the subset of SMOs with a bot score of > 0.50; observations are consistent.

**Countermovement SMOs:** Previous research shows that countermovement SMOs utilize strategies such as alternative narrative or framing [55], hashtag hijacking and spamming [38], and spreading counter-protest hashtags [32] to attack and discredit the “offending” movement. To ensure the SMOs under examination are in fact supportive of BlackLivesMatter and Women’s Rights, we apply network clustering to identify and remove the subset of SMOs that belong to the countermovements.

First, we define two directed graphs $G_{blm} = (N_{blm}, E_{blm})$, and $G_{women} = (N_{women}, E_{women})$. Here a node $u \in N_{blm}$ if $u$ is an SMO and $u$ participated in the BlackLivesMatter movement by using at least one of the related hashtags at least once. A directed edge $e_{u,v} \in E_{blm}$ from $u$ to $v$ exists if $u$ is followed by $v$. We apply the same procedure to generate $G_{women}$. Graphs are given in Figure 1.

Both graphs contain a small cluster of nodes, approximately 10% in size and colored in red, that are far removed from the main cluster. To ascertain that these are in fact countermovement SMOs, we randomly sample 100 tweets from BlackLivesMatter, each posted by a distinct account from the red subset, and manually label them as supportive or opposing. We note that 79 tweets objected the movement. We conduct a similar analysis on Women’s Rights and observe a comparable pattern. We remove these accounts for the subsequent analyses.

**Robustness Check:** To ensure our observations are not simply due to individuals’ accounts being misclassified as SMOs, as a robustness check, we use Youten’s Index [28] to select optimal probability cut-off values for our classifiers to limit the false positive rate to only 2% for accounts belonging to the random strata. Results obtained using the 26K and 50K SMOs datasets are consistent.

### 4.2 Comparing SMOs’ to Other Organizations and Individuals

We observe that 33.7K and 19.6K SMOs participated in BlackLivesMatter and Women’s Rights respectively. Despite being a very small fraction of all accounts, SMOs contributed a substantial fraction of tweets, and received a considerable fraction of endorsements (retweets), and acknowledgments (mentions). In this section, we go beyond direct contributions by providing a more in-depth comparison of SMOs’ involvement in online protests to that of OTHOs and individuals using the following 5 metrics: commitment, knowledge sharing, community building, structural significance, and recruitment. We select these metrics by adopting from existing literature focused on SMOs online strategies [3, 34, 56] and related network cascading theory [33]. Here, we also separate individuals...
We denote these individuals as \( \text{indv(H)} \), with \( H \) representing high structural closeness to SMOs, and who are structurally close to SMOs (having at least 1 bi-directional tie with an SMO) from the rest.

**Commitment** For each group, we compute the fraction of accounts actively participated per day averaged over time. We also compute the number of days elapsed between the first and last tweet posted by an account (i.e. protest length) and the number of unique days an account protested.

**Knowledge Sharing** Previous studies on SMOs’ social media strategies identify the use of URLs as a knowledge sharing strategy [3, 34, 56]. We compute the total number of unique URLs and domains shared by each group; we also calculate the number of URLs shared by each account.

**Community Building** Existing literature suggests SMOs use hashtags more frequently than the baseline usage on Twitter for community-building purposes [34]; they can be discovered more easily through hashtag based searches on Twitter and bring interested parties together. To evaluate whether SMOs indeed reach out to more protest communities, we construct hashtag-hashtag co-occurrence graphs and cluster similar hashtags into communities. 17 We then derive the number of communities each group chose to focus on.

**Structural Significance** We use two metrics to assess SMOs’ structural significance: 1) \( k\)-core score, which measures a participant’s ability in recruitment and protest cascading [33], and 2) in-degree, which captures the participant’s reputation [10]. First, we define two directed graphs \( G_{blm} = (N_{blm}, E_{blm}) \), and \( G_{women} = (N_{women}, E_{women}) \). Here a node \( u \in N_{blm} \) if \( u \) participated in the BlackLivesMatter movement by using at least one of the related hashtags, and an edge \( e_{uv} \in E_{blm} \) if \( u \) mentions or retweets \( v \) at least once (similar construction for \( G_{women} \)).\(^{18}\) We compute the in-degree and \( k\)-core value of nodes corresponding to SMOs, OTHOs, and individuals.

**Recruitment** We measure the number of recruited activists as follows: We first identify the set of activists \( A_{blm} \) and \( A_{women} \) that participated in BlackLivesMatter and Women’s Rights movements by using at least one relevant hashtag. Next for each activist \( a_{blm} \in A_{blm} \) (and similarly for Women’s Rights), we identify the first tweet \( t_{a_{blm}} \) of \( a_{blm} \) in that movement. We identify whether \( t_{a_{blm}} \) mentions or retweets another activist \( a'_{blm} \). If so and if \( a' \) had already been participating in the movement(i.e.

17 We define similarity between hashtags \( h_i \) and \( h_j \) as the Jaccard similarity between \( T_i \) and \( T_j \) where \( T_i (T_j) \) is the set of tweets containing hashtags \( h_i \) (\( h_j \)). We then build a graph where an edge exists between pairs of hashtags that have non-zero Jaccard similarity and the Jaccard similarity score denotes the edge weight. With the constructed graph, we apply Louvain heuristics to compute partitions of highest modularity [9] and identify 7 communities for BlackLivesMatter and 5 communities for Women’s Rights. Sample Hashtags belonging to the same community are #wearesilent and #wearehere. The results are consistent with what is presented here.

18 We also analyze structural patterns when edges \( e_{uv} \) are based solely on retweeting or solely on mentioning behavior. The results are consistent with what is presented here.

### Table 4. SMOs Selected Contribution Overview

<table>
<thead>
<tr>
<th>Dimension</th>
<th>Measurements</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commitment</td>
<td>mean(median) fraction of accounts active per day</td>
</tr>
<tr>
<td></td>
<td>BLM SMO</td>
</tr>
<tr>
<td></td>
<td>2.28% (1.60%)</td>
</tr>
<tr>
<td>Structural Significance</td>
<td>mean(median) kcore</td>
</tr>
<tr>
<td></td>
<td>32.13(4)</td>
</tr>
<tr>
<td>Knowledge Sharing</td>
<td>mean(median) number of URLs</td>
</tr>
<tr>
<td></td>
<td>40.94(3)</td>
</tr>
<tr>
<td>Community Building</td>
<td>mean(median) number of protest communities</td>
</tr>
<tr>
<td></td>
<td>1.83(1)</td>
</tr>
<tr>
<td>Recruitment</td>
<td>total number (fraction) of recruits</td>
</tr>
<tr>
<td></td>
<td>BLM SMO</td>
</tr>
<tr>
<td></td>
<td>mean(median) number of recruits</td>
</tr>
<tr>
<td></td>
<td>355.34K</td>
</tr>
<tr>
<td></td>
<td>(10.76%)</td>
</tr>
</tbody>
</table>

|               | mean(median) fraction of recruits                                           |
|               | (15.60%)                      | (41.9%)                       | (41.9%)       | (41.9%)   |
|               | 10.55(0)                      | 3.62(0)                       | 1.63(0)       | 0.37(0)   |
|               | 23.39(0)                      | 2.06(0)                       | 1.2(0)        | 0.72(0)   |

|               | mean(median) kcore                                                                 |
|               | (18.35%)                      | (5.67%)                       | (15.60%)      | (59.37%)  |
|               | (15.60%)                      | (41.9%)                       | (41.9%)       | (41.9%)   |
|               | (15.60%)                      | (41.9%)                       | (41.9%)       | (41.9%)   |
|               | 40.94(3)                      | 8.74(2)                       | 10.44(2)      | 3.05(1)    | 6.46(2)   | 2.78(1)     | 2.94(1)     | 1.58(1)   |
|               | 1.83(1)                       | 1.65(1)                       | 1.81(1)       | 1.34(1)    | 1.26(1)   | 1.13(1)     | 1.19(1)     | 1.05(1)   |
|               | 355.34K                       | 585.67K                       | 983.34K       | 1.48M     | 458.88K   | 166.91K     | 390.29K     | 1.48M     |
|               | (10.76%)                      | (17.68%)                      | (29.68%)      | (41.9%)   | (18.35%)  | (5.67%)     | (15.60%)    | (59.37%)  |
|               | (15.60%)                      | (41.9%)                       | (41.9%)       | (41.9%)   |
|               | (15.60%)                      | (41.9%)                       | (41.9%)       | (41.9%)   |
|               | (15.60%)                      | (41.9%)                       | (41.9%)       | (41.9%)   |

\(^{17}\) We define similarity between hashtags \( h_i \) and \( h_j \) as the Jaccard similarity between \( T_i \) and \( T_j \) where \( T_i (T_j) \) is the set of tweets containing hashtags \( h_i \) (\( h_j \)). We then build a graph where an edge exists between pairs of hashtags that have non-zero Jaccard similarity and the Jaccard similarity score denotes the edge weight. With the constructed graph, we apply Louvain heuristics to compute partitions of highest modularity [9] and identify 7 communities for BlackLivesMatter and 5 communities for Women’s Rights. Sample Hashtags belonging to the same community are #wearesilent and #wearehere. The results are consistent with what is presented here.

\(^{18}\) We also analyze structural patterns when edges \( e_{uv} \) are based solely on retweeting or solely on mentioning behavior. The results are consistent with what is presented here.
timestamp of $t_{a^{blm}_t}$ is less than $t_{a^{blm}_a}$, we denote $a'$ as the recruiter of $a$ into the corresponding movement\(^\text{19}\). Then we aggregate the total number of recruitments for each account $a^{blm}_t$.

### Results

Measurements from each dimension are summarized in Table 4. Due to space limitation, only a representative subset of the metrics are selected; the omitted measures are consistent with what’s shown. We observe that, on average, SMOs indeed play a more significant role in online protests. For example, in BlackLivesMatter, SMOs on average have a kcore value of 32, which is 2 times that of indv(H) despite their structural closeness, and 5 times that of what is observed for individuals on average. The average number of recruits by BlackLivesMatter SMOs is 11, and OTHOs is 4 and only 2 for indv(H).

More interestingly, however, we see that the averages summarized below are particularly high for SMOs due to the small fraction of highly influential accounts. For instance, the top 5% quantile SMOs received $\geq 135$ retweets, while the number is 5 and 15 for the top 5% quantile individuals and OTHOs respectively. Indeed, an average SMO (characterized by medians listed in Table 4) looks surprisingly similar to an average individual. For instance, an average BlackLivesMatter SMO only contributed 1 or 2 protest tweets, is structurally insignificant to the movement, and has 0 recruitment. Our study reveals the existence of a long tail of SMOs that studies only focus on eye-catchers may have missed. Our subsequent analysis focuses on unpacking the characteristics of these long tail SMOs and their mostly “supportive” role in online protests.

### Table 5. Samples of SMI Clustering, Precision, and Profile

<table>
<thead>
<tr>
<th>SMI Cluster</th>
<th>Precision</th>
<th>Sample Account Profile</th>
</tr>
</thead>
</table>
| Christianity (BLM)   | 0.96      | 1. these are updates, information and prayers for the #downtown congregation of #redeemer presbyterian #church.  
|                      |           | 2. north coast training helps you craft strong, stable ministries that prepare your church to break though barriers, overcome plateaus, and prime for growth.  
|                      |           | 3. hello from westside unitarian universalist church! we’re proud to be a progressive voice in ft worth. check out our website & drop in for a visit.  |
| Occupy Wall Street (BLM) | 0.68     | 4. in solidarity with occupy movements worldwide. #r##n# non violent. pro justice  
|                      |           | 5. occupy, politics, anti-corruption, anti-megacorp, against dangerous levels of power in any form. for the people.  
|                      |           | 6. west hollywood division of occupy los angeles. be on the right side of history. stands in solidarity with #ows #ola.  |
| African American (BLM) | 0.92      | 7. black is beautiful #black lives matter #civil rights for all #free and unfettered #individually unconditionally.  
|                      |           | 8. #blacklivesmatter is an affirmation and embrace of the resistance and resilience of black people.  
|                      |           | 9. an auxiliary organization on college campuses nationwide directly related to, and in turn shares the ideas and views of, the 100 black men of america.  |
| Women (Women)        | 0.80      | 10. world pulse is the leading network using the power of digital media to connect women worldwide and bring them a global voice.  
|                      |           | 11. exposing corrupt cops in frisco texas. we believe the constitution is more than a piece of paper. we expose social media frauds, child killers/molesters.  
|                      |           | 12. the country’s largest provider of specialist services for women and children escaping domestic violence. twitter account staffed mon-fri 9:30-5:30.  
|                      |           | 13. mywork is an online lgbt professional network. we connect individuals, gay and lesbian friendly companies, associations and local businesses.  
|                      |           | 14. michigan’s only statewide anti-violence and advocacy organization serving the lesbian, gay, bisexual, and transgender communities for over 20 years.  
|                      |           | 15. re-defining a civil rights movement for the 21st century. gay lesbian bisexual transgender queer lgbt lgbtq  |

### 4.3 Comparing SMOs from Different SMIs

One likely explanation for the considerable variance in SMOs involvement in online protests is that primary objectives, thus SMIs, of SMOs vary widely. Here, we provide detailed analyses of the role differences between SMOs from the core SMI and the ones from peripheral SMIs.  

\(^{19}\)If the first tweet by $a^{blm}_a$ contains multiple mentions and/or retweets, each account is considered a recruiter.
4.3.1 Categorize SMOs into SMIs. We first apply part-of-speech (POS) tagging to each SMO’s profile description. We focus on noun tokens given their strength in extracting semantically meaningful topics. For the set of nouns derived, we examine the subset that occur 100 times or more to assess their semantic value, and remove the ones that lack contextual cues. In addition, we manually examine the most frequently occurring non-noun tokens and selectively keep the ones that are contextually relevant. This results in dictionaries of size 1.7K and 1.6K for BlackLivesMatter and Women’s Rights respectively. We keep the set of accounts that have 4 or more relevant tokens in their profiles and discard the rest, resulting in 22K matching accounts for BlackLivesMatter and 15K for Women’s Rights. For each movement, we first translate tokens of the remaining accounts into a sparse document term matrix and apply the kmeans elbow method to determine the optimal number of document clusters; we then use kmeans clustering. Finally, we randomly select a sample of 25 accounts from each of the resulting clusters and manually assess their primary objectives.

Using this approach, we identify 12 distinct SMIs for BlackLivesMatter, and 3 for Women’s Rights. Randomly selected accounts from a representative subset of SMIs and the corresponding sample precisions are listed in Table 5. We will first examine SMIs in BlackLivesMatter follow by Women’s Rights. For both, we reapply our analyses from the previous section including commitment, knowledge sharing, community building, structural significance and recruitment to assess, with SMI context, SMOs’ role as the educator, recruiter, coordinator, and sustainer for the movements.

4.3.2 BlackLivesMatter. Alongside the SMOs of the core African American SMI, an extensive set of SMOs from Youth, Student, Christianity, Research Institutes, LGBTQ, Social Welfare, Non-African American Minorities, Occupy Wall Street (OWS) and News SMI participated to support BlackLivesMatter, highlighting the strength of social media in enabling collaboration between SMOs with vastly different primary objectives. Here, we select a representative subset of the SMIs: African American, Christianity, LGBTQ, News, OWS, and aggregate all others into the Other category.

---

20We apply spaCy [36].
21Sample non-noun tokens we keep include “black”—an adjective, but highly relevant to the context; “occupy”, normally a verb, but here signals relation to the Occupy movement.
22We explore the use of LDA (latent dirichlet allocation) and have find the topics to be less coherent. We also try to use profile similarity measurements between pairs of SMO accounts to create weighted edges and apply existing community detection algorithms on the corresponding network, which is also unfruitful.
23All identified SMIs have a random sample precision of approximately 70% or above.
24Note that News SMOs differ from mainstream corporate media firms in that News SMOs center their objectives around shining light into social, political, or economic issues, and/or bringing about positive depictions of certain groups.
As shown in Figure 2, SMO accounts belonging to the African American SMI, denoted as $A_{aa}$, are more central to BlackLivesMatter than the subset of SMOs that participated in solidarity such as $A_{christianity}$ and $A_{lgbtq}$. The median tweet contribution by $A_{aa}$ is 8, and 2 for both $A_{christianity}$ and $A_{lgbtq}$; in addition, $A_{aa}$ were also more active in community building with 22% of all $A_{aa}$ engaged in 3 or more protest communities. In comparison, less than 10% of $A_{lgbtq}$ depicted similar effort. Similar patterns are also observed in knowledge sharing, structural significance and recruitment.

Interestingly, both $A_{news}$ and $A_{ows}$ exceeded $A_{aa}$ in all 5 dimensions. For instance, the median tweet contribution by $A_{news}$ is 32, 4 times that of $A_{aa}$. Furthermore, $A_{news}$ is also the most successful at recruiting new participants. The recruitment rate for $A_{news}$ is 0.83 per tweet, approximately 4 times that of the second highest group $A_{ows}$. Additionally, the median number of URLs contributed by $A_{news}$ is 7 in comparison to $A_{aa}$’s single URL. These observations suggest that $A_{news}$ is much better at employing social media mechanisms, perhaps due to the nature of its industry.

While the critical role of progressive news organizations in BlackLivesMatter can be explained by the need of engaging and educating others, what’s more surprising is that $A_{ows}$ surpassed both $A_{news}$ and $A_{aa}$ in their commitment to BlackLivesMatter. The median tweet contribution by $A_{ows}$ is 54, the highest amongst all the groups. In fact, as depicted in Figure 2, $A_{ows}$ is the most dedicated amongst all SMIs as measured by number of days in protest and number of protest communities engaged. Consequently, $A_{ows}$ also possess the most favorable network position for recruitment. The median kcore value for $A_{ows}$ is 55 comparing to $A_{aa}$’s 41 and $A_{aa}$’s 11.

The observation of $A_{ows}$ being an integral recruiter and sustainer for BlackLivesMatter is initially surprising. Further analysis reveals a plausible explanation—our dataset capture the early stage of African American SMOs’ engagement in BlackLivesMatter where movement specific SMOs have yet to fully mature.25 Indeed, over 35% of all $A_{aa}$ accounts on Twitter were created after February, 2014, a time when the BlackLivesMatter movement started to gain national recognition. This number is only 2% for $A_{ows}$. The Occupy movement, which started in 2011, was well developed with a mature and stable social media presence by 2014. Furthermore, as the BlackLivesMatter movement progressed, the protest activity level, measured by tweet count, of $A_{ows}$ waned when that of $A_{aa}$ rose. In fact, as shown in Figure 2(c), $A_{aa}$ is the only SMI that depicted a rise in average participation level.26 This is consistent with Resource Mobilization[51] which posits that as a movement grows and gains capital, professional movement-specific SMOs will eventually emerge.

4.3.3 Women’s Rights. Unlike the extensive collaborative effort shown for BlackLivesMatter, here, we only identify 3 distinct SMIs for Women’s Rights: the core SMI Women, and peripheral SMIs Christianity,27 and LGBTQ. Further, we observe that SMOs within Women are divided into subgroups focused on distinct issues pertaining to women: domestic abuse, leadership skill for young girls, women’s reproductive health, et cetera. None of the subgroups demonstrates substantial difference in their role; thus, for our subsequent analyses, we omit the distinction between them.

We observe that the median protest tweet contribution by all three SMIs is 2, implying that more than half of the SMOs from the core SMI behaved just like the ones from the peripheral SMIs. Nevertheless, we do see more outliers from $A_{women}$, some of which contributed more than 1000 tweets in the span of a year while none from the other SMIs did. In addition, as shown in Figure 2, we see a modest effort by $A_{women}$ in building communities to facilitate coordination: over 7.5% of $A_{women}$

25Within the scope of our dataset, blklivesmatter, the official Twitter account for the movement, has 34K followers, whereas the current number is at 249K.

26Here, the $x$ axis represents the number of days since the start of the movement, and the $y$ axis denotes the number of tweet contributions each day. The colored lines are the fitted regression lines $y \sim x$ of each SMI.

27We ensure that SMOs under this SMI are in fact supportive of Women’s Rights, such as being Pro-Choice, by manually sample 100 accounts and observe that over 90% of them self identify as progressive religious groups.
engaged with 2 or more protest communities, while less than 2% of \( A_{\text{christianity}} \) and almost none of \( A_{\text{lgbtq}} \) did the same. Additionally, the recruitment rate for \( A_{\text{women}} \) is 5.40 per tweet, approximately 2 and 25 times that of \( A_{\text{lgbtq}} \) and \( A_{\text{christianity}} \) respectively. Finally, as shown in Figure 2(d), the average participation intensity of \( A_{\text{women}} \) demonstrates a downward trend similar to \( A_{\text{christianity}} \) and \( A_{\text{lgbtq}} \) as the Women’s Rights movement progresses.

As a whole, we show that \( A_{\text{women}} \) demonstrates comparable commitment level to \( A_{\text{christianity}} \) and \( A_{\text{lgbtq}} \) with some outliers being more committed to sustain the movement. Furthermore, \( A_{\text{women}} \) is more invested in building communities and is more successful with recruitment. The differences are moderate in comparison to BlackLivesMatter, however. One possible explanation is that during the timespan of our dataset, multiple high profile and polarizing events (e.g. Ferguson March) had occurred in BlackLivesMatter, while Women’s Rights movement remained in relative abeyance.

4.4 Predictive Modeling of SMOs’ Mobilization Volume

Existing social movement literature has used mobilization volume as an informative metric in evaluating SMOs role and importance [45, 56]. Our findings presented in Section 4.2 show that SMOs vary significantly in this dimension. In this section, focusing on BlackLivesMatter, we assess to what extent SMOs’ account characteristics, participation pattern, strategic choices, and network structure factors explain the variance in their mobilization volume within online protest communities. Below, we formally define measures related to our modeling task.

**Mobilization (MZ):** Let \( S_{\text{blm}} \) be the set of SMOs that participated in BlackLivesMatter. For each \( s \in S_{\text{blm}} \), we evaluate the mobilization volume using 2 metrics: i) the number of \( s \)’s followers that participated in the movement after the first protest tweet contributed by \( s \), denoted as \( MZ_{\text{blm}, s}^1 \), and ii) recruitment defined in Section 4.2, \( MZ_{\text{blm}, s}^2 \). These two metrics provide subtly different operationalization of mobilization volume. We use them both to ensure our qualitative findings are robust. For both metrics, we fit the following regression model:

\[
MZ_{\text{blm}, s} = \beta_0 + \beta M_{\text{blm}, s} + \epsilon_i
\]

where \( 1 \times n \) matrix \( M_{\text{blm}, s} \) represents the entire set of explanatory variables (e.g. account characteristics of \( s \)) and \( \beta = (\beta_0, \beta_1, \ldots) \) is the correlation coefficient matrix.

**Account Characteristics:** We derive the total number of tweets (irrespective of whether they are related to BlackLivesMatter) posted by \( s \), its account creation timestamp, total numbers of friends and followers as well as the ratio between the two. This set of attributes captures the account’s overall activity level on Twitter, its account age, and the scope of connections it has.

**Participation Patterns:** We determine the total number of protest tweets, the difference in days between the first and last protest tweet contributed by \( s \) as well as the ratio between protest tweets and total tweets. Finally, we extract the difference in days between the start of the BlackLivesMatter movement and the first protest tweet contributed by \( s \) to capture how early \( s \) joined the movement.

**SMO to SMO Network Attributes:** We derive 3 categories of network structural factors: i) direct ties, ii) prestige, iii) diversity and brokerage.

- **SMO to SMO Direct Ties:** We determine the number of SMOs that are \( s \)’s friends, followers, or both (follows and is followed by \( s \)), as well as the ratio between the number of friends and followers.

- **Prestige:** Curtis and Zurcher [18], and Aveni [4] posit that the more prestigious an SMO’s allies are, the more prestigious and effective the SMO itself. Within the network analysis literature, this is analogous to the assertion that the more influential a node’s neighbors are, the more important and capable the node itself. This concept is operationalized using the *PageRank* [12] score. To calculate pagerank, we reuse the directed graphs \( G_{\text{blm}} = (N_{\text{blm}}, E_{\text{blm}}) \) described in Section 4.1. We then use SNAP [44], a popular network analysis tool, to derive the pagerank score for \( s \).
Diversity and Brokerage: Aveni [4] theorizes that the more diverse an SMO’s linkages to other organizations, the more different resources it can utilize to sustain itself and strive for its objectives. This concept is similar to previous studies on network brokerage and betweenness centrality. Here, we also make a distinction between local and global betweenness centrality. Local betweenness centrality, or local transitivity, measures the fraction of s’s allies that are allies themselves. Prior work [16] suggests that ideas proposed by those with high local transitivity are more likely to be viewed as novel and valuable. In contrast, global betweenness centrality of s measures the number of shortest path between all pairs of $S_{blm}$ that go through s [31]. We use iGraph to derive local transitivity and the SNAP global betweenness centrality of s.

Strategic Choices: we broadly partition SMO strategies into 4 categories: knowledge sharing, appeal to emotion, direct lobbying, and media effort.

Knowledge Sharing: SMOs have a much higher usage of hyperlinks and hashtags than the baseline Twitter average for the purpose of sharing information beyond the 140 character limitation set by Twitter [24, 34]. We calculate the fraction of protest tweets contributed by s that contains at least 1 hyperlink, and the average number of hashtags per tweet.

Appeal to Emotion: Related work suggests that political tweets with negative emotional sentiment are more likely to be shared [65]. Here, we first manually label a subset of protest tweets as positive, negative, or neutral in sentiment. 28 Next, for the labeled subset, We apply sentiment scoring methods VADAR [37] and SentiEval [43] to extract relevant text features from each protest tweet and build a supervised multiclass learner; it has 66% accuracy which is better than using each method separately. 29 We classify the remaining unlabeled protest tweets by $S_{blm}$ as positive, negative, or neutral. We observe that the vast majority of tweets, 60%, are neutral, with 32.3% of all tweets negative, and 0.7% positive. Finally, we derive the fraction of protest tweets by s that connotes positive sentiment, and the fraction with negative sentiment.

Direct Lobbying: This strategy is used by s when it directly approaches or interacts with lawmakers using social media to lobby for its cause [34]. Here, we identify Twitter accounts that belong to federal legislators by using existing dataset by Tauberer [67]. To determine accounts that belong to state, city, or county level elected officials (e.g. state senator, county clerk, et cetera) we first aggregate a list of elected positions of (i.e. job titles) 30, we then derive a list of accounts that contain at least one of the aggregated occupation titles within the user profile description field. We obtain approximately 3K such accounts. Next, we randomly select 300 accounts and examine whether each account indeed belongs to an elected official. We observe that 224 or 79% of the select subset correctly match to actual officials. We calculate the number of protest tweets by s that mentions or is a retweet of these accounts.

Media Effort: Prior studies observe that SMOs actively engage with newspapers and journalists to bring coverage and push public agenda aligned with their goals [2]. We identity 4.4K news 31 and
The adjusted $R^2$ values for all models estimated through cross validation\(^{33}\) are shown in Table 6. We see that the complete $MZ_{1blm}$ models for $A_{aa}$ and $A_{all}$ have adjusted $R^2$ of 0.95 and 0.93 respectively; that is, we are able to explain a substantial fraction of the variance in SMOs volume with respect to $MZ_{blm}$. Furthermore, account characteristics and network attributes are much more predictive of SMOs volume comparing to participation patterns and strategies. In fact, the later two categories have adjusted $R^2$ of only 0.08 and 0.064 respectively. In addition, while network attributes, accounting for 92% of all variance, dominated all the other categories of predictors for $A_{all}$, account characteristics are as equally predictive as network attributes for $A_{aa}$. In fact, account characteristics alone are able to explain 81.9% of all variance in $A_{aa}$. This is in line with prior observations under Section 4.3: our dataset contains the early period of the BlackLivesMatter movement during which movement specific SMO accounts have yet to build network connections with other SMOs, making the individual account characteristics of $A_{aa}$ as indicative of their volume as network attributes. For $MZ_{2blm}$, our models have a more modest predictive power for $A_{aa}$ and $A_{all}$: $R^2$ of 0.50, and 0.52 respectively. Additionally, we also see that variables in the participation patterns category, performs better at predicting overall volume in $MZ_{2blm}$. One intuitive explanation is that for a follower of $s$, it matters little when or how intensely $s$ participates given that $s$’s tweets show up on a follower’s feeds regardless; but, for someone who does not follow $s$, that person’s exposure to $s$ is likely dependent on $s$’s participation patterns such as how early $s$ joined the movement. However, the significance of network attributes is consistent across the two definitions.

Coefficients estimates of each predictor for the complete $MZ_{1blm}$ model using $A_{aa}$ are plotted in Figure 3. As depicted, within the account characteristics category, the coefficients for the number of followers and friends are 1070.8 and -308.1 respectively (i.e. one standard deviation change in follower count is correlated with an additional 1.1K followers being mobilized), implying that having more followers and fewer friends are positively correlated with SMOs being more successful at mobilization. For network attributes, we observe that having higher betweenness centrality is positively associated with greater mobilization volume, implying that SMOs with increased “brokerage” or having access to more varied information, are able to better mobilize their followers. In addition, the number of bidirectional ties with other SMOs are also positively correlated with mobilization volume. Finally, SMOs that participated earlier in movements and/or have a higher engagement with news or reporter accounts also have a higher mobilization volume.

5 DISCUSSION & LIMITATIONS

In this paper, we provided the first automated method in classifying social movement organizations (SMOs) at scale. Using this method, we identified over 50K SMOs participating in two significant social media protests: BlackLivesMatter and Women’s Rights. We conducted in-depth comparisons of SMOs’ involvement in online protests to that of other organizations (OTHOs) and individuals, while also taking into account the number of protest tweets by $s$ that mentions or is a retweet of these accounts in the BlackLivesMatter movement.

Model Performance: Using Equation 1, We fit and evaluate 5 separate models; 4 of which are partial models using only predictors from a single category: i) account characteristics, ii) participation patterns, iii) network attributes, iv) strategic factors, and 1 complete model containing all predictors. In addition, we assess each model using 2 distinct sets of SMOs: i) SMOs from the African American SMI, denoted as $A_{aa}$, and ii) SMOs from all SMIs, $A_{all}$. We make this distinction to differentiate SMOs belonging to core SMI from SMOs of more peripheral SMIs.

We first aggregate a list of news media occupation such as reporter or journalist, we then filter and select the subset of users that listed any one of the relevant occupations in the profile description field.

We first assign data into 10 bins using the value of $MZ_{blm}$; we then split data using the bin number into 10 stratified folds (training and test datasets). Finally, we use reassess $R^2$ for out of sample test data.
Table 6. Adjusted $R^2$ for all Mobilization Models.

<table>
<thead>
<tr>
<th>Metric</th>
<th>Dataset</th>
<th>$R^2$ Account Characteristics</th>
<th>$R^2$ Network Attributes</th>
<th>$R^2$ Participation Pattern</th>
<th>$R^2$ Strategies</th>
<th>$R^2$ Complete</th>
</tr>
</thead>
<tbody>
<tr>
<td>$MZ_{SMO}$</td>
<td>African American SMI</td>
<td>0.819</td>
<td>0.896</td>
<td>0.08</td>
<td>0.064</td>
<td>0.956</td>
</tr>
<tr>
<td></td>
<td>All SMIs</td>
<td>0.293</td>
<td>0.919</td>
<td>0.164</td>
<td>0.104</td>
<td>0.928</td>
</tr>
<tr>
<td>$MZ_{SMO}$</td>
<td>African American SMI</td>
<td>0.137</td>
<td>0.342</td>
<td>0.313</td>
<td>0.151</td>
<td>0.495</td>
</tr>
<tr>
<td></td>
<td>All SMIs</td>
<td>0.178</td>
<td>0.37</td>
<td>0.339</td>
<td>0.195</td>
<td>0.519</td>
</tr>
</tbody>
</table>

Fig. 3. Coefficients Plot of the Complete $MZ_{SMO}$ Model for SMOs in the African American SMI. Note*: Some variables were removed due to having a variance inflation factor (VIF) higher that 2.5[1].

and demonstrated that beyond the eye-catcher SMOs which are highly visible to the movements, an average SMO is very similar to an average individual both in terms of behavior and significance. We also observed that a large number of SMOs from varied SMIs participated in solidarity, lending their Twitter network to assist a social movement not of their immediate domain, as exemplified by the surprisingly assertive role of Occupy SMOs within the BlackLivesMatter movement. Finally, we proposed models that are highly predictive of SMOs mobilization volume.

There are several limitations and future directions worth noting. First, our analyses rely on Twitter data and do not address SMOs’ characteristics and role outside of the platform. Second, we focus on two successful and high profile movements. Future work that extends this understanding to other—less popular and successful—movements is necessary to broaden our understanding. Third, our method in categorizing SMOs into SMIs is unable to assign a fraction of SMOs into coherent SMIs. Fourth, future work should distinguish individuals who are members of SMOs from non-members to further explore SMOs induced impact on social media activism.

Lastly, we discuss several important implications of our study. First, considering the extensive involvement of SMOs from peripheral SMIs in BlackLivesMatter, We posit that social media affordances are carving out new pathways for SMOs to engage and cooperate with each other, allowing them to easily and cheaply pool in certain types of social capital to sustain and expand online social movements. It will be crucial for future work to unpack these new dynamics, compare behavioral differences, cooperations (or even competitions) amongst the different groups, across varied movements, times, and locations. Next, the labels collected and classifiers built, and the clustering technique implemented provide a great opportunity for future research in organization theory and collective action to study SMOs at a scale never possible before. In addition, our model highlighted the importance of network structural attributes in relation to SMOs mobilization volume which potentially have real world applications for organizational leaders and platform owners. Based on our observations, SMOs can possibly improve their mobilization volume by focusing on strategically building connections with others SMOs from a more diverse set of SMIs. In fact, the SMOs dataset we gathered can serve as valuable candidates. Finally, platform owners can also explore the SMOs network and build a recommendations system for SMOs to make additional organizational connections.

and demonstrated that beyond the eye-catcher SMOs which are highly visible to the movements, an average SMO is very similar to an average individual both in terms of behavior and significance. We also observed that a large number of SMOs from varied SMIs participated in solidarity, lending their Twitter network to assist a social movement not of their immediate domain, as exemplified by the surprisingly assertive role of Occupy SMOs within the BlackLivesMatter movement. Finally, we proposed models that are highly predictive of SMOs mobilization volume.

There are several limitations and future directions worth noting. First, our analyses rely on Twitter data and do not address SMOs’ characteristics and role outside of the platform. Second, we focus on two successful and high profile movements. Future work that extends this understanding to other—less popular and successful—movements is necessary to broaden our understanding. Third, our method in categorizing SMOs into SMIs is unable to assign a fraction of SMOs into coherent SMIs. Fourth, future work should distinguish individuals who are members of SMOs from non-members to further explore SMOs induced impact on social media activism.

Lastly, we discuss several important implications of our study. First, considering the extensive involvement of SMOs from peripheral SMIs in BlackLivesMatter, We posit that social media affordances are carving out new pathways for SMOs to engage and cooperate with each other, allowing them to easily and cheaply pool in certain types of social capital to sustain and expand online social movements. It will be crucial for future work to unpack these new dynamics, compare behavioral differences, cooperations (or even competitions) amongst the different groups, across varied movements, times, and locations. Next, the labels collected and classifiers built, and the clustering technique implemented provide a great opportunity for future research in organization theory and collective action to study SMOs at a scale never possible before. In addition, our model highlighted the importance of network structural attributes in relation to SMOs mobilization volume which potentially have real world applications for organizational leaders and platform owners. Based on our observations, SMOs can possibly improve their mobilization volume by focusing on strategically building connections with others SMOs from a more diverse set of SMIs. In fact, the SMOs dataset we gathered can serve as valuable candidates. Finally, platform owners can also explore the SMOs network and build a recommendations system for SMOs to make additional organizational connections.
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Vol. 1, No. 1, Article . Publication date: April 2018.
Social Movement Organizations in Online Protests


