Understanding collective action through scalable, multi-mode, social action identification

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Abstract

We create a computational framework for understanding collective action and demonstrate how this framework can be used to build an open-source event detection tool with scalable statistical machine learning algorithms and a subsampled database of over 600 million geotagged Tweets from around the world. These Tweets were collected between April 1st, 2014 and April 30th, 2015, most notably when the Black Lives Matter movement began. We demonstrate how these methods can be used diagnostically—by researchers, government officials and the public—to understand peaceful and violent collective action at very fine-grained levels of time and geography.

As violent forms of collective action continue to erupt around the globe, there is a growing need to understand the conditions leading to them. Violent collective action not only poses significant dangers to the individuals and communities directly affected by it, but also tends to diminish the legitimacy of the causes associated with it (1,2), potentially hindering needed social change. For researchers, an automated means of identifying violent and peaceful collective action can provide a rich source of data that will expand the scope of knowledge and understanding of modern social movements and overcome the inherent data availability limitations which have restricted the study of social movements to either detailed case studies (3,4) or news media sources (5). From a public safety perspective, citizens can benefit from a tool which could warn them about areas in which violent activity is currently occurring or where it is likely to occur so that these areas can be avoided. From a mobilization perspective, utility may also be derived from a tool which can help potential participants discriminate between the types of activities that they would like to participate in.

In this paper, we create a computational framework for identifying different forms of social action and use this framework as the basis for a series of scalable event-detection algorithms that can be used to identify, track and study violent and non-violent collective action at fine-grained temporal and geographic levels. We build these algorithms using a subsample of an over 600

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millions of geo-coded Tweet database collected between April 1, 2014 and April 30, 2015. Using these algorithms, we explore the linguistic and spatial features of Tweets, describe those related to peaceful and forceful forms of collective action, and then demonstrate how these algorithms can be used to build databases which contain metrics of collective action.

**Framework for Social Action Identification**

Building a computational framework for social action identification requires identification of actions or observations conducted by individuals on behalf of or in concert with collectives. On social media, individuals post content (text, images, etc.) with the explicit knowledge and intention that others will be engaging with the information in some way. Thus, all activity on social media might be considered as a Weberian social action (6). This generality initiates our formalization:

**Definition 0.1.** Social actions, \( S \), form the subset of all actions in which individuals participate, \( A \), where consideration is made for the potential actions and reactions of others.

Thus, actions outside of \( S \)—asocial actions—fall entirely outside of our study, given our view through social media.

While all acts performed on social media fall in \( S \) by the Weberian definition, much of the content produced on these platforms does not comport with notions of social movements and collective action. These are our focus, so how are they distinguished? To focus in on social movements, we follow Tilly’s notion (7):

...a sustained series of interactions between powerholders and persons successfully claiming to speak on behalf of a constituency lacking formal representation, in the course of which those persons make publicly visible demands for changes in the distribution or exercise of power, and lack those demands with public demonstrations of support.

Distilling the inherently political nature of these types of actions, which hinge on representation, constituency, and power dynamics, we refine \( S \) as follows:

**Definition 0.2.** Political actions, \( P \subseteq S \), are the subset of social actions in which individuals and groups exercise or express power on behalf of themselves or others.

Tilly’s formalization around power, constituency, and representation winnows the actions represented on social media to, perhaps, a more interesting subset. Furthermore, the distillation of Tilly’s notions lead us to explore two natural refinements that are hinted at in his definition. These emerge from two questions:

1) What are the scales of acting entities?

2) In what manners do entities exercise power?
We see specific political actions as falling along one-dimensional spectra with respect to each question; e.g., (1) small-to-large scales, ranging from individuals, to teams, to collectives, to states; or; (2) civil-to-unruly manners, ranging from exhibition, to negotiation, to declaration, to enforcement. A specific numeric value on each spectrum is difficult to identify, so we approach these initially by establishing criteria that represent each as a simple dichotomy:

**Definition 0.3.** Actor scales refine the space of political actions into *singular* actions, $I$, conducted by individuals, and *collective* actions, $C$, conducted by groups operating in unison. Singular and collective actions disjointly partition the political actions: $C \cup I = P$; $C \cap I = \emptyset$.

**Definition 0.4.** Action manners refine the space of political actions into *peaceful* actions, $U$, for which all powers exercised respect the wills of all engaged parties and *forceful* actions, $V$, for which some power is exercised in violation of the will of another. Likewise, peaceful and forceful actions disjointly partition the political actions: $U \cup V = P$; $U \cap V = \emptyset$.

While each of our refinements of the political actions partition $P$, scales and manners interact in non-trivial ways. For example, groups may act forcefully, and individuals may act peacefully, etcetera. Thus, the full range of actions distinguished under our framework is now a partition of $P$ into four *modes*:

**Definition 0.5.** Singular peace actions, $I \cap U$, are those conducted by individuals that respect the wills of others, including negotiations, arguments, condemnation, and expressions of empathy and support.

**Definition 0.6.** Singular force actions, $I \cap V$, are those conducted by individuals that violate the wills of others, including assassinations, slander, shootings and other individually conducted assertions.

**Definition 0.7.** Collective peace actions, $C \cap U$, are those conducted by groups that respect the wills of others, including vigils/singing, lawful congregation, food/blood drives, and petitions.

**Definition 0.8.** Collective force actions, $C \cap V$, are those conducted by groups that violate the wills of others, including suppression, blockades, unlawful congregation, and rioting.

Note that some actions may be categorized differently, according to the prevailing circumstances in which they are carried out, e.g., the action of a vandal acting alone would fall under singular force, while another’s performance in a riot would fall under collective force.

**Building a social action classifier**

To explore the measurement of social action under our model, we utilize a database of over 600 million high-precision geographically-tagged messages from the Twitter social network collected over April 2014 to April 2015, which most notably covers the beginning of the Black Lives Matter movement...
(BLM) movement extensively. This dataset was collected from Twitter’s public (spritzer) API and is of particular importance for Twitter’s policies around location tagging at the time of collection.

At the time, when a user opted in for location tagging from a mobile device, a tweet sent would automatically be accompanied by high-precision latitude and longitude coordinates. Since then, Twitter enacted a policy that resulted in the adjustment of their system to default the option of soft-locations, which users specify (for example, one could set their location to Philadelphia and then go on to tweet from anywhere else in the world, with tweet meta-data always listed as Philadelphia). Since the rate at which tweets were geo-tagged was approximately 1% at the time of collection, and the (1% stream) public API was restricted to only location-tagged tweets, it is arguable that this dataset constitutes a near-complete collection of geo-tagged tweets during this period.

On account of the vastness of the Twitter database, we construct a filter that enables us to identify sets of Tweets more likely related to protest activity over the time period. While this kind of information can be technically accessed through newspaper accounts of protest activity, identifying the locations and exact times that protests took place around the world using newspaper accounts would require collecting a massive database of newspaper articles in different languages from around the world.

Instead, we leveraged an Associated Press image database containing thousands of images and extracted the relevant metadata contained therein, which included the exact time and location that photos of protest activity were taken (see Supplementary Materials for details). With this information, we build a Tweet “protest filter” for our coding of social action (assuming this sample to be particularly potent in representation of the actions of interest) (8).

Using approximately 10% (18,000) of the tweets sampled from the AP-filtered protest times and locations, in addition to all tweets from Alameda county, California on the night of Nov. 24th (a place and time that was known internationally to have violent protest activity), we coded tweets individually for the presence of the four modes of social action. From the total 22,626, a breakdown of the positively coded tweets is given in Tab.1.

We use the coded tweets as input for binary naïve Bayes classifiers, which, for each of the four action modes, run in parallel. These standard naïve Bayes classifiers are also modified with an enhanced input feature space of both single and multiword expressions. This process is accomplished through a recently developed (9) multiword expression segmentation method, which, intuitively, bases our classifiers on integrated collections of words and phrases. We refer to the resulting systems as “adept” Bayes classifiers, whose features have two notable advantages:

1. independent, semantic accuracy, and
2. out-of-context human interpretability.

So for example, basing the adept classifier on the expression tear gas (see 5th ranked word in Fig.3 right) sidesteps confounding statistical effects in the frequencies of the words tear and gas, and at the same time may be interpreted by a diagnostician to appropriately mean a crowd suppression device. Interpreted separately, these words might indicate an epidemic of indigestion.
From classifier to diagnostic utility

In addition to improving the Bayes classifier used in our experiments, the usage of phrases as features allows for greater interpretability of classifications. Our adept Bayes classifier has an advantage of being explorable, as a “white box” method that can be opened to show the features most relevant to classifications. In particular, looking at a document as a bag of phrases \( d = w_1, w_2, \cdots, w_N \), counted with frequencies \( f(w_1), f(w_2), \cdots, f(w_N) \), their impact on the adept Bayes classification is largely due to the likelihood function, \( \Lambda \) (determined in training), which, often computed as a sum of logarithms, is linear in frequencies:

\[
- \sum_{i=1}^{N} f(w_i) \log_{10} \Lambda(w_i \mid c). \tag{1}
\]

Note: \( c \) is the mode’s presence (positive/negative), and the terms are negated for an entropic framing. If a diagnostician wishes to understand why a tweet was classified as positive (\( c_+ \)) over negative (\( c_- \)), the difference may be computed:

\[
- \sum_{i=1}^{N} f(w_i) \left( \log_{10} \Lambda(w_i \mid c_+) - \log_{10} \Lambda(w_i \mid c_-) \right). \tag{2}
\]

Such a difference affords a ranking of features by the (absolute) terms of the sum, i.e., each word, \( w_i : i = 1, \cdots, N \), can be compared according to the relative impact on classification:

\[
f(w_i) \left( \log_{10} \Lambda(w_i \mid c_+) - \log_{10} \Lambda(w_i \mid c_-) \right). \tag{3}
\]

Thus, for diagnostic value we display the ranked values of Eq. 3 along a vertical bar plot, which we call a phrase shift (see Figs. 1, 3, and 2).

Evaluation

We examine the performance of our classifier by performing a tenfold cross-validation on the coded tweets data set. The results of this validation are recorded in Table 1. Treating the Bayes posterior probability as a tunable threshold for classification, we measure precision and recall, and optimize the threshold probability over \( F_1 \) to tune each given classifier. Observing these results, we see that collective force is, individually, the best predicted action type. This is encouraging, as collective force often represents the most serious actions. While classifier performance at predicting collective peace and singular force is lower, we do see that the most prevalent type of action, singular peace, is predicted well. When the classifiers are collapsed to less-specific types of action (Collective, Singular, Peace, and Force) performance decreases from the best cases (singular peace and collective force), but when all action types are combined (All), we see a significant performance improvement in all measures.
Table 1: Tenfold cross-validation results from application of the naïve Bayes classifier for the different modes of action. These results are also presented for less-refined modes. Each labeled row indicates the number of positive codings in the training data set (Abundance), and the $F_1$-optimal posterior probability (Threshold) for classification, in addition to its the corresponding values of precision (P), recall (R), and combined $F_1$. Out-of-domain evaluations are presented parenthetically, adjacent to their corresponding in-domain values.

<table>
<thead>
<tr>
<th>Action</th>
<th>Abundance</th>
<th>Threshold</th>
<th>P</th>
<th>R</th>
<th>$F_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collective force</td>
<td>795 (99)</td>
<td>0.08 (0.35)</td>
<td>74.08 (64.44)</td>
<td>76.01 (58.59)</td>
<td>74.94 (61.38)</td>
</tr>
<tr>
<td>Collective peace</td>
<td>474 (111)</td>
<td>0.78 (0.04)</td>
<td>51.92 (45.87)</td>
<td>55.25 (45.05)</td>
<td>53.29 (45.45)</td>
</tr>
<tr>
<td>Singular force</td>
<td>351 (6)</td>
<td>0.92 (0.42)</td>
<td>57.39 (0.25)</td>
<td>41.19 (16.67)</td>
<td>47.38 (20)</td>
</tr>
<tr>
<td>Singular peace</td>
<td>1,823 (96)</td>
<td>0.85 (0.11)</td>
<td>73.52 (44.68)</td>
<td>67.61 (43.75)</td>
<td>70.38 (44.21)</td>
</tr>
<tr>
<td>Collective</td>
<td>1,116 (168)</td>
<td>0.79 (0.17)</td>
<td>74.54 (75.91)</td>
<td>68.8 (61.90)</td>
<td>71.48 (68.20)</td>
</tr>
<tr>
<td>Singular</td>
<td>1,951 (101)</td>
<td>0.87 (0.36)</td>
<td>71.44 (41.18)</td>
<td>68.57 (55.45)</td>
<td>69.90 (47.26)</td>
</tr>
<tr>
<td>Force</td>
<td>1,107 (103)</td>
<td>0.71 (0.21)</td>
<td>66.94 (60.19)</td>
<td>67.54 (63.11)</td>
<td>67.22 (61.61)</td>
</tr>
<tr>
<td>Peace</td>
<td>2,092 (178)</td>
<td>0.88 (0.23)</td>
<td>71.5 (53.69)</td>
<td>72.2 (61.24)</td>
<td>71.78 (57.22)</td>
</tr>
<tr>
<td>All</td>
<td>2,596 (226)</td>
<td>0.93 (0.24)</td>
<td>80.71 (65.52)</td>
<td>74.42 (75.66)</td>
<td>77.39 (70.23)</td>
</tr>
</tbody>
</table>

While we cannot quantify our models performance in application to real-time data yet, we can hint at its performance on out-of-domain data by separating known distinct events in the training data. In addition to the BLM movement, the coded data significantly cover a portion of the Hong Kong democracy protests. Using the data from Hong Kong for testing, and all other data for training, we see somewhat different results (see Tab. I parentheticals), and generalize to note some potential challenges with using this data (that only covers a limited set of events) to build a classifier and apply it to data representing unknown and unforeseen events.

First, the subject matter (democracy) from the Hong Kong tweets is very different from that of the BLM movement (institutionalized racism), making the discourse present in the singular peace test tweets largely unrelated to that from training. As a result, this previously predictable category now exhibits substantially decreased performance. Furthermore, of the nearly 900 tweets coded from Hong Kong, only 6 were found to be representative of singular force, so there is essentially nothing to predict for this category.

For the collective actions we see very different numbers, especially for collective force. This is likely as a result of the similar collective tactics employed on both sides of both movements (e.g., blockades, non-lethal pacification, etc.). When the different action type are collapsed, we see more and more performance improvements, indicating that the collapsed categories may be the most reliable. However, since the Hong Kong tweets are actually part of the training of the overall classifier, we note that the performance of our model when applied to real-time data will likely be better than that reported in Tab. I (parentheticals), and importantly, for the most serious type of action—collective force—our results in performance are largely upheld.
Interpretation

To exhibit the manner in which our classifier might be used, we apply our trained classifier to data from outside of training, taken from Ferguson, MO. during the initial wave of protest activity, over August of 2014. In Fig. 1 we plot a time series of this period, showing the abundance of the four types of social action, as measured by the sum of posterior probabilities of all tweets under the application of our classifiers. Here, it can be seen that the largest spikes occurred on the first night of protesting (Aug. 10th). While singular peace (black line) exhibits a substantial, periodic signature even under normal circumstances (the discourse it covers is regular and common), collective force (red line) emerges aberrantly during the protest events, overshadowing the presence of the other action types.

Taking a closer look at the presence of collective force at the largest spike, we zoom in to a map of the first night of protesting in Fig. 1 and plot clusters of tweets with the positive classifications represented as proportional areas. Here, we can see a larger cluster just south of the freeway, on West Florissant Avenue, which corresponds to the time and location of the burning of the QuikTrip convenience store and gas station (set to fire by protestors). This action is actually hinted at in the phrase shift (bar plot, right), by terms such as “burning” and “on fire.” While the first night of protesting was violent and unexpected, the actions that took place were spread out, and involved fewer mass confrontations with the police, which later became more militarized and can be observed in figures depicting subsequent evenings.

We additionally present the result of our models application to the Hong Kong democracy protests that lasted for approximately two months in the fall of 2014. On the map in Fig. 3, we see clusters of collective force activity at the three main protest sites: Admiralty, Causeway Bay, and Mong Kok. Tactics similar to those reported by Twitter users during the Ferguson protests were employed by the Hong Kong police as well, as is indicated by a phrase shift (Fig. 3 right) that shows highly-impactive phrases such as “tear gas,” “stand off,” and “riot police.” So for the collective force category, we see a large degree of accord in the lexical features that indicate the presence of the action (which we quantify below, in Tab. 3(parentheticals)), indicating the possibility of applicability to out-of-domain data, and future events.

Building a Protest Activity Database

While the literature discusses many aspects of protests, one of the central political questions surrounding protest activity involves its effects on public opinion (10–12) and its ability to influence policymakers. The effects of protest activity on public opinion are especially important to understand because the former typically influences the latter. To construct measures of protest activity researchers have mostly relied on compiling databases of newspaper coverage of protest activity (5). While these databases arguably capture some of the most impactful protest activity, they have limited the study of protests to those picked up by media sources.

Here, we demonstrate that our software can be used to build a database of measurable protest
activity at the county level in the United States. Using our software, we explore patterns of protest activity across the United States shortly after the grand jury acquittal of Officer Darren Wilson in Ferguson, MO on November 24th and construct measures of protest activity using a subsample of 3.5 million classified Tweets. The Fig. [4] map contains measures of overall political activity across the United States—notably centralized in Missouri—after the acquittal of Darren Wilson on November 24th, 2014.

**Discussion**

As collective action in the digital age increasingly becomes a phenomenon which occurs simultaneously on social media and in geographic spaces, a theory which is able to map textual data and metadata onto events occurring on the ground provides a means by which these data can be harnessed to better understand the evolution of modern social movements. In this paper, we present a framework for identifying social actions which we argue accomplishes this task and demonstrate how this framework can be used to identify collective action and other social phenomena with high precision in a machine learning context. While the software and model discussed above were constructed using Twitter data, this method can be applied to any text-based form of real-time streaming social media. As such, this paper adds to a growing body of work focused on the automatic detection of events from social media streams in general, such as (13–19), to name a few. The information we have depicted in Figs. [1] [2] and [3] serve as examples of the diagnostic utility that our developed framework and methods can provide.

**References**


Figure 1: Above. Time series showing the total presence of social action types in Ferguson, MO the week after the shooting of Michael Brown by Officer Darren Wilson on August 9, 2014. The presence of each action type is determined by our adept Bayes classifier and measured as the sum of posterior probabilities over all tweets from each hour in the plotted span of time. Left. Map of Ferguson, MO depicting clusters of collective force activity over one hour around 12 AM, on August 11th. The size of each cluster-circle represents the area from which tweets emerged (not the number of tweets contained), and the portion of each circle colored red indicates the portion of tweets classified to represent the collective force action. Right. A phrase shift showing the most impactful features present in all tweets classified as being representative of collective force. Phrases on the right pull the classifier toward a positive classification, and phrases on the left pull the classifier towards a negative classification.
Figure 2: Above. A time series showing the total presence of social action types during the week of the Peoples Climate March which began on September 21, 2014. Left. Map of New York, NY depicting clusters of collective force and collective peace activity over one hour around 12 PM on September 21st during a climate change protest. The size of each cluster-circle represents the area from which tweets emerged (not the number of tweets contained), and the portion of each circle colored red indicates the portion of tweets classified to represent the collective force action. Right. A phrase shift showing the most impactful features present in all tweets classified as being representative of collective force. Phrases on the right pull the classifier toward a positive classification, and phrases on the left pull the classifier towards a negative classification.
Figure 3: Above. A time series showing the total presence of social action types during the week of the Occupy Central with Love and Peace movement which began on September 28th, 2014. Left. Map of Hong Kong depicting clusters of collective force activity over one hour around 11 AM, on September 29th. Right. A phrase shift showing the most impactful features present in all tweets classified as being representative of collective force. Note: points and bars represent analogous quantities to those in Figs. [1] and [2].
Figure 4: Ferguson-related political action across US counties on November 24th and 25th, 2014 as measured by the percentage of Tweets related to any form of political action.