

On Predicting Social Unrest Using Social Media

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Abstract—We study the possibility of predicting a social protest (planned, or unplanned) based on social media messaging. We consider the process called mobilization, described in the literature as the precursor of participation. Mobilization includes four stages: being sympathetic to the cause, being aware of the movement, motivation to take part and ability to participate. We suggest that expressions of mobilization in communications of individuals may be used to predict the approaching protest. We have utilized several Natural Language Processing techniques to create a methodology to identify mobilization in social media communication.

Results of experimentation with Twitter data collected before and during the 2015 Baltimore events and the information on actual protests taken from news media show a correlation over time between volume of Twitter communications related to mobilization and occurrences of protest at certain geographical locations. We conclude with discussion of possible theoretical explanations and practical applications of these results.

I. INTRODUCTION

Human society has a long history of social protests in various forms [1]. The use of digital communications including social media has become a salient feature of protests in recent years. Scholars have established the link between individual's social media use and political involvement [2]. For example, scholarly studies have considered the role of social media in recruitment for protest [3], dissemination of situational information during protest [4], [5] and relation between social media use and activism [2]. If digital communications can be used to facilitate the social protest, then can it be possible to use these communications to predict the protest as well? This study provides a positive answer to this question.

We hypothesize that there is a relationship between the volume of particular types of social media communications and actual occurrences of protests. The challenge in this approach lies in identifying the relevant messages in a very large stream of social media. To tackle this challenge we developed a methodology that intergrates research findings from the social and political sciences with recent advances in natural language processing and information extraction. We have applied this methodology to the Twitter data gathered before and during 2015 Baltimore protests and found empirical support for our hypothesis.

This paper provides a more detailed review of related research in both social science and data analysis followed by a discussion of the theoretical foundations of our methodology and then a description of our empirical testing of the pertinent theoretical constructs. We conclude by reporting results and setting forth directions for future work.

A. Related Work

This study is related to three research areas: social and political science on antecedents of protest behavior, research concerning forecasting events and behaviors using social media data, extracting information from social media.

There is an abundance of research on protest in the fields of social and political sciences, using various approaches to the subject. Studies have been done at the macro level: looking at the influence of the political and economic situation in general on protest moods [1] and viewing protests as organized social movements [6]. From the perspective of an individual, scholarly research has been concerned with recruitment and activism [7], [8] and factors and cognitive processes affecting individual participation in protests [9], [10], [11]. Such factors have also been used for modeling protest participation, e.g. in [9], [10], [12], and in a recent study combining social science with computational simulation of dynamics of participants [13]. Recent reviews of literature concerning individual protest participation can be found in [9], [10].

Since the online social media gained their worldwide popularity, a wide stream of research has emerged on extraction and structuring of the available information [14]. Among the various social media websites, Twitter is especially popular among scholars due to the availability of large numbers of data that can be collected while the event is unfolding - a naturally occurring experiment. Approaches to extracting information from Twitter are described, for example, in [15] and [16]. Scholarly works taking advantage of these technologies have been concerned with public response to extreme events [17], [18], [19], modeling human behavior [20], [21], [22], and forecasting actions [21], [22], attitudes [23] or even election results [24].

Research on the role of social media in protests has emerged after the Arab Spring, when its contribution to the

emergence of revolutions in Arab countries became apparent. Studies were undertaken on the role of social media in revolutions [4], [25], information dissemination during protests [2], [5], and activism and support of social movements [3], [23], [26].

Despite the general abundance of research concerning social media and protest, studies focused on the prediction of a protest using data from social media are scarce. In one of these papers [27], the authors compare the prediction of a protest with the prediction of election results. A study described in [28] presents a solution, relying on the constructed vocabulary. Recent research [29] addresses the problem using influence cascades as a predictor of protest. This study, however, also relies on a constructed vocabulary. Authors of [30] exploit previous activity of a social media user to predict whether her next message will be related to protest. The relationship between social media activity and protests during the Arab Spring was established in [31], using hashtags to filter relevant messages. Our approach also uses geographical and topical grouping of messages and our results confirm main finding of these studies, which is that social media activity can be used to forecast a protest. The notable difference in our approach, which we consider our main contribution, is that we ground our method of finding relevant messages on social science [9], [11], thus linking observations based on the data to underlying social and cognitive processes.

II. THEORETICAL CONSIDERATIONS

A. Introduction to Mobilization

Social science literature [9], [11] defines action mobilization, which we refer to simply as ‘mobilization’ throughout this paper, as a four-stage cognitive process resulting in an individual’s decision to participate in a collective action, such as to protest. These stages are as follows.

Sympathy to the cause

Every potential protest has a cause - the reason why it happens, which normally emerges from individual grievances. The first stage an individual enters before participating in the mobilization process is to become sympathetic to a particular cause, or have a particular grievance. Those sympathetic to the cause are considered the ‘recruitment pool for further stages of the process [11].

Awareness of the protest

At this stage the individual, sympathetic to a certain cause, becomes either the target of recruitment for action related to this cause, or acquires the knowledge of a planned action, i.e. a protest.

Motivation to take part

Being sympathetic to a cause and aware of an upcoming protest, the individual becomes willing to take part in it. However, this still doesn’t assure participation in the protest, as there may be obstacles to this particular individual’s participation in this event.

Ability to take part

At this point a motivated individual either doesn’t have any obstacles to participation, or successfully overcomes them.

As mobilization must precede protest participation, being able to identify individuals at different stages and to quantitatively measure the progress of mobilization enables one to make inferences about the upcoming protest.

B. Mobilization in Social Media

In order to utilize social media data we need a method to detect and measure mobilization. Assuming we can label individual messages according to mobilization stages (or lack thereof), what do we expect to observe?

Typically, research on social phenomena, such as protest, employs surveys conducted after the fact. While it has been found that mobilization precedes individual participation in a protest [11], we do not know, based upon empirical research, how mobilization develops over time in order to result in a protest.

Consider a closed community, in which all individuals initially sympathetic to the cause of a potential protest are known. As individuals are mobilizing, we would expect to observe a growing number of people at later stages of mobilization compared to those who don’t progress beyond sympathy. This consideration, however, is not relevant in social media because we can only identify an individual’s mobilization status if this individual voluntarily chooses to communicate it. Thus, unlike the post-hoc survey study, for a longitudinal study using social media data it is unreasonable to assume a static set of initial sympathizers (recruitment pool) for two reasons. First, different users may be vocal at each observation, and second, new sympathizers may emerge as a result of increased social media activity. This is due to the fact that communications are not targeted just at sympathizers, but also at those who are neutral towards the issue (e.g. due to being unaware of it). In [21], [22] it has been shown that social media activity may contribute to spreading of the behavior even among those who do not communicate about it, a phenomenon that we have no reason to rule out in our case.

Considering the above, we suggest that the social media activity related to approaching protest can cause more users to reveal their mobilization in messages. Therefore, we hypothesize that the amount of social media activity related to mobilization for a protest over a certain cause can be used to predict the timing of the protest action. In further sections we describe the empirical evidence in support of this hypothesis.

III. EXPERIMENTS

A. Data

For our experiments we purchased the Twitter Firehose data for selected locations in the USA starting from April 12, 2015 and ending on May 7, 2015. No keywords were used for message selection; the only criterion was location. Locations were determined as series of rectangular areas around the following American cities: Baltimore, Maryland, Washington, D.C., New York, New York, Philadelphia, Pennsylvania, Saint Louis, Missouri, San Francisco/Oakland, California, Los Angeles, California, Seattle, Washington, Minneapolis/Saint Paul, Minnesota, and Chicago, Illinois. The total number of messages is 18,694,604. Dates were selected so that the dataset covers the

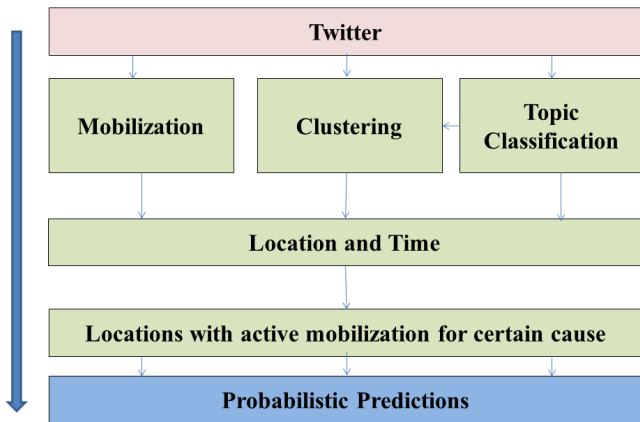


Fig. 1: Experiment framework.

whole development around 2015 Baltimore protests, starting from the very beginning: arrest of Freddie Gray on April 12. Some of the locations hosted events related to Baltimore protests, while other big cities where no known events occurred were randomly selected to provide negative examples in the data. For annotation of messages according to mobilization stages a set of tweets from a different source was used. These are 6,521 tweets sampled from the Twitter data collected via Apollo Social Sensing Toolkit [32] using keywords ‘protests’ and ‘rally’. Actual occurrences of protest events were manually coded based on open information sources¹ as binary outcomes: ‘1’ if the protest took place on the day at a given location, and ‘0’ if no such information is available.

B. Framework

The goal of the experiment is to discover a relationship between mobilization-related Twitter activity and information on actual protests. Considering the entire dataset is not viable due to multiple locations, and, more importantly, multiple causes of protests being present in the data at the same time. To overcome this difficulty we propose the following process (see also Fig. 1):

- 1) Cluster messages according to their topic. This allows separating different possible protest causes;
- 2) Separate tweets by geographic location. Locations of the authors based on GPS or user profiles are provided in the Twitter data. Also, this was our criterion for initial selection of tweets;
- 3) Detect and measure activity related to mobilization for each location-topic pair separately.

Let us describe the two latter steps in more detail.

1) *Topic Clustering*: Twitter messages are versatile by nature. People tweet about everything, from their personal lives to breaking news. In order to extract useful information for our study, we made the following assumption: *Hashtags have a good coverage of newsworthy topics*. A hashtag is a type of label or metadata tag used on social network and microblogging services, which makes it easier for users to find

messages with a specific theme or content. Users create and use hashtags by placing ‘#’ in front of a word or unspaced phrase, either in the main text of a message or at the end.² Taking advantage of this user-supplied information about their topics, we group tweets into clusters as follows:

Firstly, the most popular K hashtags are extracted from data. Each of these hashtags identifies a topically coherent cluster. A tweet is assigned to a cluster if the hashtag of that cluster appears in this tweet. If a tweet contains multiple hashtags, it will appear in multiple clusters. If a tweet does not contain any hashtags, the term vector of this tweet is compared to the term vector of every single cluster.³ The tweet is assigned to the most similar cluster based on the cosine similarity between term vectors. A threshold is applied for the cosine similarity because there exist a substantial number of tweets, which are not similar to any clusters. If the most similar cluster of a tweet has a similarity lower than the threshold, this tweet is viewed as off-topic and disregarded for our experiments.

Using hashtags has difficulties: only about 1/3 of messages in the dataset have hashtags, and usage is not consistent in time (they appear and disappear). Additionally, the active usage of a certain hashtag means that an associated topic has already gained sufficient popularity, thus we cannot identify when the topic first emerged. In future extensions of this research we may develop an approach that will not use hashtags for topic clustering. This will require methods to recover the actual topics of clusters, as hashtags also provide easy indication of topic.

2) *Detection of Relevant Messages*: We trained a Support Vector Machine (SVM) based classifier using 6,521 tweets manually annotated with mobilization stages. As said above, these tweets originate from a different source from the main dataset. We provide some details on the annotation below. We divided these tweet messages into 5 categories representing: (1). sympathy toward the protest cause, (2). awareness of the protest, (3). motivation to take part, (4). ability to take part, and (5). off-topic (not related to protest or mobilization). The detailed definition of these categories is as follows.

- 1) *Sympathy to the cause*. This category includes messages expressing positive attitude toward a certain protest cause, such as support of certain ideologies, anger or frustration about certain events, and support of protests already planned. Examples are (the original spelling and grammar are preserved for all examples): ‘How can you look at this and not protest or at least sign petitions?’; ‘We don’t want to lose our #blackcabs’.
- 2) *Awareness of the protest*. Messages in this category express knowledge of upcoming events or individuals and groups sharing sympathies with the author, such as spreading the information on upcoming protests. Note that the message must not communicate the author’s intent to take part, as this would indicate

²<https://en.wikipedia.org/wiki/Hashtag>

³We use the bag-of-words representation to get the term vector for each tweet. The term vector of a cluster is the bag-of-words representation of an aggregation of all the tweets within this cluster.

¹For Baltimore protests and related events we used the Wikipedia article (http://en.wikipedia.org/wiki/2015_Baltimore_protests) for reference. If the article mentions a protest on the date; we coded the outcome as ‘1’

a different stage. Examples are: ‘*Protest planned in response to video of 15-year-old’s arrest*’; ‘*Protest tomorrow outside the Saudi embassy in Ldn against the bombing of Yemen*’.

- 3) **Motivation to take part.** This category includes messages indicating the author’s willingness to attend the protest, but not assertively stating that the author plans to attend. This may include seeking additional information about the event, seeking companions to attend, or making excuses for non-attendance. Examples are: ‘*there’s an anti-war protest in albany tomorrow. does anyone want to go w me?*’; ‘*I’d join a demonstration in support of Leicestershire police at this point*’.
- 4) **Ability to take part.** This category includes messages that indicate that the author is planning to participate in a protest and there are no obstacles to doing so. These may include assertive statements about participation, sharing details about upcoming events with the indication that the author will be there, or offering help for others to attend the protest. Examples are: ‘*I’ll be partaking in this protest and I expect any fellow Brummies to be showing support for our club*’; ‘*Join us on the square for a PEACEFUL demonstration*’.
- 5) **Off-topic.** All other messages go into this category.

We used these annotated tweets to train an SVM-based classifier for stages of mobilization. Among the 6,521 tweets, 255 tweets are in Sympathy category, 312 tweets in Awareness category, 33 tweets in Motivation category, 116 tweets in Ability category, and 5,805 off-topic tweets. Considering the overwhelming number of tweets annotated as off-topic, we first sampled down off-topic tweets to make their number equal to the number of tweets in other categories. Then we trained a two-step mobilization classifier based on SVM model. The first classifier is to filter out the off-topic tweets, and the second one is to classify the mobilization stages of the remaining tweets. We use two types of features to train the classifiers:

- frequency-inverse document frequency (tf-idf): the tf-idf weight can measure how important a term is within a document. We regard each tweet as a document, and for each term t in a document d , we define t ’s tf-idf weight as $\text{tf-idf}_{t,d} = \text{tf}_{t,d} \times \text{idf}_f$, where $\text{tf}_{t,d}$ is the raw term frequency in a document, and idf_f is the inverse document frequency, which is a measure of how much information the term provides.
- Linguistic Inquiry and Word Count (LIWC) [33]: We choose the following features derived from the LIWC lexicon: ‘*future*’, ‘*past*’, ‘*posemo*’, ‘*negemo*’, ‘*sad*’, ‘*anx*’, ‘*anger*’, ‘*tentat*’, ‘*certain*’.

The accuracy score for the classifier in step one using five-fold cross-validation is 0.85, and 0.82 in step two.

C. Experiment Design

We applied the above process to the data. This yielded a total of 2210 topics and 10427 locations (locations were distinguished as city/town names). 102 locations have more than 10,000 tweets.

To check our hypothesis we used logistic regression [34] to establish the correlation between mobilization-related social media messaging and protest occurrences. We chose logistic regression because we have actual protests coded as a binary variable. We then applied the fitted model to estimate probability of the protest for a certain time period. A description of this process is as follows.

As noted, we chose the binary representation of the occurrences of protest as the dependent variable. We investigated using as the independent variable a measure representing the dynamics of tweets related to different stages of mobilization. However, in section II we noted that such an approach is not viable for a longitudinal study of social media messaging due to the impossibility of observing the same population every time period. In fact, numbers of tweets related to different mobilization stages appear to be correlated. Because of this we were unable to use tweet counts for each stage as separate independent variables. However, this correlation does mean that a linear combination of message counts can serve as a proxy variable for mobilization. We used the sum of tweet counts for all 4 mobilization stages.

We considered two location-topic pairs: Baltimore, Maryland/#freddiegray and Baltimore, Maryland/#nowplaying. The first hashtag is related to Freddie Gray, a person whose arrest and later death at the police department became the reason for Baltimore protests. This was the most popular hashtag related to Baltimore protests [26]. Thus, messages with this hashtag in Baltimore can be considered related to an actual protest. The second hashtag is intended for sharing information on the music currently being listened to by the author. We have no knowledge of protests or mobilization related to the second topic, and do not expect this issue ever to become a protest cause. For each pair we extracted numbers of mobilization-related tweets on each day included in the data. We coded outcomes for protest occurrences as ‘1’ for each day when protests over Freddie Gray’s death occurred in Baltimore, and ‘0’ otherwise for the first pair, and ‘0’ for each day for the second pair. We concatenated respective vectors of values for both pairs, thus obtaining our independent and dependent variables representing 52 data points.

It could be beneficial to use a larger portion of data in this training phase of the experiment. However, we do not have sufficient confirmed cases of protest for the period; involving more locations would create a bias towards negative examples and limit the availability of data for testing of the model.

D. Results and Discussion

Results of logistic regression summarized in the table below show significant correlation between mobilization related Twitter activity and occurrence of protest ($p = 0.0003$).

Variable	Coefficient	p-value
<i>Tweets</i>	0.0203	0.027
<i>Constant</i>	-2.5816	0.000
$(p = 0.0003)$		

Interpretation of logistic regression results allows to estimate a probability of the $y = 1$ outcome (in our case -

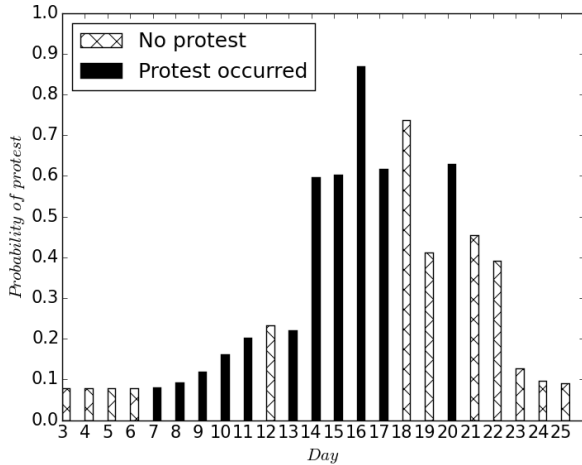


Fig. 2: Estimated probabilities for Baltimore and #freddiegray.

occurrence of a protest) as $\Pr(y = 1) = \frac{1}{1 + e^{-(ax+b)}}$, where a , b are regression coefficients [34].

However, above results only show the correlation between Twitter activity and protest occurrence on the same day. To enable the prediction and make the probability estimation feasible, we repeated the experiment using modified independent variable. Instead of a number of mobilization related tweets on day d we used the average of that number for days $d-3$, $d-2$ and $d-1$ (Avg_{d-1}). In this case we still observe statistically significant correlation ($p < 0.01$).

Variable	Coefficient	p-value
Avg_{d-1}	0.0165	0.005
Constant	-2.4617	0.000

($p = 0.0024$)

Now we estimate probabilities of protest occurrence. Fig. 2 shows results for Baltimore and hashtag #freddiegray (same hashtag used in further figures), which is the same data used to estimate the model. To illustrate the performance on new data, Fig. 3 shows results for New York City, where we know that a protest in support of Baltimore events occurred on April 29, 2015. Fig. 4 shows results for San Francisco, where no protests are known. On these figures heights of bars represent our estimates of protest probability for each day. Black bar indicates that the protest actually occurred on the day according to Wikipedia.

We can make the following observations from our results:

- 1) The estimated probability of the protest increases before the occurrence of the actual protest (can be seen especially clearly on Fig. 3);
- 2) No significant changes in probability can be observed where no protest occurred (Fig. 4);
- 3) Estimates are affected by peaks of protest activity: we used the 2015 Baltimore protests for training, which spanned multiple days reaching the peak around day 15 of our dataset. This, along with the fact that our calculations ignore the scale of the protest, explains the lack of significant probability growth before the first protests on Fig. 2;

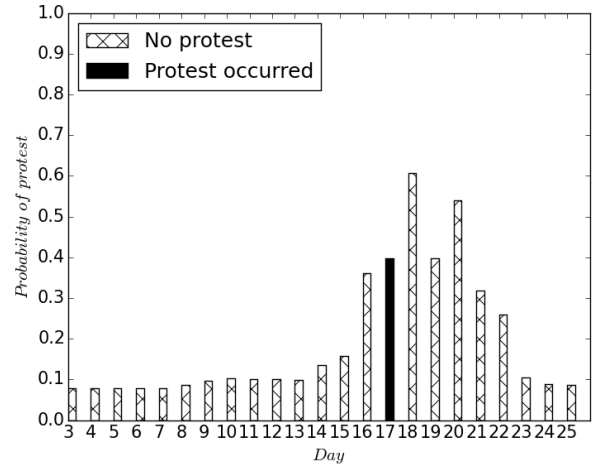


Fig. 3: Estimated probabilities for New York City and #freddiegray.

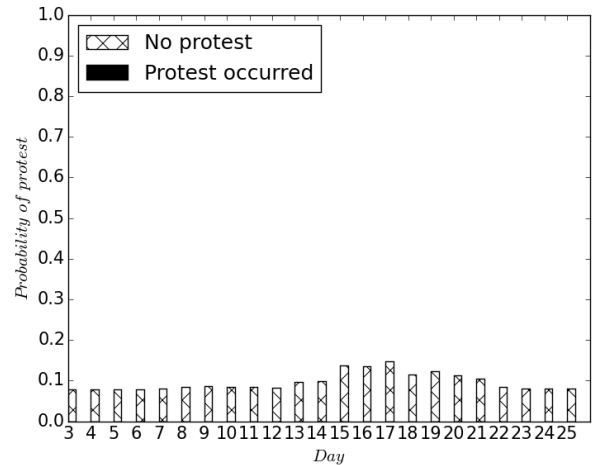


Fig. 4: Estimated probabilities for San Francisco and #freddiegray.

- 4) Actual protest occurrences influence estimates for subsequent days, creating a prolonged cool down, which can be observed on Fig. 2 and Fig. 3.

Thus, our approach allows prediction of protest occurrence in the case of the short-time events (1-2 days), or peaks of protest activity in case of longer-spanning events. In estimating multiple-day protests the binary representation ignores the scale of the protest activity. In our case this resulted in equal treatment of first protests in Baltimore (before April 25 or day 13), with hundreds of participants and no significant disruptions in normal city life, and the activity peak (April 25 and after), with thousands of participants, violence and serious disruptions. A different approach to measurement of the actual protest activity, e.g. incorporating numbers of participants, may resolve this issue.

The prolonged cool down, which makes the accurate predictions of new protests shortly after the recent occurrence difficult, emerges because the Twitter data from previous days is used to estimate probability. Naturally, when the protest is actually going on, it is actively discussed in social media, including sharing of sympathies, support and situational in-

formation. Such tweets are likely to be classified as related to mobilization, which affects our predictions for subsequent days. However, from a practical point of view, this may not be such a pressing issue: the responsible authorities do not need our predictions to already be on alert for continued activity. Additionally, we observe that the effect eventually vanishes after a few days.

IV. CONCLUSIONS AND FUTURE WORK

In this paper we have shown empirical evidence in favor of the possibility of predicting social unrest using social media communications. Our approach utilizes the findings of social science to inform and guide the information extraction and data mining. Our observations are not yet sufficient to make a claim that we can directly measure mobilization, or any other similar construct, using social media. However, they provide an avenue for closer collaboration with scholars in social science to explain phenomena underlying our observations.

We have shown that actual occurrences of protests are preceded by growth of their probability estimated using our approach. In addition our framework facilitates identifying the event(s) that caused the protest mobilization exploiting the fact that we use topically coherent clusters to produce our estimates. This enables us to identify particular grievances, group identities, etc., which may expose the social and cognitive factors explaining the empirical observations. Such explanations may result in improvement of predictions, and, more importantly, better understanding of the factors underlying these predictions will enable and inform the design of measures in response to the development of protest activity.

ACKNOWLEDGMENT

The authors gratefully acknowledge support from NSF Grant 1124827. This material is also based partially upon work sponsored by the Army Research Lab under cooperative agreement number W911NF-09-2-0053 (the ARL Network Science CTA) and by Department of Homeland Security through the Command, Control, and Interoperability Center for Advanced Data Analysis Center of Excellence. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory, or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation here on.

We would also like to acknowledge contributions made to this research by Xiaohui Lu, Tongtao Zhang and David Mendonça, and thank anonymous reviewers for their suggestions.

REFERENCES

- [1] R. Dalton, A. Van Sickle, and S. Weldon, "The Individual-Institutional Nexus of Protest Behaviour," *British Journal of Political Science*, vol. 40, no. 01, p. 51, dec 2009.
- [2] S. Valenzuela, "Unpacking the Use of Social Media for Protest Behavior: The Roles of Information, Opinion Expression, and Activism," *American Behavioral Scientist*, vol. 57, no. 7, pp. 920–942, 2013.
- [3] S. González-Bailón, J. Borge-Holthoefer, A. Rivero, and Y. Moreno, "The dynamics of protest recruitment through an online network," *Scientific reports*, vol. 1, 2011.
- [4] O. Oh, C. Eom, and H. R. Rao, "Research Note Role of Social Media in Social Change: An Analysis of Collective Sense Making During the 2011 Egypt Revolution," *Information Systems Research*, vol. 26, no. 1, pp. 210–223, 2015.
- [5] K. Starbird and L. Palen, "(how) will the revolution be retweeted?: Information diffusion and the 2011 egyptian uprising," in *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, ser. CSCW '12. New York, NY, USA: ACM, 2012, pp. 7–16.
- [6] D. Della Porta and M. Diani, *Social movements: An introduction*. John Wiley & Sons, 2009.
- [7] S. Walgrave and R. Wouters, "The missing link in the diffusion of protest: Asking others!" *American Journal of Sociology*, vol. 119, no. 6, pp. 1670–1709, 2014.
- [8] J. Verhulst and S. Walgrave, "The first time is the hardest? A cross-national and cross-issue comparison of first-time protest participants," *Political Behavior*, vol. 31, no. 3, pp. 455–484, 2009.
- [9] J. van Stekelenburg and B. Klandermans, "The social psychology of protest," *Current Sociology*, vol. 61, no. 5–6, pp. 886–905, mar 2013.
- [10] J. Van Stekelenburg, "The Political Psychology of Protest," *European psychologist*, 2013.
- [11] B. Klandermans and D. Oegema, "Potentials, networks, motivations, and barriers: Steps towards participation in social movements," *American sociological review*, vol. 52, no. 4, pp. 519–531, 1987. [Online]. Available: <http://www.jstor.org/stable/2095297>
- [12] E. K. Kelloway, L. Francis, V. M. Catano, and M. Teed, "Predicting Protest," *Basic and Applied Social Psychology*, vol. 29, no. 1, pp. 13–22, 2007.
- [13] P. Lu, "Predicting peak of participants in collective action," *Applied Mathematics and Computation*, vol. 274, pp. 318–330, 2015.
- [14] D. J. Watts, "Computational social science: Exciting progress and future directions," *The Bridge on Frontiers of Engineering*, vol. 43, no. 4, pp. 5–10, 2013.
- [15] S. Kumar, F. Morstatter, and H. Liu, *Twitter data analytics*. Springer, 2014.
- [16] M. Imran, S. Elbassuoni, C. Castillo, F. Diaz, and P. Meier, "Extracting information nuggets from disaster-related messages in social media," in *Proceedings of the 10th International ISCRAM Conference Baden-Baden, Germany, May 2013*, no. May, 2013, pp. 1–10.
- [17] Y. Tyshchuk, H. Li, H. Ji, and W. A. Wallace, "Evolution of Communities on Twitter and the Role of their Leaders during Emergencies," in *Proceedings of The 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM2013)*, 2013, pp. 727–733.
- [18] Y. Tyshchuk, W. A. Wallace, H. Li, H. Ji, and S. E. Kase, "The Nature of Communications and Emerging Communities on Twitter Following the 2013 Syria Sarin Gas Attacks," in *JISIC*, 2014, pp. 41–47.
- [19] S. Vieweg, "Situational awareness in mass emergency: A behavioral and linguistic analysis of microblogged communications. PhD Thesis," PhD Thesis, University of Colorado, 2012.
- [20] Y. Tyshchuk, "Modeling Human Behavior in the Context of Social Media during Extreme Events Caused by Natural Hazards," Ph.D. dissertation, RENSSELAER POLYTECHNIC INSTITUTE, 2015.
- [21] R. Korolov, J. Peabody, A. Lavoie, S. Das, M. Magdon-ismail, and W. Wallace, "Actions Are Louder than Words in Social Media," in *Proceedings of the 2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM 2015)*, J. T. Jian Pei, Fabrizio Silvestri, Ed., Paris, France, 2015, pp. 292–297.
- [22] R. Korolov, J. Peabody, A. Lavoie, S. Das, M. Magdon-ismail, and W. Wallace, "Predicting charitable donations using social media," *Social Network Analysis and Mining*, vol. 6, no. 1, pp. 1–10, 2016.
- [23] W. Magdy, K. Darwish, and I. Weber, "# FailedRevolutions: Using Twitter to study the antecedents of ISIS support," *First Monday*, vol. 21, no. 2, 2016.
- [24] A. Tumasjan, T. O. Sprenger, P. G. Sandner, and I. M. Welpe, "Predict-

- ing elections with twitter: What 140 characters reveal about political sentiment." *ICWSM*, vol. 10, pp. 178–185, 2010.
- [25] Z. Tufekci and C. Wilson, "Social media and the decision to participate in political protest: Observations from tahrir square," *Journal of Communication*, vol. 62, no. 2, pp. 363–379, 2012.
- [26] D. G. Freelon, C. D. McIlwain, and M. D. Clark, "Beyond the Hashtags: #Ferguson, #Blacklivesmatter, and the Online Struggle for Offline Justice," *Available at SSRN*, 2016.
- [27] A. A. Filchenkov, A. A. Azarov, and M. V. Abramov, "What is more predictable in social media," *Proceedings of the 2014 Conference on Electronic Governance and Open Society: Challenges in Eurasia - EGOSE '14*, pp. 157–161, 2014.
- [28] R. Compton, C. Lee, T.-C. Lu, L. De Silva, and M. Macy, "Detecting future social unrest in unprocessed twitter data:emerging phenomena and big data," in *Intelligence and Security Informatics (ISI), 2013 IEEE International Conference On*. IEEE, 2013, pp. 56–60.
- [29] J. Cadena, G. Korkmaz, C. J. Kuhlman, A. Marathe, N. Ramakrishnan, and A. Vullikanti, "Forecasting social unrest using activity cascades," *PloS one*, vol. 10, no. 6, p. e0128879, 2015.
- [30] S. Ranganath, F. Morstatter, X. Hu, J. Tang, S. Wang, and H. Liu, "Predicting online protest participation of social media users," in *Thirtieth AAAI Conference on Artificial Intelligence*, 2016.
- [31] Z. C. Steinert-Threlkeld, D. Mocanu, A. Vespignani, and J. Fowler, "Online social networks and offline protest," *EPJ Data Science*, vol. 4, no. 1, p. 1, 2015.
- [32] H. K. Le, J. Pasternack, H. Ahmadi, M. Gupta, Y. Sun, T. Abdelzaher, J. Han, D. Roth, B. Szymanski, and S. Adali, "Apollo: Towards factfinding in participatory sensing," in *Information Processing in Sensor Networks (IPSN), 2011 10th International Conference on*. IEEE, 2011, pp. 129–130.
- [33] J. W. Pennebaker, R. L. Boyd, K. Jordan, and K. Blackburn, "The development and psychometric properties of liwc2015," *UT Faculty/Researcher Works*, 2015.
- [34] D. R. Cox, "The regression analysis of binary sequences," *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 215–242, 1958.