An Agent-based Model of Posting Behavior During Times of Societal Unrest

Krishna C. Bathina[1] ⋆, Aruna Jammalamadaka[2] Jiejun Xu[2], and Tsai-Ching Lu[2]

[1] Indiana University, Bloomington IN 47408, USA,
bathina@indiana.edu,
[2] HRL Laboratories, LLC, Malibu, CA 90265,
{ajammalamadaka, jxu, tlu}@hrl.com

Abstract. Social media is increasingly monitored during periods of societal unrest to gauge public response and estimate the duration and severity of related protest events. To this end, we build an agent-based simulation model that accurately describes the shift in posting behavior of users as related to a real historical event. First we define an appropriate indication that an agent has become an “activist”, or someone who disseminates protest-related posts during times of unrest. We then build an agent-based model based on parameters estimated from before and during the protest. We validate our model using a complete collection of Tumblr data from six months prior to the Ferguson protest of 2014, until the state of emergency was lifted. Validation is performed by visual inspection of the similarity of simulated distributions of established emergent metrics to the empirically observed data. Our results show that our model has potential for predicting posting behavior during future protests.

Keywords: agent based model, information diffusion, social media, political unrest, Tumblr

1 Introduction

Agent-based models (ABMs) are computational models with autonomous agents, an environment, and mechanistic behaviors that can be used to represent and simulate emergent behavior from complex, non-linear mathematical systems [1]. In this paper, we focus on building an ABM that accurately models social media behavior during an actual protest by switching rules for agents during the protest depending on whether or not they become an ”activist”. A cartoon representation of our model is shown in Figure 1. In the upper left corner, an agent (i.e., an online social media user) chooses to adapt a meme #4 from its neighbor. Subsequently, in the upper right corner, the same agent updates its memory so that the oldest meme is removed and #4 is added. In the lower left corner, the agent can choose to post either a novel meme (e.g.,#5) or chose existing memes

⋆ This work was conducted while the first author was doing an internship at HRL Laboratories, LLC.

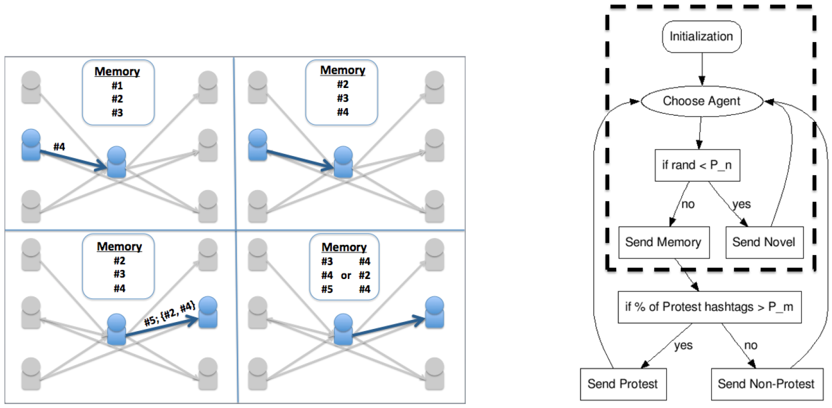


Fig. 1: The cartoon, on the left, is a visualization of the agent-based model for online social media users before a protest event. The flowchart, on the right, represents the *During* model. The *Before* model is shown in the dashed box. Both algorithms are described in the text.

from memory (e.g., #2, #4). Finally, in the bottom right quadrant, similar to above, the memory of the agent is updated, either with #5 or with #2 and #4. Such a diffusion style is inspired by the work in [5]. We choose the Ferguson protest of 2014 as the topic of our case study due to its national popularity.

2 Data Collection

We used data from Tumblr, a popular microblogging social network, for our analysis. Users can upload blog posts, unilaterally follow other users, and re-blog content. Typical social media APIs only allow for a partial data collection, or implement waiting times that make the collection of a complete dataset very difficult. Our case study differs in that we have the full dataset from 2012 to 2014, and thus our model can be accurately validated.

For our experiment, we first obtained a list of memes such as “justiceformike-brown”, “handsupdontshoot”, and “fergusonshooting” that were in support of the Ferguson protest (for a full list of the memes used please refer to [4]). We then defined two time periods in our dataset and for our model: May to August 8th as *Before* the protest and August 9th to September 3rd as *During* the protest. *Before* corresponds to three months before the protest (used for modeling non-protest behavior) and *During* corresponds to the period from the killing of Michael Brown to the day the national emergency was lifted (for modeling protest behavior). We then found all users that used any of the above protests memes at least once in *During*. Once the user population was collected, we extracted all of their posts and re-blogs from both *Before* and *During*. We label all memes that are not in the list above as *non-protest memes* in the context of this study. We also extracted all posts and re-blogs for the same time periods from 10,000 random users that never used one of the above protest memes as a control group, in order to first test if there is a statistical difference in the behavior of this group and the protest-meme-using group. In total, we extracted 220 million posts and 764 million memes. During the protest, about 1.7% of the posts and 2.1% of the tags were about the Ferguson protest. From this dataset, we are able to extract the full re-blog network and analyze every blog and re-blog. This network consists of 413,867 nodes and around 23 million total edges.

2.1 Preliminary Analysis

To describe our data, we use the four emergent metrics for quantifying social media behavior shown in Table 1. The Meme Time, Meme Popularity, User Entropy, and User Attention are averaged over only days that had posts; days without any posts were ignored.

Table 1: Emergent metrics for validation, from [5].

Metric	Definition
Meme Time	longest consecutive number of days a meme was posted
Meme Popularity	average number of posts of a meme per day
User Entropy	average entropy of the memes posted by a given user per day
User Attention	the average number of re-blogs per user per day

In order to determine whether a change in ABM rules during the protest was needed, we performed four different preliminary statistical analyses, results of which are shown in Table 2. Protesters are individuals who posted at least one protest meme during the time period of the study. Non-protesters, which are only used for analysis A, were chosen by finding all users that did not use any of the protest hashtags, followed by randomly sampling a set of 10,000 users to prevent any bias. $\Delta\widetilde{x}$ is the difference in median between both groups, or the effect size, and Z is the test statistic from the Kolmogorov-Smirnov test. The *Meme Time* was normalized over the total number of days, allowing the continuous assumptions of the KS test to hold. P-values are not reported because $-\log p > 30$ for each test, and thus were significant. For most comparisons, the $\Delta\widetilde{x}$ were very small. Analyses C and D, on the other hand, show that the protest memes had much more *Popularity* than all non-protest memes. Also, Analyses A and B show that the *User Attention* for both non-protesters and protesters before the protest was larger than protesters during the protest. Our results show that a difference exists between all compared groups, especially the *Popularity* of memes and the *Attention* of users.

Table 2: Preliminary analyses showing statistical differences in posting behavior.

Comparison	Popularity		Time		Attention		Entropy	
	$\Delta\widetilde{x}$	Z	$\Delta\widetilde{x}$	Z	$\Delta\widetilde{x}$	Z	$\Delta\widetilde{x}$	Z
A. Non-protesters during vs protesters during	-0.19	0.02	0.07	0.10	-12.79	0.28	-2.14	0.31
B. Protesters before vs protesters during	-0.05	0.03	-0.03	0.89	-10.65	0.01	-1.63	0.02
C. Non-protest memes during vs protest memes during	2.35	0.78	0.52	0.89				
D. Non-protest memes before vs protest memes during	12.95	0.82	0.47	0.89				

3 Model Description

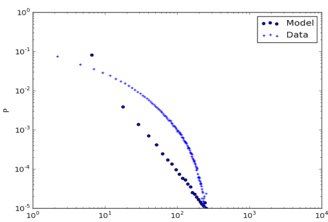
Our model, built using Python, is meant to mimic the natural posting patterns and influence of connected users during protest and non-protest periods. The model consists of Tumblr users as agents and the re-blog network as their environment, where directed edges represent the *flow* of memes. Each time step in our model represents one day. The total number of posts in the *Before* and *During* simulation periods are equal to the observed total number of posts during those periods, and an equal number of posts occur on each day of the simulation. Agents have a finite-sized *Memory* that contains a list of memes with repetitions. The memory is finite to model the limited attention that is evident among social media users [3]. If new memes are added to the memory, the oldest memes are removed from the list, representing the discovery that the number of memes to which a user can pay attention is bound, and therefore the injection and survival of new memes comes at the expense of others [5]. In line with this work, we utilize the following five model parameters:

- $\mathbf{P_n}$: probability of posting a novel meme
- $\mathbf{P_r}$: probability of posting multiple memes per post before the protest
- $\mathbf{P_{rn}}$: probability of posting multiple non-protest memes during the protest
- $\mathbf{P_{rp}}$: probability of posting multiple protest memes during the protest
- $\mathbf{P_m}$: proportion of protest memes needed in memory to post about the protest

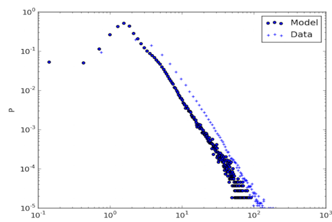
The novel aspects of our model come from splitting the model into two time periods; *Before* and *During* the protest. At initialization, the largest connected component (containing 412,803 nodes) of the re-blog network for the data is loaded into the model. The agents' memories are then loaded with random hashtags. At each iteration, an agent is chosen to post with a probability proportional to their out-degree [2]. This agent then either posts a novel hashtag with probability P_n, or posts a set of hashtags from memory. If the agent is posting from memory, each hashtag in memory is added to the post with probability P_r. After every post, the agent's memory, along with the memories of its neighbors are updated with the posted memes as shown in Figure 1. The *During* model is initialized with the agent attributes and network from the end of the *Before* model. An initial number of agents, equal to the number of actual protestors on the first day of the protest, are randomly chosen as protesters, and protest memes with frequencies proportional to the observed counts on the first day, are added to their memory. The model itself is identical to the *Before* model until an agent chooses to post from memory. If the percentage of protest memes in their memory is greater than P_m, the agent has become an *activist*, and consequently, this agent posts only protest memes. Each protest meme is chosen with probability P_{rp} with each post containing at least one meme. If the percentage in memory is not greater than P_m, the agents posts only non-protest memes, each with probability P_{rn}. To clarify, all agents in our model are protesters; they become activists once more than P_m percent of their memory is filled with protest memes. Again, after every post, the agent's memory along with the memories of its neighbors are updated accordingly. All parameters are found empirically. P_n

(=0.2657) is calculated by finding the average number of posts with a new meme per unit time (day). The P_r parameter family is calculated by the average number of memes per post divided by the length of the agent's *Memory*. P_r (0.2624) represents the average number of memes per post before the protest, while P_{rp} (0.3145) represents the average number of memes per post during the protest for posts that include protest memes and similarly, P_{rn} (0.2622) is calculated by the average number of memes per post during the protest for posts that do not include protest memes. P_m (0.6) and the size of the *Memory* (10) are tunable parameters.

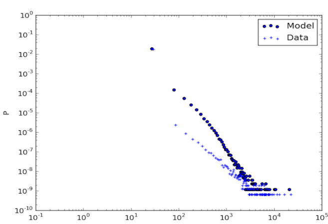
4 Results and Discussion



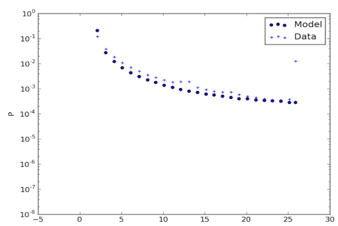
(a) User Attention



(b) Entropy



(c) Meme Popularity



(d) Meme Time

Fig. 2: The above plots show the comparison between model results and observed data via normalized histograms of the defined metrics. All plots are shown on a log-log scale except for (d) Meme Time, which is shown on a linear-log scale.

Overall, our ABM metrics show that results from the *Before* and *During* model are quite similar to empirical results from observed data. In this section we choose to focus on the emergent results from the *During* model because it is the major part of our contribution. These results are shown in the normalized histograms of Figure 2. Figure 2a shows that the *User Attention* from our model did not match that from data as well as we expected. Our model shows a linear distribution because of our proportionality assumption. However, the results indicate that the number of Tumblr users with a moderate average number of posts per day are higher than we expected. Even with this mismatch, we believe our assumption is reasonable based on previous studies, and we hesitate to overfit our model by incorporating the observed data. The *Entropy* (Figure 2b), of the model did match the data with a slight increase to a peak around 1.0, and then a rapid decrease afterwards. This suggests that most users tended to post with very little variety per day. In the model, *Entropy* is a factor of the rate of novel memes, protest memes, and non-protest memes. Increasing the rate of novel memes, P_n, would increase the average user entropy while increasing the rate of protest and non-protest memes would decrease the entropy. Figure 2c shows that although the model and data distributions have similar shapes, the model tended to overestimate the *Meme Popularity*. This is most likely due to our posting behavior assumption since *Meme Popularity* is a function of what memes are posted, and thus, which users are posting. But, with such a low difference in probabilities and a similar distribution shape, we believe the deviances are reasonable. The *Meme Time* for the model and data in Figure 2d show similar distributions, with both flattening out as the time increases, suggesting that the majority of Tumblr hashtags are not re-blogged. *Meme Time* is a function of the re-blog parameters, P_r, P_{rp}, P_{rn}; increasing their values would cause an increase in the lifetime of the meme.

The results from the *During* model in Figure 2 may look very similar to the data simply due to a large proportion of non-protest memes. Therefore, to capture the true effect of the model, we also computed unnormalized histograms for only the protest memes. We found similar behavior between *Meme Times* in the "During“ model and the data, with the model tending to slightly underestimate the times. Similarly, the *Meme Popularity* showed that the shape of the model results and data distributions match well, but the model tends to overestimate the popularity by about a factor of 10. Overall, the difference in model and empirical results are small, therefore we believe that our model successfully and accurately describes the full Tumblr dataset.

In summary, we built a new ABM which uses a real protest event to represent a radical change in behavior of a sub-population of the agents. We then validated our model empirically by analyzing Tumblr data during the Ferguson protest of 2014. We acknowledge that this is an empirical study, and validation on an entirely new protest dataset is required in order for the model to be proven usable for prediction and simulation of future events. We chose not to perform cross-validation by sub-sampling the network used in this study, opting instead for the more realistic analysis of posting interactions that ensues from analyzing the full Tumblr re-blog network. However, we believe that our model, and the extensions of it described below, can still be useful in quantifying and simulation social media posting behavior during times of protest.

References

1. Bruch, E., Atwell, J.: Agent-based models in empirical social research. Sociological methods & research p. 0049124113506405 (2013)
2. Chung, F., Lu, L.: The average distances in random graphs with given expected degrees. Proceedings of the National Academy of Sciences 99(25), 15879–15882 (2002)
3. Hodas, N.O.: How limited visibility and divided attention constrain social contagion. In: In SocialCom. Citeseer (2012)
4. Jules, B.: Hashtags of ferguson (2014), `https://medium.com/on-archivy/hashtags-of-ferguson-8f52a0aced87.vbia14pwu`
5. Weng, L., Flammini, A., Vespignani, A., Menczer, F.: Competition among memes in a world with limited attention. Scientific reports 2 (2012)