Information Processing on Social Media Networks as Emergent Collective Intelligence

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1. INTRODUCTION

This research explores the dynamics of information-processing on social media service platforms. Our research application-domain of interest is the manifestation of mass-mobilization political movements, particularly those directed against authoritarian governments. However, our model dynamics are agnostic as to a particular application domain. Rather, our model simply describes the mechanism by which a network of individuals computes the flow of information across itself, thereby manifesting an expression of collective intelligence. Our conceptualization of collective intelligence as the dynamic computation of information draws simultaneously on Couzin's identification of "collective cognition in animal groups" [Couzin 2009], on Holland's specification of "emergent phenomena" [Holland 1997], and similarly on Arthur's description of the market economy as a system "in-motion…perpetually computing itself" [Arthur 2014]. Couzin observed that "important commonalities exist with the understanding of neuronal processes" and animal group behavior, and that "much could be learned by considering collective animal behavior in the framework of cognitive science" [Couzin 2009]. Per an analogy drawn by Hawking [Swartz 2014], our model of information processing on social media platforms may bear similarity to the processing of information by neurons in the brain. Exploring this similarity may yield valuable insights on the operation of both social and neuronal systems.

1.1 Mobilization Movements as Socio-technological Systems

Our research looks to understand the dynamic information-generating process yielding an observed waveform in the time-series of social media content-generation during the "revolutionary moment" of a mass-mobilization movement [Baxandall 1968]. The observed waveform presents a trace of content-generating activity by a platform's user-base during the mobilization process. Content-generating activity encompasses both new content generation (a Facebook user posts new content to their 'Timeline;' a Twitter user issues a 'Tweet'), as well as sharing existing content (a Facebook user shares content already posted on the Timeline of another Facebook user, a Twitter user retweets another user's Tweet).

The toppling of an authoritarian regime is an occasion of heightened content-generating activity (both on social media and on conventional news media platforms), and it is unsurprising that a spike in the volume of content generated should attend these events. More interesting, however, is the observed variation in activity observed in the days *preceding* these events. One may argue that this activity is simply a reflection of the popular *zeitgeist* – i.e., that this activity is at-best an instrumental indicator of the larger societal phenomenon already underway. However, Shirky [2011] observes that mobilization movements are increasingly influenced by the sharing of information on social media

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platforms. The use of these technologies is therefore integral to the mobilization process, insofar as it serves to facilitate the collective processing of information by platform-users.

Sun et al. observe that the propagation of “fanning” behavior on the Facebook platform occurs per a contagion process [Sun et al 2009]. Users may express affinity for a particular celebrity, organization, etc. by electing to ‘fan’ (i.e., to become a ‘fan’ of) the associated Facebook Page. As users fan a particular Page, other users in their friend-network are notified, and are presented the option to do so as well. Centola [2018] observes that complex behavioral contagions require more than mere “awareness;” people do not necessarily engage in a complex behavior simply because they observe another person doing so, but must rather observe several others engaged in the behavior before they do so themselves. However, Sun et al. indicate that notification about one of one’s friends’ fanning of a Facebook Page is sufficient to motivate a notified user to do likewise, revealing that users’ behavior on social media platforms can propagate per a simple contagion process. Accordingly, we model the propagation of content-generating (or, ‘participatory’) behavior as a simple contagion: the inclination to participate in content-generating behavior is understood to propagate directly from one individual to the next, regardless of whether others in the network-neighborhood are behaving similarly (cf. Suler’s identification of the “online disinhibition effect” [Suler 2004]).

Borrowing the language of epidemiology, our participatory-behavioral propagation process may then be described as a simple ‘*SIS*’ contagion: individuals transition from behaviorally ‘susceptible’ (state S) to behaviorally ‘infected’ (state I) per their exposure to the behavioral contagion, and then back again (‘recovery’). In a homogeneous population (i.e., one in which the network of individuals may be represented as a geometric random graph), such contagion processes are well-described by a (canonical) system of two time-dependent ordinary differential equations, with the time-rate of transitions between states governed by two scalar parameters: a contagion spreading-rate parameter β and a recovery parameter γ. (The ratio of the spreading rate to the recovery rate defines the “critical threshold” λ_c for epidemic contagion [Scarpino and Petri 2019]; to proliferate as an epidemic, a contagion process must manifest $\lambda_c > 1$).

1.2 Conditions

Centola and Macy [2007] identify an influence of network graph topology on the time-rate of information flow across a network graph. Accordingly, we posit that localized variation in the graph of a social media network will serve to modulate the effective participatory-behavioral contagion-spreading rate.

CONJECTURE 1.1. *The effective spreading-rate parameter for a simple contagion process propagated on a social network graph will exhibit variation in time as the contagion wavefront transits graph regions of varying connectivity.*

As the participatory-behavioral contagion propagates across a social media platform’s follower-network, it first saturates a densely-connected origination cluster, then propagates across more sparsely-connected interstitial regions *en route* to other clusters, eventually reaching the network's densely-connected core region. The effect of this variation in the substrate network graph is that the contagion spreading parameter β appears to vary in time. As the contagion transits more densely-connected regions of the graph, the spreading-rate parameter will appear to increase, while in sparsely-connected regions, it will appear to diminish.

We simulate the effect of variation in graph topology on the spreading rate parameter β by varying its magnitude sinusoidally in time. (We implement time variation in β computationally by iterating the Doob-Gillespie algorithm, recursively). As we are embedding the effect of variation in graph topology within the contagion spreading-rate parameter, we control for structural artifacts of the substrate graph by propagating the contagion process on an undifferentiated toroidal grid lattice.

CONJECTURE 1.2. *The number of susceptible users grows exponentially in time.*

While the contagion process propagates across the network, the content generated reaches an exponentially-growing number of users. The effect of content-generating behavior is then an exponential growth in the number of contagion-susceptible individuals, as the consumption of content delivers ever-larger volumes of users as input-feedstock to the behavioral contagion process. We simulate this exponential growth in susceptible individuals by increasing the size of the substrate toroidal lattice exponentially in time.

Content generation is understood to occur as individuals transition from state S (non-participatory state) to state I (content-generating state). Counting the number of transitions from the S to the I states for a given interval (t_i, t_{i+1}) yields a model representation of the volume of content generated during that interval. We find that binning counts of $S \rightarrow I$ transitions for our combined simple contagion and exponential information-propagation model yields simulated aggregate-activity time-series resembling empirical observations for real-world mass-mobilization events (fig. 1).

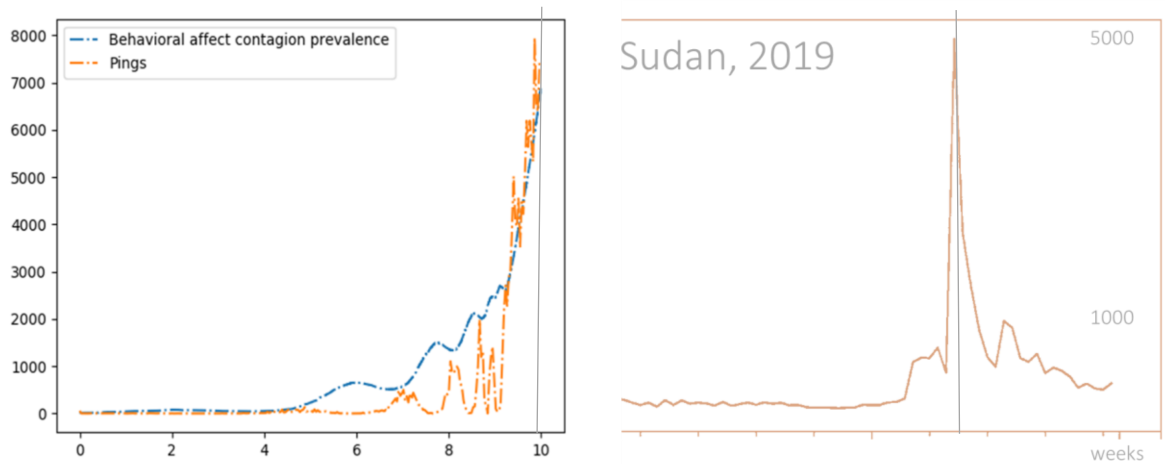

Fig. 1. Left: simulated behavioral-affect contagion prevalence (blue) and resulting behavioral output time-series ('Pings,' orange) for time-varying contagion process propagating on exponentially-growing toroidal lattice graphs. Right: empirical Tweet volume time-series data for Sudan mass-mobilization event (April 2019).

1.3 Current Work

In this paper, we simulate the *effects* of (1) variation in a social network graph's connectivity and (2) the flow of information on the propagation of content-generating behavior and the waveform of content-volume time-series data. Next, we seek to characterize the waveform of the time-series as the contagion wavefront transits the network graph. We look to employ hyperbolic random graph (HRG) construction to generate graphs objects for simulation modeling. HRGs were first described by Krioukov et al. [2009] and were observed to exhibit structural characteristics that "resemble complex real world networks" [Bläsius et al. 2019]. A recent review by Sharpee [2019] indicates that the neural networks may also be modeled using hyperbolic geometry.

Currently, we seek to identify a graph-construction 'recipe' that produces graph objects having similar structural characteristics to the graphs of real-world social media follower-networks. Work by Ugander et al. [2011] reveals that the structure of these graph objects may exhibit universality. Accordingly, we seek to reliably produce HRG objects having structural characteristics similar to those that Ugander et al. identified.

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