Mass-Mobilization Emergence on Social Media Network Graphs

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Introduction

This research is directed toward understanding the emergence of mass-mobilization political phenomena under conditions of rapid information propagation; i.e., of the kind facilitated by widespread adoption of social media and mobile internet information and communication technologies (ICT). Where earlier work in political economy applied agent-based approaches (e.g., Epstein 20002), this research described here draws on work by Sornette et al.4 which sought to identify an observable signal in the behavior of financial market indices in the run-up to a market crash. Sornette’s work seeks to characterize market behavior per the log-periodic power law singularity model (LPPLS), which captures pre-crash financial market index behaviors. Sornette identified this log-periodic power law behavior following similar work on the characteristics of catastrophic failures in aerospace industry gas pressure tanks. He speculated that LPPLS models may also be applied to describe emergent social behaviors. Building on data from Islamic Republic of Iran in late 2017 and applying a computational modeling approach, the work described here aims to test the applicability of Sornette’s LPPLS model to emergent political phenomena.

What is ‘emergence’?

‘Emergence’ is a feature of complex adaptive systems. Emergence manifests per mutual interactions between system components. Emergence is not simply the additive effect of these interactions, but is rather the result of the combined effect of those interactions over time. This means that, the final state of the system cannot be reliably predicted from initial conditions (nor can the system state for any time).

What about emergent mass-mobilizations, in particular?

Emergent mobilization phenomena precipitate from conditions that historically have been regarded as opaque to observation. This opacity is not simply an observational problem, but also occurs due to preference falsification4 by individuals living under conditions where political expression is costly. In other words: our phenomenon of interest actively resists our attempts to observe it! This opacity has made emergent mass-mobilizations difficult to anticipate and impossible to predict a priori.

The near-total diffusion of social media services bears important implications for the speed and scale of mass-mobilization emergence. Social media services offer individuals ‘lower-cost’ fora for preference revelation and are increasingly the vehicle by which information about mobilization activity is broadcast. This ‘low-effort’ capacity serves to ameliorate information asymmetry among individuals.

Behavioral affect traces a waveform in time as it propagates across a social-media network graph Twitter activity for the hashtag #السودان (‘al-Sudan’) during 2019 exhibits a striking pattern in the form of its time-series. A marked increase in activity corresponding to the overthrow of the al-Bashir regime was preceded by at least one pre-cursor ‘event.’ The form of the time-series is an artefact of the unseen behavioral contagion process as it propagates across the underlying social network graph.

Modeling mass-mobilization events as LPPLS processes

The LPPLS model was originally developed by Anifrani, le Floch, Sornette and Soullard11 to explain an observed pattern in acoustic emissions from aerospace industry gas pressure tanks as they were subjected to increasing pressures. Sornette et al11 later used the model to explain an observed pattern in stock index valuation prior to a market crash. Sornette’s model specification converges to singularity at the time of the crash (‘critical time’, t∗). This research aims to understand the emergence of a mass-mobilization event using Sornette et al’s LPPLS framework.

LPPLS model fit versus ordinary exponential growth fits for 1987 ‘Black Monday’ market crash.2 The LPPLS model fit may be written as:

\[ E(\ln p(t)) = A + B (t^*_c - t)^\gamma + C (t^*_c - t)^\mu \cos \left( \omega (t^*_c - t) - \varphi \right) \]

where:

- \( p(t) \) time series data, \( p(t) \in [0,1] \)
- \( t^*_c \) critical time (time at singularity)
- \( \gamma \) power-law growth parameter
- \( \omega \) angular log-frequency parameter
- \( A,B,C \) linear fit parameters
- \( \varphi \) phase-angle fit parameter

The key parameters of interest are the exponential growth index A, the angular log-frequency index \( \omega \) and the critical time \( t^*_c \).

Research roadmap

On-going research aims to explain the manifestation of the LPPLS signal in social-media activity time-series data in terms of contagion propagation dynamics.

Preliminary work: modeling contagion dynamics on simulated multiplex social media networks

Our modeling approach is specified as follows:

- Identify a simulated social media network topology that captures the essential features of real-world social media network graphs: simulated graphs are constructed as a multilayer network of Holme-Kim6 graphs. (Network graphs are generated using the NetworkX Python software module originally developed by Aric Hagberg, Dan Schult, and Pieter Swart).
- Our goal has been to develop a simulated network topology that mimics the characteristics of a real-world social media network graph.
- Introduce the preference revelation and falsification contagion processes; record the time-series of revelation contagion prevalence on the graph. (Contagion processes are modeled using the Epidemics on Networks (EoN) Python software module developed by Bill C. Miller16).
- Identify the contagion process specifications that yield the LPPLS signal in the contagion prevalence time series data. (Curve-fitting is performed using the Dragon_Kings LPPLS curve-fitting Python script developed by Dylan Albrecht, GitHub.com/NonAbelian).

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References