Revolutionary Fervor as Contagion: A Network Model of Rebellion*

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Abstract

In this project, we model revolutionary activism on networks. Revolutionary fervor spreads through the network like a contagion, but depends on the revolutionary thresholds and grievance levels of each node. We provide for nodal removal and rewiring to better capture the underlying dynamics that drive revolutions and endogenize regime legitimacy. Our model deviates from existing work insofar as we arrange actors along a continuum, allowing for counter-revolutionaries and police to eventually be coopted into the revolution. This is a crucial condition for successful revolutions, which is too often gainsaid. Ultimately, we find that initial network structure has a negligible effect on long-run dynamics and that under many parameter settings the system equilibrates to a steady state after a transitory period and phase transition.

1 Introduction

Recent events in Iran have demonstrated the inability of autocratic regimes to readily suppress civil demonstrations, cascading into national protests. In this project, we explore this phenomenon through a series of networks (including lattice, small world and scale free models), which attempt to simulate the social embeddedness inherent in any social interaction (Granovetter 1985).[1] Previous work has ignored the importance of basic human relationships in the spread and success of revolutionary movements, a failure that we hope to address through embedding actors in networks.

Having generated these different networks (representing varying social structures within society), we model the spread of revolutionary fervor as a contagion. The virulence and rapidity of this contagion depends on the revolutionary

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[1]Granovetter, Mark. 1985. "Economic Action and Social Structure: The Problem of Embeddedness." *American Journal of Sociology* 91(3): 481-510.

thresholds and grievance levels of each node, which are randomly distributed within a given network. We provide for nodal removal and rewiring to better capture the underlying dynamics that drive revolutions; namely, the creation of assortative groupings representing revolutionary cells, which further foment resistance. Our model deviates from existing work insofar as we arrange actors along a continuum, allowing for counter-revolutionaries and police to eventually be co-opted into the revolution. This is a crucial condition for successful revolutions, which is too often gainsaid. Finally, we endogenize regime legitimacy by linking individual node grievance levels with local conditions (e.g. the removal of a neighboring, connected node).

Ultimately, through investigating various network structures and conducting comparative static analysis on model parameters, we interrogate the following questions: 1) What drives revolutionary dynamics? 2) Does revolutionary success require cooptation of the coercive apparatus (i.e. police)? and 3) How do network properties alter revolutionary dynamics, are these effects constant across systems? The succeeding exposition proceeds as follows. Section 2 will survey the antecedent theory and existing models of revolutionary dynamics. Following from these model's failures and inadequacies, we construct a network model, which we summarily describe in Section 3. Next, we present our results in Section 4. Finally, we conclude with Section 5, offering a brief discussion of future work.

2 Antecedent Theory and Extant Models

We draw from a robust and dynamic literature, exploring various aspects of civil violence, revolutions and regime change. Within the social sciences, there are a panoply of competing models, varying in scope and method, that try to capture the underlying dynamics within mass movements and revolutions. Many of these models differ significantly in their behavioral postulates, operational assumptions and, ultimately, model predictions. The succeeding sections will briefly survey this literature and the disparate theories, focusing in particular on the model assumptions, implications and problems. Ultimately, we will demonstrate that our computational approach answers these problems and, derivatively, offers significant advances in modeling revolutionary dynamics.

Social-Psych Theories The earliest models of revolutions drew largely from sociology and psychology, arguing that individual, micro-level determinants explain participation in revolutions. Ted Gurr (1970) was one of the first social scientists to employ these methods, proposing the theory of relative deprivation.[2] This theory propounds that revolutions result when individuals are frustrated by the difference between their perceived socio-economic status and what they believe that they deserve. Individuals evaluate this perceived deprivation relative to their neighbors, rather than in absolute terms. James Chowning Davies

[2]Gurr, Ted. 1970. *Why Men Rebel*. Princeton, NJ: Princeton University Press.

J-curve expanded on relative deprivation by explaining revolutionary dynamics over time. Both these theories, however, fail to model macro social structures or account for the emergent, non-linear dynamics that characterize mass social movements.

Analytical Threshold Models With the introduction of formal modeling and economic theory, social scientific models of revolutions grew increasingly sophisticated. Timur Kuran's (1991) "Now Out of Nowhere" is one of the seminal papers in this literature.[3] Kuran argues that the rapid collapse of the Eastern European bloc was not only unpredictable and inexplicable for conventional models, but *no theory* could possibly explain the rise of revolutions. Like Lohmann (1991),[4] Kuran formalizes the problem as one of non-linear social cascades. Revolutionary coordination is difficult because individuals hold unobserved thresholds (part grievance and part risk aversion) for participation. As regime legitimacy is challenged, decreasing costs and risks to participation, these latent thresholds are surpassed, thus activating more citizens. This model predicts revolutions should resemble general phase transitions: successful revolutions begin with a trickle until a sufficient number of citizens participate, lowering costs significantly and precipitating society-wide participation.

However sophisticated, these analytical models are not without their flaws. While attempting to explain dynamics, the model is ultimately static, employing a closed-form solution concept. Although analytically tractable, the model fails to precisely characterize the dynamic and non-linear aspects of participation.

Computational Models Computational methods, by contrast, can simulate these dynamic processes and thus provide greater precision in the types of distributions and initial conditions needed to achieve successful revolutions. Accordingly, we now consider computational models of revolution. Most notably, Epstein (2002) formalizes Kuran's (1991) model, transforming the simple analytic construction into a computational model of dynamic, interactive agents.[5] Epstein's computational model of civil violence is nearly identical to Kuran's; individual agents have thresholds that capture their respective grievance and risk aversion, which if surpassed, induces revolt. Additionally, Epstein includes police (with limited, local vision) who patrol the space and arrest rioters. Epstein replicates Kuran's findings from the analytic model and further discovers underlying emergent behavior where simple automata display seemingly sophisticated, coordinated violence while shirking police patrols. However significant, Epstein's model fails to account for social structure. His agents are anonymous and interchangeable. Such a characterization is problematic when studying revolutions because social relations play a profound role in the organization

[3]Kuran, Timur. 1991. "Now Out of Never: The Element of Surprise in the East European Revolution of 1989." *World Politics*, 44: 7-48.

[4]Lohmann, Susanne. 1994. "The Dynamics of Informational Cascades: The Monday Demonstrations in Leipzig, East Germany, 1989-91." *World Politics*.

[5]Epstein, Joshua. 2002. "Modeling Civil Violence: An Agent-Based Computational Approach." *Proceedings of the National Academy of Sciences*, 99: 7243-7250.

and coordination within mass movements. Stripping agents of this embeddness deprives them of their interpersonal ties, central in forming macro collectives capable of rebellion.

3 The Model

Although coordination is difficult, it is not impossible even in the most repressive of regimes. Often, revolutionary fervor spreads within social groups, who spread their ideas and beliefs to their friends, family members and other social associations. Thus, we conjecture that the structure of these social networks should play an important role in the successful spread of revolutionary ideas. Accordingly, we model this process similar to a contagion on a network. We will now briefly describe the model.

Network Generation We begin by generating a series of networks of varying structure, degree distribution and size. We provide parameters for easy generation of lattice, scale free and small world networks. Additionally, we offer the user control over the number of nodes in the network and the relative density of different types of actors (i.e. police vs. citizen nodes). (For an image of the full set of options included in the model, see Figure 3.1 in the Appendix).

Nodes and Thresholds Each node in a network is assigned two thresholds τ_l and τ_h and a grievance level γ. When γ falls below τ_l, a citizen will join the counter-revolutionaries (hereon called *Contras*). However, if γ rises above τ_h, a citizen joins the active revolutionaries (hereon called *Actives*). If a citizen's grievance level does not cross either threshold, then she is not activated and is called a *Passive*. The cutpoints reflect each individual's propensity to join either the revolutionary Actives, or support the regime and suppress rebellion by joining the Contras. These thresholds capture both risk aversion associated with participating in either group and the individual's support for the status quo regime. It is only when one's personal grievance level exceeds one of these threshold's will participation be preferred to passivity. Unlike Epstein, our model allows for actors to fall along a continuum of types, from openly rebelling to supporting the regime.

Revolutions, however, are not confined to the citizenry. In fact, their success or failure often relies on co-opting other pivotal actors, in particular, the police. Accordingly, the police similarly join these factions if their grievance levels cross the respective cutpoints, yet they begin biased conservatively and thus closer to τ_l, capturing the broad loyalty of the coercive apparatus to the regime. It is essential that police can also join the revolution because the co-optation of the police and military is often a critical, if not necessary, step in successful revolts. Without the tools of suppression, even the most brutal tyrant will fall.

Spreading and Re-wiring Having constructed the networks and distributing different thresholds and grievance levels, we now consider the spreading and re-wiring mechanisms. All nodes can: 1) spread fervor and beliefs to neighbors, thus activating other nodes from Passives to either Actives or Contras, 2) re-wire links (i.e. make new friends, thus building cells and sub-networks of like-minded partisans), and 3) remove nodes (i.e. kill other citizens).

The grievance of all nodes is updated in parallel, with the grievances probabilistically becoming closer to that of their neighbours. The probability of their grievance becoming closer to their neighbours increases with difference between the nodes grievance and the mean grievance of their neighbours, $\delta = |\gamma - \langle\gamma\rangle_n|$, where $\langle\gamma\rangle_n$ is the mean grievance of the node's neighbours. The probability of a node's grievance moving closer to the mean of its neigbours in a given time step is then calculated as,

$$P_g = 1 - 0.5e^{-(\delta/(\delta+1))}. \tag{1}$$

For a value $\delta = 0$, γ will move up or down with equal probability, and as $\gamma \to \infty$, $P_g \approx 0.82$. At every time step the γ will move by a fixed value set by the user, the direction of which is determined probabilistically by Equation (1).

The network is rewired by adding and removing links. Links between agents can be added in one of either two ways. The first aims to encode random encounters– with probability p_{LR} an agent will form a link with another agent selected randomly from the set of all other agents he is not linked to. The second captures introductions between agents with a mutual contact– with probability p_{SR} an agent forms link with an agent randomly selected from the set of its neighbours' neighbours. An agent may lose a link with a randomly selected neighbour with probability p_{rm}

The probabilities for adding and removing links are multiplied by a factor proportional to the difference in the two agents' grievances raised to some power. This is intended to mimic the grouping of like minded individuals. When this power is 0 there is no bias from the grievance levels on the rewiring process.

While we experimented on citizens removing (killing) nodes, in the end we settled on only police being able to remove nodes. At every time step a number of nodes equal to the number of *Passive* plus *Contra* police is selected. If any of the nodes selected in this way is *Active* it is removed from the network, and a new node of the same type (Citizen, or Police) is introduced into the network.

Removing a node from the network has the added effect of shifting the threshold of the nodes neighbours. All neighbours of a removed node have their thresholds shifted down by a predetermined amount set by the user. This results in an increased probability that neighbours of a removed node will become *Active* themselves, and a reduced probability of them becoming a *Contra*.

4 Results

The model was run under several combinations of parameter settings so as to isolate individual effects of various parameters and highlight potential interactions that may be otherwise unintuitive. Preliminary results indicate that initial network structure ultimately has a negligible effect on long-run dynamics and that under many parameter settings, the system equilibrates to a steady state after a transitory period and phase transition.

Trial 1, our baseline model, does not include re-wiring and uses a modest grievance step of .10 (i.e. nodes adjust their grievance levels by 10%). Additionally, the baseline model and all subsequent trials include the following settings: there are 200 nodes; the mean grievance level is .45; the police density is .06; and threshold step size is .13. For every trial, the model is run five times for each of the three network structures. Trials 2-6 experiment with different levels of re-wiring, including both long and short re-wirings. Trial 7 zeroes re-wiring again and considers the effect of an increased grievance step size of .30.

A summary of these seven trials and their runs are below. Dominant faction is the group that eventually dominates the system, either Passives or Actives. Column two reports the number of runs for which each group dominated. Time to Domination reflects the lock-in time (measured in model ticks) at which one group reaches a majority and subsequently increases rapidly at the expense of the other group. Domination represents a point of lock-in, where one group reaches a majority and there are no more cycles between groups. Finally, Time to Saturation reports the time when one group completely saturates the system, having converted all opponents. If no group reaches saturation by 3000 ticks (which occurred 13 out of 105 trials), the run was aborted. These trials, while recorded, are not included in the succeeding statistical analysis.

Table 4.1: Descriptive Statistics for Different Network Types

Network Type	**Dominant Faction**	**Time to Saturation**	**Time to Domination**
Lattice			
	Actives:11	Min. : 274.0	Min. : 75.0
	Contras:18	Mean : 879.4	Mean : 323.7
		Max. :2832.0	Max. :1350.0
Scale Free			
	Actives:13	Min. : 269.0	Min. : 78.0
	Contras:20	Mean : 943.5	Mean : 280.8
		Max. :2880.0	Max. :1071.0
Small World			
	Actives:14	Min. : 245.0	Min. : 86.0
	Contras:17	Mean : 824.5	Mean : 349.6
		Max. :2355.0	Max. :1855.0

In the baseline model (Trial 1), Contras generally prevail: Contras saturate the system in 14 out of 15 trials. In the one exception, Actives eventually dominate but never reach saturation. Due to an initial distribution favorable to the Actives, Contras are surrounded and prevented from spreading, serving as a firewall. The simulation was aborted after 3000 ticks, at which time only remote pockets of Contras persisted (Figure 4.1 in the Appendix is a screen shot of this trial and graphs depicting grievance and degree distributions). Without re-wiring, small pockets remain highly partisan while the mean grievance continues to rise globally. Despite this aberrant trial, the baseline represents the modal outcome for revolutions, where the revolt fails and regime supporters suppress revolutionaries. Accordingly, we use this null model for comparative static analysis, isolating key parameters through small perturbations.

Trials 2-6 reveal surprising dynamics from re-wiring. Trials 2 and 3 introduce long re-wiring, of .05 and .10, respectively, while leaving short re-wiring at zero. Long re-wiring probabilistically re-wires two remote nodes in the network, thus decreasing the average path length. In Trial 2, the Actives dominate in 12 out of 15 runs, a significant departure from the baseline where Contras regularly saturated the system. There is considerable variance, however, in the times to domination and saturation. The time to domination ranges from 86 ticks to 1610, while the saturation times are even more varied, spanning from 309 to 2880 ticks. This variation is likely to due to the model's sensitivity to initial conditions and distribution. Although each network begins with a roughly constant mean of .45,[6] and conditions favoring the Actives, Contras occasionally survive because of a distribution supporting local spread that quickly locks-in before the Actives can counter. In Trial 3, the long re-wiring probability is increased to .10, resulting in much more definitive results: Actives saturate the system in every run and there is significantly less variance.

Trials 4 and 5 consider the effect of short re-wiring, which increases local clustering analogous to the development of tight, revolutionary cells. However, in contrast to the long re-wiring of Trials 2 and 3, short re-wiring does not benefit Actives. Instead, Contras continue to dominate as in the baseline, saturating the system 28 out of 30 runs for Trials 4 and 5. Although short re-wiring encourages cell development early on, the police and Contras suppress this spread, arresting the revolution.

Finally, Trial 6 offers a model that includes both long and short re-wiring (each set to .05). These processes generate tightly clustered cells connected by long links spanning the network. This web resembles a popular structure within revolutionary and insurgent groups where each cell is relatively insulated from the others, which are only loosely connected. In a reversal from Trials 4 and 5, under this scenario Actives dominate 14 out of 15 runs.

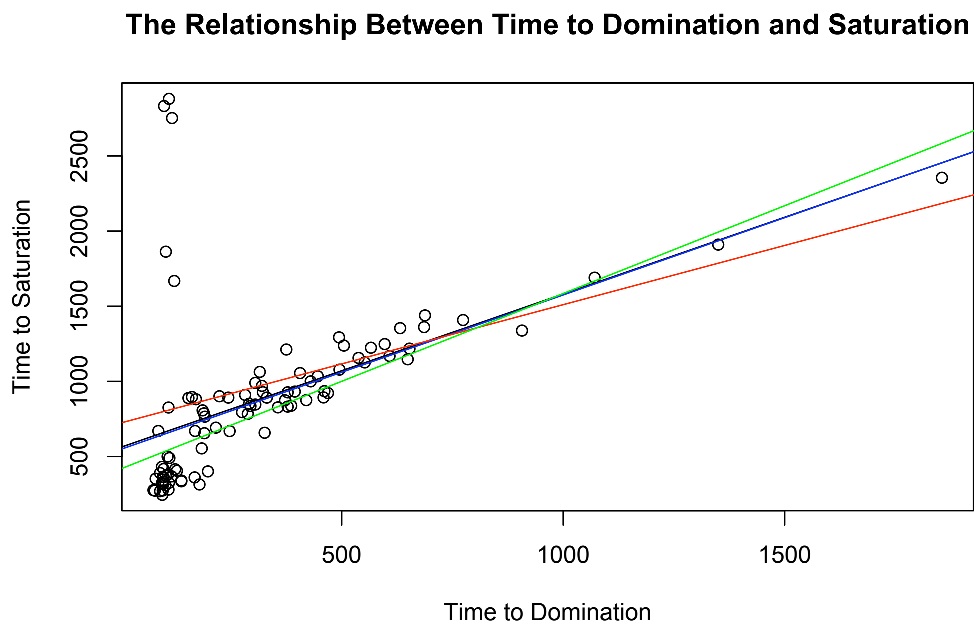
In addition to the re-wiring probabilities, we also considered the effect of modifying various other parameters. First, increasing the grievance step-size (Trial 7) does not change the general dynamics of the baseline. Contras have an evolutionary advantage under these settings and as before they either saturate the environment (9 out of 15 times) or otherwise hold out indefinitely, i.e. past 3000 ticks. When Contras fail to saturate, they usually start out poorly due to adverse initial conditions and never recover. Eventually, they reach a fragile equilibrium with Actives. Second, neither police density nor rioter-kill-probability have a significant effect on the baseline results. Increasing police density only moderately accelerates Contras' saturation, while the rioter-kill-

[6]This mean is part stochastic and is .45 only in expectation.

probability has a mitigating effect as Passives survive longer and decrease the rate at which Contras dominate.

Lastly, we aggregate these trials and regress the Time to Domination on Time to Saturation. After dropping the 13 aborted runs, we have 92 units. The regression coefficients, partitioned by network type, are reported in Table 4.2 in the Appendix. The estimated parameters are highly significant (with p-values of less than .01) in the full model, and both the lattice and small world restricted models. The significance of the scale free estimation is much lower, falling outside conventional statistical cutoffs.

These four regressions are depicted in the graph below. The black line represents the full model with a slope of 1.021. This effect is statistically indistinguishable from the Lattice only model (the blue line), with a slope coefficient of 1.029. In fact, these two models are so close they are nearly identical graphically. However, there is considerable difference in the scale free model (the red line), with a larger intercept but smaller slope (0.788), and the small world model (green line), which starts lower with a steeper slope (1.168). Ultimately, there appears to be a close, linear relationship between the time to domination and time to saturation, irrespective of the initial network structure.



5 Future Work

Revolutions are characterized by adaptive agents interacting at a micro-level, which results in macro-level emergent behavior, like that witnessed across Eastern Europe in the late 1980s. Successful revolutions generally resemble cascading dynamics in revolutionary activism and participation, a process similar to a phase transition. We have seen these types of transitions within our model, particularly when long and short re-wiring are included. These settings allow for the development of highly clustered yet interconnected cells of Actives to spread throughout a network. This process appears crucial in the spread of revolutionary fervor, even more salient than the network structure. Although there are significant differences in the rate at which systems equilibrate (i.e. times to domination and saturation), our results suggest that this variation is relatively minor. Network type does not significantly affect the final outcome, only exerting a marginal effect on the rate.

Future work will investigate ways to validate the model empirically. First we must determine what data are available for empirical verification. Recent work has mapped civil violence networks in Nigeria. Is this sufficient for inferring generally, given concerns of external validity? Beyond simply corroborating our model's findings, emprical testing can help determine what parameters settings and network sturcutre is most plausible. Our model results indicate that revolutionary success is extremely sensitive to initial conditions, demanding we be careful not only in how we levy the results but operationlize the model. Again, empirical investigation can help ensure robust results in these future endeavors.

Appendix

Figure 3.1: Screen Shot of NetLogo Model Sliders

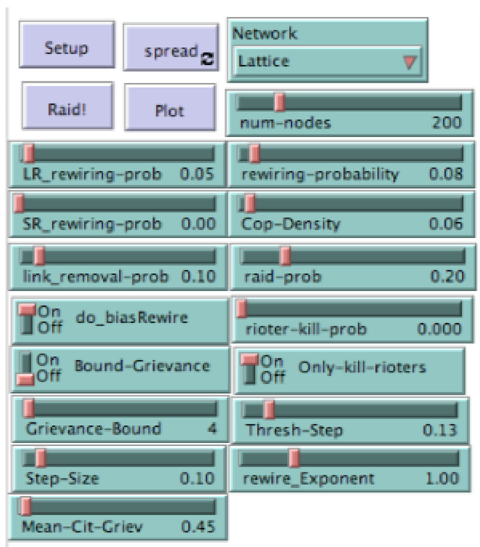


Figure 4.1: Screen Shot of Trial 1, Lattice.

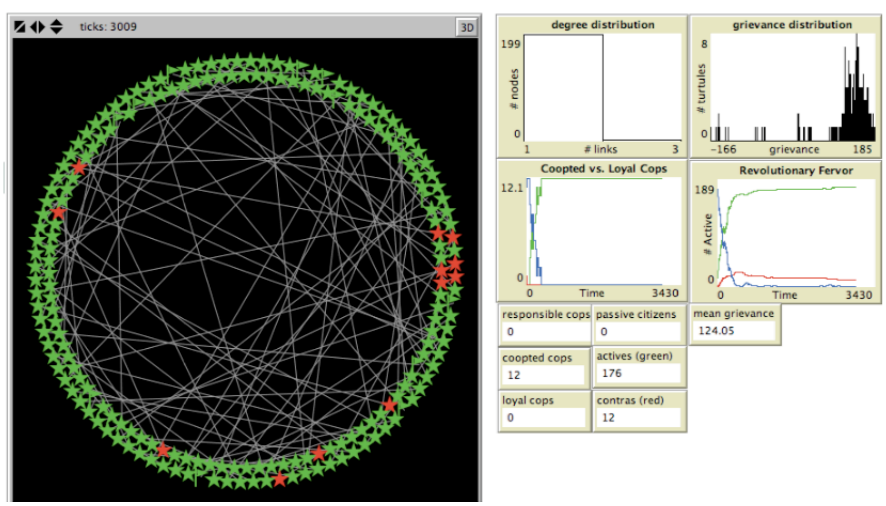


Table 4.2: Regressing Time to Domination on Time to Saturation.

		Estimate	Std. Error	t value	Pr(>|t|)
Full Model					
	Intercept	560.0154	73.0453	7.67	0.0000
	Dom. Time	1.0212	0.1716	5.95	0.0000
Lattice					
	Intercept	546.4268	132.0488	4.14	0.0003
	Dom. Time	1.0286	0.3090	3.33	0.0025
Scale Free					
	Intercept	722.2076	175.3561	4.12	0.0003
	Dom. Time	0.7881	0.4981	1.58	0.1237
Small World					
	Intercept	416.0434	68.7785	6.05	0.0000
	Dom. Time	1.1684	0.1402	8.34	0.0000