A Universal Methodology for Learning Cascading Failure Dynamics in Complex Systems

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Cascading failures, a ubiquitous phenomenon in a variety of natural, social and technical systems, have been attracting the attention of researchers from social science, engineering, epidemiology, ecology and information science, to name a few. The prevalent methodologies, as we collectively call the “forward approach” in studying cascading failures, typically presume a network topology and a specific failure propagation mechanism (SFPM), and seek to understand how they (non-linearly) affect the cascading failure outcomes such as the size of the largest connected cluster (a.k.a. giant component). Though granting critical insights into the linkage between (static) system properties and system behaviors, the forward approach faces three challenges: firstly, real-world network topologies are not always available, which in some cases inhibits reaching reasonable assumptions on network topologies for the forward approach; secondly, system dynamics are only tractable at equilibrium conditions, making it intricate to learn cascading failure processes where systems are constantly changing (i.e. non-equilibrium) through the forward approach; and thirdly, the SFPMs may vary across different systems, and SFPM-specific models and findings in the forward approach have limited generalizability in an interdisciplinary context. For example, when interdependencies (which can be viewed as an SFPM) are present in a system, the cascading failure process and outcomes are dramatically altered compared to when no interdependencies are involved.

To address these challenges, we propose a modeling framework to infer and reconstruct the cascading failure process, given only the observed cascading failure outcomes, primarily the time of failure for each node in the network(s). A MLE-based formulation is devised to mathematically describe how four generalized failure propagation mechanisms (GFPMs) – external, temporal, spatial and functional – drive the progress of cascading failures and give rise to the observed failure outcomes. Maximum likelihood estimation (MLE) is employed to estimate the model parameters associated with the four GFPMs. This modeling framework, as we call the “backward approach”, is tested and validated with three simulation studies: one for cascading failures in interdependent power and transportation networks, one for influenza epidemics, and one test case for congestion cascade in a benchmark transportation network.

Our simulation results demonstrate remarkable capability of the backward approach in learning the dynamics of GFPMs underlying the observed cascading failure outcomes, and accurately reconstructing the cascading failure process in all three simulation studies. The simulation of influenza epidemics and congestion cascade also reveals the versatility and robustness of the model. In the influenza epidemic case where SFPMs (such as human mobility and population density) are known, these SFPMs can be well integrated into our model and their dynamics can be accurately captured. And in the congestion cascade case, it is shown that the model still demonstrates good performance when only the GFPMs are incorporated in its formulation while the data of cascading failure outcomes is independently generated using a well-established SFPM, i.e. flow redistributions. Considering the model’s accuracy, its versatility to incorporate known SFPMs and its robustness against (potentially unknown) SFPMs, we envision the backward approach to be a potential channel to a universal framework for modeling, understanding and controlling cascading failures in a variety of systems.