Early Warning for Critical Transitions in Epidemics: A Generative Dynamical Systems Approach

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Disease outbreaks are dynamical systems that can abruptly cross critical transitions and escalate into epidemics. While early warning of epidemics is essential for life-saving interventions, current surveillance methods are post-hoc and statistical predictors are unreliable. This research introduces a generative approach that exploits disease-invariant dynamics near transitions to infer hidden system stability and provide early warning, despite the challenges of noisy data, partial observability, and disease heterogeneity. A novel eigenanalysis establishes that the critical slowing down signal predicted by the center manifold theorem is obscured by multi-timescale interactions between disease, behavioral and policy processes. The signal projects weakly onto observed infection data, explaining the failure of classical indicators. Accordingly, a multi-timescale generative model encoding these interactions was developed, with epidemic thresholds analytically derived using the next-generation matrix method. A deep learning classifier trained on 100,000 generated outbreaks was used to identify the transition structure. Latent space analysis of the classifier is consistent with a shared transition manifold, with clustering 18x stronger by regime than disease. Empirical validation on 5,274 outbreaks across multiple diseases and regions confirms the manifold transfers to real-world epidemic data and provides a new early-warning basis. The novel generative approach is the first to consistently deliver early warning across all tested diseases and regions, outperforming existing methods by 2.5x-15.3x. It can enable early warning for newly emerging diseases and extends to systems with multi-timescale structures such as power grids, ecosystems and financial systems.

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