Epidemiological Dynamics with Adaptive Behavior - Global & Local Information

Introduction

Classical epidemiological models represent the population in homogeneous compartments. The present model is a variation of the classical "Susceptible-Infectious-Removed" model (Kermack & McKendrick, 1927), with 1000 agents embedded on a [-50,50] toroidal grid.

The simulations are divided into three behavioral conditions. The first is a simple spatial embedding of the SIR model with randomly-moving agents. The second and third feature expand this with adaptation, featuring global and local information respectively. Results suggest that locally-informed agents more successfuly prevent spread.

Simulation 0 - Base Model

The results of Simulation 0 illustrate that the base model's dynamics resembles those of the SIR model, despite violating the assumption of homogeneous mixing. Each agent takes one trip per day, randomly directed with distance drawn from the normal distribution, mean-centered on 0, and with a standard deviation controlled by a walk_length parameter. Transmission occurs to each other Susceptible agent within a given radius.

The transmissibility parameter was set to 0.3. The removal rate was set to 0.1. The radius parameter was set to 3. The walk_length parameter was set to 2.

Simulation 1 - Global Information

Simulation 1 investigated how adaptive agent behavior interacts with disease dynamics. Borrowing from Epstein et al. (2008), the adaptive models feature self-isolating agents, preventing interaction. Agents self-isolate probabilistically, accounting for the size of the Infectious component and a fear strength parameter, here set to 20.

As the infectious component grows, more agents self-isolate and infections increase. Similarly, as the infectious component shrinks, fewer agents self-isolate and infections decrease. A feedback cycle causes the incidence curve to plateau until the disease dies out.

Simulation 2 - Local Information

Simulation 2 explored how information's source affects the dynamics. Self-isolation scales with the infectiousness of nearby agents, rather than the infectiousness of the entire population.

The main result is that local information is more effective than global information. However, the dynamics are similar, with linear behavior in all compartments. Further, the local-global dichotomy is not a hard one. This indicates there may be an optimal spatial scale for agents to monitor locally to prevent epidemiological spread.

Note that Figure 2.1 shows Fear Strength = 5.

Endpoint Analysis

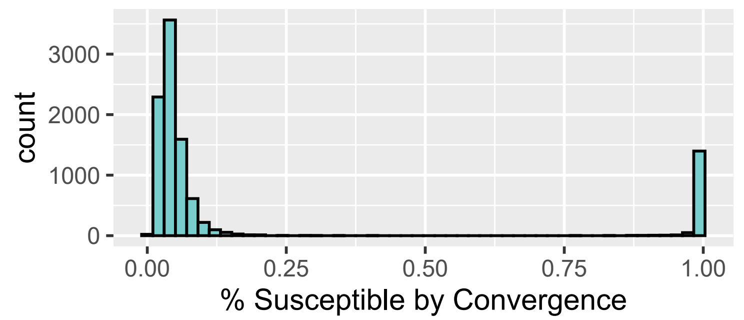
Endpoint analysis reveals the attractor states in the state-space. It also quantifies potential interventions.

Like the classic SIR model, the base model displays a strong dichotomy between major and minor epidemics. This shows that even potent viruses may not permeate the population, but once they reach a critical threshold, they are extremely unlikely to be contained.

The other conditions do not display this strong dichotomy. This indicates that adaptive behavior may be required to explain middeling permeation values.

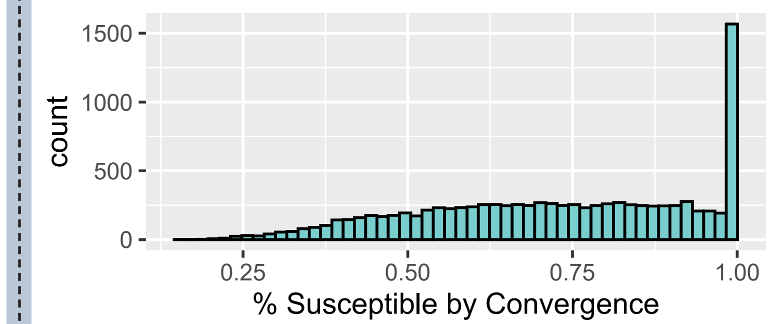
10,000 runs are shown for each condition.

Figure 0.0
Endpoint Distribution



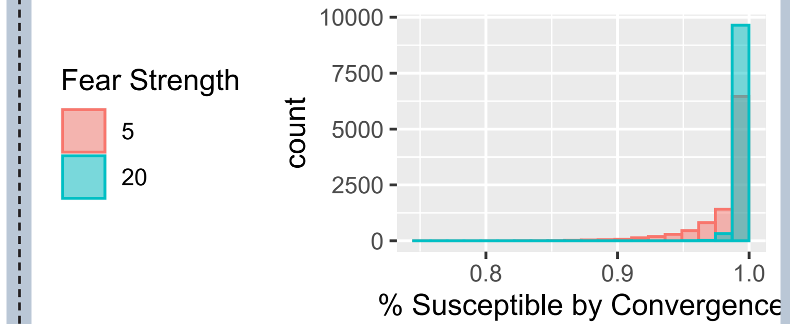
The outcome distribution is highly bimodal.

Figure 1.0
Endpoint Distribution



Self-isolation helps mitigate the epidemic.

Figure 2.0
Endpoint Distribution



Local information leads to greater success.

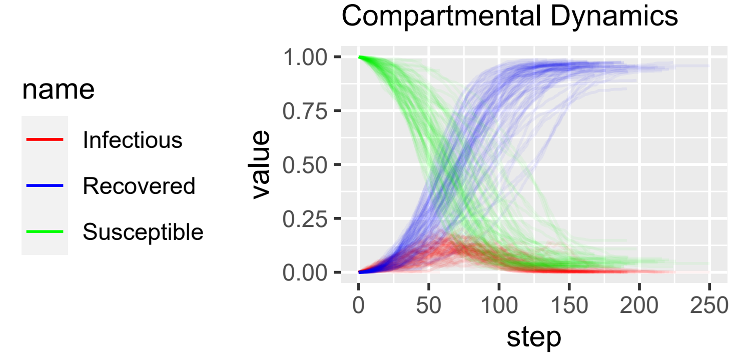
Compartmental Dynamics

Compartmental sizes most clearly display the model's dynamics. In all conditions, the magnitude of the Infectious component drives the rate of change in the Removed and Susceptible components. Note that each run terminates when it converges. This hides significant variation in outcome in favor of highlighting dynamics.

In the case of the base model, we see nonlinear dynamics reminiscient of the SIR model. In the adaptive conditions, a feedback loop drives the model into linear dynamics.

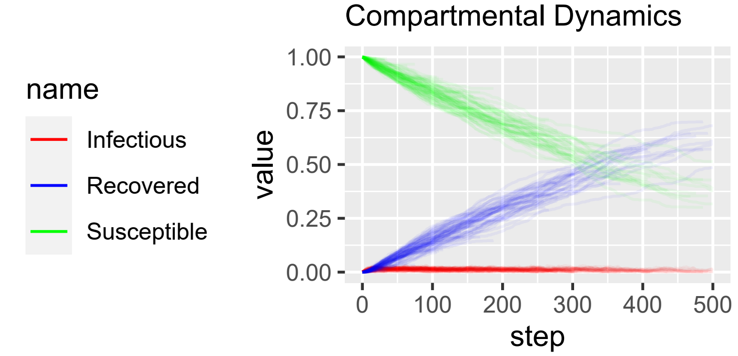
100 runs are shown for each condition.

Figure 0.1
Compartmental Dynamics



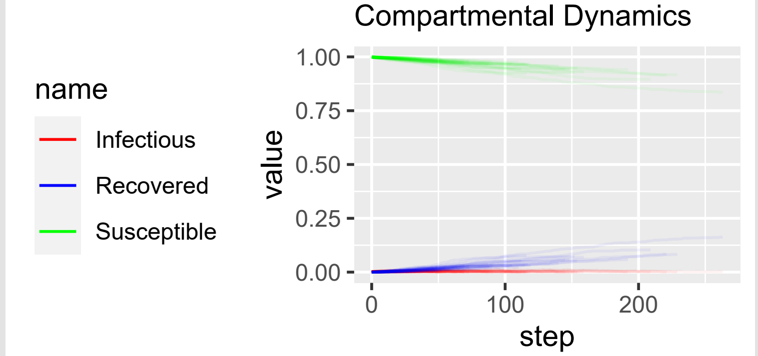
As before, the compartments behave linearly.

Figure 1.1
Compartmental Dynamics



Feedback drives the system to a linear regime.

Figure 2.1
Compartmental Dynamics



As before, the compartments behave linearly.

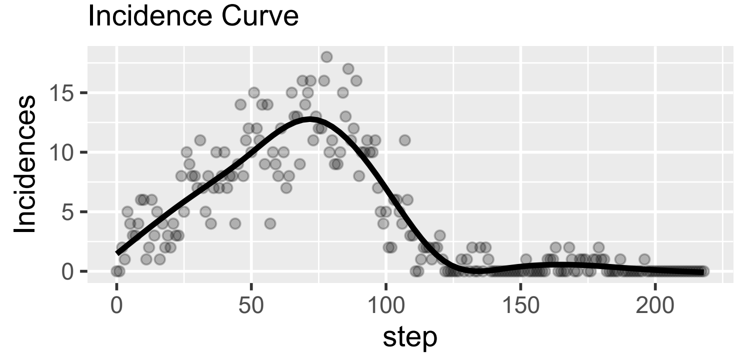
Incidence Curves

Popular media and public communications commonly use "incidence curves" to display recent data about ongoing epidemics. These curves are smoothed case-rates, similar to the curves displayed here, and determine the growth of the Infective compartment.

The nonlinear base model produces a single large spike in incidences. The linear adaptive models produce a flat incidence curve, suggesting feedback may be critical to flatten the curve. Results for the Local Information condition resemble those of the Global Information condition.

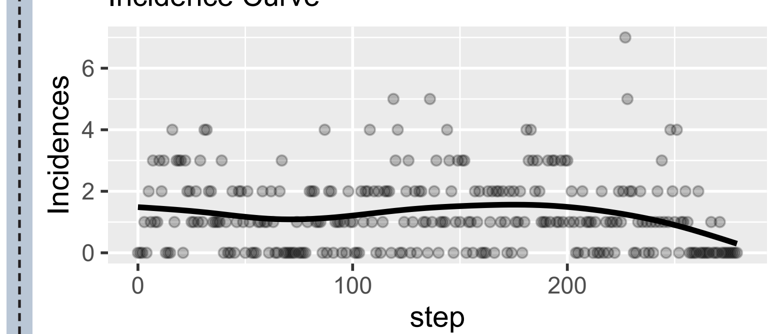
One run is shown in each image here.

Figure 0.2
Incidence Curve



The incidence curve first increases, then decreases.

Figure 1.2
Incidence Curve



Linear regimes correspond to a "flat curve."

Works Cited

Kermack, W. O., & McKendrick, A. G. (1927). A contribution to the mathematical theory of epidemics. Proceedings of the royal society of london. Series A, Containing papers of a mathematical and physical character, 115(772), 700-721.

Epstein, J. M., Parker, J., Cummings, D., & Hammond, R. A. (2008). Coupled contagion dynamics of fear and disease: mathematical and computational explorations. PLoS One, 3(12), e3955.

Many thanks to S. Church for design help. The model was implemented in NetLogo. Images were made in R with the tidyverse.

For all code, see, https://github.com/LeoMNC/Spatial_Pandemic.