# Diffusion through Networks

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#### 7.1 The Bass Model

- *p* is rate of innovation, *q* is rate of imitation
- *F*(*t*) is the fraction of agents that have adopted by time *t*

F(t) = F(t-1) + p(1 - F(t-1)) + q(1 - F(t-1))F(t-1)

dF(t) / dt = (p + qF(t))(1 - F(t))

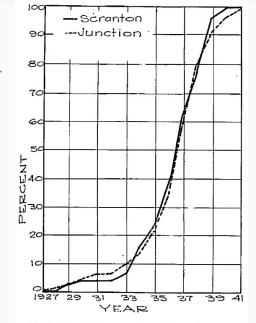


Fig. 1. Cumulative percentages of operators accepting hybrid seed in the two communities during each year of the diffusion process.

## 7.2.1 Percolation, Component Size, Immunity and Diffusion

- Percolation asks if there is a path across the network
- Immunity corresponds to percolation with a fraction  $\pi$  of nodes removed uniformly at random
- Giant component emerges at the threshold

$$< d^2 >_{\pi} = 2 < d >_{\pi}$$

#### 7.2.1 Percolation, Component Size, Immunity and Diffusion

Degree distribution after removing nodes is

$$P_{\pi}(d) = \sum_{d' \ge d} P(d') \binom{d'}{d} (1 - \pi)^d \pi^{d' - d}$$

Giant component emerges when

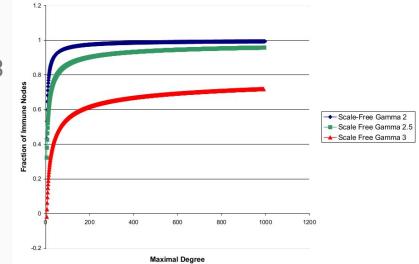
$$\pi = \frac{\langle d^2 \rangle - 2 \langle d \rangle}{\langle d^2 \rangle - \langle d \rangle}$$

### 7.2.1 Percolation, Component Size, Immunity and Diffusion

Regular network of degree 
$$\overline{d}$$
:  $\pi = (\overline{d} - 2)/(\overline{d} - 1)$ 

Poisson random network: 
$$\pi = 1 - \frac{1}{(n-1)p}$$

Scale free network has threshold 0 when  $\gamma$  < 3



# 7.2.2 Breakdown, Attack and Failure of Networks, and Immunization

- Removing the  $\pi$  nodes with highest degree will remove more than  $\pi$  links
- Proportion of removed links is:

$$f(\pi) = \frac{\sum_{d=\overline{d}(\pi)+1}^{\infty} P(d)d}{\langle d \rangle}$$

Threshold for a giant component to exist becomes:

$$\langle d^2 | d \leq \overline{d}(\pi) \rangle (1 - f(\pi)) = \langle d | d \leq \overline{d}(\pi) \rangle (2 - f(\pi))$$

# 7.2.2 Breakdown, Attack and Failure of Networks, and Immunization

- In a scale-free distribution with density  $(\gamma 1)d^{-\gamma}$ ,  $\pi = 0.056$
- Uniform immunization leads to threshold of 0
- When  $\gamma$  = 2.5 immunizing nodes with degrees in highest 5% leads to eliminating  $\frac{1}{3}$  of links and all nodes with degree 4 or higher

#### 7.2.4 The SIR Model

- Susceptible, Infected, Removed model
  - Infected nodes are eventually removed from the system or become immune (chicken pox)
- Model duration of infection as *t*, where neighbours have a probability *t* chance of being infected
- Equivalent to percolation case with  $\pi = 1 t$

#### 7.2.5 The SIS Model

- Susceptible-Infected-Susceptible model
- Match model variant where probability of meeting a node with degree  $d_i$  is given by: P(d)d

$$\rho = \sum P(d)\rho(d)$$

#### 7.2.5 The SIS Model

• Chance interaction with infected individual, θ, given by:

$$\theta = \frac{\sum P(d)\rho(d)d}{\langle d \rangle}$$

- Let v be the rate of transmission and  $\delta$  be the rate of recovery.
- Chance of infection for individual with degree d given by:

 $u \theta d$ 

#### **Thresholds and Steady-State Infection Rates**

- If there is a finite set of agents, the long-run steady-state will approach zero when the infection dies out.
- If there is an infinite set of agents, then v among the unaffected will equal δ among the infected:

$$0 = (1 - \rho(d))\nu\theta d - \rho(d)\delta$$

#### Thresholds and Steady-State Infection Rates

• Let  $\lambda = v / \delta$ , then solving for  $\rho(d)$ , we get:

$$\rho(d) = \frac{\lambda \theta d}{\lambda \theta d + 1}$$

• Combining this equation with the equation for ρ, we get:

$$\theta = \sum_{d} \frac{P(d)\lambda\theta d^2}{\langle d \rangle \left(\lambda\theta d + 1\right)}$$

#### Non-Zero Steady State Infection Rates

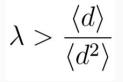
- Let H(θ) be the number of people infected given that we start at θ.
- H'(θ) describes if an infection can be sustained in the steady state.

$$H(\theta) = \sum \frac{P(d)d}{\langle d \rangle} \left( \frac{\lambda d\theta}{\lambda d\theta + 1} \right)$$

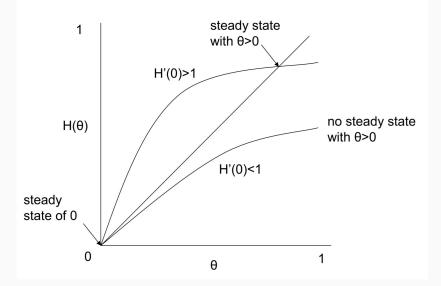
$$H'(\theta) = \sum \frac{P(d)d}{\langle d \rangle} \left( \frac{\lambda d}{(\lambda \theta d + 1)^2} \right)$$

#### Non-Zero Steady State Infection Rates

- H values for various infections.
- Steady-state at H(0) = 0
- Able to derive equation from H'(0):



• Individuals with high degrees serve as conduits for infection.



### Comparisons of Infections Across Network Structure

- How does infection change as network structure is varied?
- First order stochastic domination: One network outperforms another network as its degree distribution is right-shifted.
- Strict mean-preserving spread: Shift some weight to higher degree nodes and some weight to lower degree nodes
- Proposition 7.2.1: Steady-state infection rates depend on network structure differently based on high and low infection rates.

PROPOSITION 7.2.1 [Jackson and Rogers [336]] Consider two distributions P' and P, with corresponding highest steady-state average neighbor infection rates  $\overline{\theta}'$  and  $\overline{\theta}$ , and largest steady-state overall average infection rates  $\overline{\rho}'$  and  $\overline{\rho}$ ; and suppose that  $\overline{\theta} > 0$ .

- (I) If P' and  $\tilde{P}'$  strictly first order stochastic dominate P and  $\tilde{P}$ , respectively, then the infection rates are higher under P' than P (so  $\bar{\theta}' > \bar{\theta}$  and  $\bar{\rho}' > \bar{\rho}$ ).
- (II) If P' is a strict mean-preserving spread of P, then the average neighbor infection rate increases  $\overline{\theta}' > \overline{\theta}$ . Moreover, there exist bounds on the relative infection to recovery rate,  $\underline{\lambda} \leq \overline{\lambda}$ , such that
  - If the infection to recovery rate is below the lower bound, so that  $\frac{\nu}{\delta} < \underline{\lambda}$ , then the steady-state average infection rate is higher under P', so  $\overline{\rho}' > \overline{\rho}$ .
  - If the infection to recovery rate is above the upper bound, so that  $\frac{\nu}{\delta} > \overline{\lambda}$ , then the steady-state average infection rate is higher under P', so  $\overline{\rho}' < \overline{\rho}$ .

#### 7.2.6 Remarks on Models of Diffusion

- Higher variance in degree distribution lead to lower infection thresholds
- Higher degree density increases infection rates, lowers thresholds

- Analyses did not study the effect of loops or cycles, always assumed neighbour's degrees are independent
- No study of how a network might react to a process