Social Contagion

Principles of Complex Systems
CSYS/MATH 300, Fall, 2010

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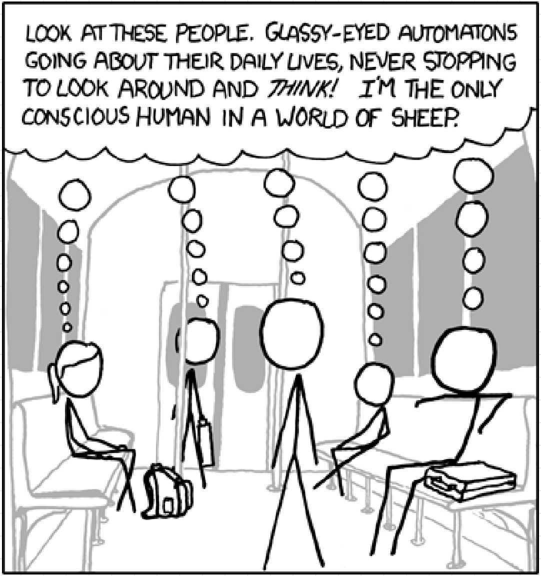
Outline

Social Contagion Models
Background
Granovetter's model
Network version
Groups
Chaos
References

Outline

Social Contagion



http://xkcd.com/610/ (⊞)

Social Contagion

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Examples abound

- fashion
- striking
- smoking (⊞) [6]
- residential segregation [16]
- ipods
- obesity (⊞) [5]
- Harry Potter
- voting
- gossip
- Rubik's cube 
- religious beliefs
- leaving lectures

SIR and SIRS contagion possible

- Classes of behavior versus specific behavior

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SIR and SIRS contagion possible

- Classes of behavior versus specific behavior: dieting

Framingham heart study:

Evolving network stories (Christakis and Fowler):

- The spread of quitting smoking (⊞) [6]
- The spread of spreading (⊞) [5]
- Also: happiness (⊞) [8], loneliness, ...
- The book: Connected: The Surprising Power of Our Social Networks and How They Shape Our Lives (⊞)

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- Are your friends making you fat? (⊞) (Clive Thomspon, NY Times, September 10, 2009).
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- Widespread media influence
- Word-of-mouth influence

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We need to understand influence

- Who influences whom?
- What kinds of influence response functions are there?
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- The infectious idea of opinion leaders (Katz and Lazarsfeld) [13]

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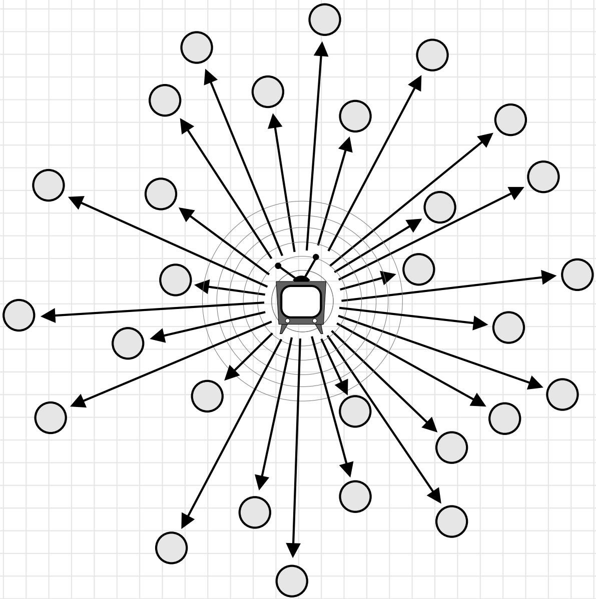
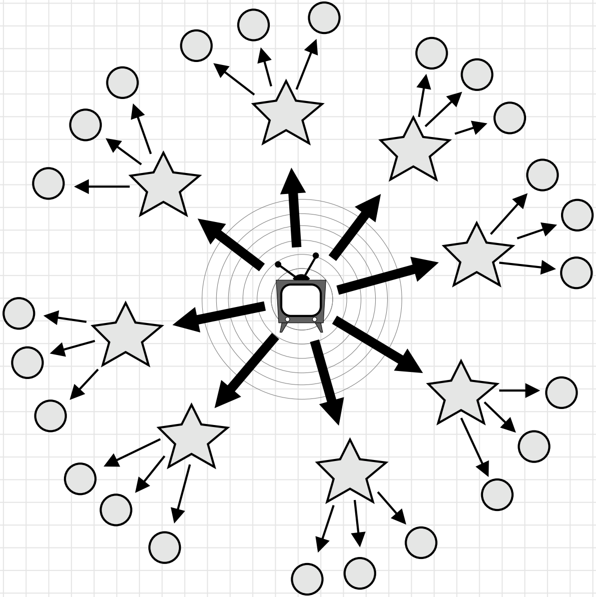
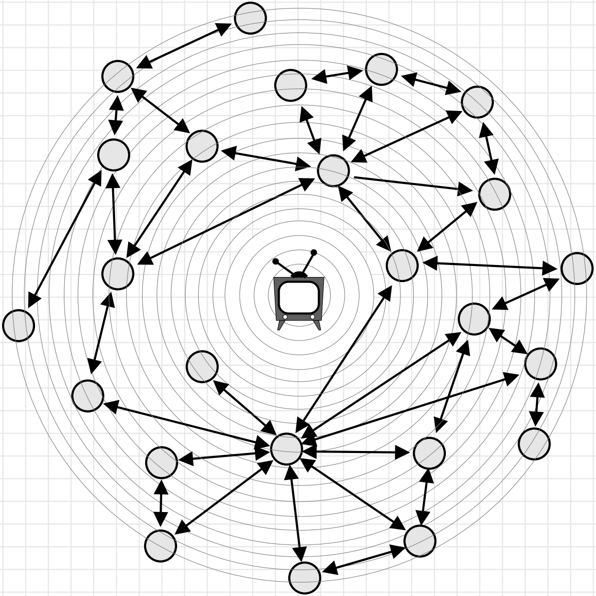
The hypodermic model of influence



The two step model of influence [13]



The general model of influence



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Why do things spread?

- Because of properties of special individuals?
- Or system level properties?
- Is the match that lights the fire important?
- Yes. But only because we are narrative-making machines...
- We like to think things happened for reasons...
- Reasons for success are usually ascribed to intrinsic properties (e.g., Mona Lisa)
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

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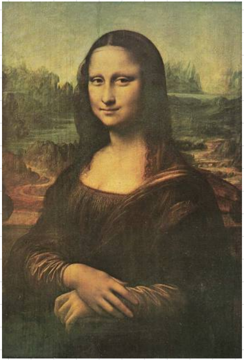

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- Not the world’s greatest painting from the start...
- Escalation through theft, vandalism,

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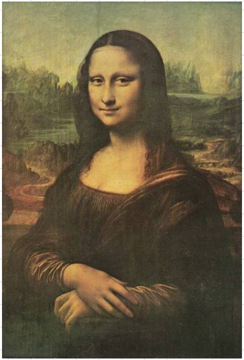

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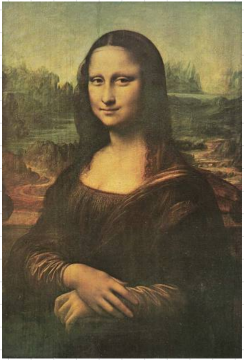

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The completely unpredicted fall of Eastern Europe

Timur Kuran: [14, 15] "Now Out of Never: The Element of Surprise in the East European Revolution of 1989"

The dismal predictive powers of editors...

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Messing with social connections

- Ads based on message content
- Buzz media
- Facebook's advertising: Beacon (⊞)

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The UNIVERSITY of VERMONT

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Getting others to do things for you

A very good book: ‘Influence’ by Robert Cialdini [7]

Six modes of influence

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2. Commitment and Consistency: *Hobgoblins of the Mind*
3. Social Proof: *Truths Are Us*
4. Liking: *The Friendly Thief*
5. Authority: *Directed Deference*
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- Reciprocation: Free samples, Hare Krishnas
- Commitment and Consistency: Hazing
- Social Proof: Catherine Genovese, Jonestown
- Liking: Separation into groups is enough to cause problems.
- Authority: Milgram's obedience to authority experiment.
- Scarcity: Prohibition.

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Some important models

- Tipping models—Schelling (1971) [16, 17, 18]
  - Simulation on checker boards
  - Idea of thresholds
  - Explore the Netlogo (⊞) implementation [21]
- Threshold models—Granovetter (1978) [10]
- Herding models—Bikhchandani, Hirschleifer, Welch (1992) [1, 2]
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Social contagion models

Thresholds

- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
- 'Others' may be everyone in a population, an individual's close friends, any reference group.
- Response can be probabilistic or deterministic.
- Individual thresholds can vary
- Assumption: order of others' adoption does not matter...
- Assumption: level of influence per person is uniform

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- Response can be probabilistic or deterministic.
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- Assumption: order of others' adoption does not matter... (unrealistic).
- Assumption: level of influence per person is uniform (unrealistic).

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
- Externalities = Effects on others not directly involved in a transaction
- Examples: telephones, fax machine, Facebook, operating systems
- An individual's utility increases with the adoption level among peers and the population in general

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Granovetter's Threshold model—definitions

- ϕ^* = threshold of an individual.
- $f(\phi_*)$ = distribution of thresholds in a population.
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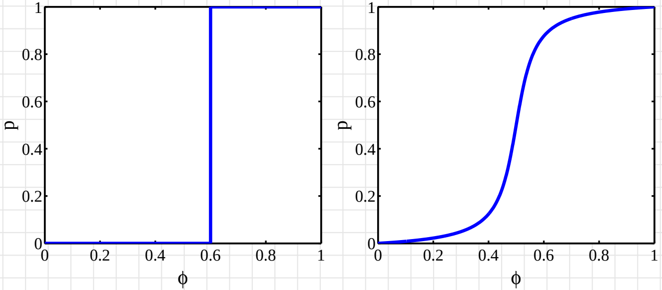

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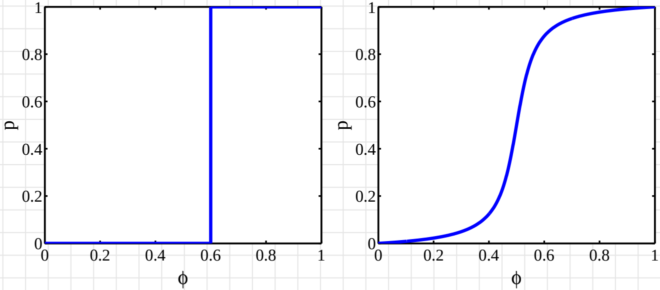

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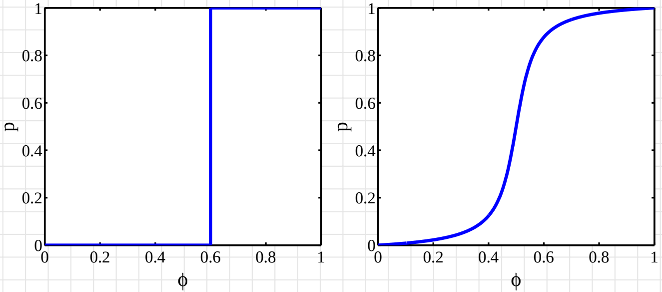

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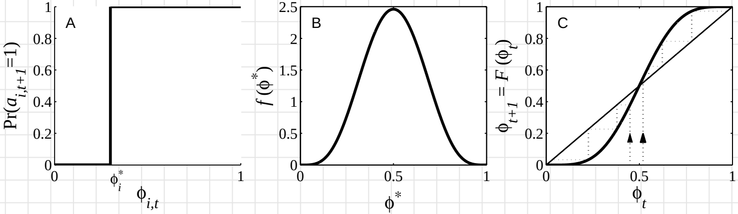

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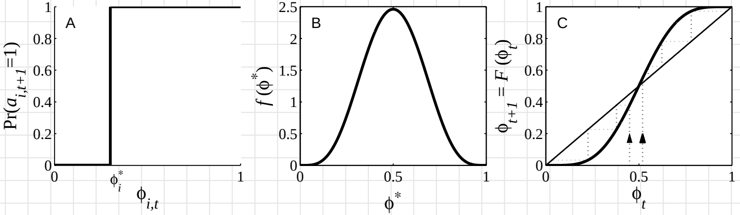

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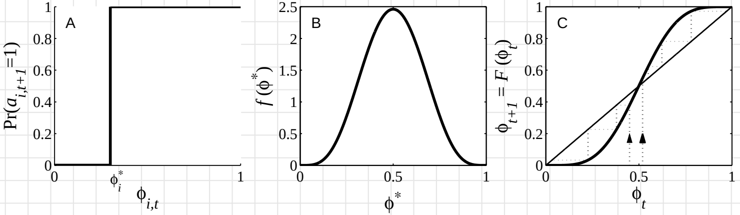

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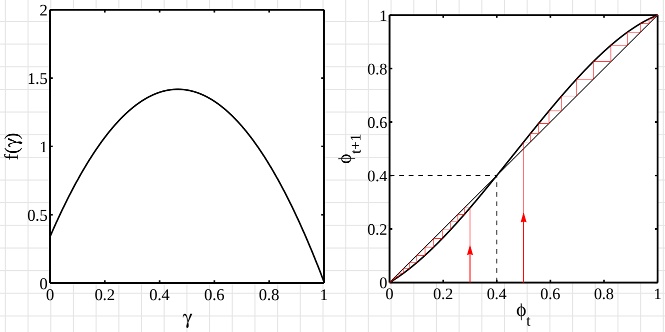

- Another example of critical mass model...

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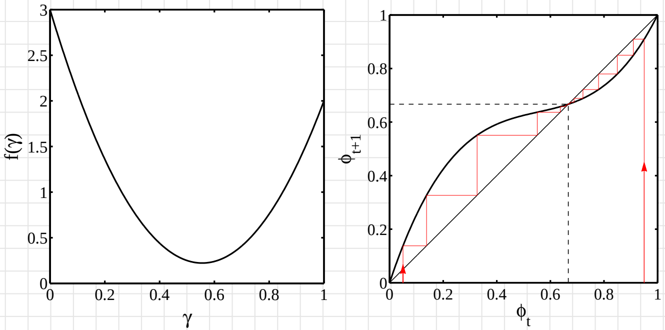

- Example of single stable state model

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Implications for collective action theory:

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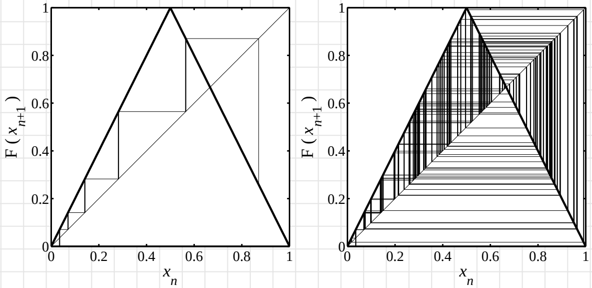

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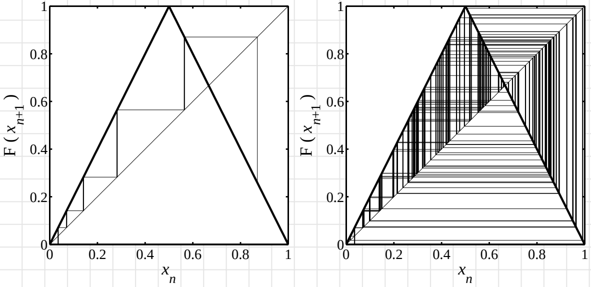

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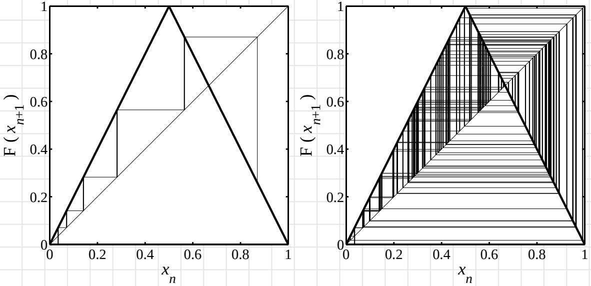

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Many years after Granovetter and Soong's work:

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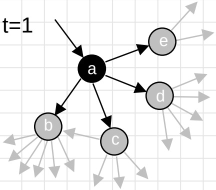

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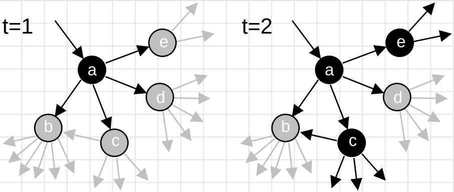

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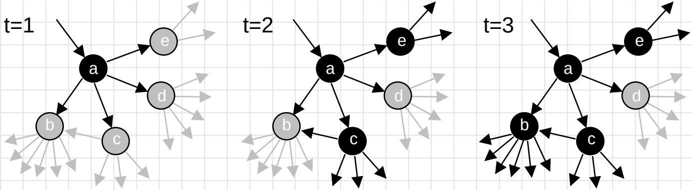

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Vulnerables:

- We call individuals who can be activated by just one contact being active vulnerables
- The vulnerability condition for node i:

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
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- Linked node is vulnerable with probability

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So... for random networks with fixed degree distributions, cacades take off when:

$$\sum_{k=1}^{\infty}(k-1) \cdot \beta_k \cdot \frac{kP_k}{\langle k \rangle} \geq 1.$$

- β_k = probability a degree k node is vulnerable.
- P_k = probability a node has degree k.

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Two special cases:

- (1) Simple disease-like spreading succeeds: $\beta_k = \beta$

$$\beta \cdot \sum_{k=1}^{\infty} (k-1) \cdot \frac{kP_k}{\langle k \rangle} \geq 1.$$

- (2) Giant component exists: $\beta = 1$

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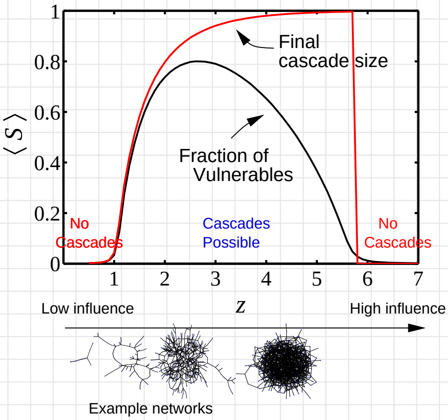
Cascades on random networks



- Cascades occur only if size of max vulnerable cluster > 0.
- System may be 'robust-yet-fragile'.
- 'Ignorance' facilitates spreading.

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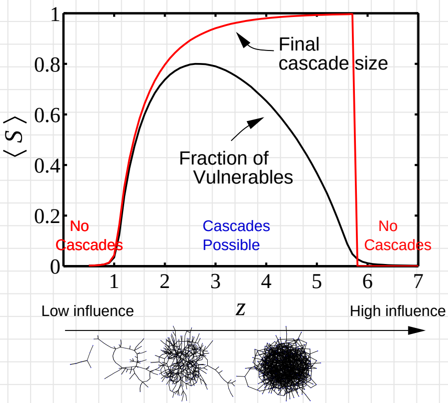

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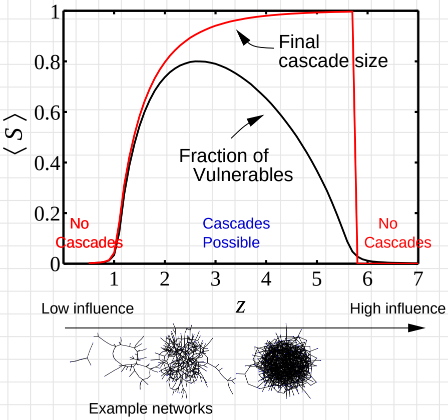

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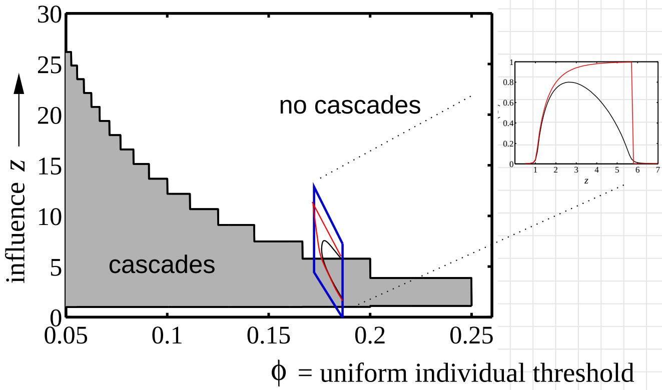
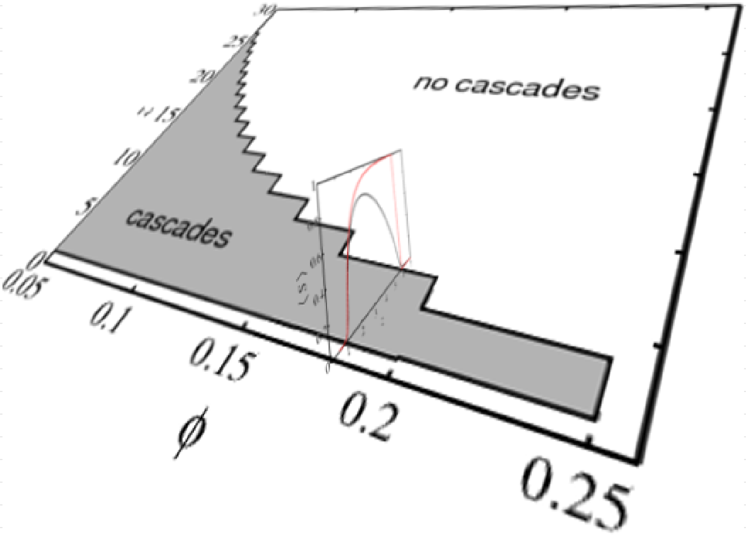
Cascade window for random networks



- ‘Cascade window’ widens as threshold ϕ decreases.
- Lower thresholds enable spreading.

Cascade window for random networks



Cascade window—summary

For our simple model of a uniform threshold:

1. Low $\langle k \rangle$: No cascades in poorly connected networks. No global clusters of any kind.
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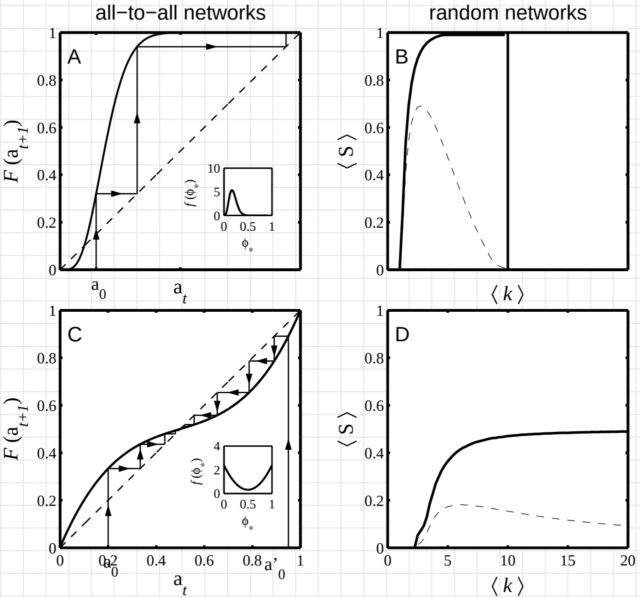
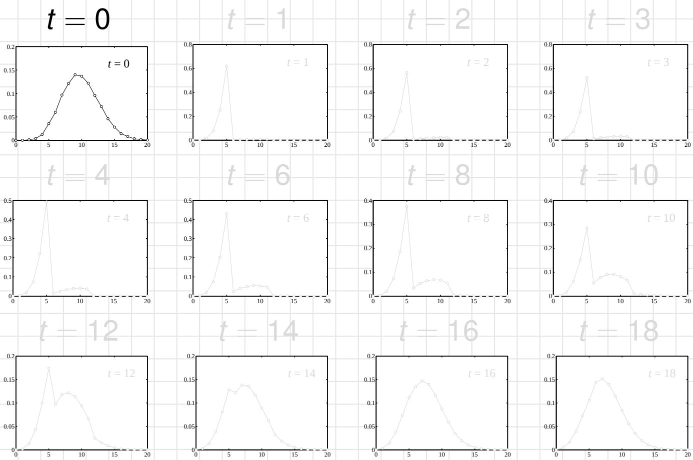
All-to-all versus random networks

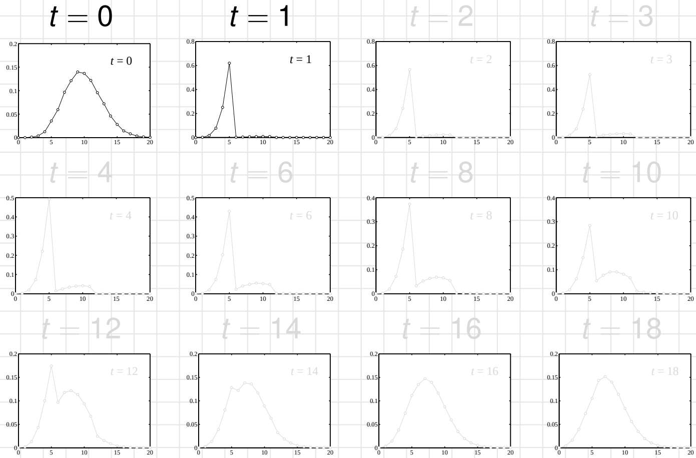


Early adopters—degree distributions



$P_{k,t}$ versus k

Early adopters—degree distributions



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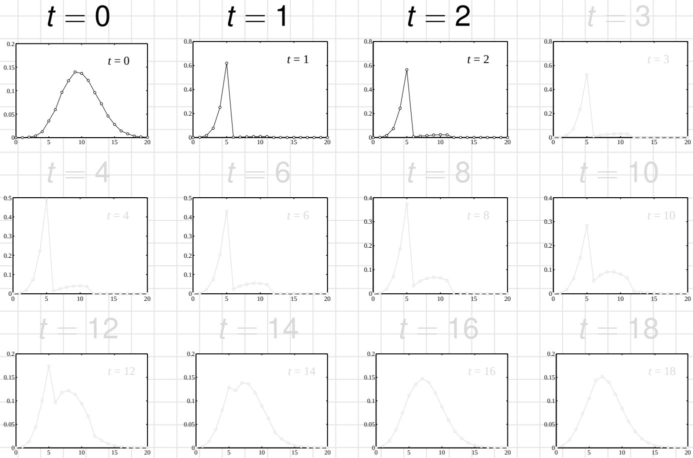

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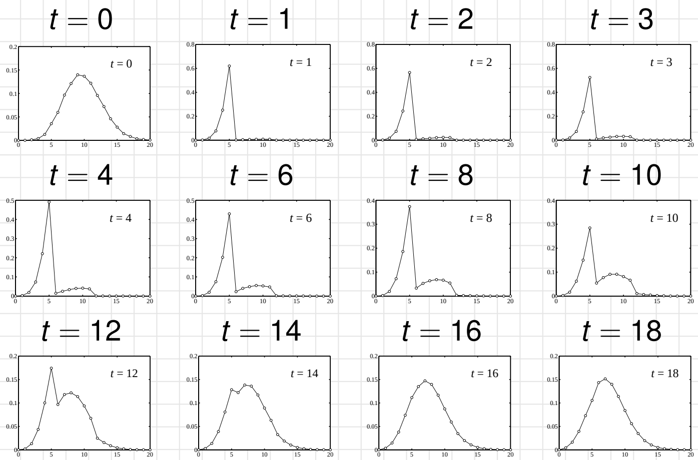
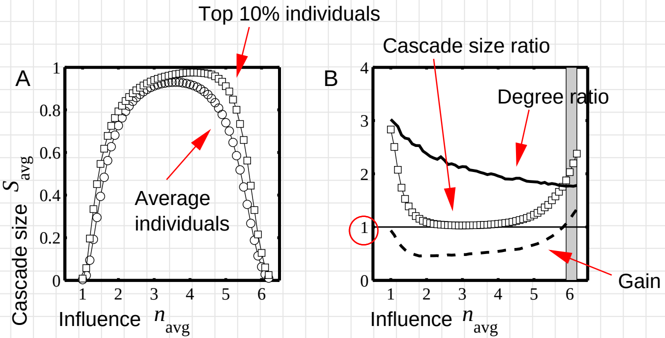


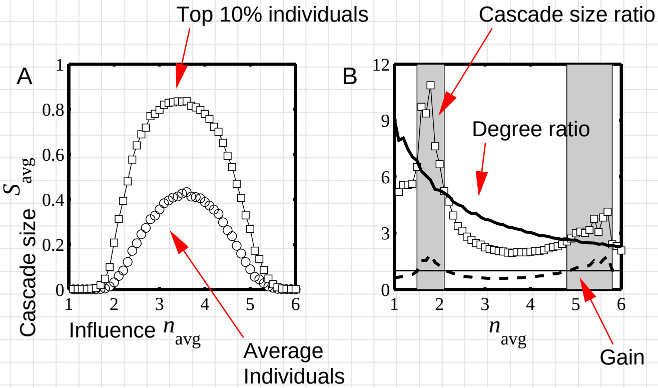
$P_{k,t}$ versus k

The multiplier effect:



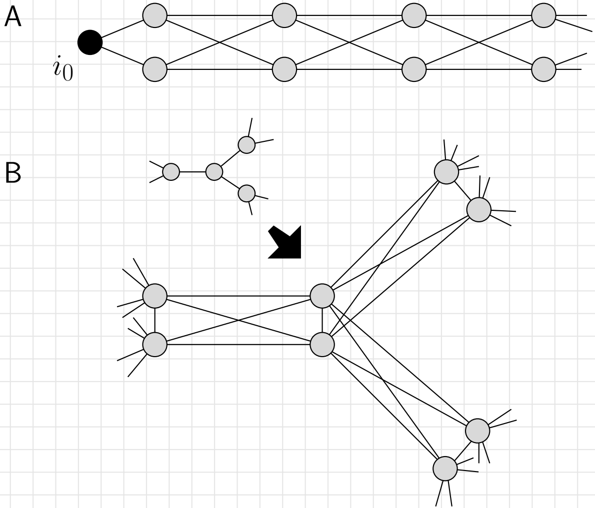
- Fairly uniform levels of individual influence.
- Multiplier effect is mostly below 1.

The multiplier effect:



- Skewed influence distribution example.

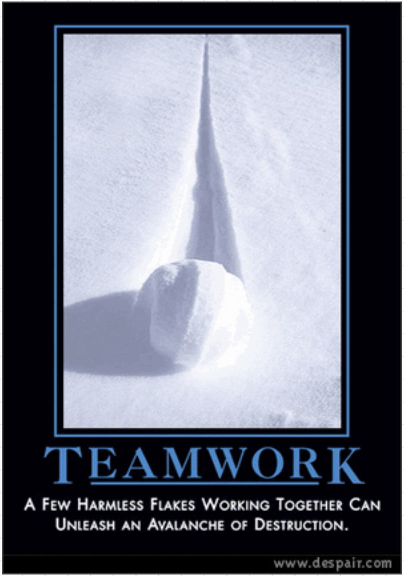
Special subnetworks can act as triggers



- $\phi = 1/3$ for all nodes

Outline

The power of groups...



despair.com

"A few harmless flakes working together can unleash an avalanche of destruction."

Extensions

- Assumption of sparse interactions is good
- Degree distribution is (generally) key to a network's function
- Still, random networks don't represent all networks
- Major element missing: group structure

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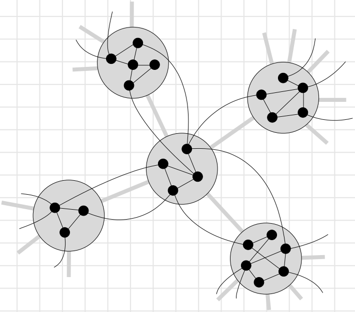
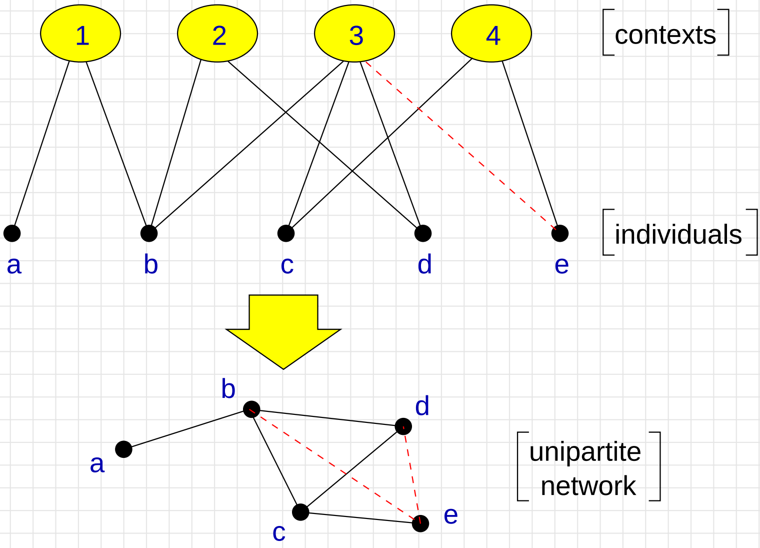
Group structure—Ramified random networks

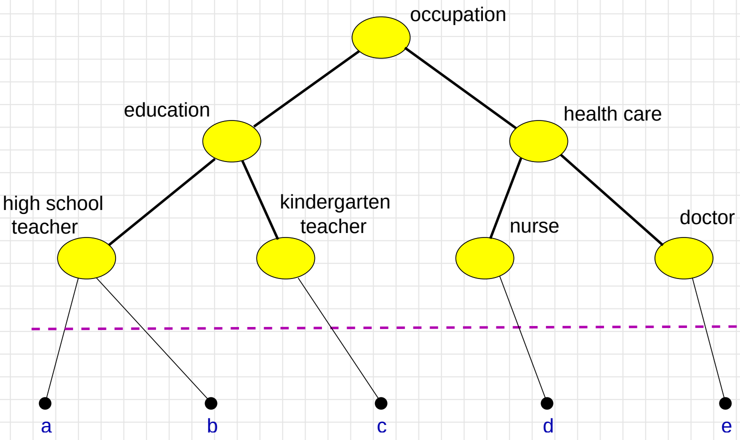


p = intergroup connection probability
q = intragroup connection probability.

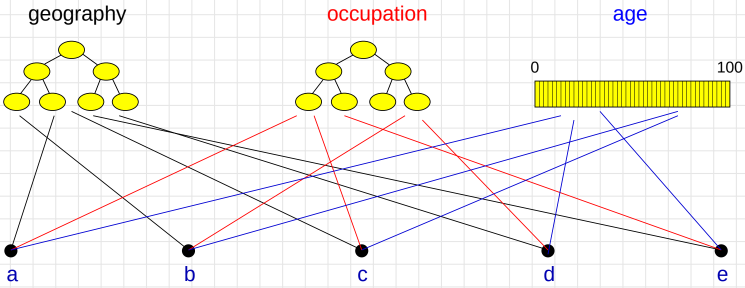
Bipartite networks



Context distance



Generalized affiliation model



(Blau & Schwartz, Simmel, Breiger)

Generalized affiliation model networks with triadic closure

- Connect nodes with probability $\propto \exp^{-\alpha d}$
  where
  α = homophily parameter
  and
  d = distance between nodes (height of lowest common ancestor)
- τ_1 = intergroup probability of friend-of-friend connection
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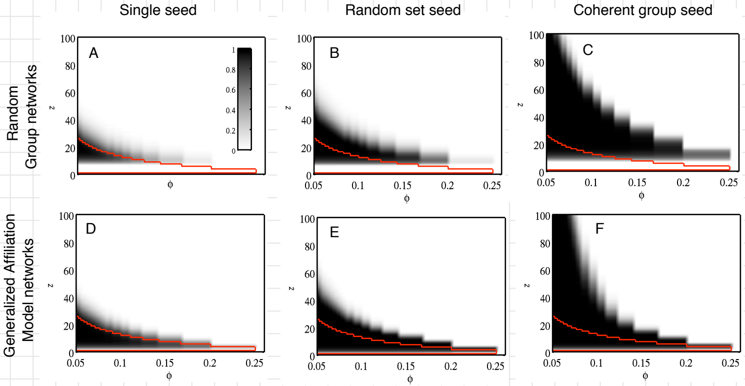
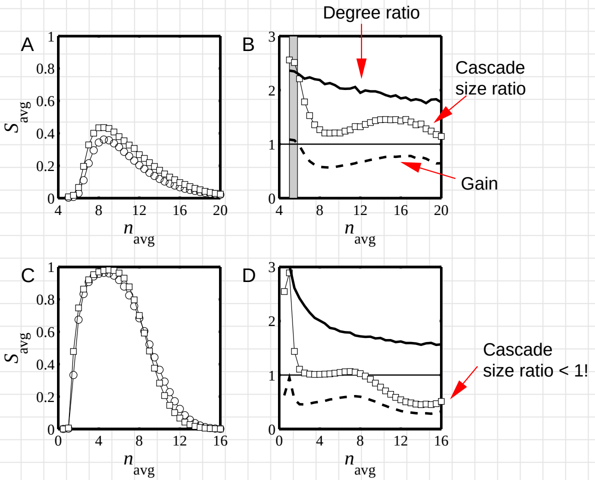
Cascade windows for group-based networks

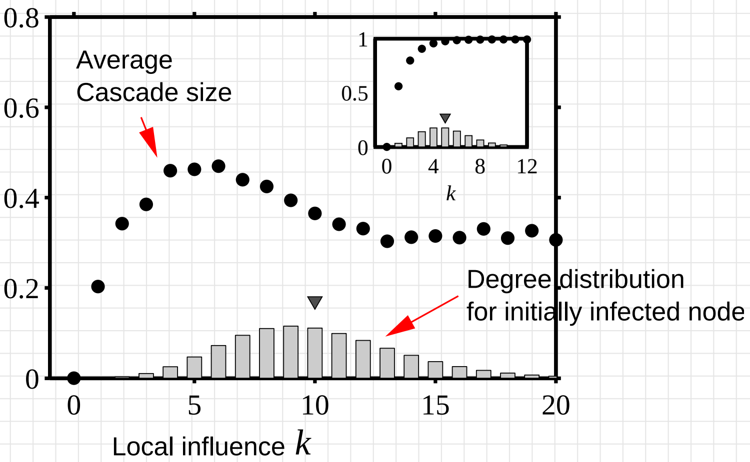


Multiplier effect for group-based networks:



- Multiplier almost always below 1.

Assortativity in group-based networks



- The most connected nodes aren't always the most 'influential.'
- Degree assortativity is the reason.

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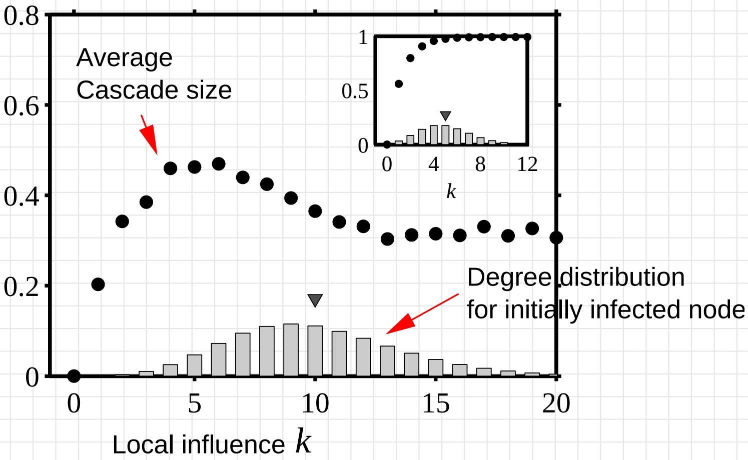

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Social contagion

Summary

- ‘Influential vulnerables’ are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
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The UNIVERSITY of VERMONT

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- Focus on the influential vulnerables.
- Create entities that can be transmitted successfully through many individuals rather than broadcast from one 'influential.'
- Only simple ideas can spread by word-of-mouth.
  (Idea of opinion leaders spreads well...)
- Want enough individuals who will adopt and display.
- Displaying can be passive = free (yo-yo's, fashion), or active = harder to achieve (political messages).
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Chaotic contagion:

- What if individual response functions are not monotonic?
- Consider a simple deterministic version:
  - Node i has an 'activation threshold' $\phi_{i,1}$

    …and a 'de-activation threshold' $\phi_{i,2}$
  - Nodes like to imitate but only up to a limit—they don't want to be like everyone else.

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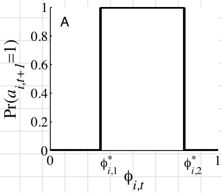

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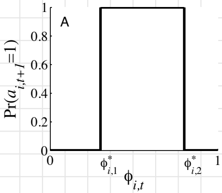

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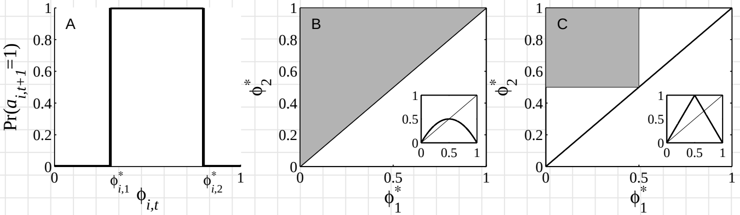

- Randomly select $(\phi_{i,1}, \phi_{i,2})$ from gray regions shown in plots B and C.
- Insets show composite response function averaged over population.
- We'll consider plot C's example: the tent map.

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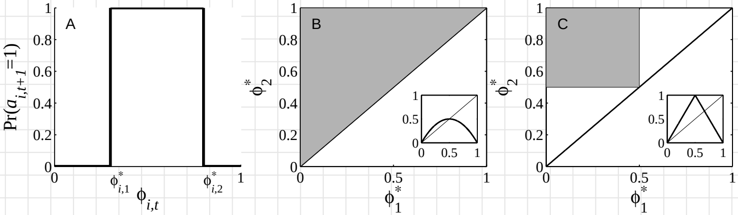

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Chaotic contagion

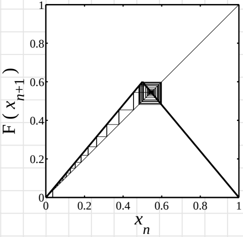
Definition of the tent map:

$$F(x) = \begin{cases} rx \text{ for } 0 \le x \le \frac{1}{2}, \\ r(1-x) \text{ for } \frac{1}{2} \le x \le 1. \end{cases}$$

- The usual business: look at how F iteratively maps the unit interval $[0, 1]$.

The tent map

Effect of increasing r from 1 to 2.



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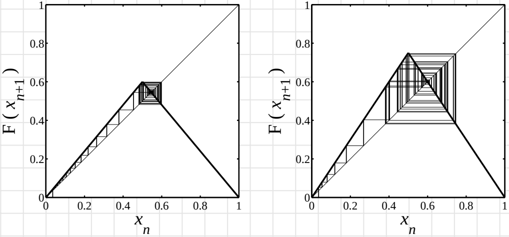

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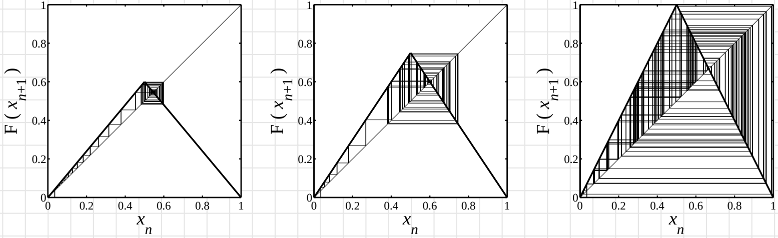

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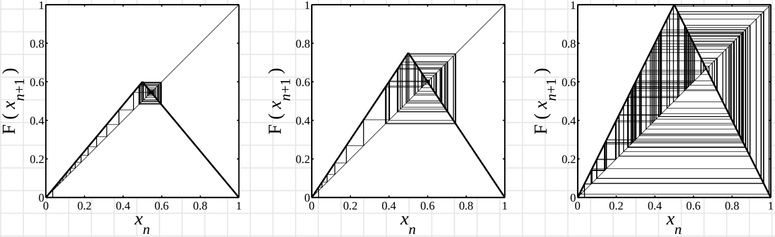
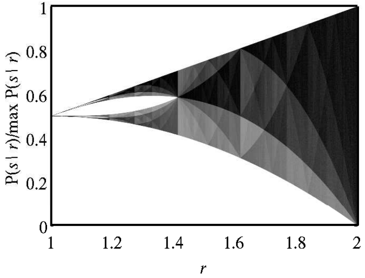


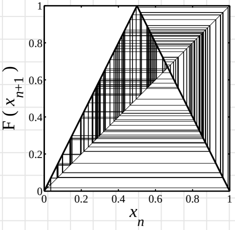


Orbit diagram:

Chaotic behavior increases as map slope r is increased.

Chaotic behavior

Take $r = 2$ case:



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- As before, allow interactions to take place on a sparse random network.
- Vary average degree $z = \langle k \rangle$, a measure of information

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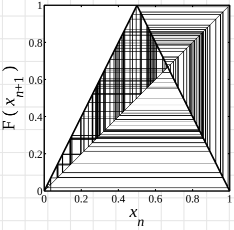

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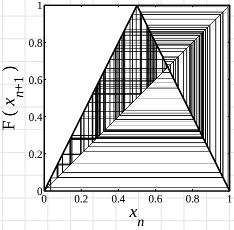

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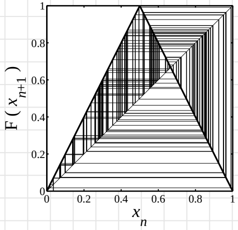

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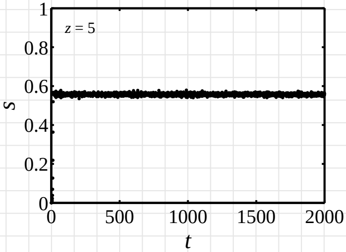
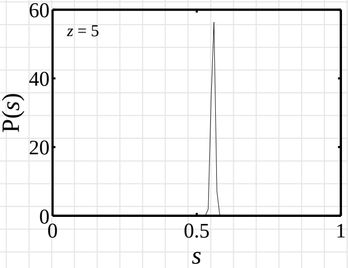
Invariant densities—stochastic response functions

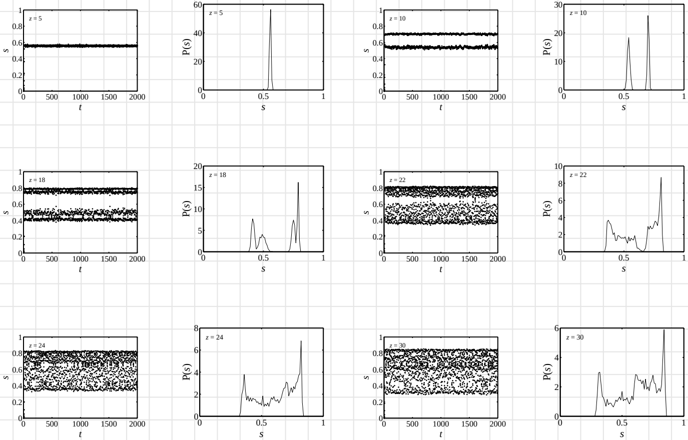


activation time series

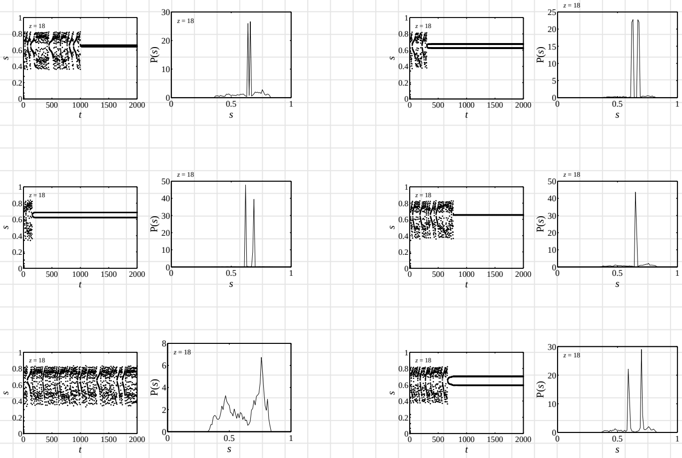


activation density

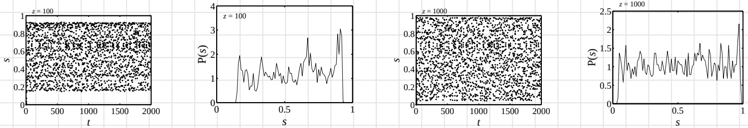
Invariant densities—stochastic response functions



Invariant densities—deterministic response functions for one specific network with $\langle k \rangle = 18$

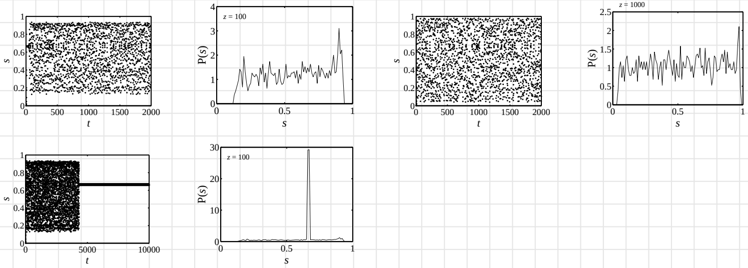


Invariant densities—stochastic response functions



Trying out higher values of $\langle k \rangle$...

Invariant densities—deterministic response functions



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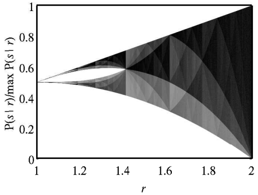
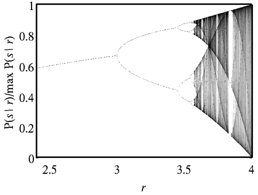
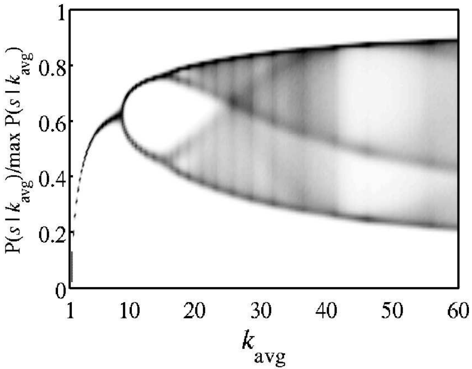
Connectivity leads to chaos:





Stochastic response functions:



Chaotic behavior in coupled systems

Coupled maps are well explored (Kaneko/Kuramoto):

$$x_{i,n+1} = f(x_{i,n}) + \sum_{j \in \mathcal{N}_i} \delta_{i,j} f(x_{j,n})$$

- $\mathcal{N}_i$ = neighborhood of node i

1. Node states are continuous
2. Increase δ and neighborhood size $|\mathcal{N}|$

$\Rightarrow$ synchronization

But for contagion model:

1. Node states are binary
2. Asynchrony remains as connectivity increases

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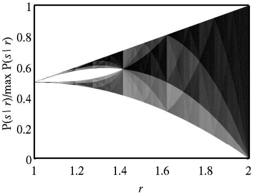
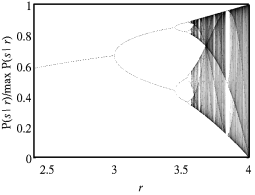
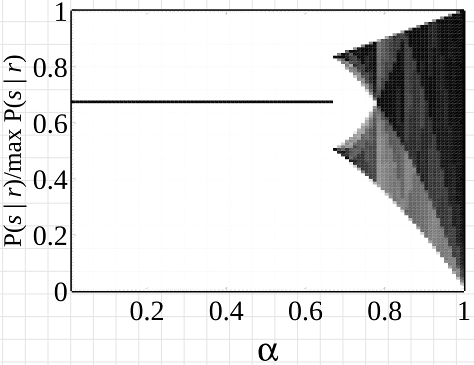
Bifurcation diagram: Asynchronous updating







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