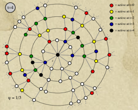
Social Contagion

Principles of Complex Systems
CSYS/MATH 300, Spring, 2013 | #SpringPoCS2013

Prof. Peter Dodds
@peterdodds

Department of Mathematics & Statistics | Center for Complex Systems |
Vermont Advanced Computing Center | University of Vermont



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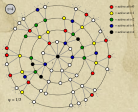
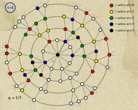


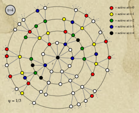
Outline



Things that spread well:

buzzfeed.com (⊞):

+ News ...



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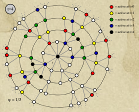
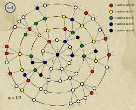
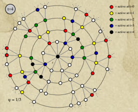


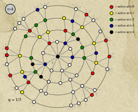
LOL + cute + fail + wtf:



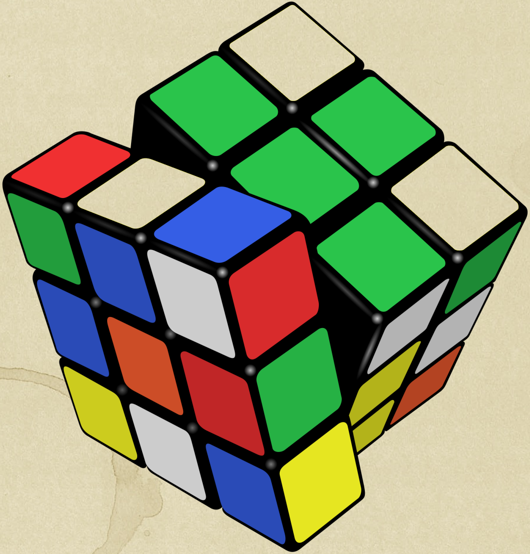
The whole lolcats thing:

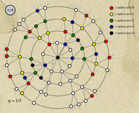


Some things really stick:



wtf + geeky + omg:





Outline

Social Contagion Models

Background

Granovetter's model

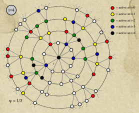
Network version

Final size

Spreading success

Groups

References



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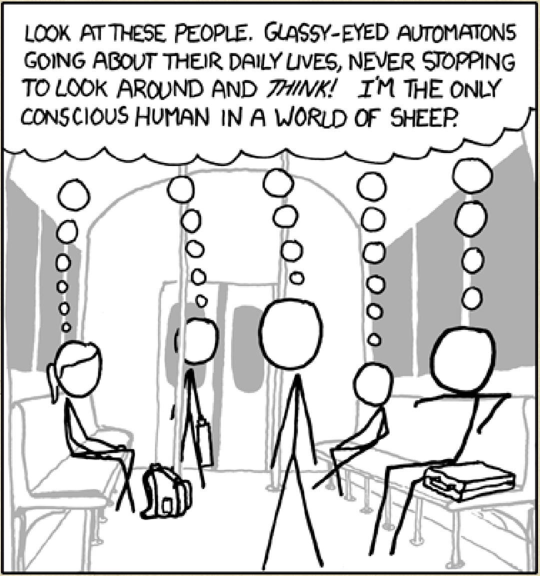
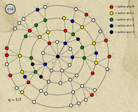


http://xkcd.com/610/ (⊞)



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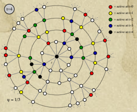
Examples abound

- fashion
- striking
- smoking (⊞) [7]
- residential segregation [19]
- ipods
- obesity (⊞) [6]
- 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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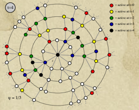

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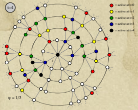

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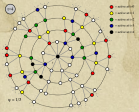
SIR and SIRS contagion possible

- Classes of behavior versus specific behavior: dieting



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Evolving network stories (Christakis and Fowler):

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- The spread of spreading (⊞) [6]
- Also: happiness (⊞) [9], loneliness, ...
- The book: Connected: The Surprising Power of Our Social Networks and How They Shape Our Lives (⊞)

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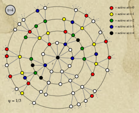

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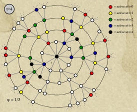

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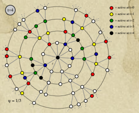

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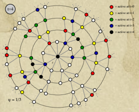

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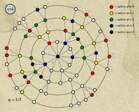


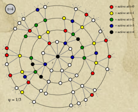
Social Contagion

Two focuses for us

- Widespread media influence
- Word-of-mouth influence

We need to understand influence

- Who influences whom?
- What kinds of influence response functions are there?
- Are some individuals super influencers?
- The infectious idea of opinion leaders (Katz and Lazarsfeld)[16]



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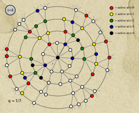

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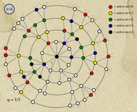

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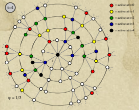

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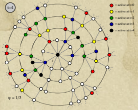

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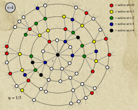

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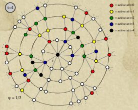

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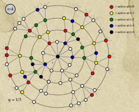

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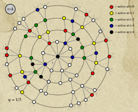

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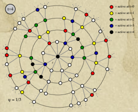
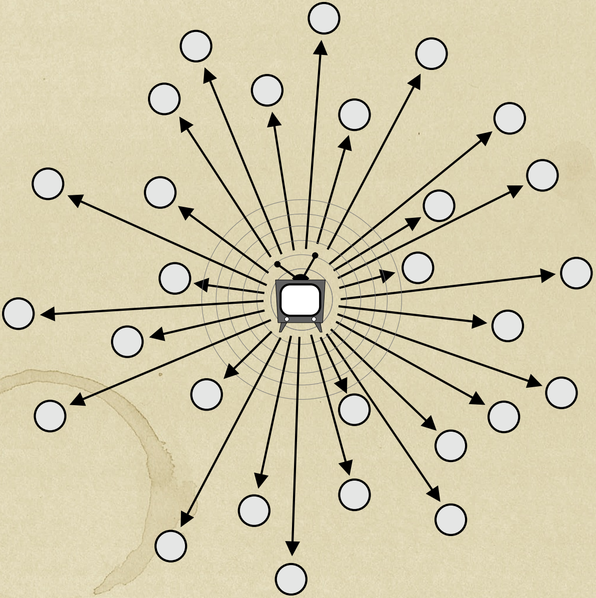
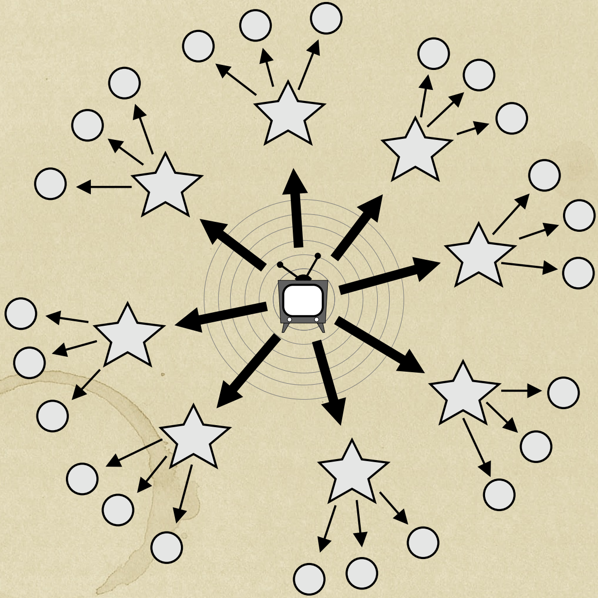


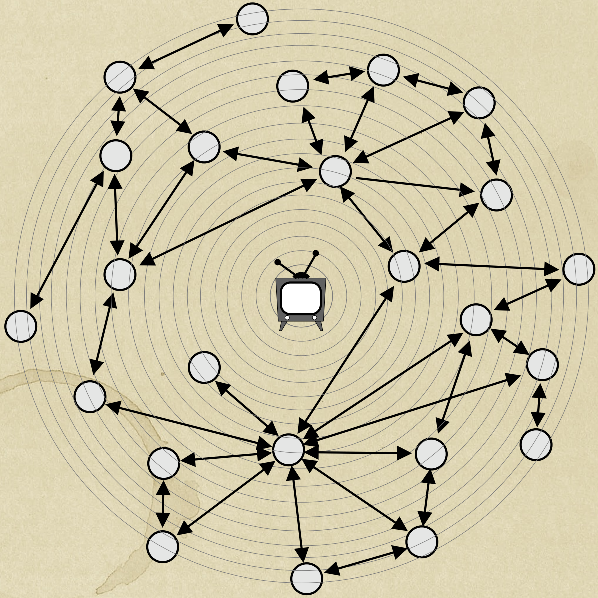
The hypodermic model of influence

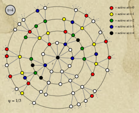


The two step model of influence [16]



The general model of influence





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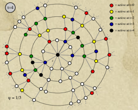
Why do things spread?

- 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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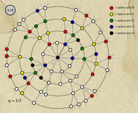

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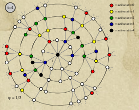

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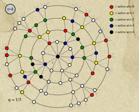

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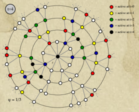

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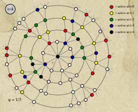

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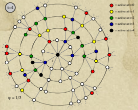

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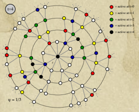

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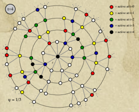

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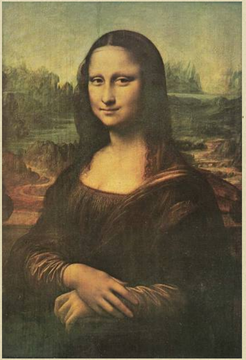

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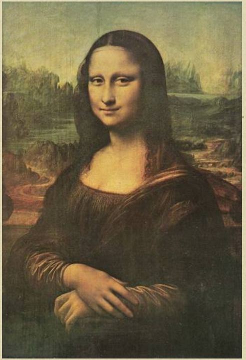

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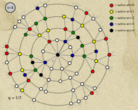

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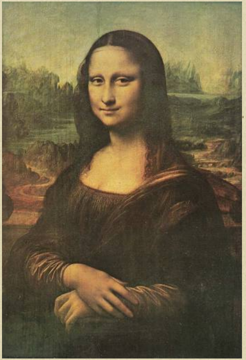

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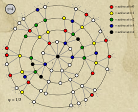

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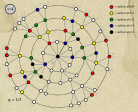

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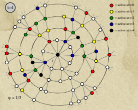

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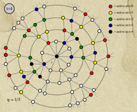
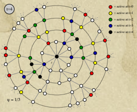
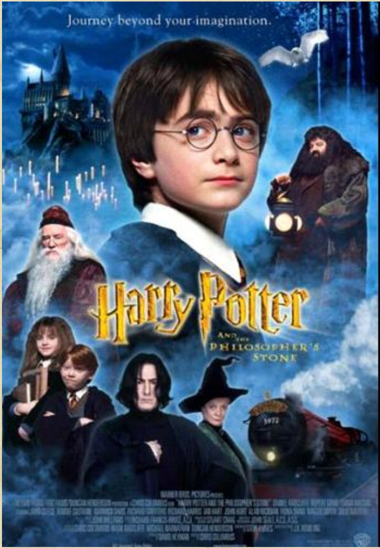


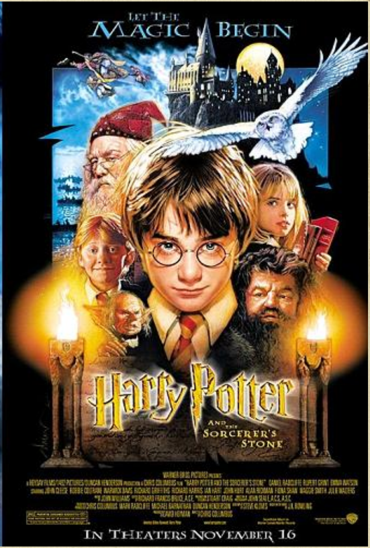
The completely unpredicted fall of Eastern Europe

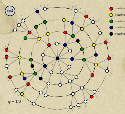
Timur Kuran:[17, 18] “Now Out of Never: The Element of Surprise in the East European Revolution of 1989”



The dismal predictive powers of editors...



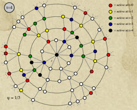




Social Contagion

Messing with social connections

- Ads based on message content
- BzzAgent (⊞)
- One of Facebook's early advertising attempts: Beacon (⊞)
- All of Facebook's advertising attempts.



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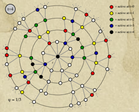

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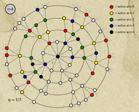

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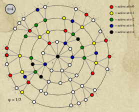

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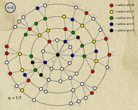

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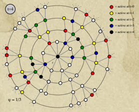

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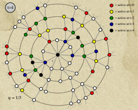

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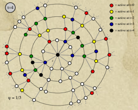

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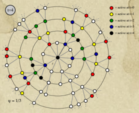

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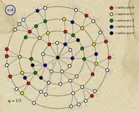

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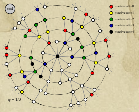

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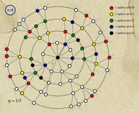

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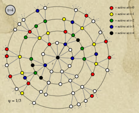

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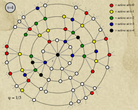
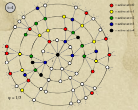


Social contagion

- Cialdini's modes are heuristics that help up us get through life.
- Useful but can be leveraged...

Other acts of influence:

- Conspicuous Consumption (Veblen, 1912)
- Conspicuous Destruction (Potlatch)



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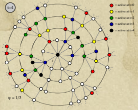

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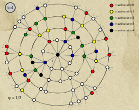

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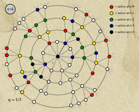

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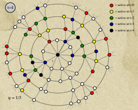

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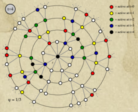

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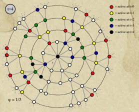

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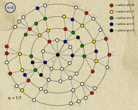

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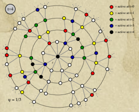

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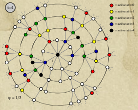

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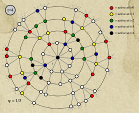

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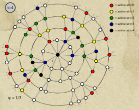

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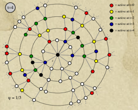

Social contagion models

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
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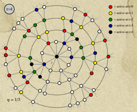

Social contagion models

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- Basic idea: individuals adopt a behavior when a certain fraction of others have adopted
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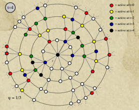

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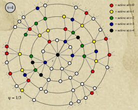

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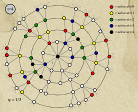

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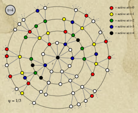

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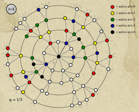

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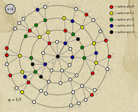

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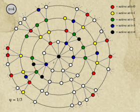

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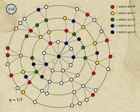
Some possible origins of thresholds:

- Inherent, evolution-devised inclination to coordinate, to conform, to imitate. [1]
- 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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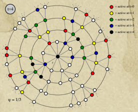

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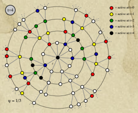

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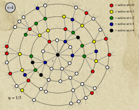

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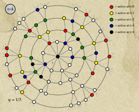

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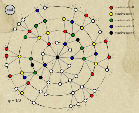

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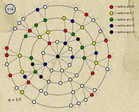
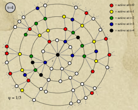
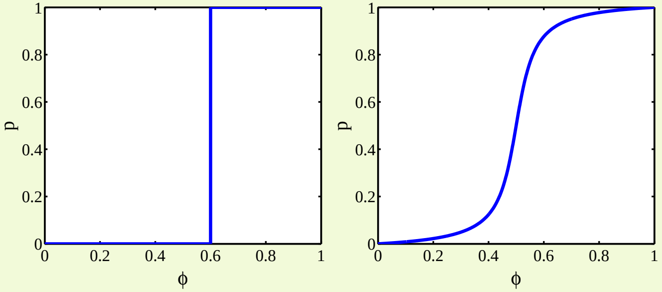


Outline



Threshold models—response functions



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- ϕ = fraction of contacts ‘on’ (e.g., rioting)
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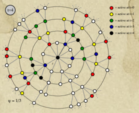

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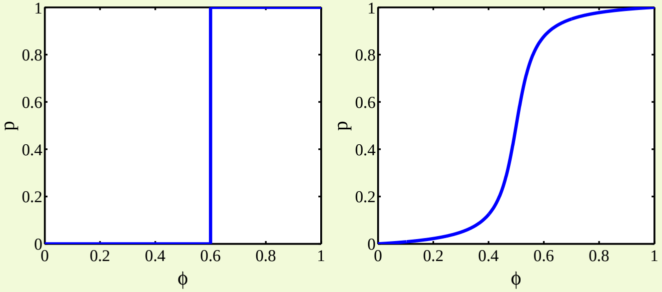

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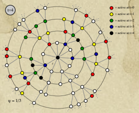

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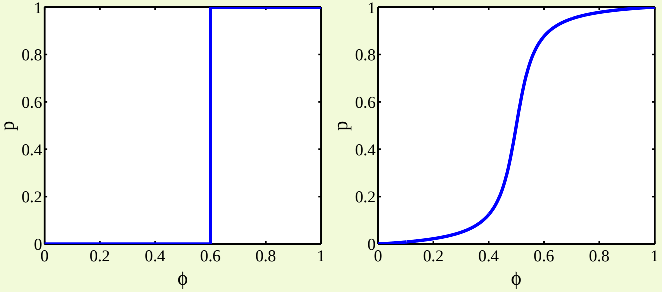

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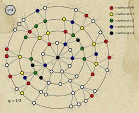

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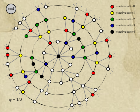

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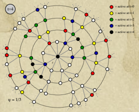

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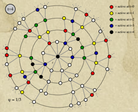

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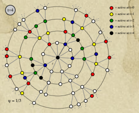

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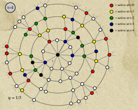

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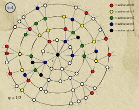

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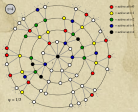

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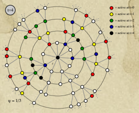
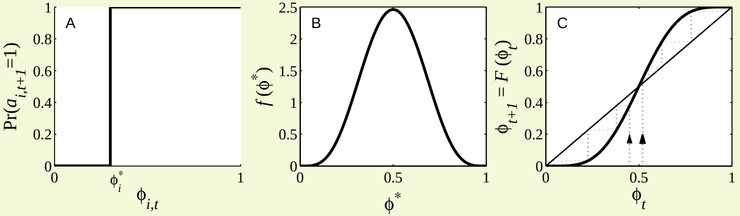


Threshold models

Action based on perceived behavior of others:



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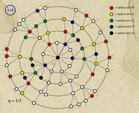
- Discrete time update (strong assumption!)
- This is a Critical mass model



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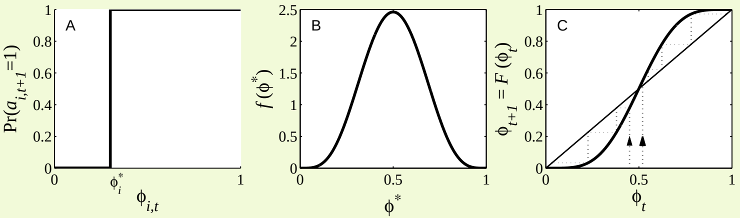

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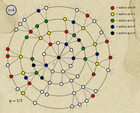

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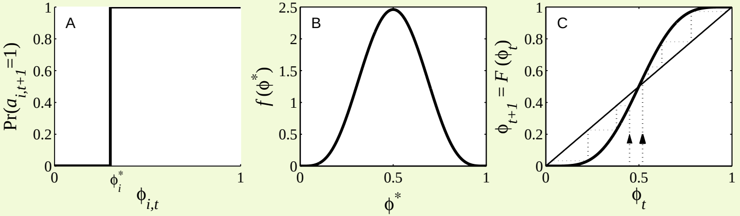

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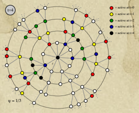
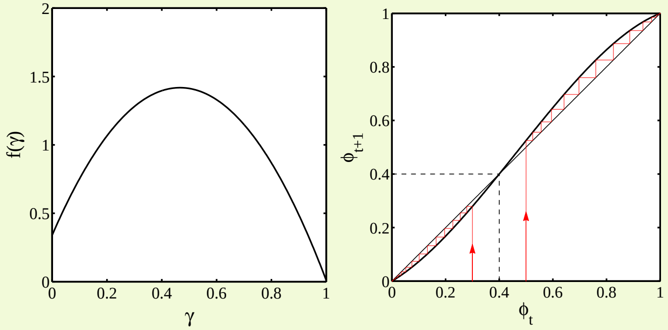
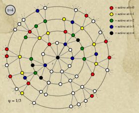


Threshold models

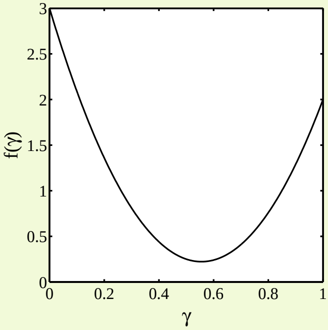
Another example of critical mass model:

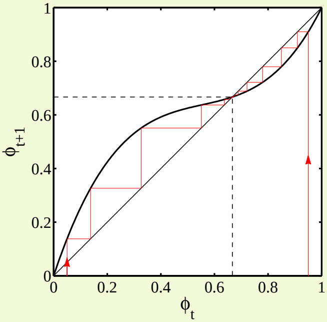


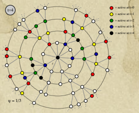


Threshold models

Example of single stable state model:

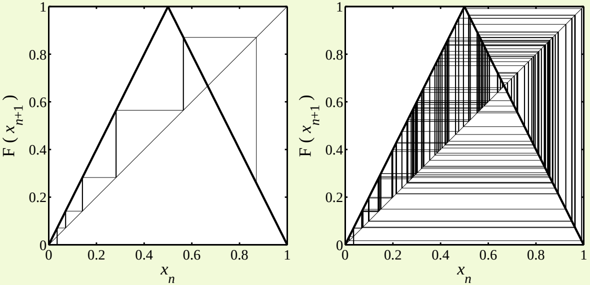




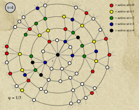


Threshold models

Chaotic behavior possible [15, 14]



- Period doubling arises as map amplitude r is increased.
- Synchronous update assumption is crucial



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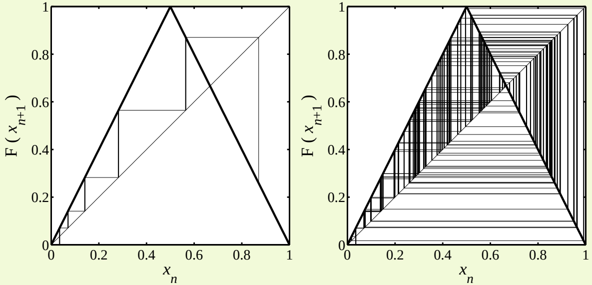
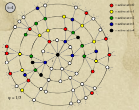


- Period doubling arises as map amplitude r is increased.
- Synchronous update assumption is crucial



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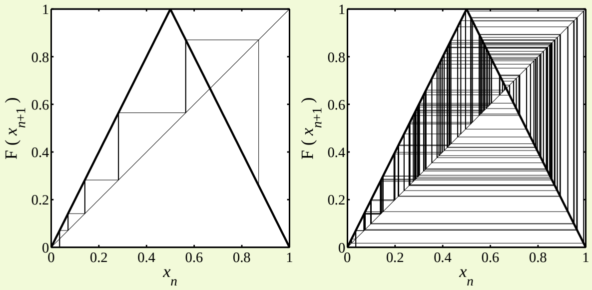

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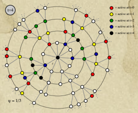
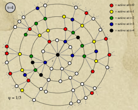


Threshold models—Nutshell

Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity
2. Small individual changes $\Rightarrow$ large global changes



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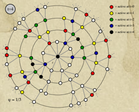

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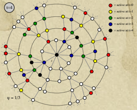
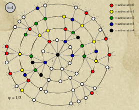


Outline



“A simple model of global cascades on random networks”

- Many years after Granovetter and Soong’s work: D. J. Watts. Proc. Natl. Acad. Sci., 2002 [23]
  - Mean field model → network model
  - Individuals now have a limited view of the world

We’ll also explore:

- “Seed size strongly affects cascades on random networks” [12]
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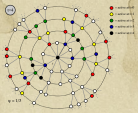

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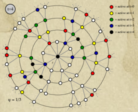

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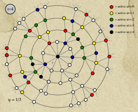

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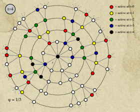

Threshold model on a network

- Interactions between individuals now represented by a network
- Network is sparse
- Individual i has k_i contacts
- Influence on each link is reciprocal and of unit weight
- Each individual i has a fixed threshold ϕ_i
- Individuals repeatedly poll contacts on network
- Synchronous, discrete time updating
- Individual i becomes active when fraction of active contacts $\frac{a_i}{k_i} \geq \phi_i$
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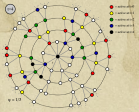

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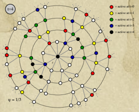

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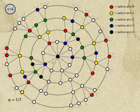

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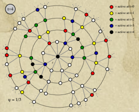

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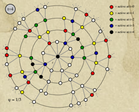

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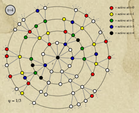

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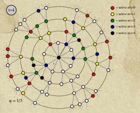

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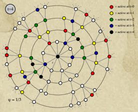

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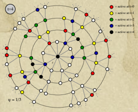

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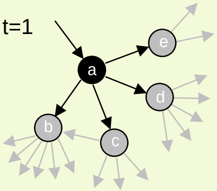

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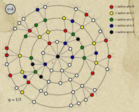

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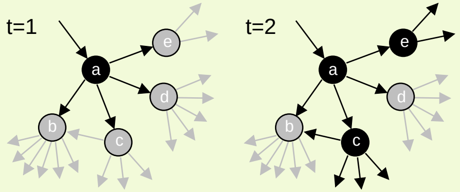

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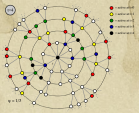

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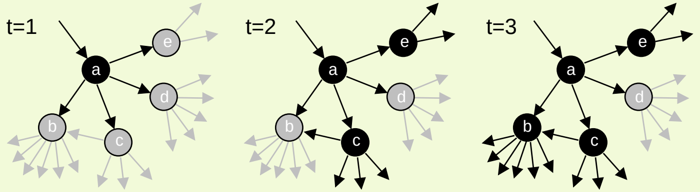

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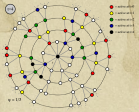


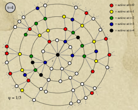
Snowballing

First study random networks:

- Start with N nodes with a degree distribution p_k
- Nodes are randomly connected (carefully so)
- Aim: Figure out when activation will propagate
- Determine a cascade condition

The Cascade Condition:

1. If one individual is initially activated, what is the probability that an activation will spread over a network?
2. What features of a network determine whether a cascade will occur or not?



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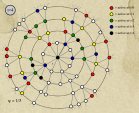

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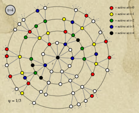

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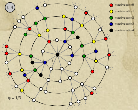

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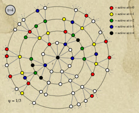

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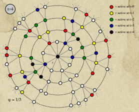

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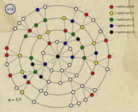
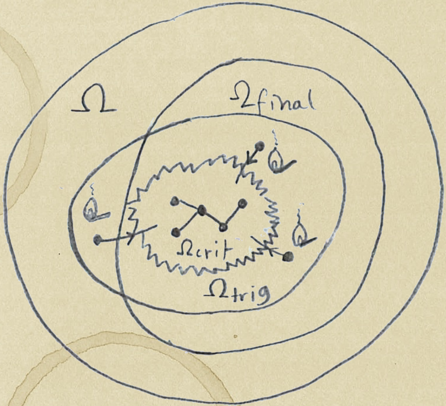
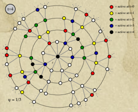


Example random network structure:



- $\Omega_{\text{crit}} = \Omega_{\text{vuln}} =$ critical mass = global vulnerable component
- $\Omega_{\text{trig}} =$ triggering component
- $\Omega_{\text{final}} =$ potential extent of spread
- $\Omega =$ entire network

$\Omega_{\text{crit}} \subset \Omega_{\text{trig}}$; $\Omega_{\text{crit}} \subset \Omega_{\text{final}}$; and $\Omega_{\text{trig}}, \Omega_{\text{final}} \subset \Omega$.



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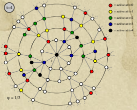
Follow active links

- An active link is a link connected to an activated node.
- If an infected link leads to at least 1 more infected link, then activation spreads.
- We need to understand which nodes can be activated when only one of their neigbors becomes active.



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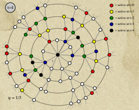

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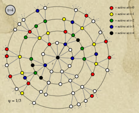

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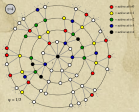

The most gullible

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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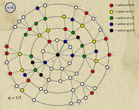
- Cluster of vulnerables = critical mass
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.



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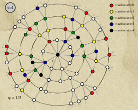

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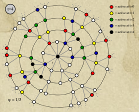

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- We call individuals who can be activated by just one contact being active vulnerables
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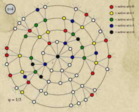

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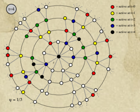

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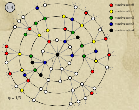

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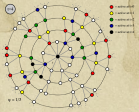


Cascade condition

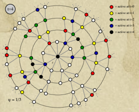
Back to following a link:

- A randomly chosen link, traversed in a random direction, leads to a degree k node with probability $\propto kP_k$.
- Follows from there being k ways to connect to a node with degree k.
- Normalization:

$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle$$

- So

$$P(\text{linked node has degree } k) = \frac{kP_k}{\langle k \rangle}$$



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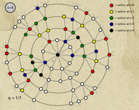

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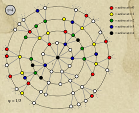

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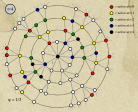

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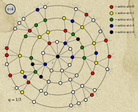

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Next: Vulnerability of linked node

- Linked node is vulnerable with probability

$$\beta_k = \int_{\phi'_*=0}^{1/k} f(\phi'_*)\mathrm{d}\phi'_*$$

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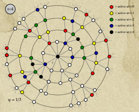

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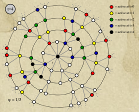

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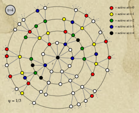

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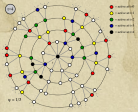

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Putting things together:

- Expected number of active edges produced by an active edge:

$$R = \underbrace{\sum_{k=1}^{\infty} (k-1) \cdot \beta_k \cdot \frac{kP_k}{\langle k \rangle}}_{\text{success}} \quad +$$

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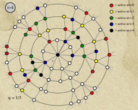

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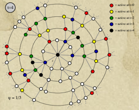

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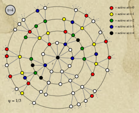

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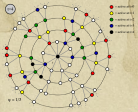
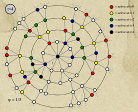


Cascade condition

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.



Cascade condition

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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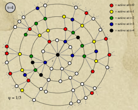

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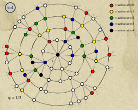

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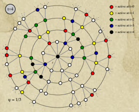

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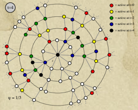

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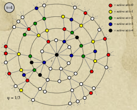
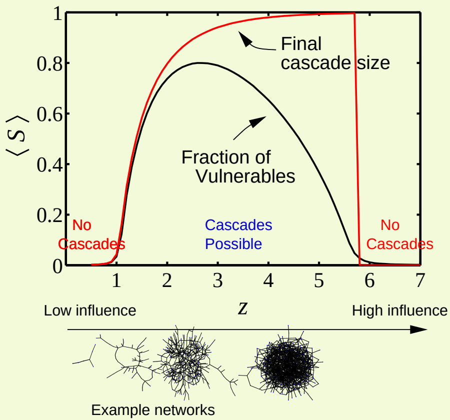
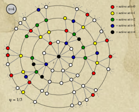


Cascades on random networks



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



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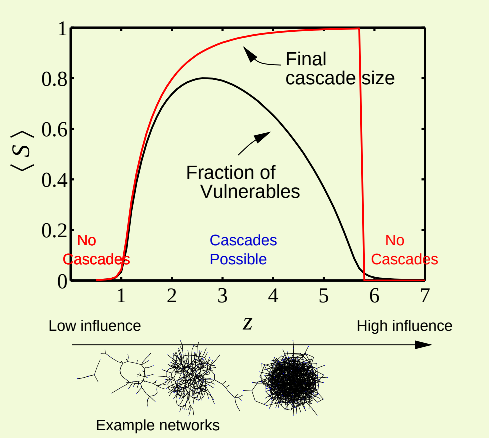

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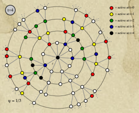

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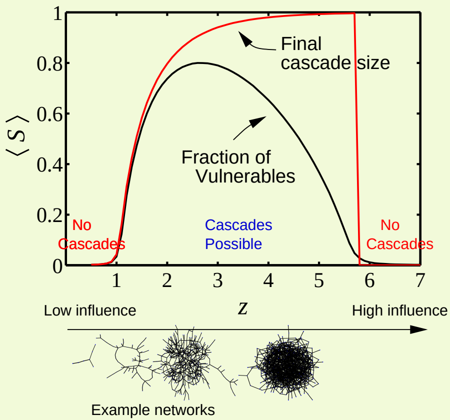

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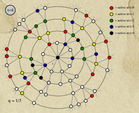
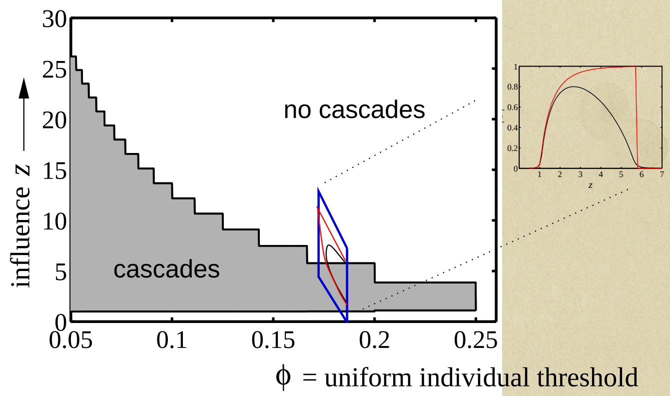
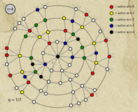


Cascade window for random networks



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



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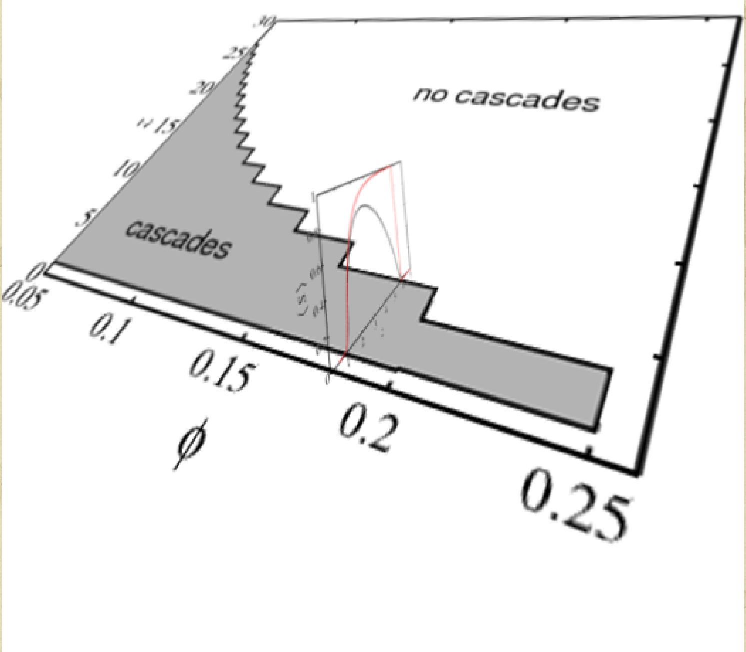
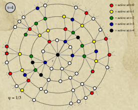
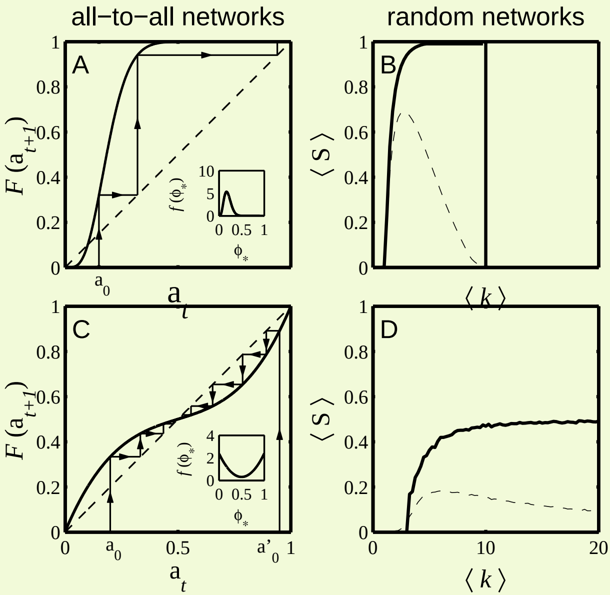
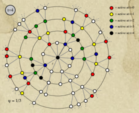




All-to-all versus random networks

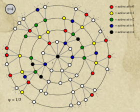




Cascade window—summary

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.
2. High $\langle k \rangle$: Giant component exists but not enough vulnerables.
3. Intermediate $\langle k \rangle$: Global cluster of vulnerables exists. Cascades are possible in "Cascade window."



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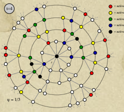

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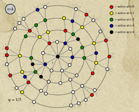

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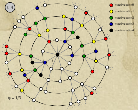
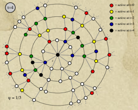


Outline



Threshold contagion on random networks

- **Next:** Find expected fractional size of spread.
- Not obvious even for uniform threshold problem.
- Difficulty is in figuring out if and when nodes that need ≥ 2 hits switch on.
- Problem solved for infinite seed case by Gleeson and Cahalane:
  "Seed size strongly affects cascades on random networks," Phys. Rev. E, 2007. [12]
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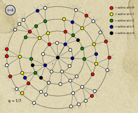

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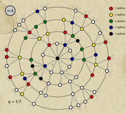

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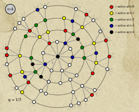

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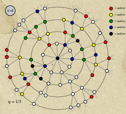

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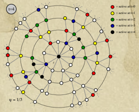

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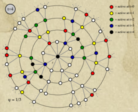

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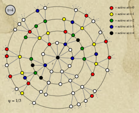

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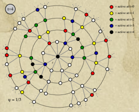

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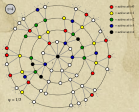

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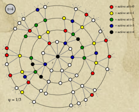

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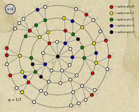

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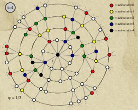

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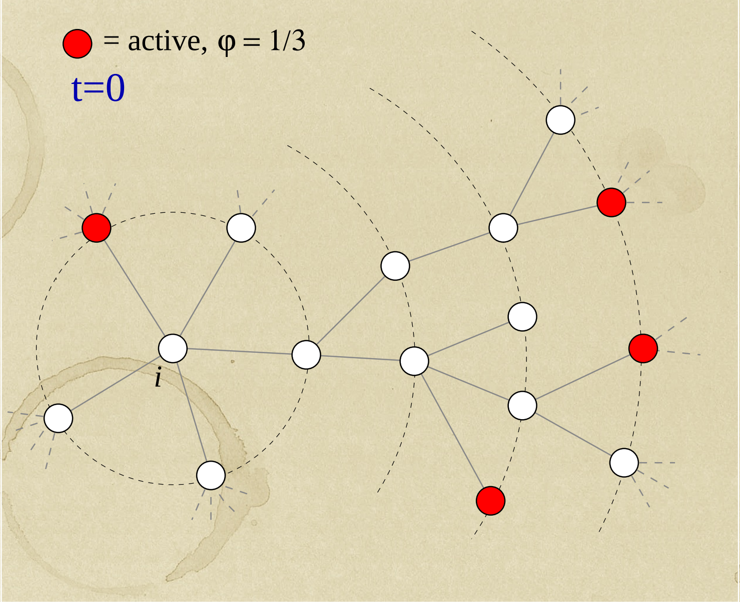

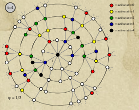

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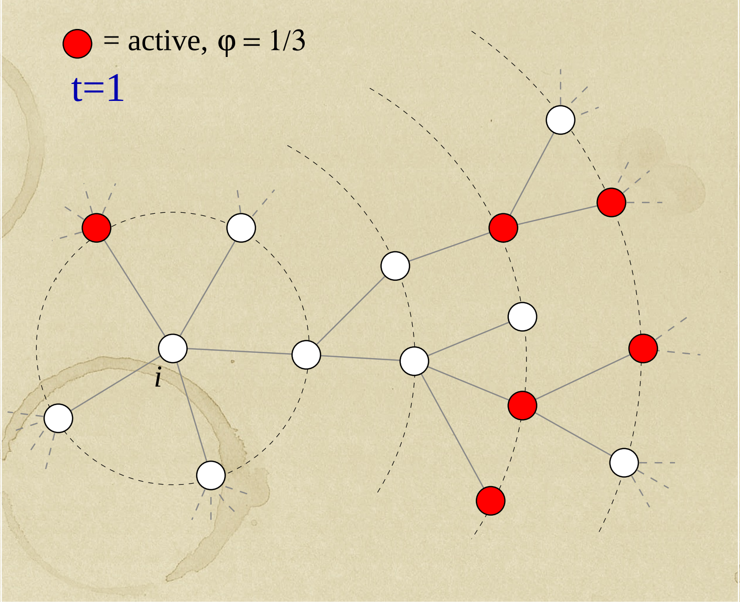

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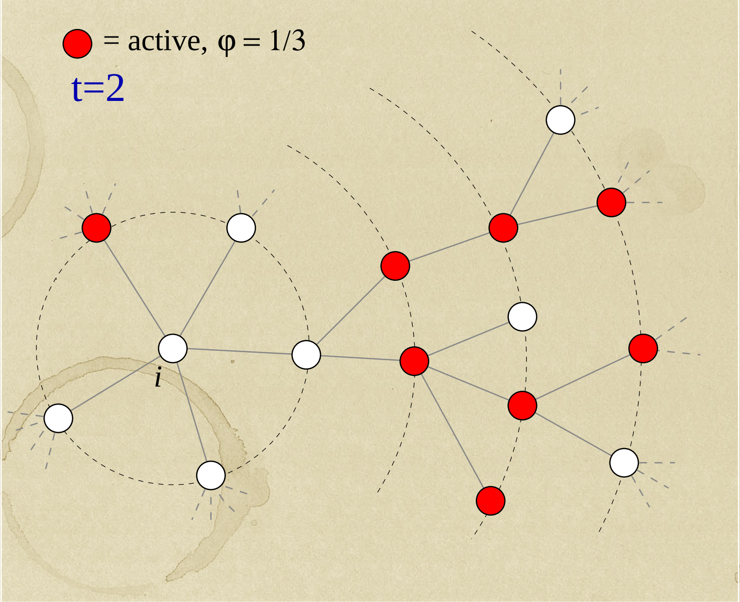

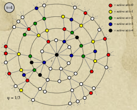

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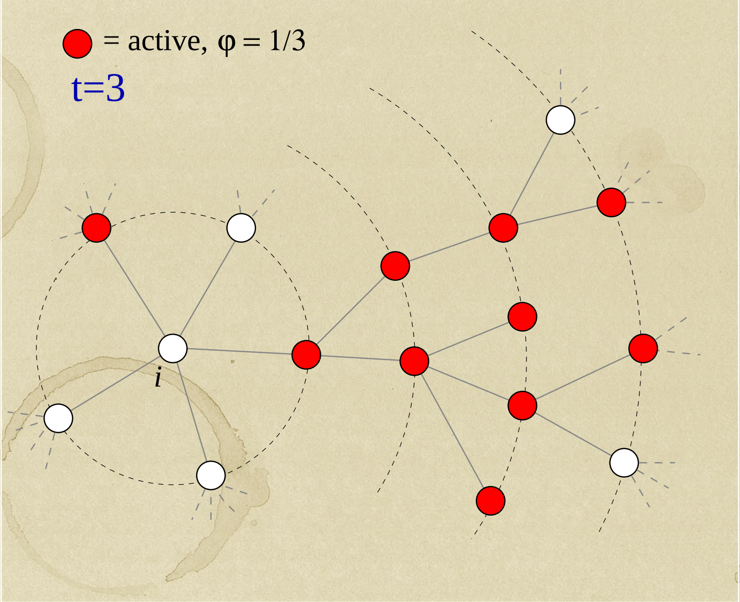

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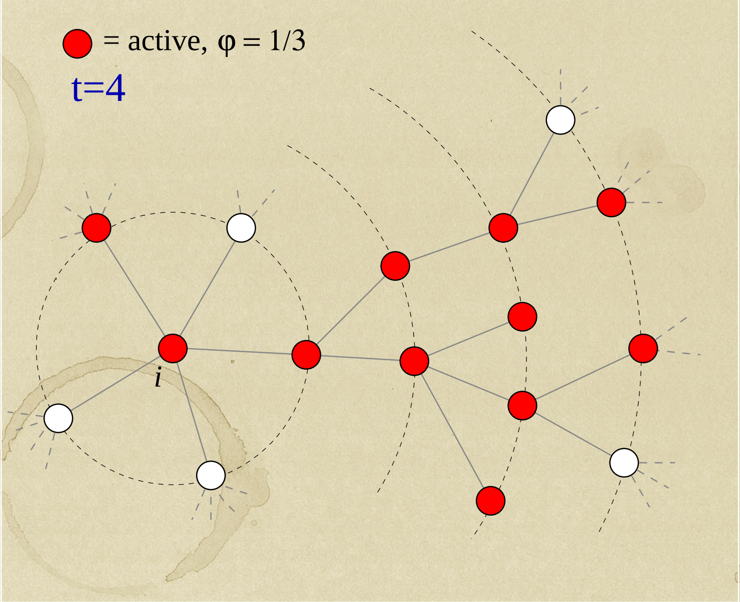

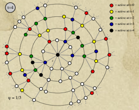

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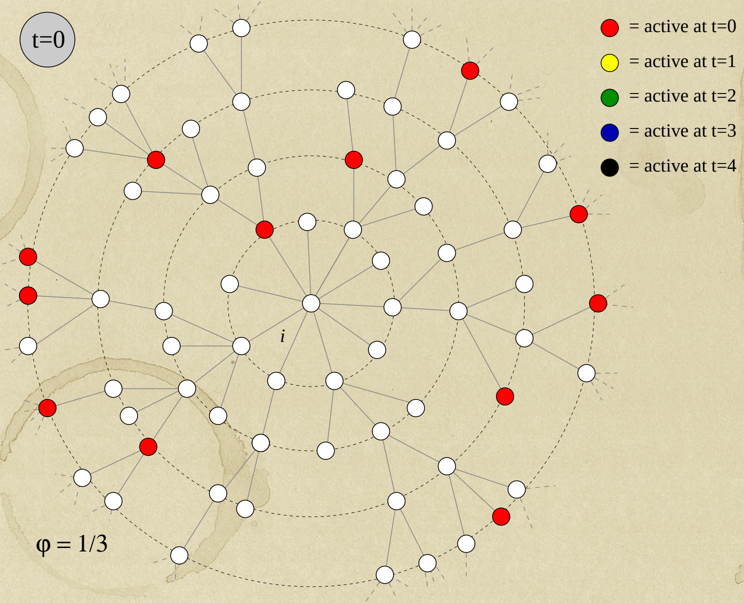

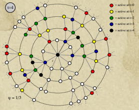

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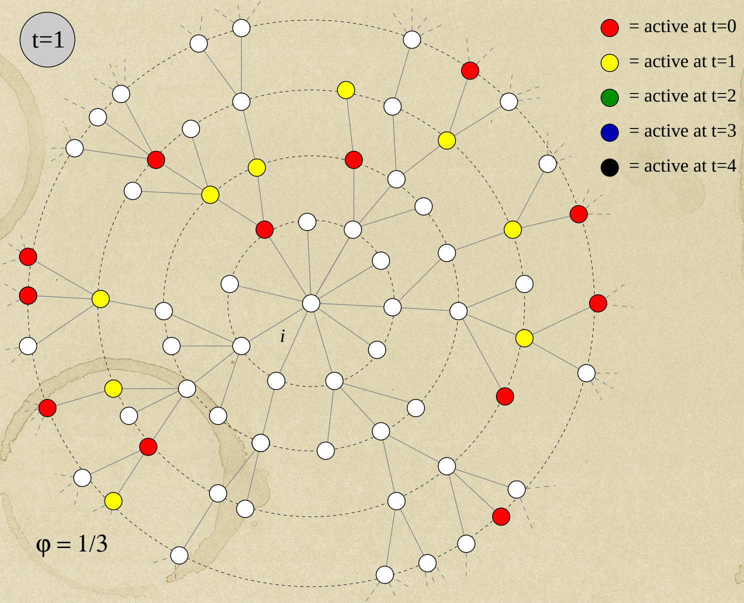

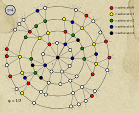

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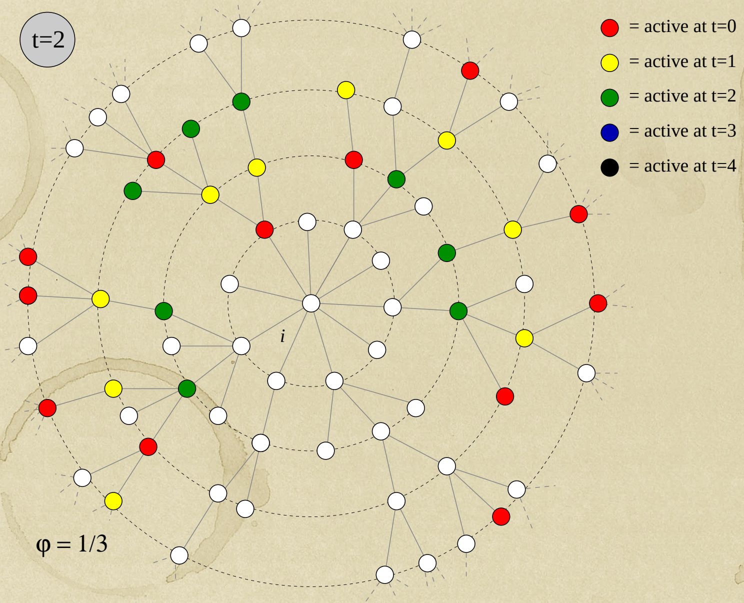

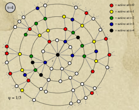

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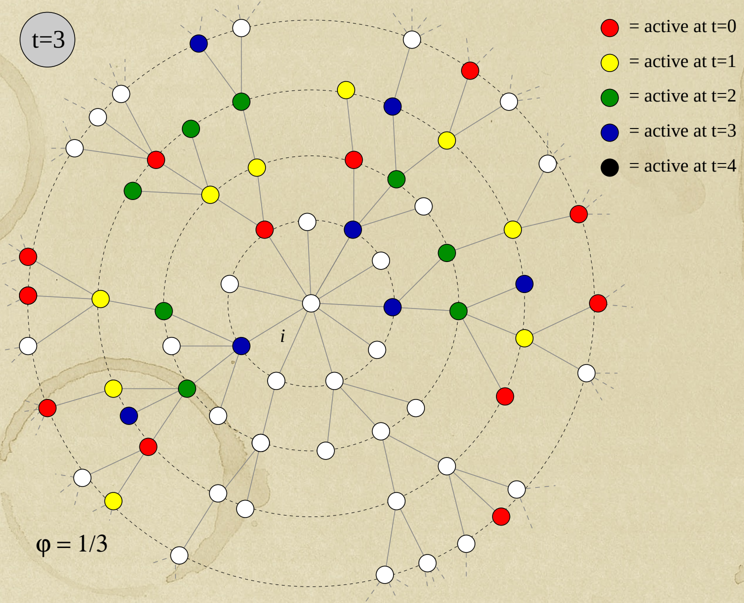

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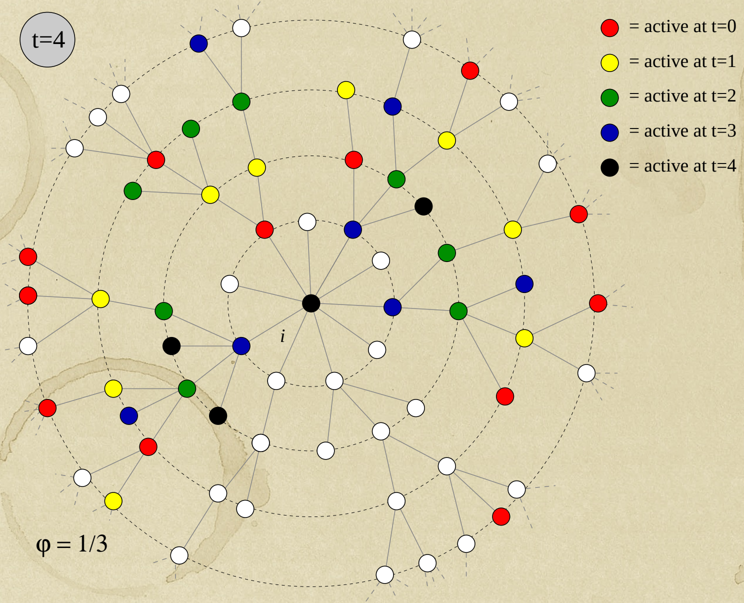

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Notes:

- Calculations are possible if nodes do not become inactive (strong restriction).
- Not just for threshold model—works for a wide range of contagion processes.
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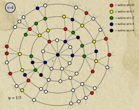

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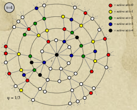

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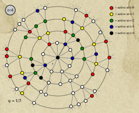

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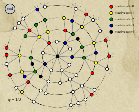

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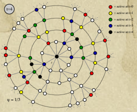

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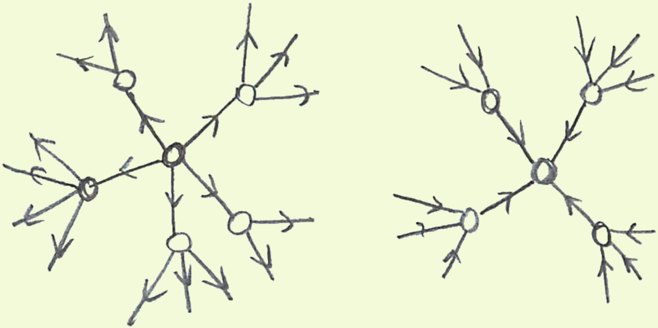
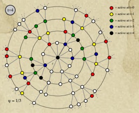
Pleasantness:

- Taking off from a single seed story is about expansion away from a node.
- Extent of spreading story is about contraction at a node.





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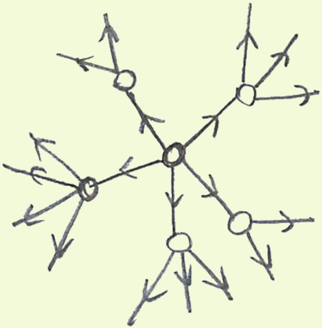

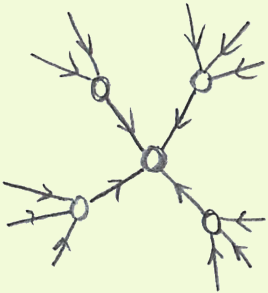

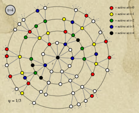

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- Notation: B_{kj} = **Pr** (a degree k node becomes active if j neighbors are active).
- Our starting point: $\phi_{k,0} = \phi_0$.
- $\binom{k}{j}\phi_0^j(1-\phi_0)^{k-j}$ = **Pr** (j of a degree k node's neighbors were seeded at time $t=0$).
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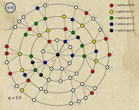

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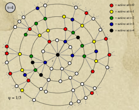

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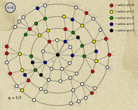

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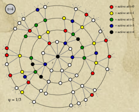

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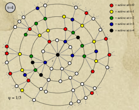

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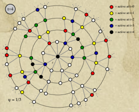

Expected size of spread

- Notation:
  $\phi_{k,t} = \mathbf{Pr}$(a degree k node is active at time t).
- Notation: $B_{kj} = \mathbf{Pr}$ (a degree k node becomes active if j neighbors are active).
- Our starting point: $\phi_{k,0} = \phi_0$.
- $\binom{k}{j}\phi_0^j(1-\phi_0)^{k-j}$ = $\mathbf{Pr}$ (j of a degree k node's neighbors were seeded at time $t = 0$).
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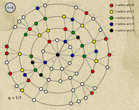

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- We already know $\theta_0 = \phi_0$.
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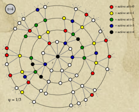

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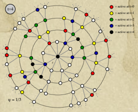

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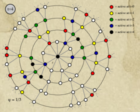

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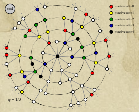

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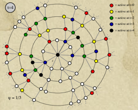

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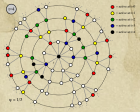

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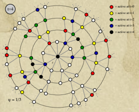

Expected size of spread

First connect θ_0 to θ_1:

- $\theta_1 = \phi_0 +$

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- $\frac{kP_k}{\langle k\rangle} = R_k$ = **Pr** (edge connects to a degree k node).
- $\sum_{j=0}^{k-1}$ piece gives **Pr**(degree node k activates) of its neighbors $k-1$ incoming neighbors are active.
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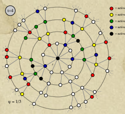

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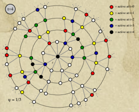


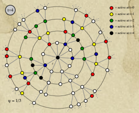
Expected size of spread

Two pieces: edges first, and then nodes

1. $$\theta_{t+1} = \underbrace{\phi_0}_{\text{exogenous}} + \underbrace{(1-\phi_0) \sum_{k=1}^{\infty} \frac{kP_k}{\langle k \rangle} \sum_{j=0}^{k-1} \binom{k-1}{j} \theta_t^{\,j} (1-\theta_t)^{k-1-j} B_{kj}}_{\text{social effects}}$$

   with $\theta_0 = \phi_0$.

2. $$\phi_{t+1} = \underbrace{\phi_0}_{\text{exogenous}} + \underbrace{(1-\phi_0) \sum_{k=0}^{\infty} P_k \sum_{j=0}^{k} \binom{k}{j} \theta_t^{\,j} (1-\theta_t)^{k-j} B_{kj}}_{\text{social effects}}.$$



Expected size of spread:

- Retrieve cascade condition for spreading from a single seed in limit $\phi_0 \to 0$.
- Depends on map $\theta_{t+1} = G(\theta_t; \phi_0)$.
- First: if self-starters are present, some activation is assured:

$$G(0; \phi_0) = \sum_{k=1}^{\infty} \frac{kP_k}{\langle k \rangle} \bullet B_{k0} > 0.$$

meaning $B_{k0} > 0$ for at least one value of $k \geq 1$.

- If $\theta = 0$ is a fixed point of G (i.e., $G(0; \phi_0) = 0$) then spreading occurs if

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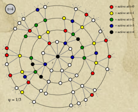

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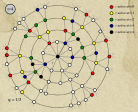

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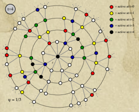

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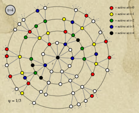


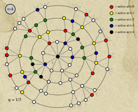
Expected size of spread:

In words:

- If $G(0;\phi_0) > 0$, spreading must occur because some nodes turn on for free.
- If G has an unstable fixed point at $\theta = 0$, then cascades are also always possible.

Non-vanishing seed case:

- Cascade condition is more complicated for $\phi_0 > 0$.
- If G has a stable fixed point at $\theta = 0$, and an unstable fixed point for some $0 < \theta_* < 1$, then for $\theta_0 > \theta_*$, spreading takes off.
- Tricky point: G depends on ϕ_0, so as we change ϕ_0, we also change G.



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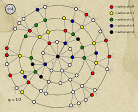

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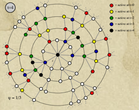

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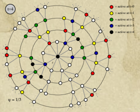

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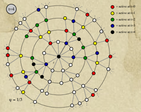
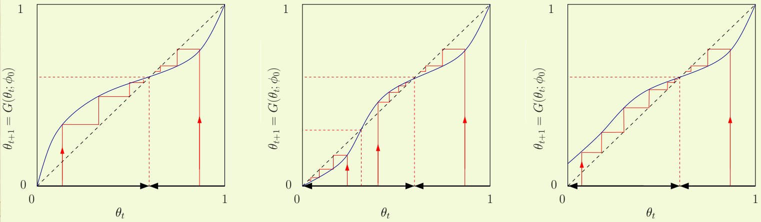


General fixed point story:



- Given $\theta_0 (= \phi_0)$, θ_∞ will be the nearest stable fixed point, either above or below.
- n.b., adjacent fixed points must have opposite stability types.
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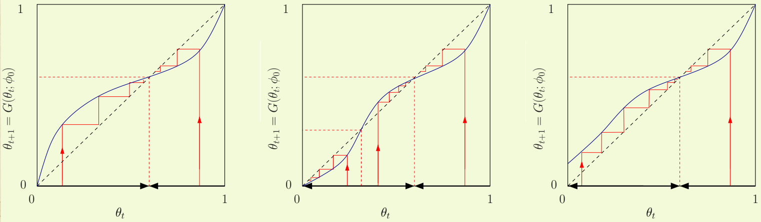

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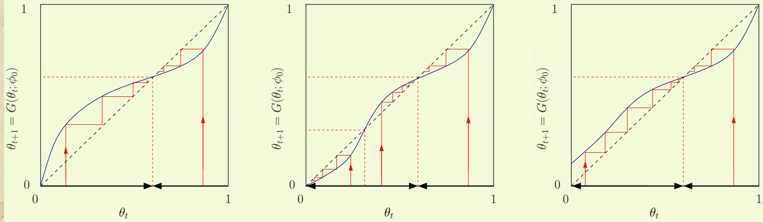

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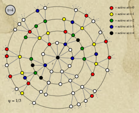

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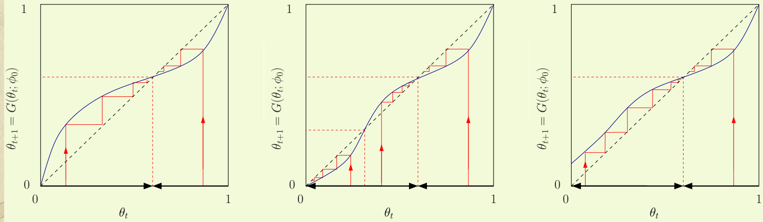

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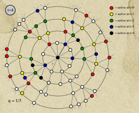
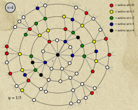
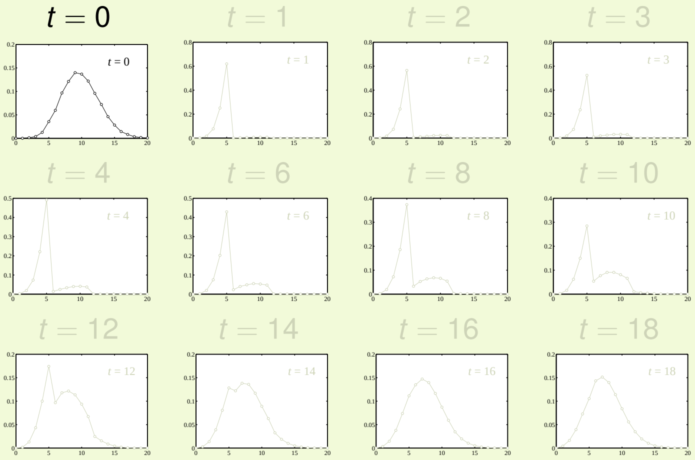


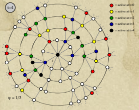
Outline



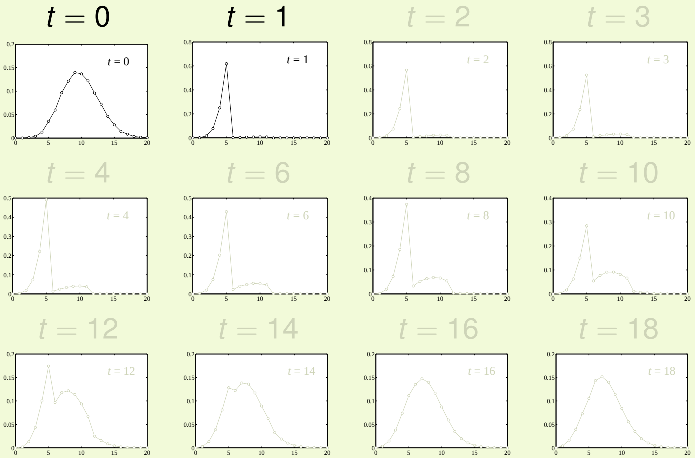
Early adopters—degree distributions



$P_{k,t}$ versus k



Early adopters—degree distributions



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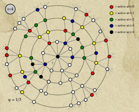

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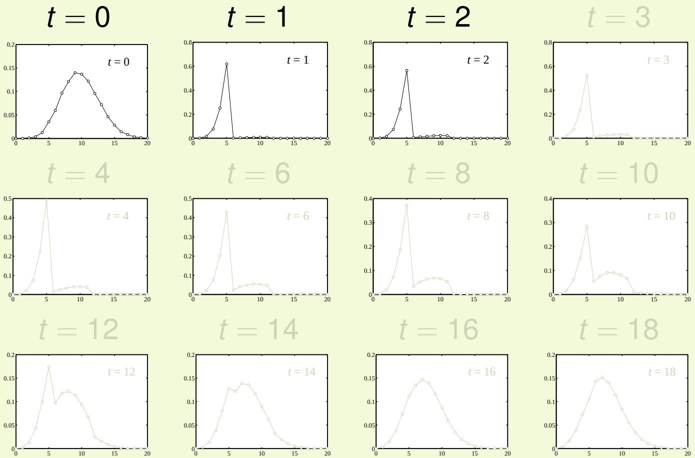

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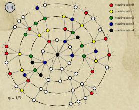

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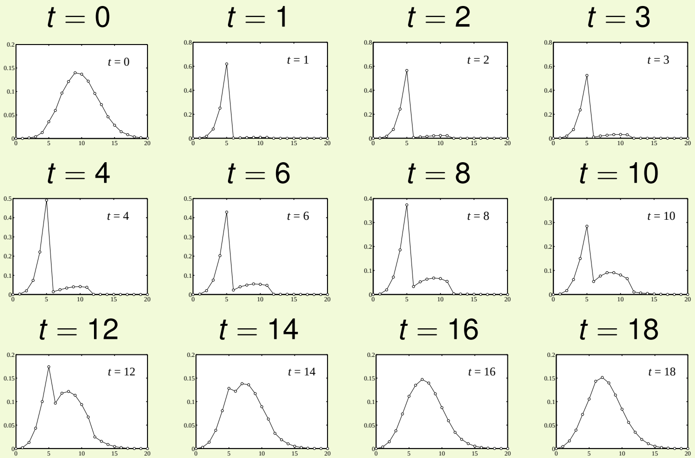

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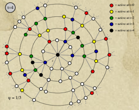
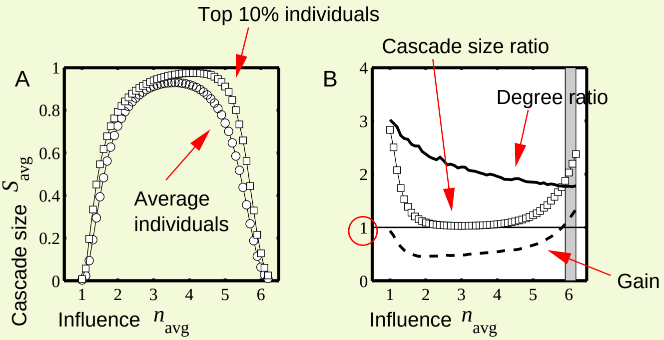


The multiplier effect:



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

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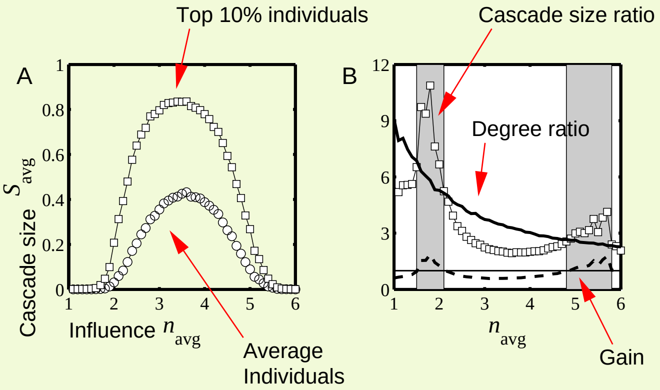
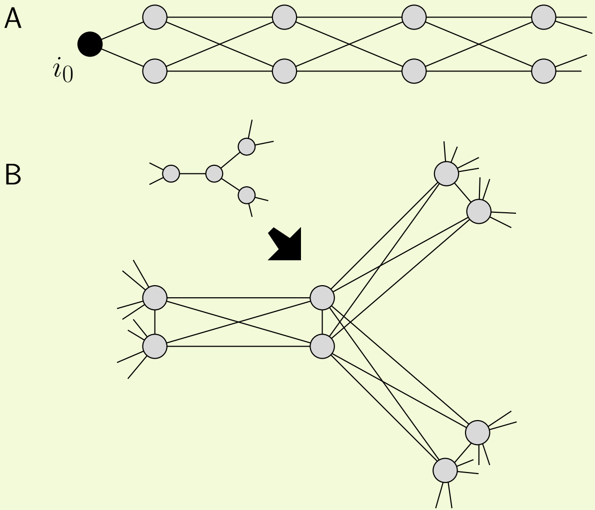
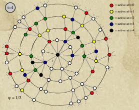


- Skewed influence distribution example.

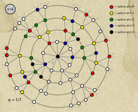
Special subnetworks can act as triggers



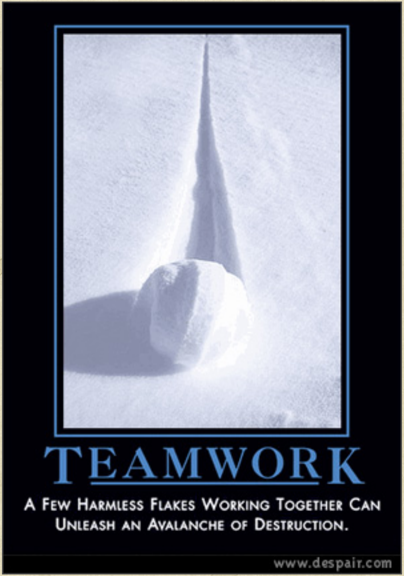
- $\phi = 1/3$ for all nodes



Outline

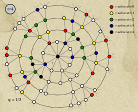


The power of groups...



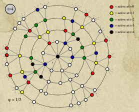
despair.com

"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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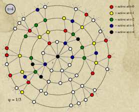

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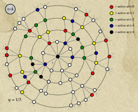

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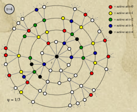
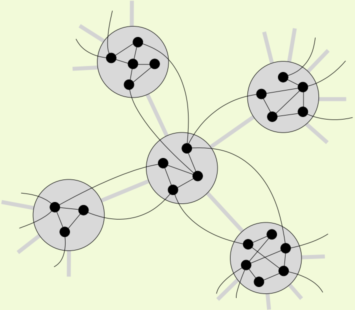
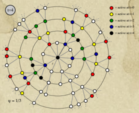


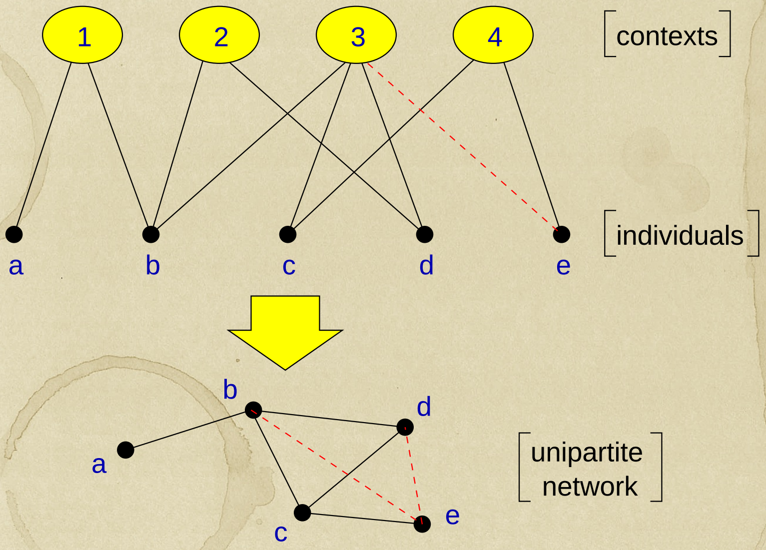
Group structure—Ramified random networks

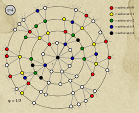


p = intergroup connection probability
q = intragroup connection probability.

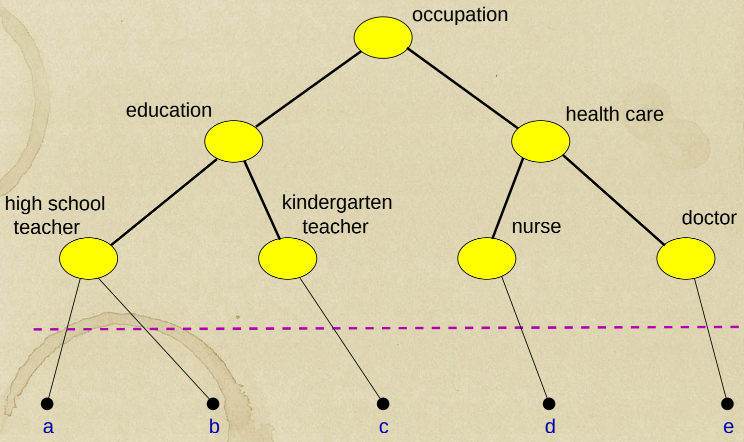


Bipartite networks

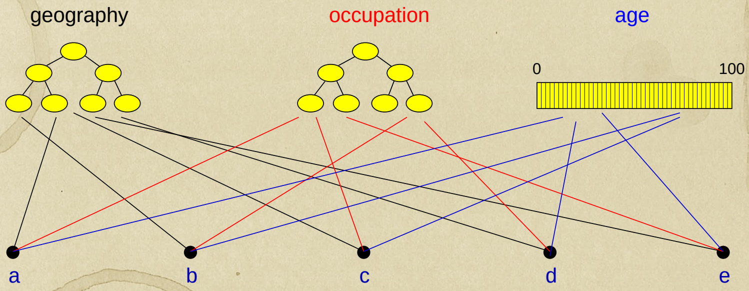




Context distance



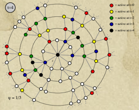
Generalized affiliation model



(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
- τ_2 = intragroup probability of friend-of-friend connection



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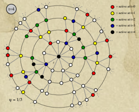

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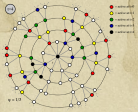
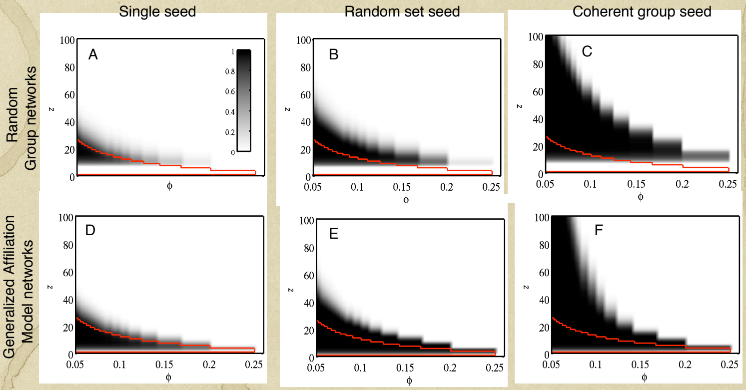
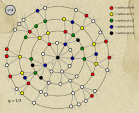
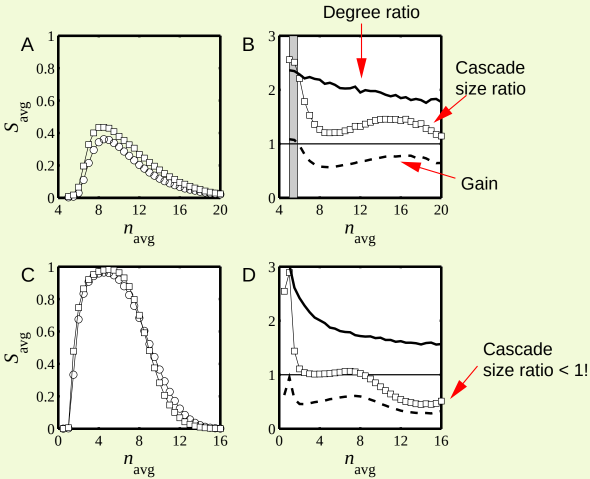


Cascade windows for group-based networks



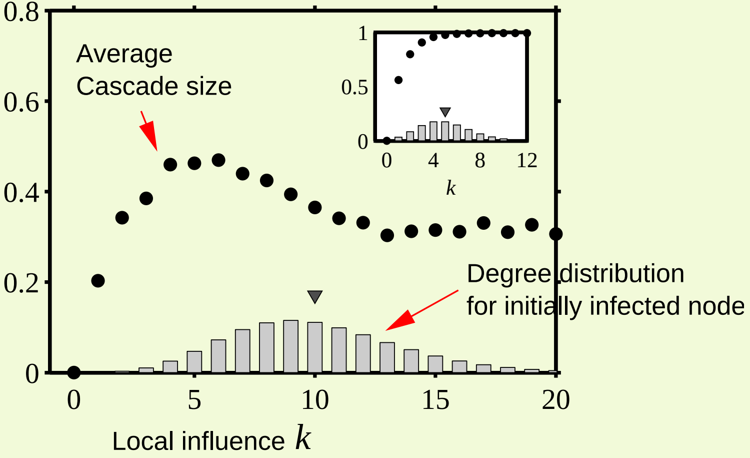


Multiplier effect for group-based networks:

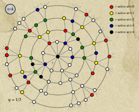


- Multiplier almost always below 1.

Assortativity in group-based networks



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



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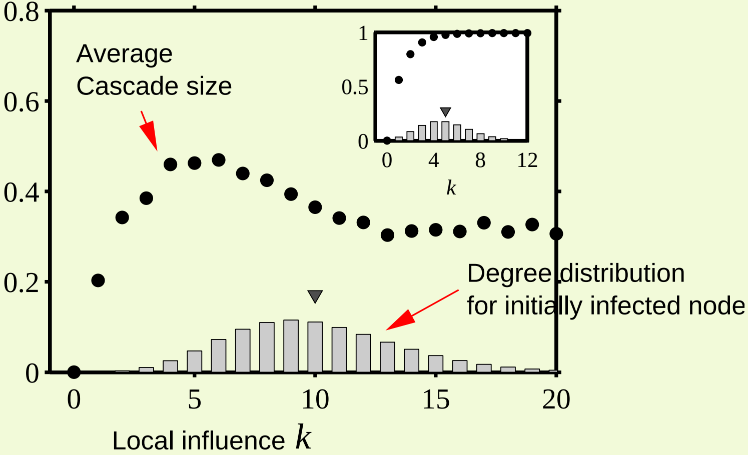

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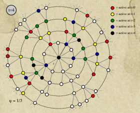
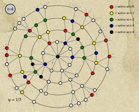


Social contagion

Summary

- ‘Influential vulnerables’ are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Groups may greatly facilitate spread.
- Seems that cascade condition is a global one.
- Most extreme/unexpected cascades occur in highly connected networks
- ‘Influentials’ are posterior constructs.
- Many potential influentials exist.



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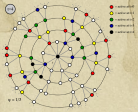

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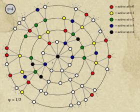

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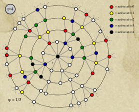

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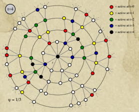

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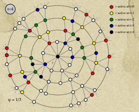

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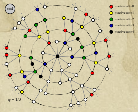

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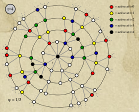
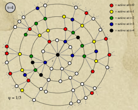


Social contagion

Implications

- 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).
- Entities can be novel or designed to combine with others, e.g. block another one.



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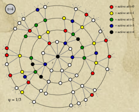

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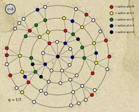

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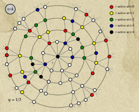

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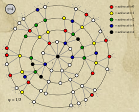

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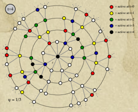

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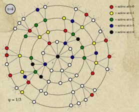

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Highly optimized tolerance: Robustness and design in complex systems.
Phys. Rev. Lett., 84(11):2529–2532, 2000. pdf (⊞)

[6] N. A. Christakis and J. H. Fowler.
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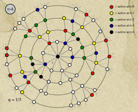
New England Journal of Medicine, 357:370–379, 2007. pdf (⊞)



References III

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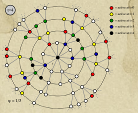

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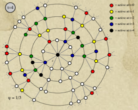

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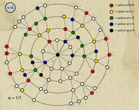

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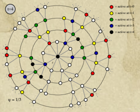

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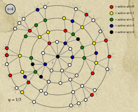

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