Contagion

Last updated: 2023/08/22, 11:48:25 EDT

Principles of Complex Systems, Vols. 1, 2, & 3D CSYS/MATH 6701, 6713, & a pretend number, 2023–2024| @pocsvox

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Computational Story Lab | Vermont Complex Systems Center
Santa Fe Institute | University of Vermont

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Outline

Contagion

Definition:

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself:
  the plague, a blight, the dreaded lurgi, ...

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Two main classes of contagion:

1. Infectious diseases:
   tuberculosis, HIV, ebola, SARS, influenza, ...
2. Social contagion:
   fashion, word usage, rumors, riots, religion, ...

Contagion models

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5. What if the seed is one or many nodes?

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Mathematical Epidemiology

The standard SIR model:

- Three states:
  - S = Susceptible
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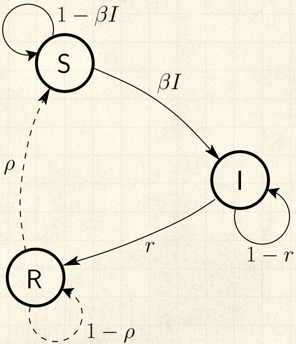
Discrete time example:



Transition Probabilities:

β for being infected given contact with infected
r for recovery
ρ for loss of immunity

Independent Interaction models

Reproduction Number R_0:

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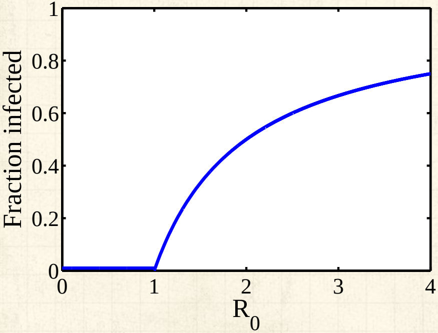

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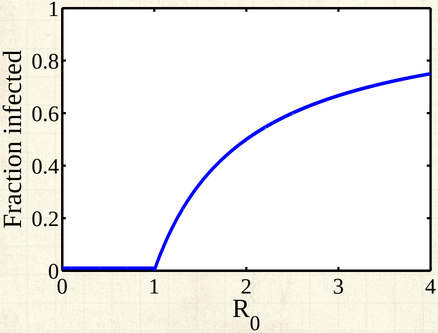

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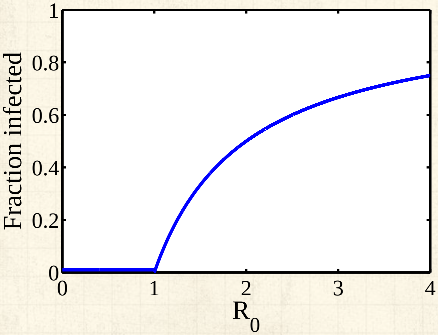

- Continuous phase transition.
- Fine idea from a simple model.

Outline

Disease spreading models

For 'novel' diseases:

1. Can we predict the size of an epidemic?
2. How important/useful is the reproduction number R_0?
3. What is the population size N?

R_0 and variation in epidemic sizes

R_0 approximately the same for all of the following:

- 1918-19 "Spanish Flu" $\sim$ 500,000 deaths in US
- 1957-58 "Asian Flu" $\sim$ 70,000 deaths in US
- 1968-69 "Hong Kong Flu" $\sim$ 34,000 deaths in US
- 2003 "SARS Epidemic" $\sim$ 800 deaths world-wide

Size distributions

Elsewhere, event size distributions are important:

- earthquakes (Gutenberg-Richter law)
- city sizes, forest fires, war fatalities
- wealth distributions
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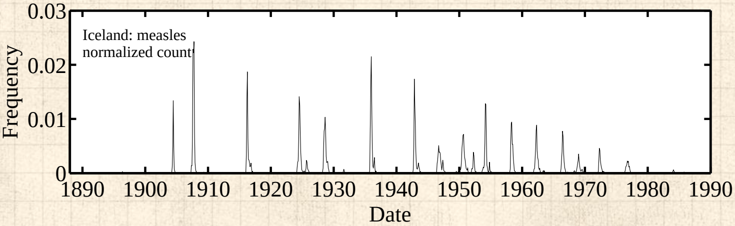
- 'popularity' (books, music, websites, ideas)
- What about Epidemics?

Power laws distributions are common but not obligatory...

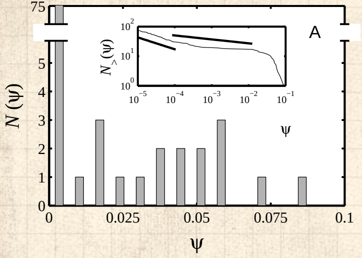
Feeling icky in Iceland

Caseload recorded monthly for range of diseases in Iceland, 1888-1990



Treat outbreaks separated in time as 'novel' diseases.

Measles



Insert plots: Complementary cumulative frequency distributions:

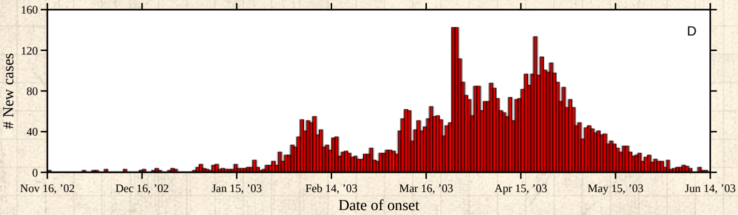
$$N_>(\Psi) \propto \Psi^{-\gamma+1}$$

Ψ = fractional epidemic size

Measured values of γ:

- measles: 1.40 (low Ψ) and 1.13 (high Ψ)
- Expect $2 \leq \gamma < 3$ (finite mean, infinite variance)
- Distribution is rather flat...

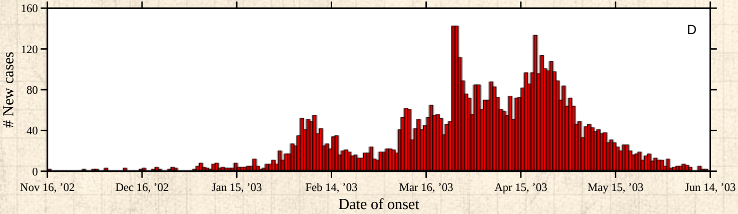
Resurgence—example of SARS



- Epidemic discovers new ‘pools’ of susceptibles: Resurgence.

The PoCSverse Contagion 16 of 83

Resurgence—example of SARS



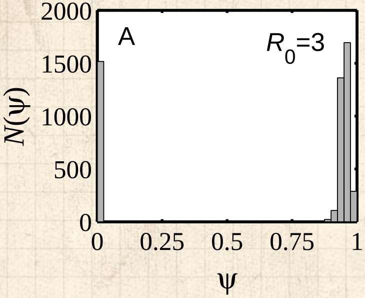
- Epidemic discovers new 'pools' of susceptibles: Resurgence.
- Importance of rare, stochastic events.

A challenge

So... can a simple model produce

1. broad epidemic distributions
   and
2. resurgence ?

Size distributions



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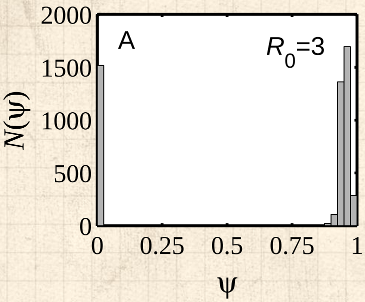

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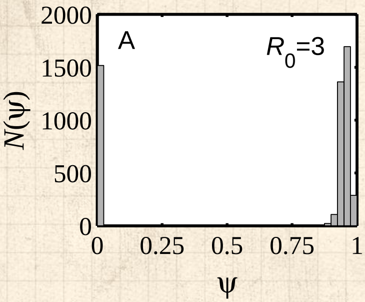

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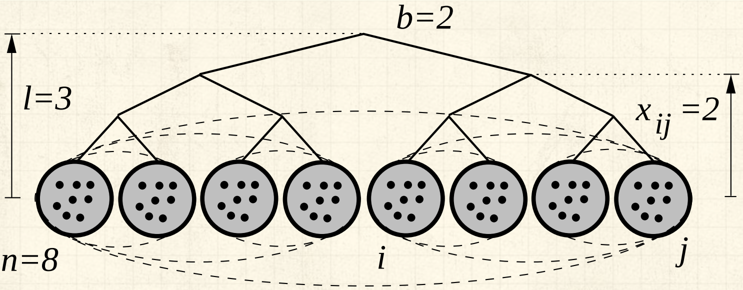
- Some exceptions:
  1. Forest fire models
  2. Sophisticated metapopulation models

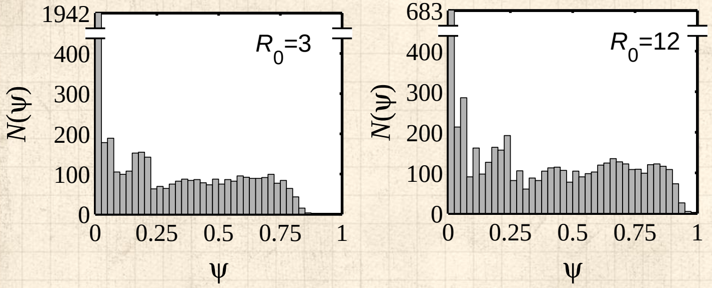
A toy agent-based model

Geography: allow people to move between contexts:



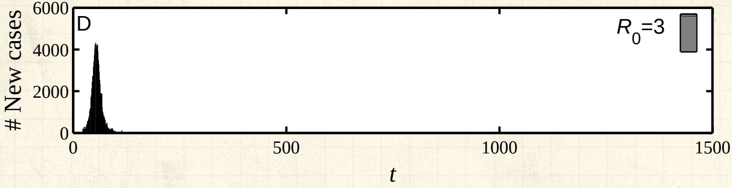
- P = probability of travel
- Movement distance: $\Pr(d) \propto \exp(-d/\xi)$
- ξ = typical travel distance

Example model output: size distributions

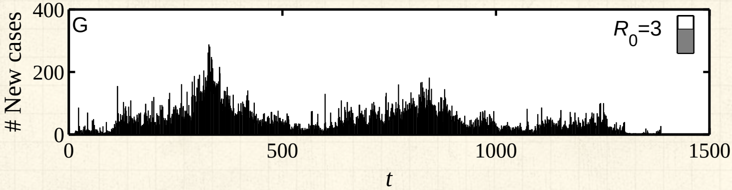


- Flat distributions are possible for certain ξ and P.
- Different R_0's may produce similar distributions
- Same epidemic sizes may arise from different R_0's

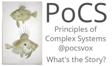
Standard model:



Standard model with transport: Resurgence



- Disease spread highly sensitive to population structure
- Rare events may matter enormously



Simple disease spreading models

Attempts to use beyond disease:

- Adoption of ideas/beliefs (Goffman & Newell, 1964)
- Spread of rumors (Daley & Kendall, 1965)
- Diffusion of innovations (Bass, 1969)
- Spread of fanatical behavior (Castillo-Chávez & Song, 2003)

Social Contagion

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Examples abound:

- being polite/rude
- strikes
- innovation
- residential segregation
- ipods
- obesity
- Harry Potter
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- religious beliefs
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SIR and SIRS contagion possible

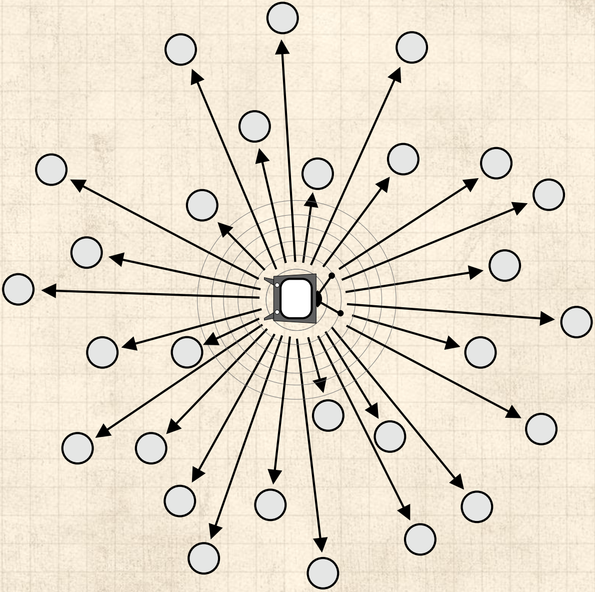
- Classes of behavior versus specific behavior: dieting

Social Contagion

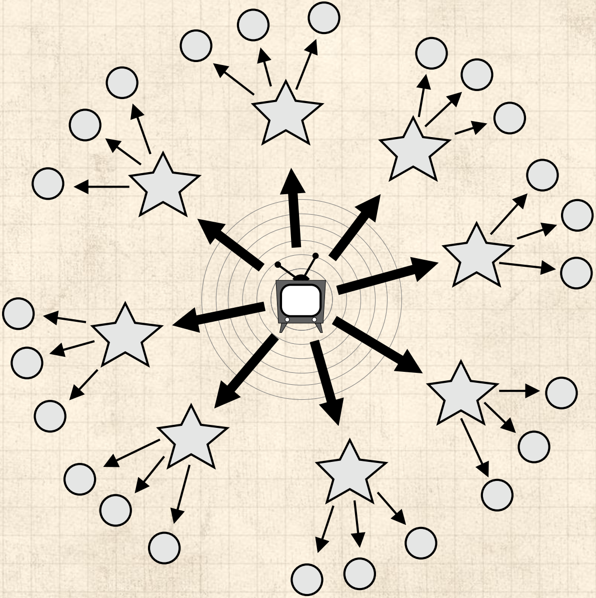
Two focuses for us:

- Widespread media influence
- Word-of-mouth influence

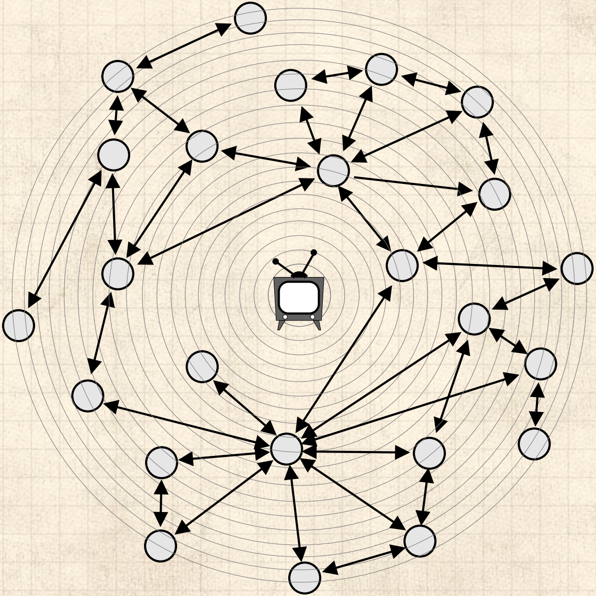
The hypodermic model of influence:



The two step model of influence:



The general model of influence:



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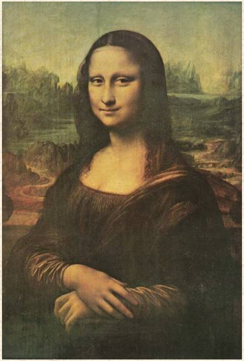
- System/group properties harder to understand
- Always good to examine what is said before and after the fact...

The Mona Lisa:



- "Becoming Mona Lisa: The Making of a Global Icon"—David Sassoon

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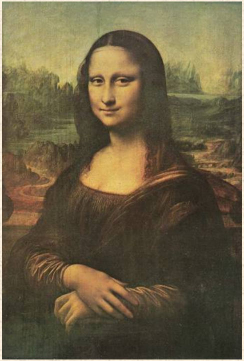

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The completely unpredicted fall of Eastern Europe:

Timur Kuran: “Now Out of Never: The Element of Surprise in the East European Revolution of 1989”

Social Contagion

Some important models:

- Tipping models—Schelling (1971)
  - Simulation on checker boards
  - Idea of thresholds

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- Tipping models—Schelling (1971)
  - Simulation on checker boards
  - Idea of thresholds
- Threshold models—Granovetter (1978)
- Herding models—Bikhchandani, Hirschleifer, Welch (1992)
  - Social learning theory, Informational cascades,...

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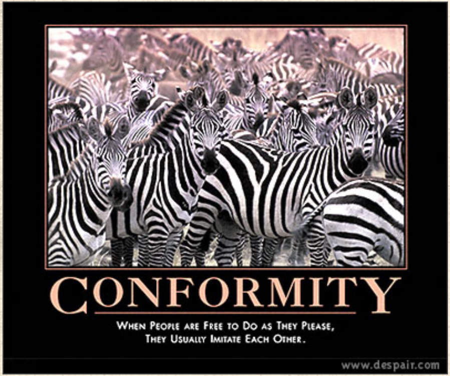
- Response can be probabilistic or deterministic.
- Individual thresholds vary.

Social Contagion

Some possible origins of thresholds:

- Desire to coordinate, to conform.
- Lack of information: impute the worth of a good or behavior based on degree of adoption (social proof)
- Economics: Network effects or network externalities
  - Telephones, Facebook, operating systems, ...

Imitation



despair.com

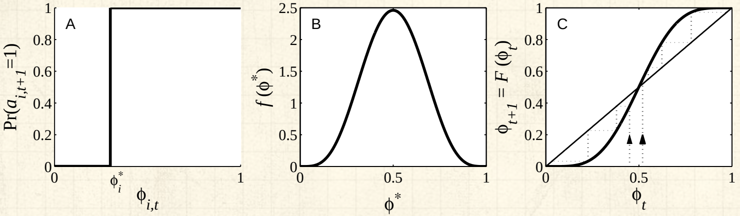
"When people are free to do as they please, they usually imitate each other."

—Eric Hoffer
"The Passionate State of Mind" [11]

Outline

Granovetter's threshold model:

Action based on perceived behavior of others:

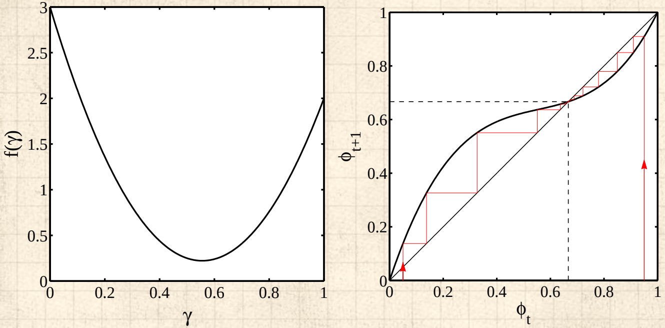


- Two states: S and I.
- ϕ = fraction of contacts 'on' (e.g., rioting)
-

$$\phi_{t+1} = \int_0^{\phi_t} f(\gamma)\mathrm{d}\gamma = F(\gamma)\big|_0^{\phi_t} = F(\phi_t)$$

- This is a Critical Mass model

Social Sciences: Threshold models



- Example of single stable state model

Social Sciences—Threshold models

Implications for collective action theory:

1. Collective uniformity $\not\Rightarrow$ individual uniformity

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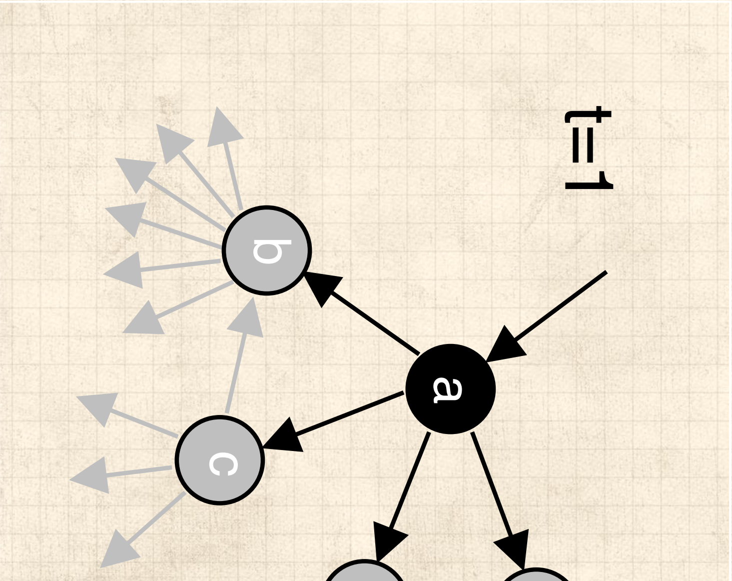
2. Small individual changes $\Rightarrow$ large global changes

Outline

Threshold model on a network



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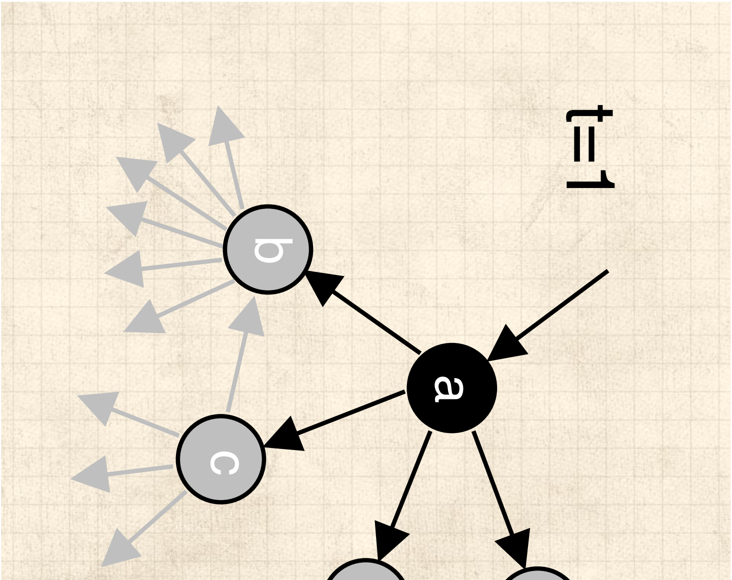

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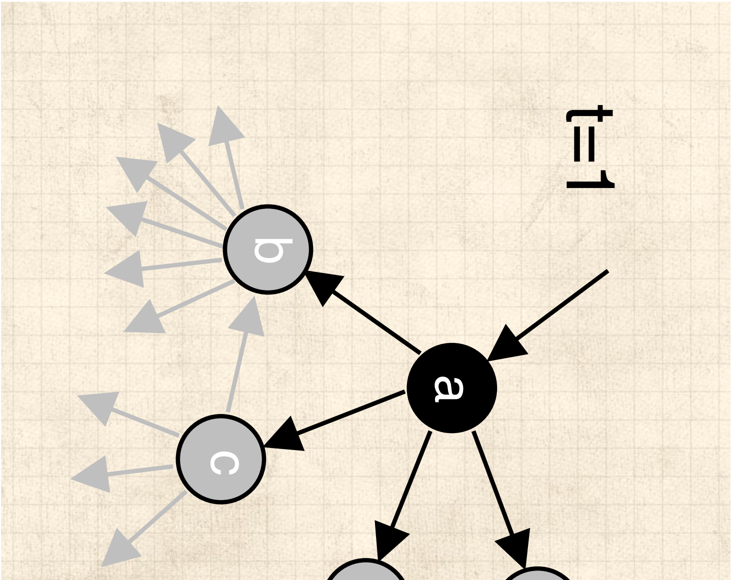

Snowballing

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

The most gullible

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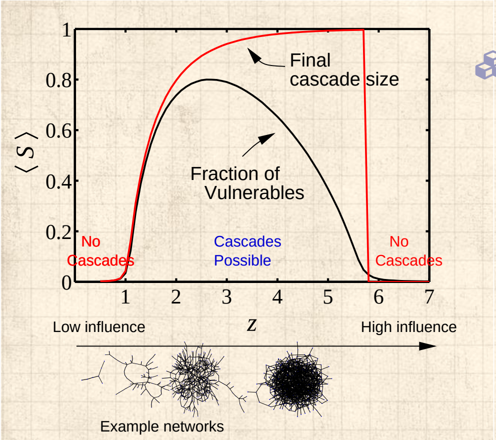
- Network story: 1 node $\rightarrow$ critical mass $\rightarrow$ everyone.

Cascades on random networks



(n.b.: $z \equiv \langle k \rangle \equiv \bar{k}$)

- Cascades occur only if size of max vulnerable cluster > 0.

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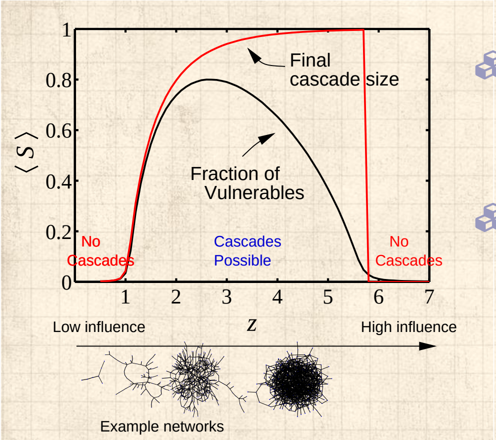

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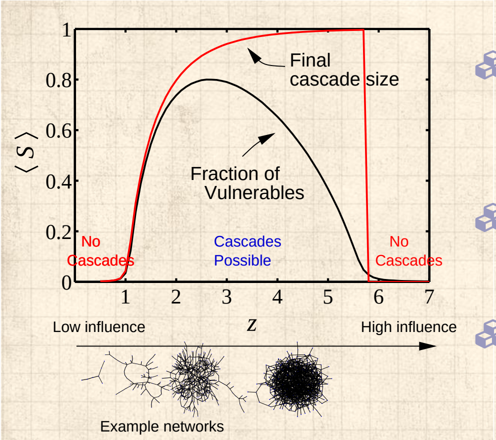

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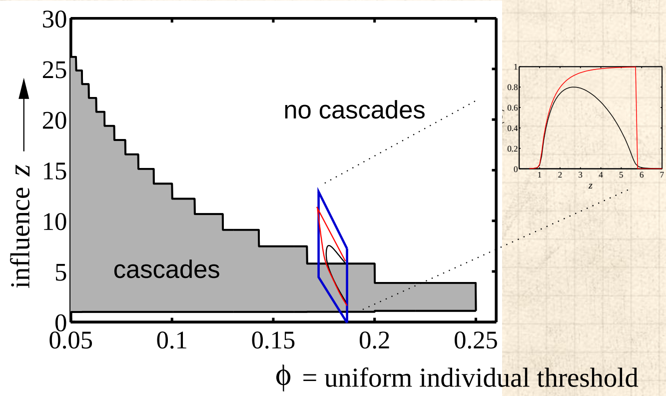
- System may be 'robust-yet-fragile'.
- 'Ignorance' facilitates spreading.

Cascade window for random networks



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

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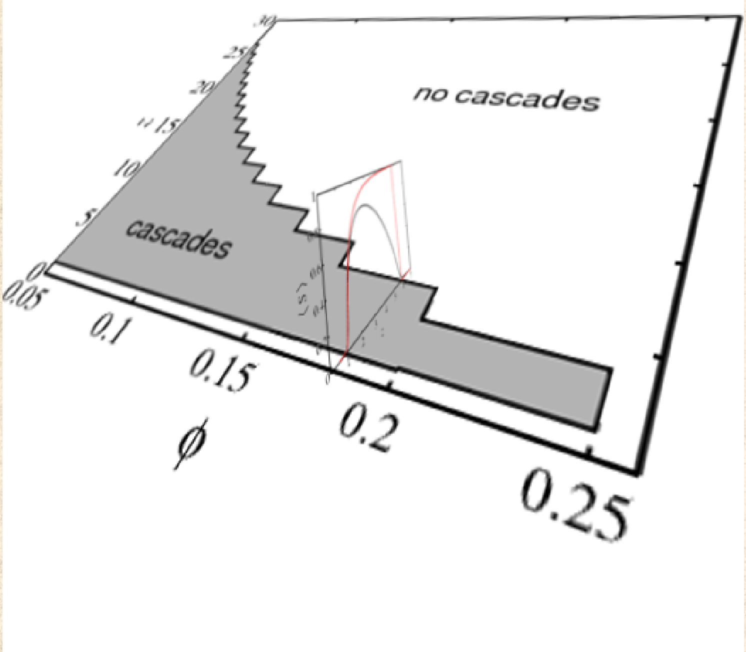

Analytic work

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- Cascade condition: [22]

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where β_k = probability a degree k node is vulnerable.

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- Spreading takes off: expansion

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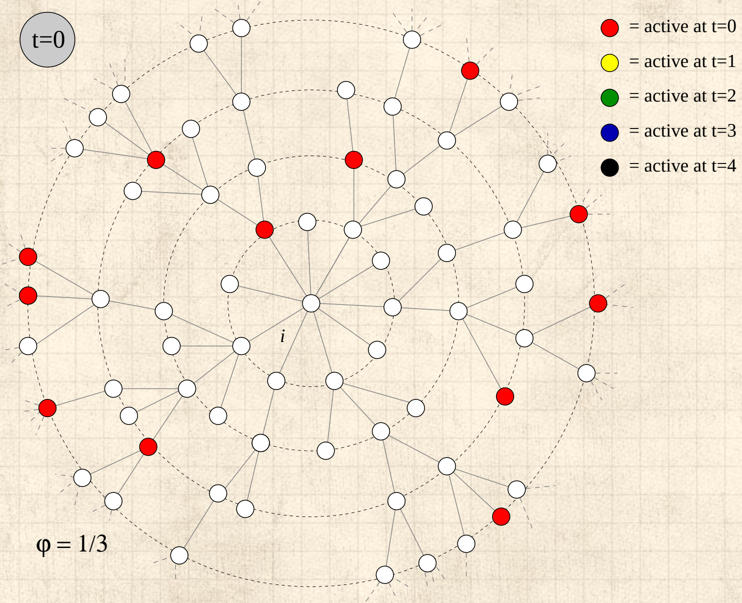
- Threshold model completely solved (by 2008):
- Cascade condition: [22]

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

where β_k = probability a degree k node is vulnerable.

- Final size of spread figured out by Gleeson and Calahane [9, 8].
- Solution involves finding fixed points of an iterative map of the interval.
- Spreading takes off: expansion
- Spreading reaches a particular node: contraction

Expected size of spread



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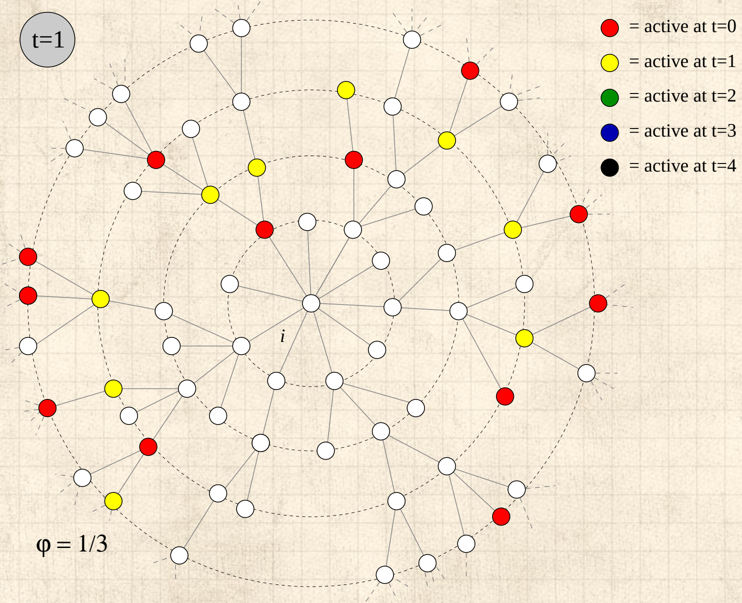

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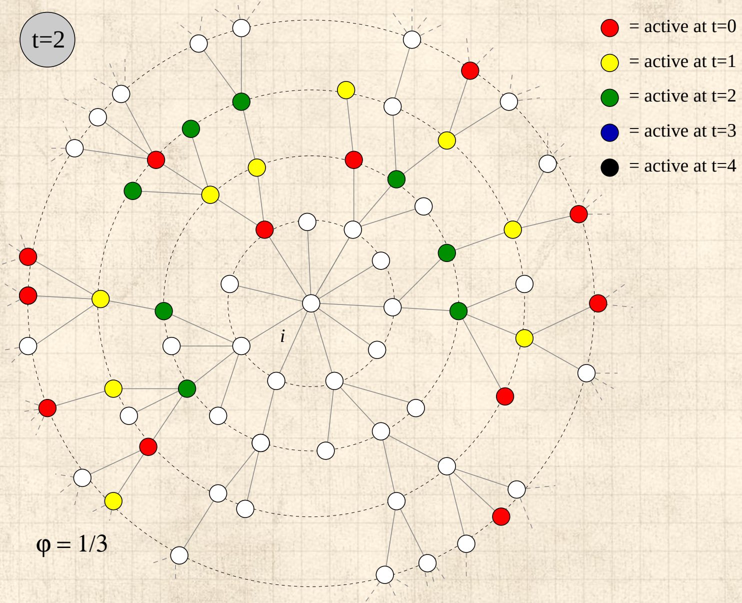

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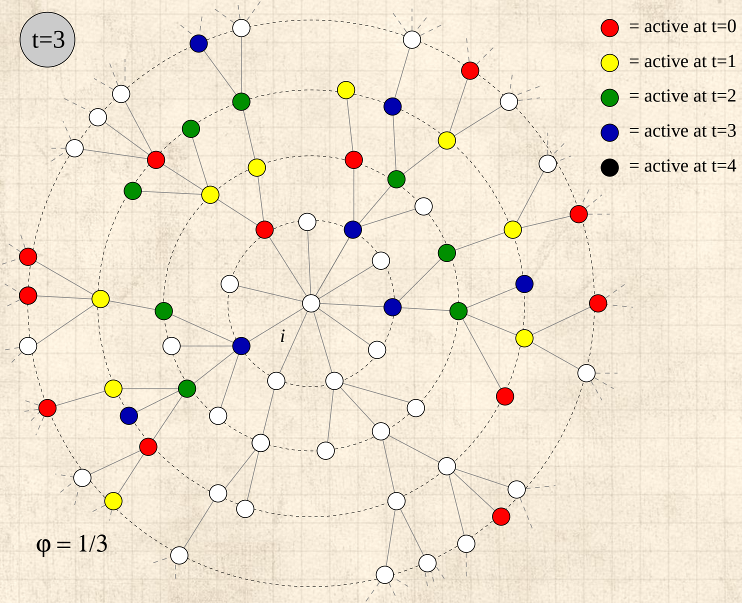

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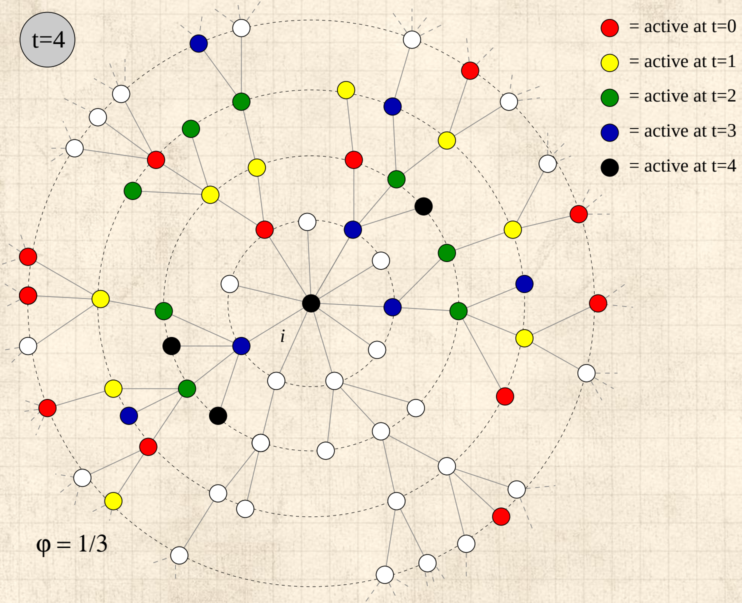
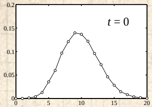


Early adopters—degree distributions

$t = 0$



$P_{k,t}$ versus k

Early adopters—degree distributions

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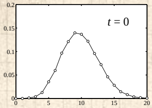
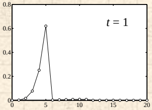


$t = 1$



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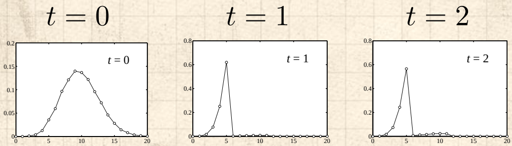
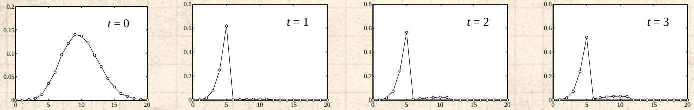


$P_{k,t}$ versus k

Early adopters—degree distributions

$t = 0$ $t = 1$ $t = 2$ $t = 3$



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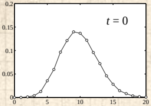

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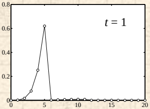
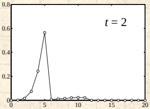
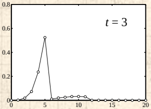


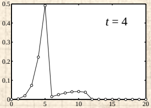
$t = 2$



$t = 3$

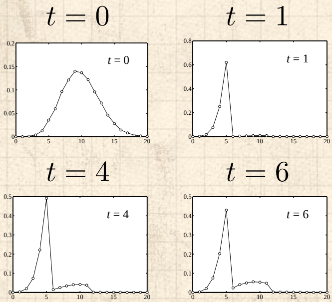


$t = 4$



$P_{k,t}$ versus k

Early adopters—degree distributions



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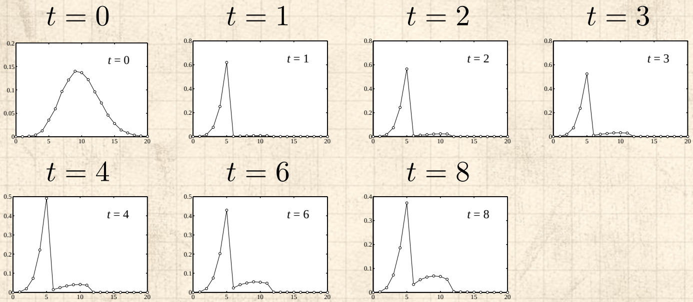

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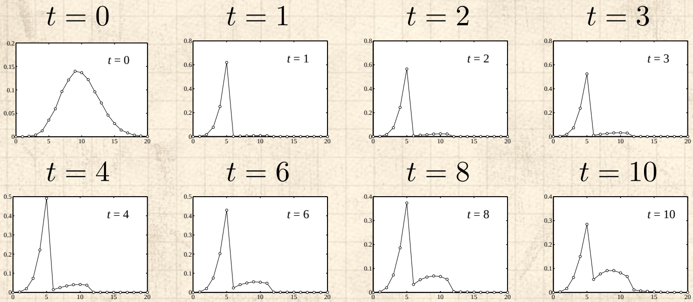
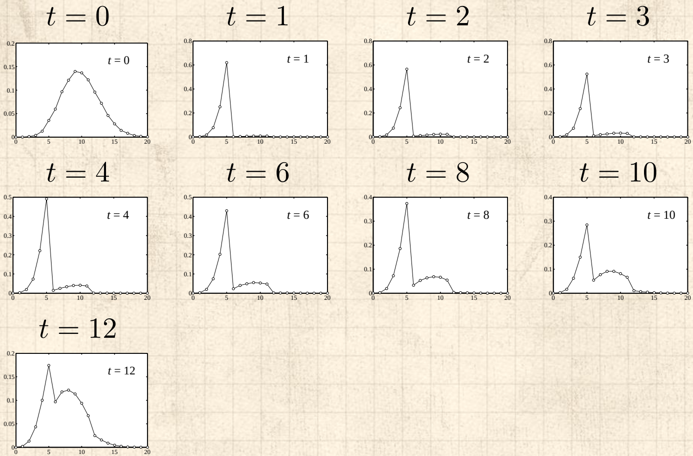
Early adopters—degree distributions



$P_{k,t}$ versus k

Early adopters—degree distributions



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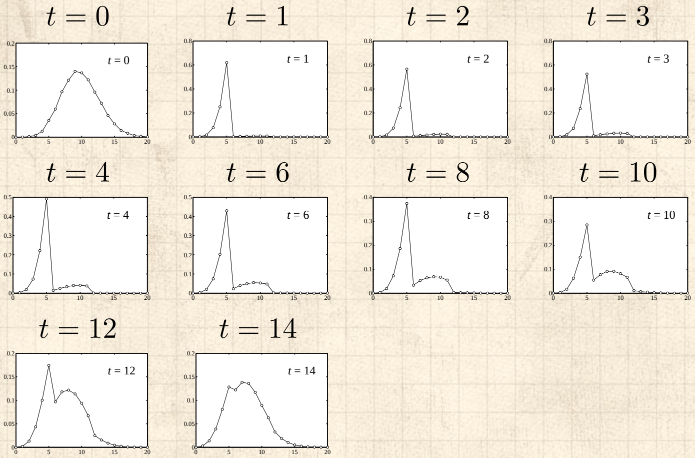
Early adopters—degree distributions



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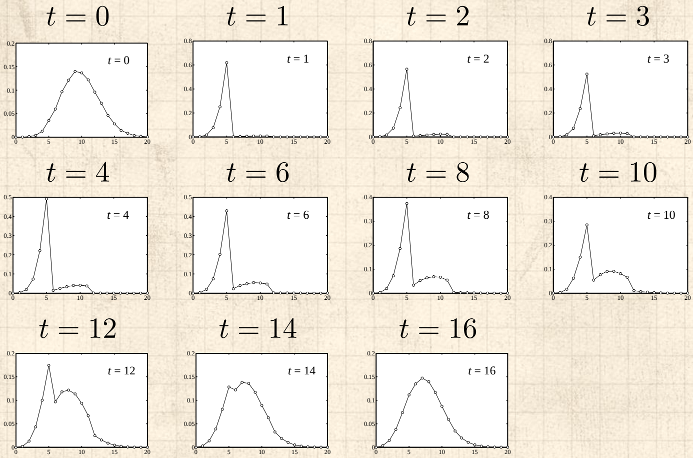

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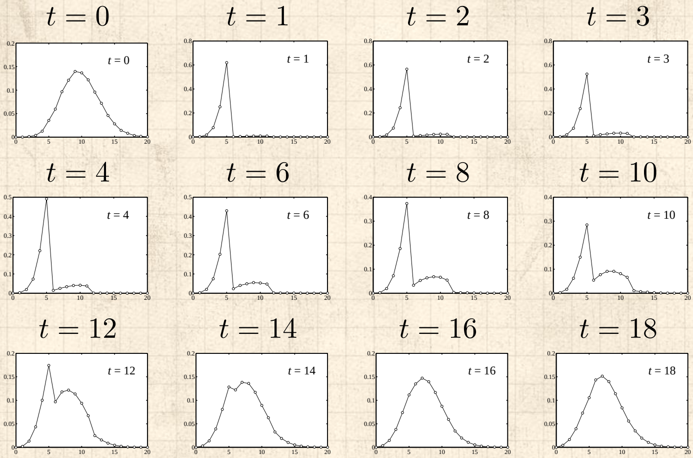


$P_{k,t}$ versus k

Outline

Introduction

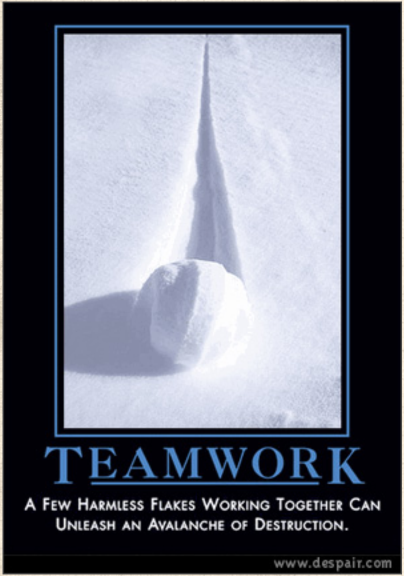
Simple Disease Spreading Models
- Background
- Prediction

Social Contagion Models
- Granovetter's model
- Network version
- Groups
- Summary

Winning: it's not for everyone
- Superstars
- Musiclab

References

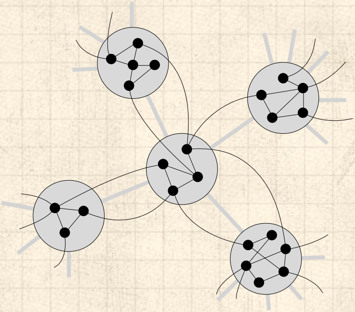
The power of groups...



despair.com

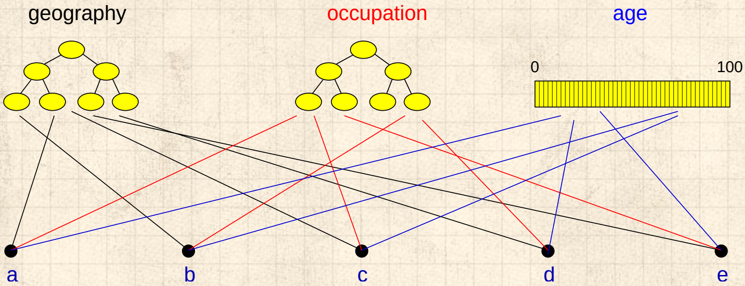
"A few harmless flakes working together can unleash an avalanche of destruction."

Group structure—Ramified random networks



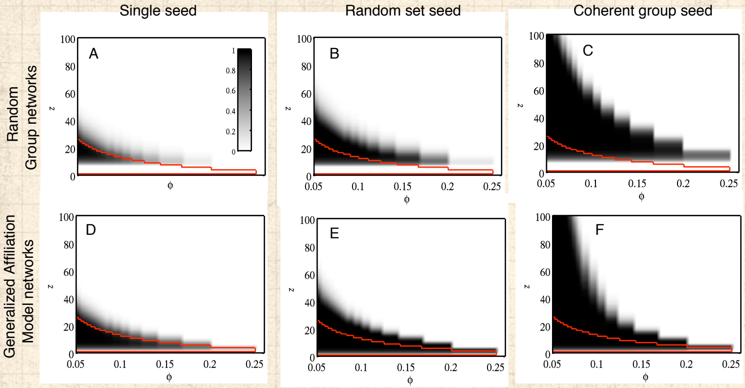
p = intergroup connection probability
q = intragroup connection probability.

Generalized affiliation model

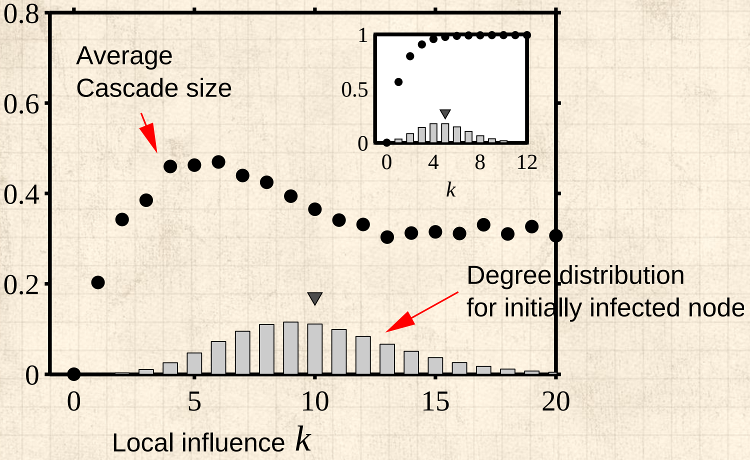


(Blau & Schwartz, Simmel, Breiger)

Cascade windows for group-based networks



Assortativity in group-based networks



- The most connected nodes aren't always the most 'influential.'

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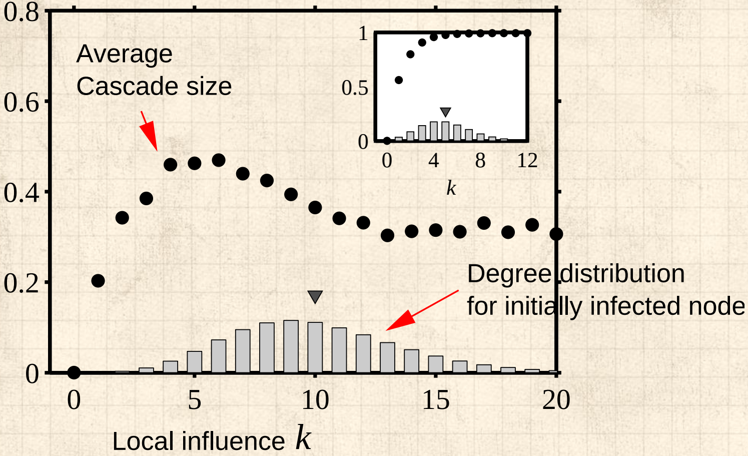

- The most connected nodes aren't always the most 'influential.'
- Degree assortativity is the reason.

Outline

Social contagion

Summary:

- 'Influential vulnerables' are key to spread.

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- 'Influentials' are posterior constructs.

PoCS
Principles of Complex Systems
@pocsvox
What's the Story?

Social contagion

Implications:

- Focus on the influential vulnerables.

Social contagion

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  (Idea of opinion leaders has spread well...)

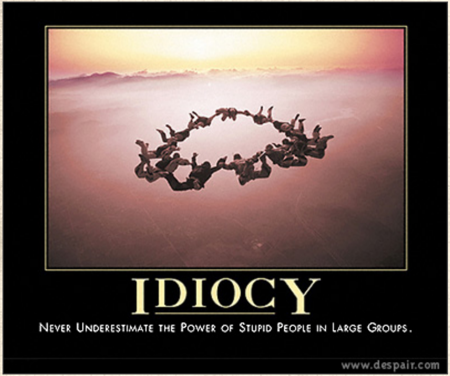
Social Contagion

Messing with social connections:

- Ads based on message content (e.g., Google and email)
- Buzz media
- Facebook's advertising (Beacon)

Arguably not always a good idea...

The collective...



despair.com

"Never Underestimate the Power of Stupid People in Large Groups."

Outline

Where do superstars come from?

Rosen (1981): "The Economics of Superstars"

Examples:

- Full-time Comedians (≈ 200)
- Soloists in Classical Music
- Economic Textbooks (the usual myopic example)

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- Highly skewed distributions again...

Superstars

Rosen's theory:

- Individual quality q maps to reward $R(q)$

Superstars

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     A very good surgeon is worth many mediocre ones
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     Media spreads & technology reduces cost of reproduction of books, songs, etc.

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- Two reasons:
  1. Imperfect substitution:
     A very good surgeon is worth many mediocre ones
  2. Technology:
     Media spreads & technology reduces cost of reproduction of books, songs, etc.
- No social element—success follows 'inherent quality'

Superstars

Adler (1985): "Stardom and Talent"

- Assumes extreme case of equal 'inherent quality'

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Superstars

Adler (1985): "Stardom and Talent"

- Assumes extreme case of equal 'inherent quality'
- Argues desire for coordination in knowledge and culture leads to differential success
- Success is then purely a social construction

Dominance hierarchies

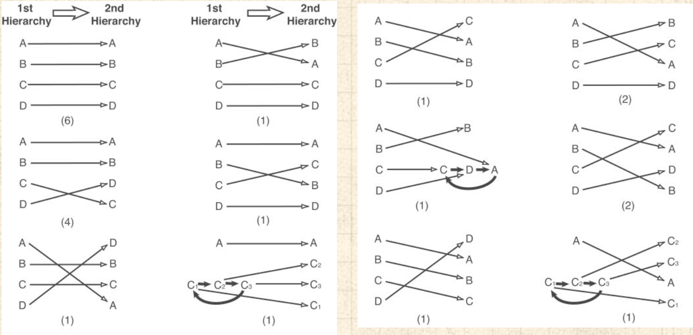
Chase et al. (2002): "Individual differences versus social dynamics in the formation of animal dominance hierarchies"

The aggressive female Metriaclima zebra:

Pecking orders for fish...

Dominance hierarchies

- Fish forget—changing of dominance hierarchies:



- 22 observations: about 3/4 of the time, hierarchy changed

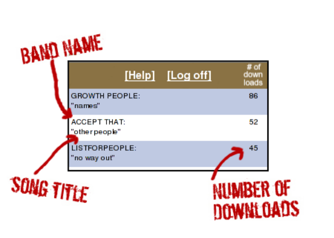
Outline

Music Lab Experiment

48 songs
30,000 participants

multiple 'worlds'
Inter-world variability

Music Lab Experiment



48 songs
30,000 participants

multiple 'worlds'
Inter-world variability

- How probable is the world?
- Can we estimate variability?
- Superstars dominate but are unpredictable. Why?

Music Lab Experiment

Music Lab – Song Selection - Mozilla Firefox

File Edit View Go Bookmarks Tools Help

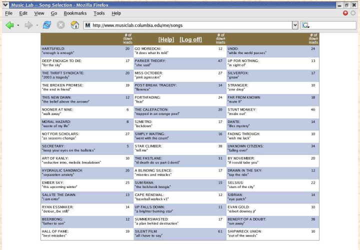
http://www.musiclab.columbia.edu/me/songs

	# of downloads	[Help] [Log off]	# of downloads		# of downloads
HARTSFIELD: "enough is enough"	20	GO MOREDCAI: "it does what its told"	12	UNDO: "while the world passes"	24
DEEP ENOUGH TO DIE: "for the sky"	17	PARKER THEORY: "she said"	47	UP FOR NOTHING: "in sight of"	13
THE THRIFT SYNDICATE: "2003 a tragedy"	20	MISS OCTOBER: "pink agression"	27	SILVERFOX: "gnaw"	17
THE BROKEN PROMISE: "the end in friend"	19	POST BREAK TRAGEDY: "florence"	14	STRANGER: "one drop"	10
THIS NEW DAWN: "the belief above the answer"	12	FORTHFADING: "fear"	24	FAR FROM KNOWN: "route 9"	18
NOONER AT NINE: "walk away"	6	THE CALEFACTION: "trapped in an orange peel"	20	STUNT MONKEY: "inside out"	46
MORAL HAZARD: "waste of my life"	8	52METRO: "lockdown"	17	DANTE: "lifes mystery"	14
NOT FOR SCHOLARS: "as seasons change"	27	SIMPLY WAITING: "went with the count"	16	FADING THROUGH: "wish me luck"	10
SECRETARY: "keep your eyes on the ballistics"	5	STAR CLIMBER: "tell me"	38	UNKNOWN CITIZENS: "falling over"	34
ART OF KANLY: "seductive intro, melodic breakdown"	10	THE FASTLANE: "til death do us part (i dont)"	31	BY NOVEMBER: "if i could take you"	20
HYDRAULIC SANDWICH: "separation anxiety"	20	A BLINDING SILENCE: "miseries and miracles"	17	DRAWN IN THE SKY: "tap the ride"	12
EMBER SKY: "this upcoming winter"	25	SUM RANA: "the bolshevik boogie"	15	SELSIUS: "stars of the city"	22
SALUTE THE DAWN: "i am error"	13	CAPE RENEWAL: "baseball warlock v1"	12	SIBRIAN: "eye patch"	14
RYAN ESSMAKER: "detour_(be still)"	14	UP FALLS DOWN: "a brighter burning star"	11	EVAN GOLD: "robert downey jr"	10
BEERBONG: "father to son"	12	SUMMERSWASTED: "a plan behind destruction"	17	BENEFIT OF A DOUBT: "run away"	38
HALL OF FAME: "best mistakes"	19	SILENT FILM: "all i have to say"	61	SHIPWRECK UNION: "out of the woods"	16

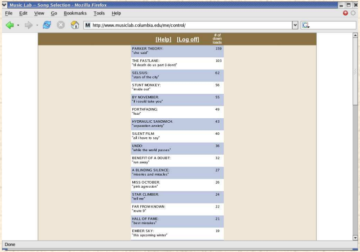
Salganik et al. (2006) "An experimental study of inequality and unpredictability in an artificial cultural market"

Music Lab Experiment

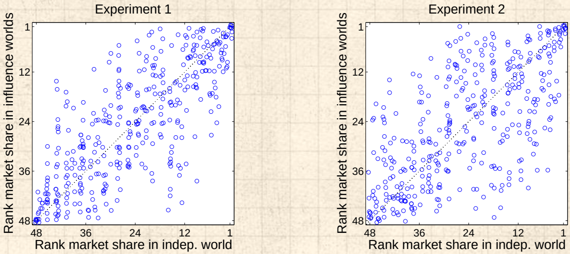
Experiment 1



Experiments 2–4

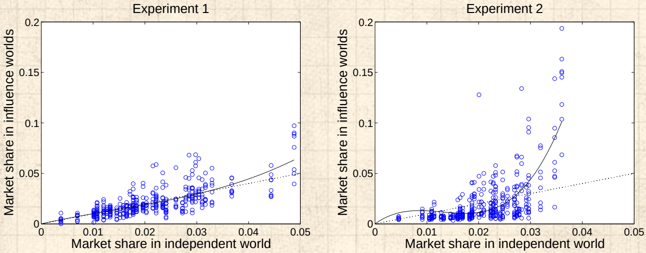


Music Lab Experiment



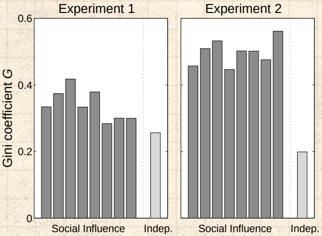
- Variability in final rank.

Music Lab Experiment



- Variability in final number of downloads.

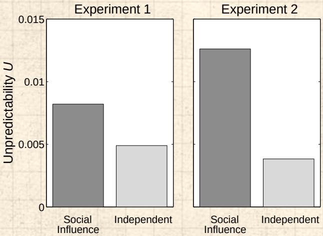
Music Lab Experiment



- Inequality as measured by Gini coefficient:

$$G = \frac{1}{(2N_{\mathrm{s}} - 1)} \sum_{i=1}^{N_{\mathrm{s}}} \sum_{j=1}^{N_{\mathrm{s}}} |m_i - m_j|$$

Music Lab Experiment



- Unpredictability

$$U = \frac{1}{N_{\mathsf{s}}\binom{N_{\mathsf{w}}}{2}} \sum_{i=1}^{N_{\mathsf{s}}} \sum_{j=1}^{N_{\mathsf{w}}} \sum_{k=j+1}^{N_{\mathsf{w}}} |m_{i,j} - m_{i,k}|$$

Music Lab Experiment

Sensible result:

- Stronger social signal leads to greater following and greater inequality.

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Very peculiar observation:

- The most unequal distributions would suggest the greatest variation in underlying 'quality.'

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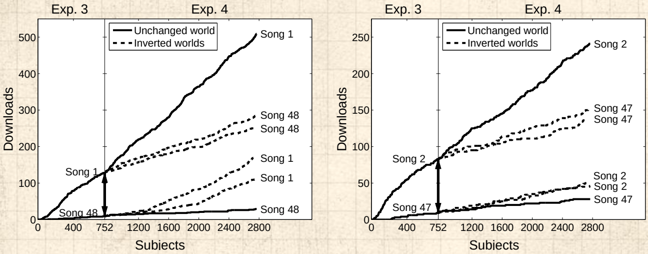
Peculiar result:

- Stronger social signal leads to greater unpredictability.

Very peculiar observation:

- The most unequal distributions would suggest the greatest variation in underlying 'quality.'
- But success may be due to social construction through following...

Music Lab Experiment—Sneakiness



- Inversion of download count

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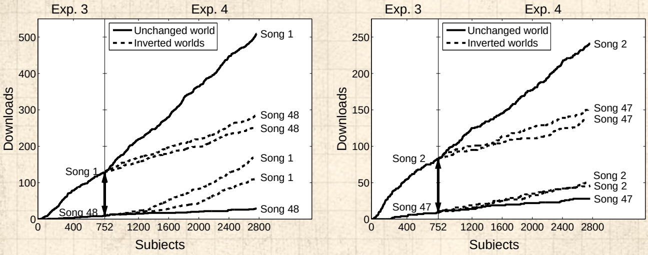

- Inversion of download count
- The 'pretend rich' get richer ...

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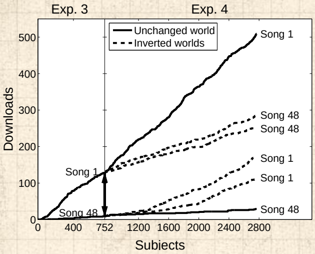

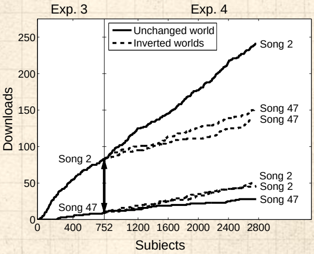

- Inversion of download count
- The 'pretend rich' get richer ...
- ... but at a slower rate

References I

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