Lecture Three

Stories of Complex Sociotechnical Systems: Measurement, Mechanisms, and Meaning
Lipari Summer School, Summer, 2012

Prof. Peter Dodds

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

Outline

Economics, Schmeconomics

Alan Greenspan (September 18, 2007):

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Jon Stewart:

"You just bummed the @*!# out of me."

wildbluffmedia.com

- From the Daily Show (⊞) (September 18, 2007)
- The full inteview is here (⊞).

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James K. Galbraith:

NYT But there are at least 15,000 professional economists in this country, and you're saying only two or three of them foresaw the mortgage crisis?

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From the New York Times, 11/02/2008 (⊞)

Collective Cooperation:

- Standard frame:

  Locally selfish behavior
  $\rightarrow$ collective cooperation.

- Different frame:

  Locally moral/fair behaviour
  $\rightarrow$ collective bad actions.

- So why do we study frame 1 instead of frame 2?
- Tragedy of the Commons is one example of frame 2.
- Better question:
  Who is it that studies frame 1 over frame 2. . . ?

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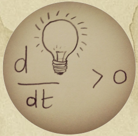

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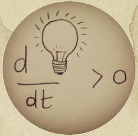

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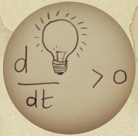

Homo Economicus

- ‘What makes people think like Economists? Evidence on Economic Cognition from the “Survey of Americans and Economists on the Economy” ’ [8] Bryan Caplan, Journal of Law and Economics, 2001

People behave like Homo economicus:

1. if they are well educated,
2. if they are male,
3. if their real income rose over the last 5 years,
4. if they expect their real income to rise over the next 5 years,
5. if they have a high degree of job security,
6. but not because of high income nor ideological conservatism.

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Wealth distribution in the United States:

Questions used in a recent study by Norton and Ariely: [29]

- What percentage of all wealth is owned by individuals grouped into quintiles?
- How do people believe wealth is distributed?
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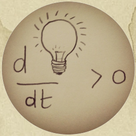

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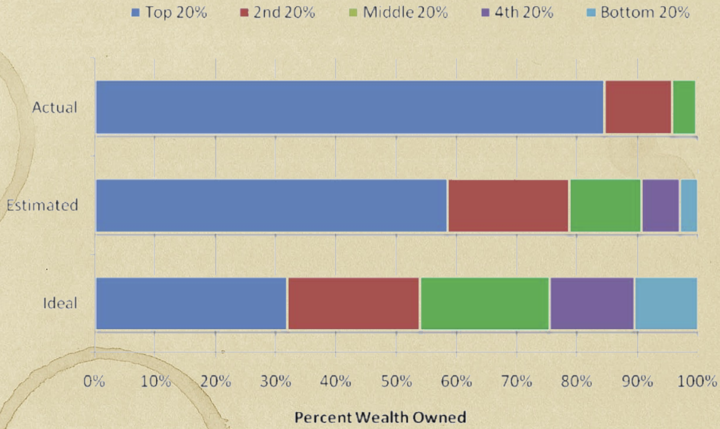

Fig. 2. The actual United States wealth distribution plotted against the estimated and ideal distributions across all respondents. Because of their small percentage share of total wealth, both the "4th 20%" value (0.2%) and the "Bottom 20%" value (0.1%) are not visible in the "Actual" distribution.

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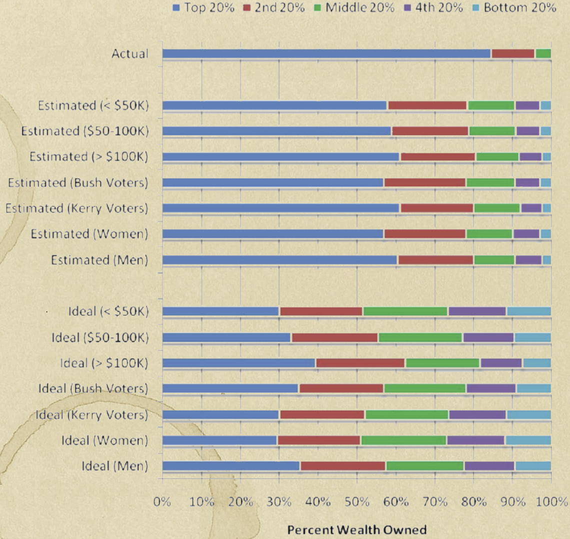

Fig. 3. The actual United States wealth distribution plotted against the estimated and ideal distributions of respondents of different income levels, political affiliations, and genders. Because of their small percentage share of total wealth, both the "4th 20%" value (0.2%) and the "Bottom 20%" value (0.1%) are not visible in the "Actual" distribution.

This is a Collateralized Debt Obligation:

Contagion

A confusion of contagions:

- Was Harry Potter some kind of virus?
- What about Vampires?
- Did Sudoku spread like a disease?
- Language? The alphabet? [17]
- Religion?
- Democracy...?

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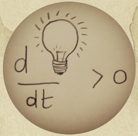

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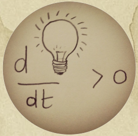

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- "The feeling was contagious."
- "The news spread like wildfire."
- "Freedom is the most contagious virus known to man."
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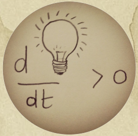

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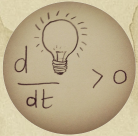

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The spread of fanaticism

Hoffer's acclaimed work: "The True Believer: Thoughts On The Nature Of Mass Movements" (1951) [20]

Quotes-aplenty:

- "We can be absolutely certain only about things we do not understand."
- "Mass movements can rise and spread without belief in a God, but never without belief in a devil."
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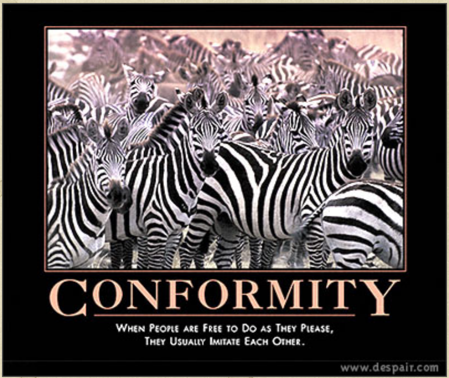
Imitation

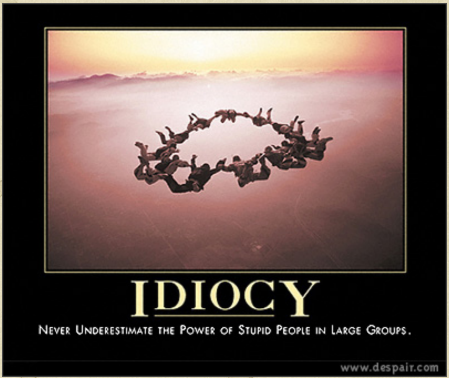


despair.com

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

—Eric Hoffer
"The Passionate State of Mind" [21]

The collective...



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

Contagion

Definitions

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself:
  the plague, a blight, the dreaded lurgi, ...
- from Latin: *con* = 'together with' + *tangere* 'to touch.'
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Interesting infections:

- Spreading of buildings in the US... (⊞)

- Viral get-out-the-vote video. (⊞)

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Contagions

Two main classes of contagion

1. Infectious diseases

2. Social contagion

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Two main classes of contagion

1. Infectious diseases:
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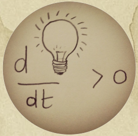
2. Social contagion:
   fashion, word usage, rumors, riots, religion, ...



Winning: it's not for everyone

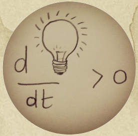
Where do superstars come from?

- Rosen (1981): "The Economics of Superstars"

Examples:

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

- Highly skewed distributions (again)...



Winning: it's not for everyone

Where do superstars come from?

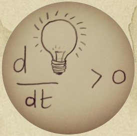
- Rosen (1981): "The Economics of Superstars"

Examples:

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

- Highly skewed distributions (again)...

Superstars



Rosen's theory:

- Individual quality q maps to reward $R(q)$
- $R(q)$ is 'convex' ($\mathrm{d}^2R/\mathrm{d}q^2 > 0$)
- Two reasons:
  1. Imperfect substitution:
  2. Technology:
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Adler (1985): "Stardom and Talent"

- Assumes extreme case of equal 'inherent quality'
- Argues desire for coordination in knowledge and culture leads to differential success
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Dominance hierarchies

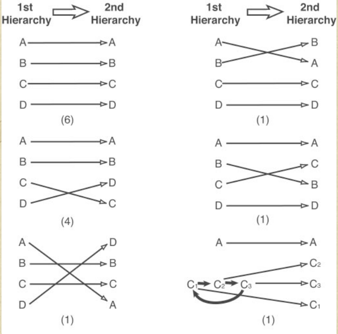
Chase et al. (2002): "Individual differences versus social dynamics in the formation of animal dominance hierarchies"[11]

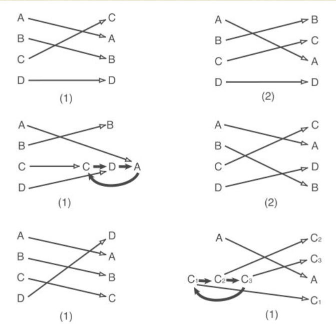
The aggressive female Metriaclima zebra (⊞):

Pecking orders for fish...

Dominance hierarchies

- Fish forget—changing of dominance hierarchies:

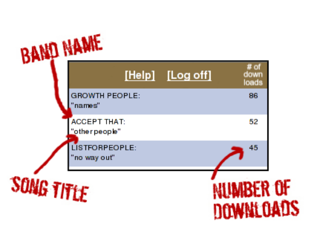




- 22 observations: about 3/4 of the time, hierarchy changed

Music Lab Experiment

48 songs
30,000 participants

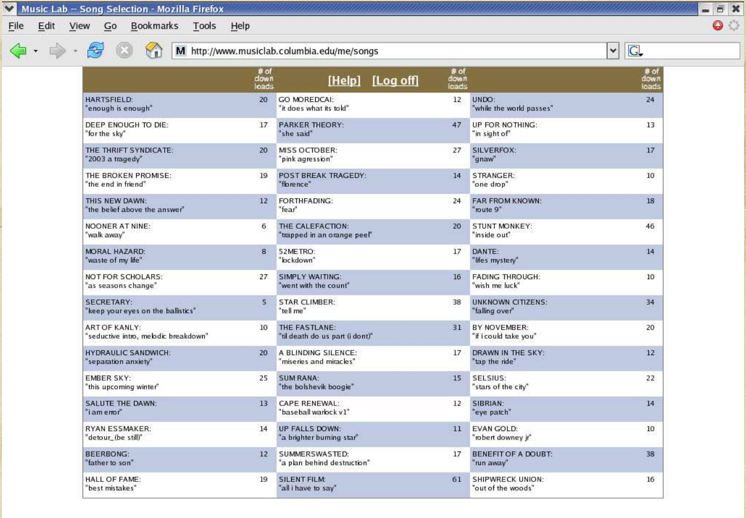


multiple 'worlds'
Inter-world variability

- How probable is a social state?
- Can we estimate variability?

Salganik et al. (2006) "An experimental study of inequality and unpredictability in an artificial cultural market" [33]

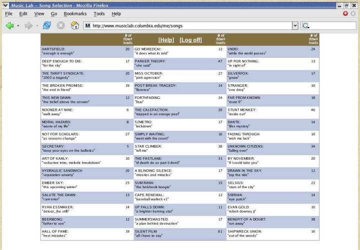
Music Lab Experiment



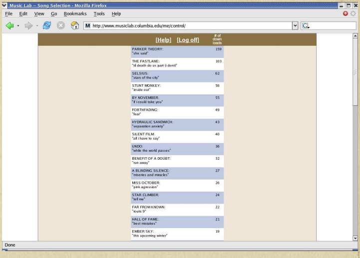
	# of downloads	[Help] [Log off]	# of downloads		# of downloads
HARTSFIELD: "enough is enough"	20	GO MOREDCAI: "it does what its told"	12	UNDO: "while the world passes"	24
DEEP ENOUGH TO DIE: "for the sky"	17	PARKER THEORY: "she said"	47	UP FOR NOTHING: "in sight of"	13
THE THRIFT SYNDICATE: "2003 a tragedy"	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

Music Lab Experiment

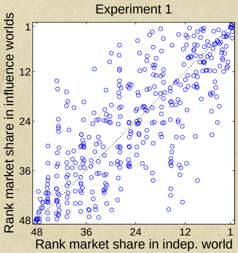
Experiment 1

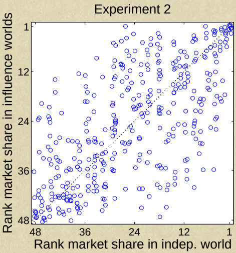


Experiments 2–4



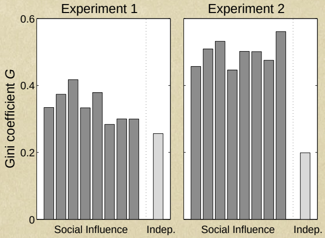
Music Lab Experiment





- Variability in final rank.

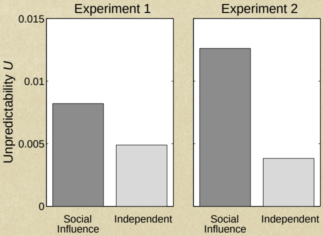
Music Lab Experiment



- Inequality as measured by Gini coefficient:

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

Music Lab Experiment



- Unpredictability

$$U = \frac{1}{N_s \binom{N_w}{2}} \sum_{i=1}^{N_s} \sum_{j=1}^{N_w} \sum_{k=j+1}^{N_w} \left| m_{i,j} - m_{i,k} \right|$$

Music Lab Experiment

Sensible result:

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

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.
- 'Payola' leads to poor system performance.

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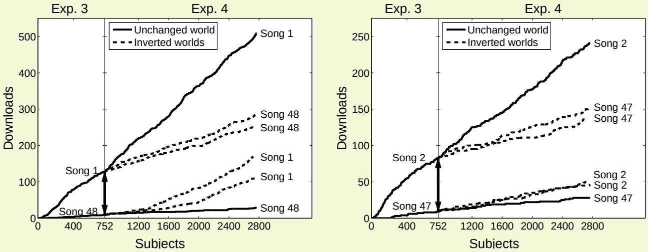
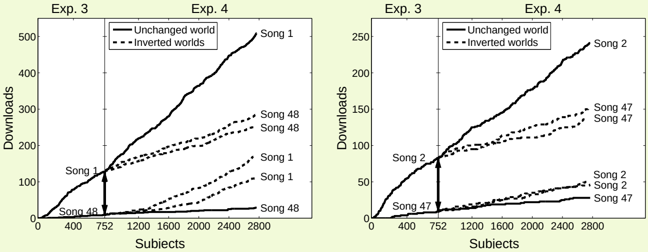
Music Lab Experiment—Sneakiness



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

A Very Dismal Science
Contagion
Winning: it's not for everyone
Social Contagion Models
Granovetter's model
Network version
Groups
Simple disease spreading models
References

Music Lab Experiment—Sneakiness



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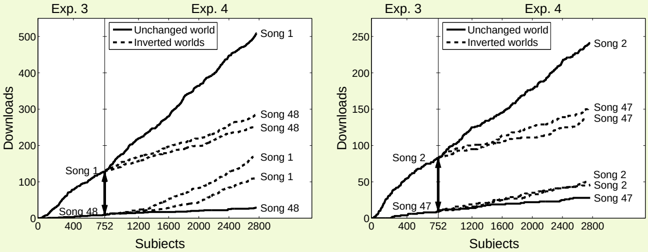

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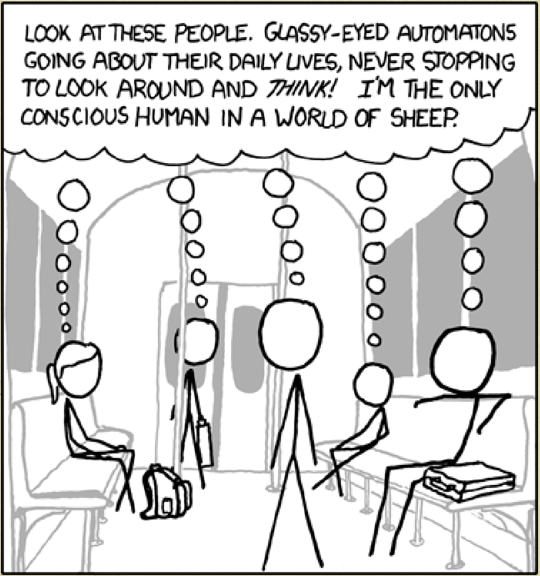
Social Contagion



http://xkcd.com/610/ (⊞)

Social Contagion

Social Contagion

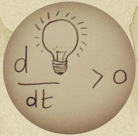
Social Contagion

Examples abound

- fashion
- striking
- smoking (⊞) [13]
- residential segregation [34]
- ipods
- obesity (⊞) [12]
- 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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- voting
- gossip
- Rubik's cube
- religious beliefs
- leaving lectures

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

We need to understand influence:

- Who influences whom?
- What kinds of influence response functions are there?
  (see Romero et al. [31], Ugander et al. [39])
- Are some individuals super influencers?
- The infectious idea of opinion leaders (Katz and Lazarsfeld)[22]

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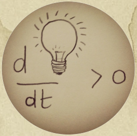

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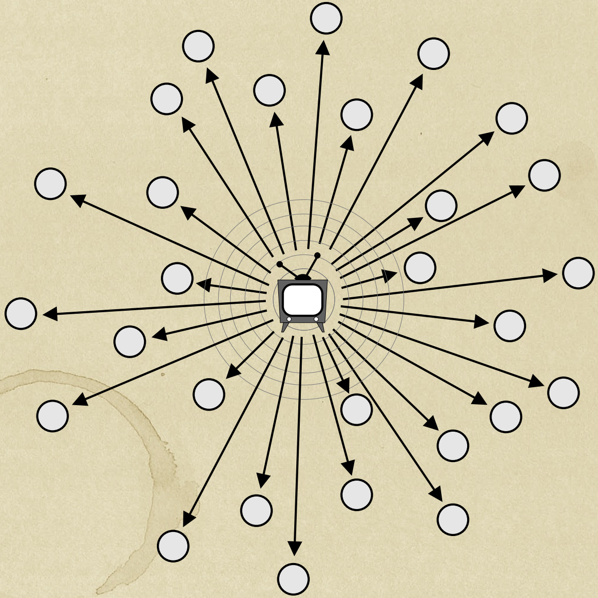
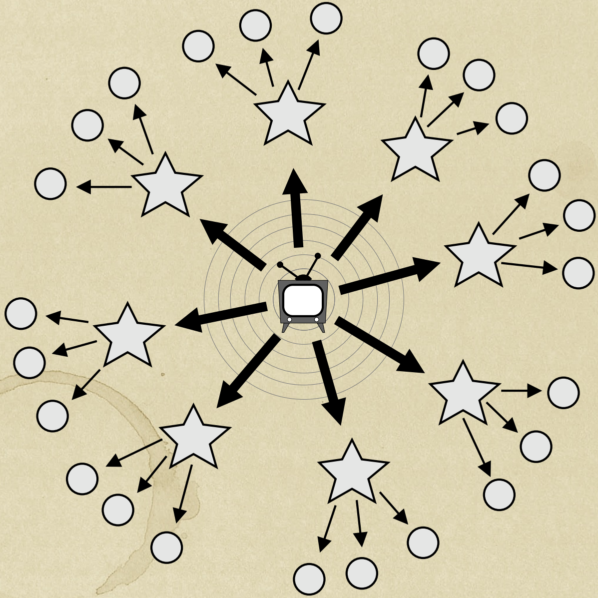
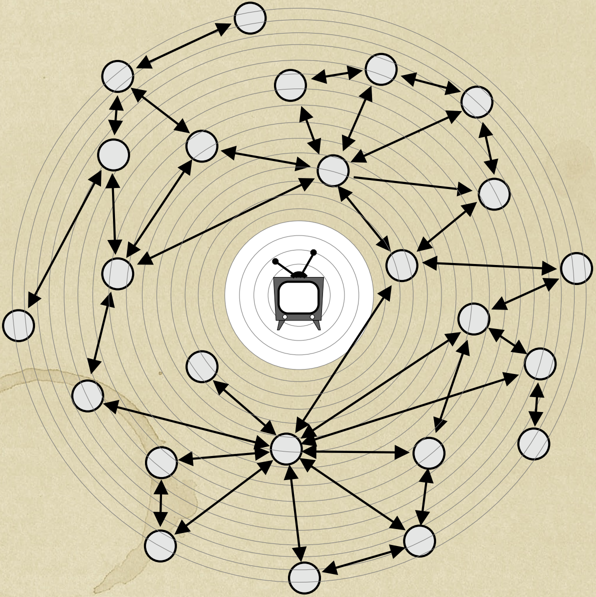
The hypodermic model of influence



The two step model of influence [22]



The general model of influence



Social Contagion

Why do things spread?

- Because 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—-no natural frame/metaphor
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The UNIVERSITY of VERMONT

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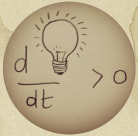

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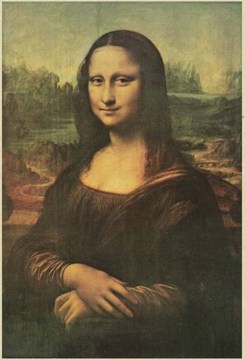
From Pratchett's "Lords and Ladies":

Granny Weatherwax (⊞) on trying to borrow the mind of a swarm of bees—

"But a swarm, a mind made up of thousands of mobile parts, was beyond her. It was the toughest test of all. She'd tried over and over again to ride on one, to see the world through ten thousand pairs of multifaceted eyes all at once, and all she'd ever got was a migraine and an inclination to make love to flowers."

(p. 42). Harper Collins, Inc. Kindle Edition.

The Mona Lisa



- "Becoming Mona Lisa: The Making of a Global Icon"—David Sassoon
- Not the world's greatest painting from the start...
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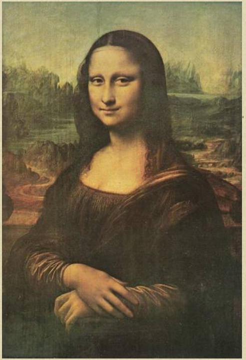
The Mona Lisa



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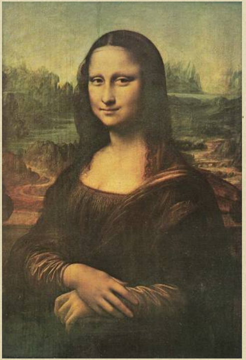

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The completely unpredicted fall of Eastern Europe

Timur Kuran:[26, 27] “Now Out of Never: The Element of Surprise in the East European Revolution of 1989”

The dismal predictive powers of editors...

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Six modes of influence:

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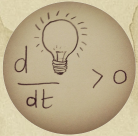

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- Very useful but can be leveraged...

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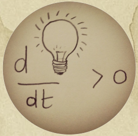

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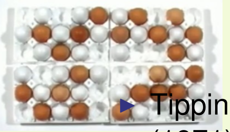

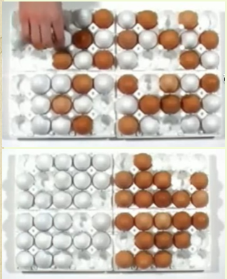

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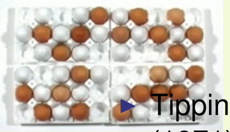
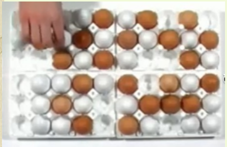
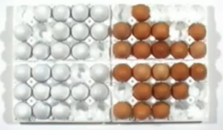

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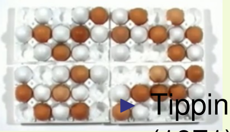
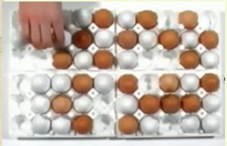
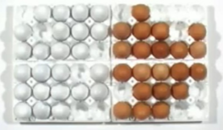

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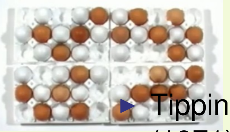
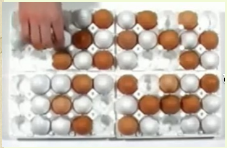
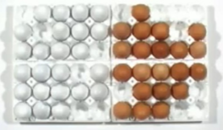

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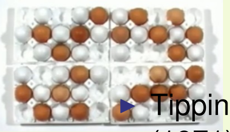

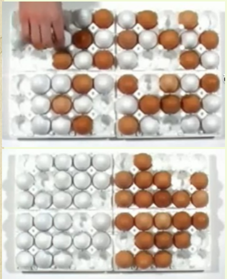

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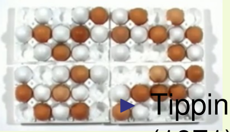

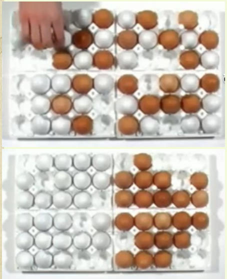

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Thresholds

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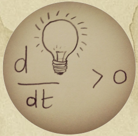

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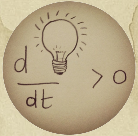

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Some possible origins of thresholds:

- Inherent, evolution-devised inclination to coordinate, to conform, to imitate. [3]
- 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
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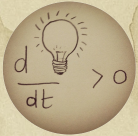

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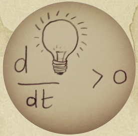

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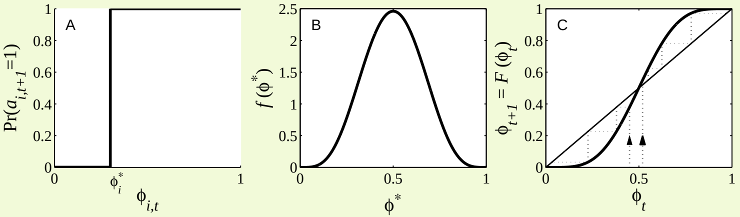

- Two states: Susceptible and Infected.
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Discrete time update (strong assumption!)
- This is a Critical mass model
- Many other kinds of dynamics are possible.

Implications for collective action theory:

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

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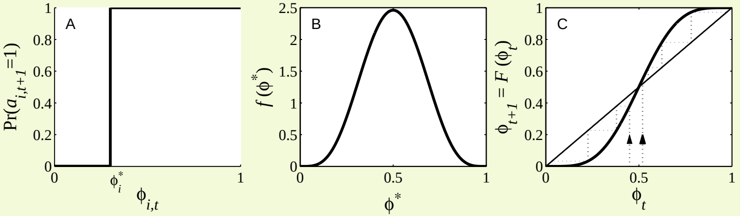

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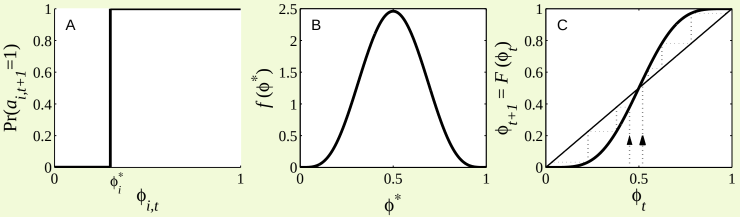

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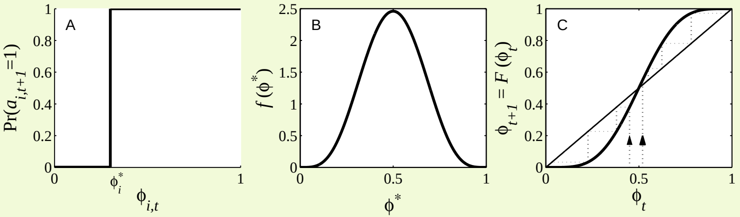

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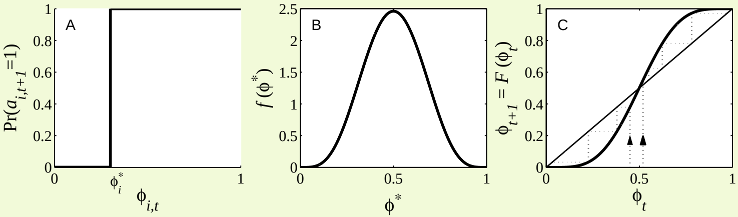

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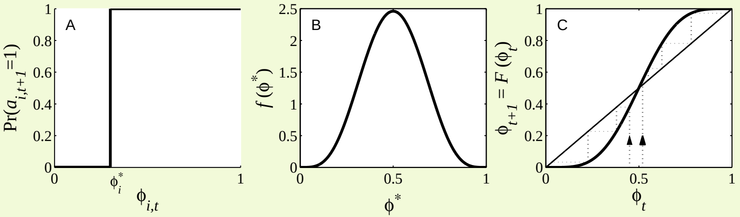
2. Small individual changes $\Rightarrow$ large global changes

Action based on perceived behavior of others:



- Two states: Susceptible and Infected.
- ϕ = fraction of contacts 'on' (e.g., rioting)
- Discrete time update (strong assumption!)
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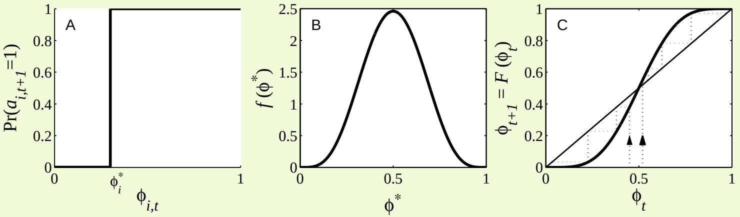

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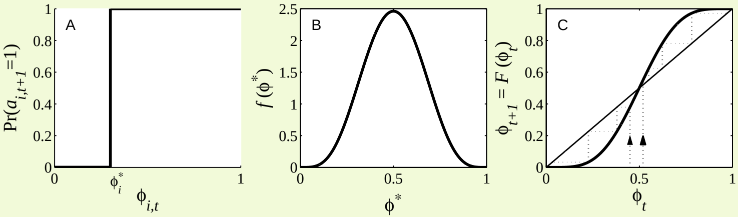

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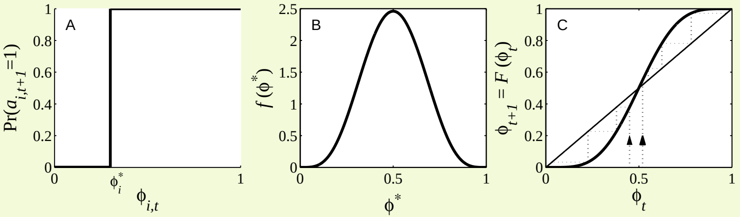

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Outline

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D. J. Watts. Proc. Natl. Acad. Sci., 2002 [40]

- Mean field model → network model
- Individuals now have a limited view of the world

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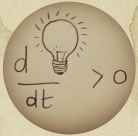

Threshold model on a network

- 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
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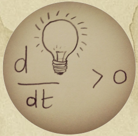

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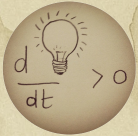

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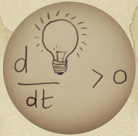

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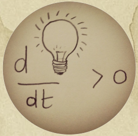

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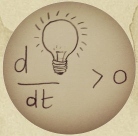

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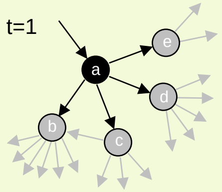

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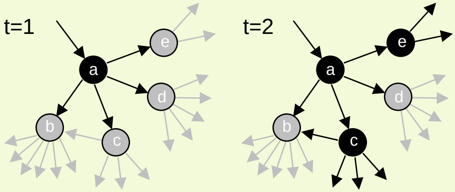

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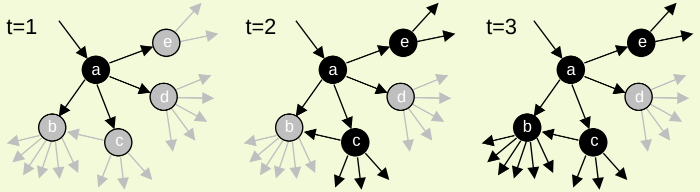

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Snowballing

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?

First study random networks:

- Start with N nodes with a degree distribution p_k
- Nodes are randomly connected (carefully so)
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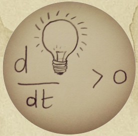

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Vulnerables:

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

$$1/k_i \geq \phi_i$$

- Which means # contacts $k_i \leq \lfloor 1/\phi_i \rfloor$
- For global cascades on random networks, must have a *global cluster of vulnerables* [40]
- Cluster of vulnerables = critical mass
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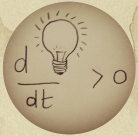

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Back to following a link:

- A randomly chosen link, traversed in a random direction, leads to a degree k node with probability $\propto kP_k$.
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$$\sum_{k=0}^{\infty} kP_k = \langle k \rangle$$

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- Linked node is vulnerable with probability

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

- If linked node is vulnerable, it produces $k-1$ new outgoing active links
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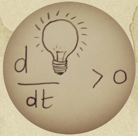

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Putting things together:

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

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

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

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

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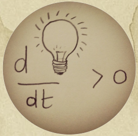

Two special cases:

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

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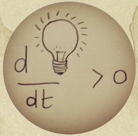

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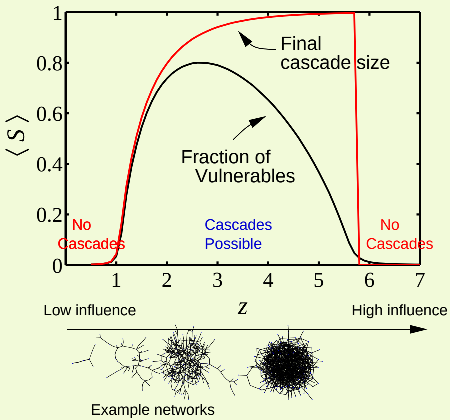
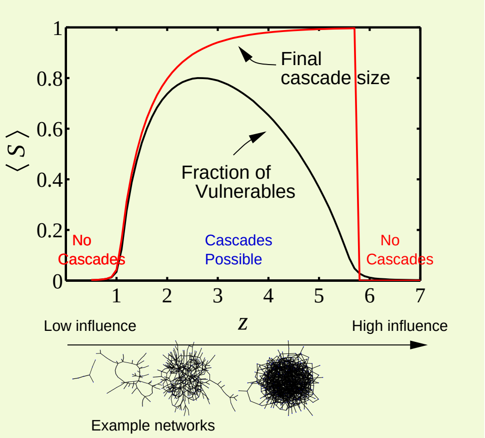
Cascades on random networks



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

Cascades on random networks



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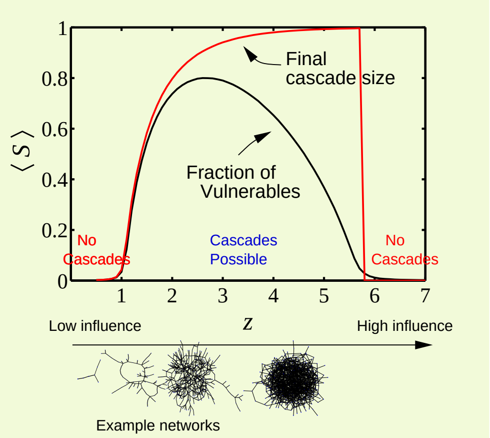

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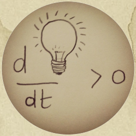
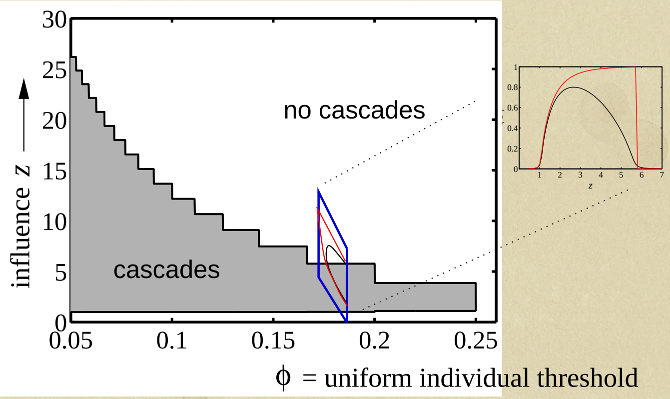
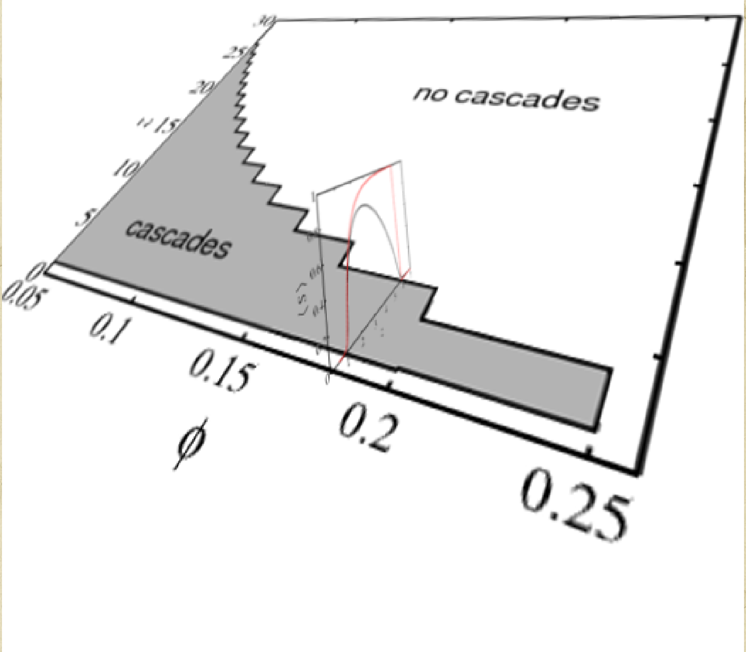


Cascade window for random networks



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

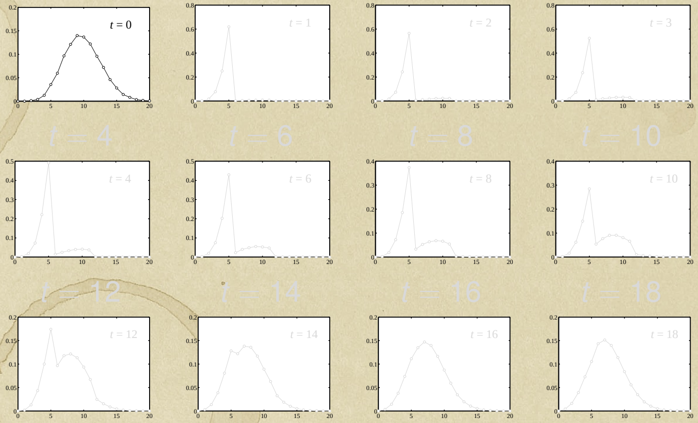
Cascade window for random networks



Early adopters are not well connected:

- Degree distributions of nodes adopting at time t:

$t = 0$



$P_{k,t}$ versus k

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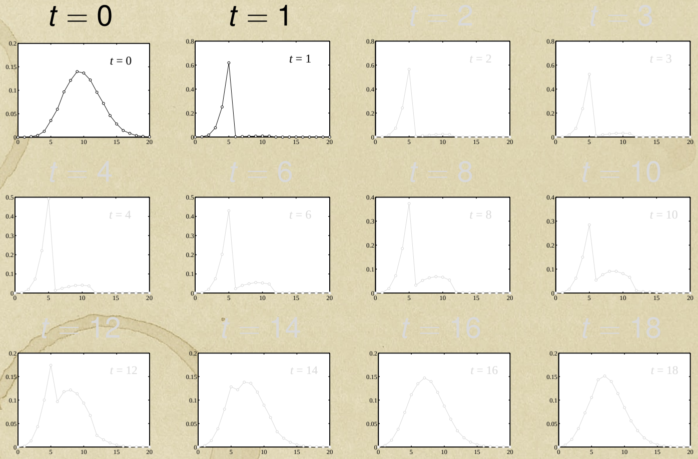

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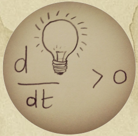

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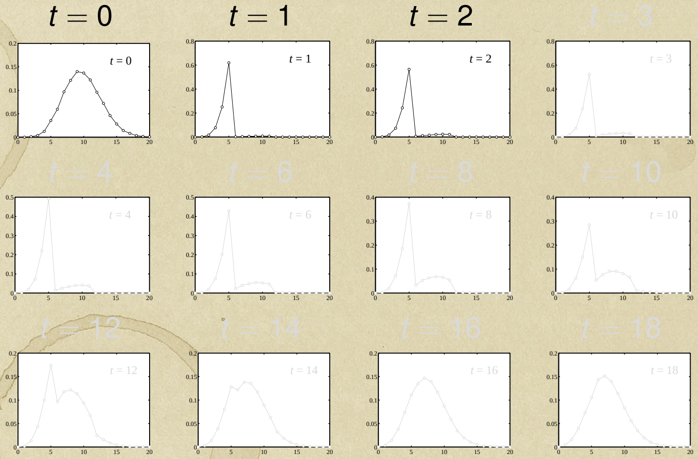

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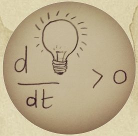

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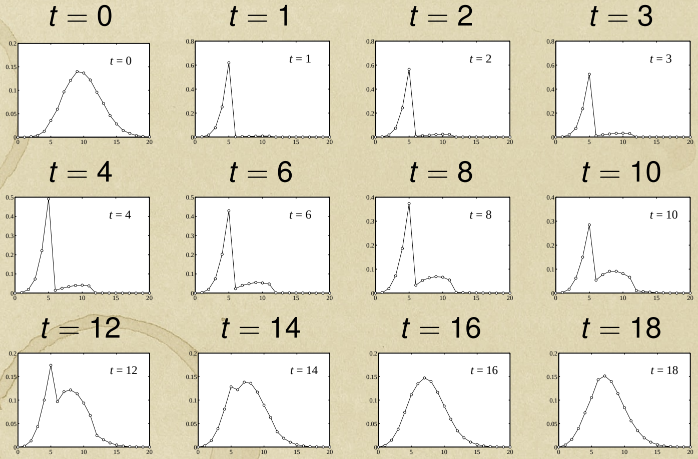
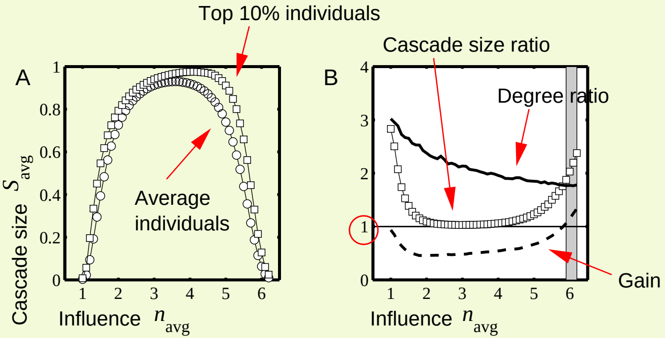


$P_{k,t}$ versus k

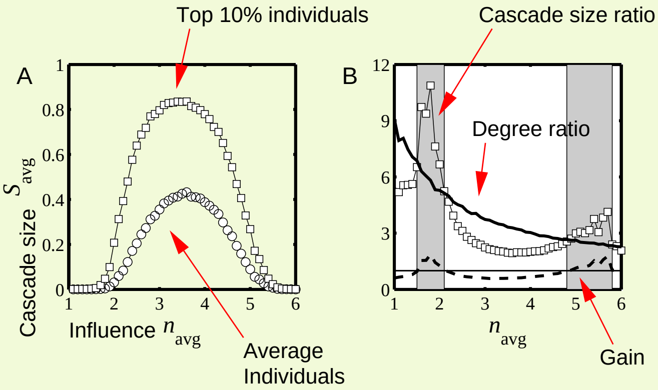
The multiplier effect:

"Influentials, Networks, and Public Opinion Formation"[41]
Journal of Consumer Research, Watts and Dodds, 2007.



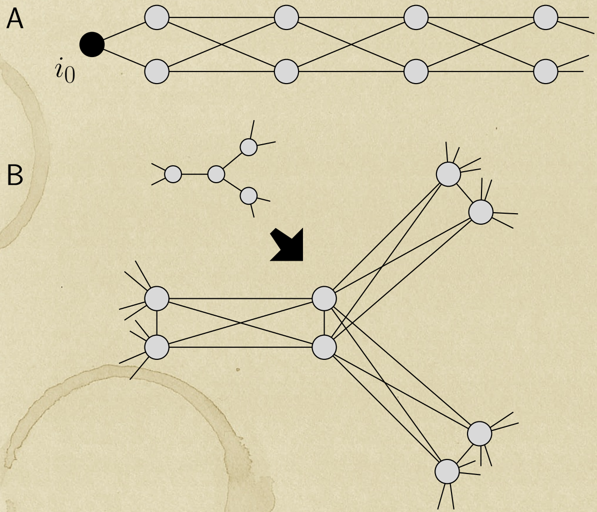
- Fairly uniform levels of individual influence.
- Multiplier effect is mostly below 1.

The multiplier effect:



- Skewed influence distribution example.

Special subnetworks can act as triggers



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

Outline

A Very Dismal Science

Contagion

Winning: it's not for everyone

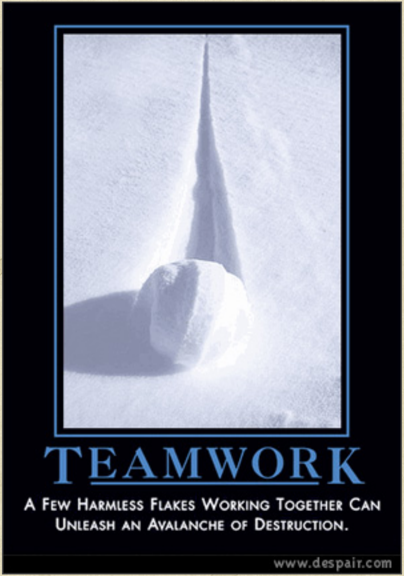
Social Contagion Models

- Granovetter's model
- Network version
- Groups

Simple disease spreading models

References

The power of groups...



despair.com

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

Incorporating social context:

- 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
- "Threshold Models of Social Influence"[42]
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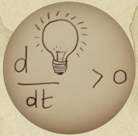
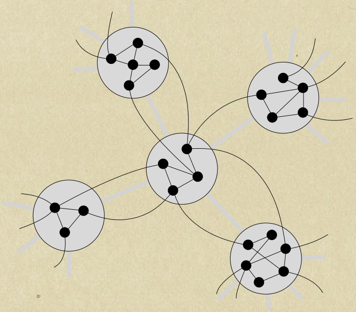
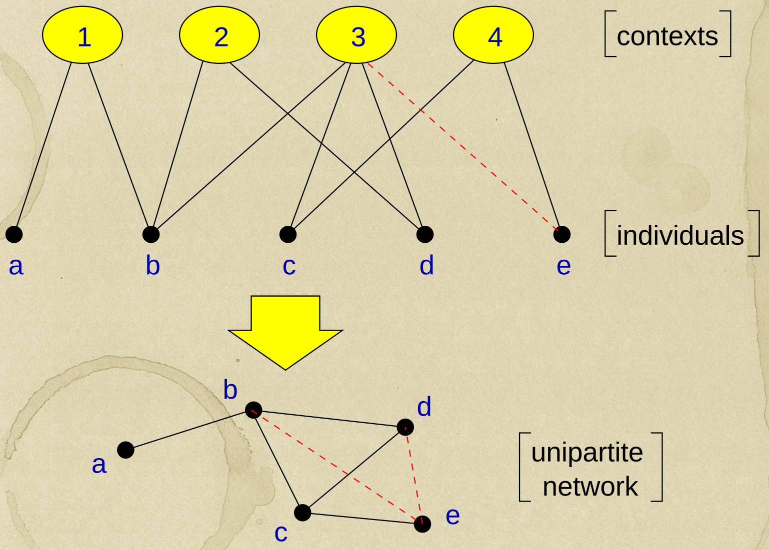


Group structure—Ramified random networks

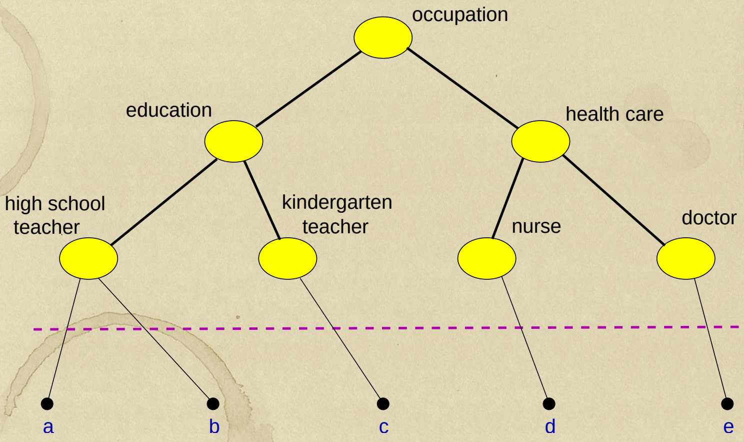


p = intergroup connection probability
q = intragroup connection probability.

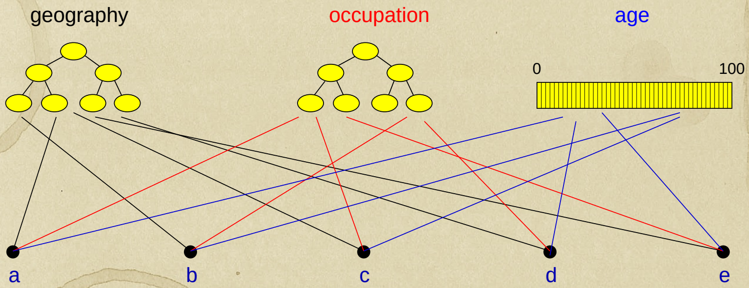
Bipartite networks



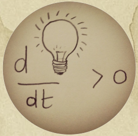
Context distance



Generalized affiliation model



(Blau & Schwartz, Simmel, Breiger)



Generalized affiliation model networks with triadic closure

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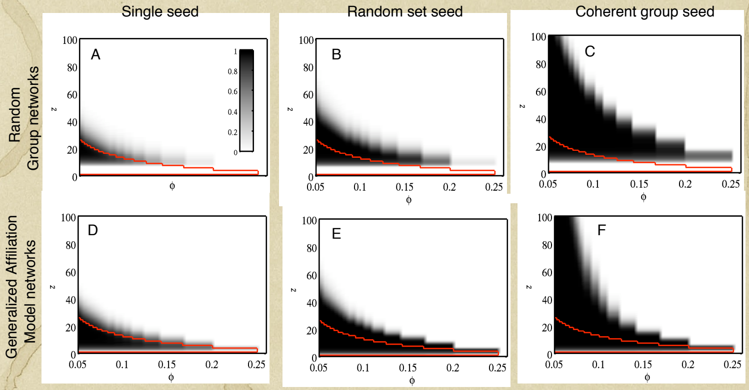
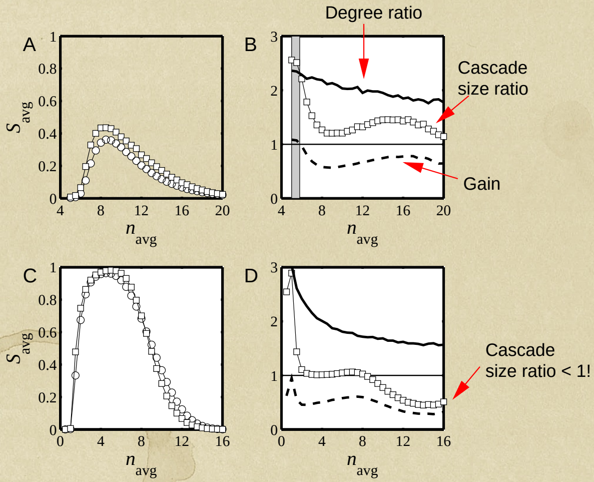
Cascade windows for group-based networks

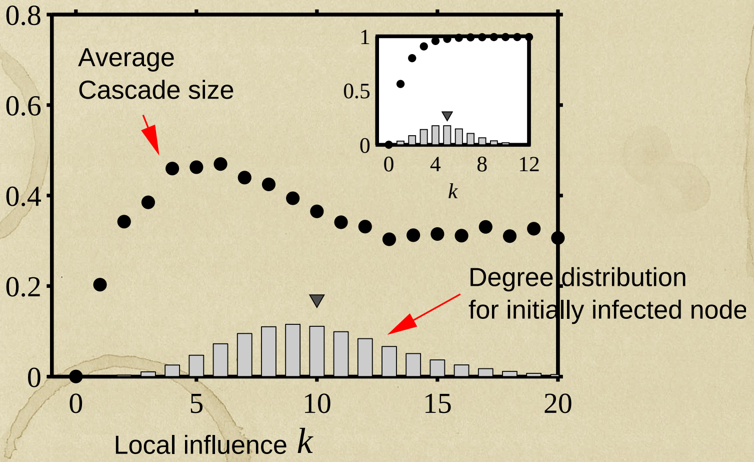


Multiplier effect for group-based networks:



- Multiplier almost always below 1.

Assortativity in group-based networks



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

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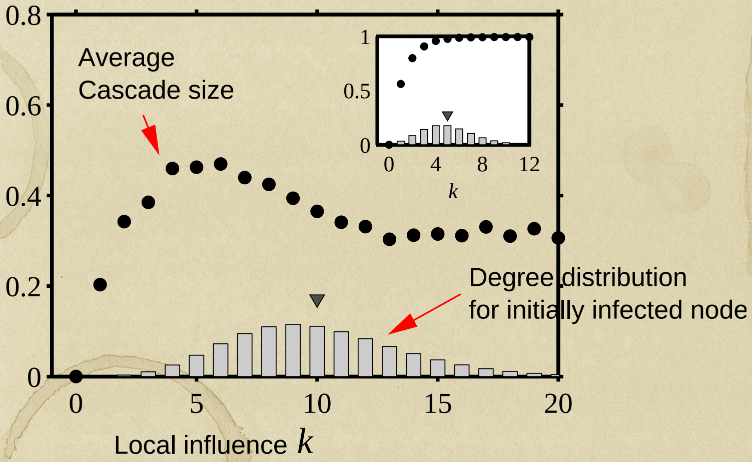

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Social contagion

Summary

- 'Influential vulnerables' are key to spread.
- Early adopters are mostly vulnerables.
- Vulnerable nodes important but not necessary.
- Vulnerable 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.
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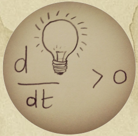
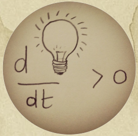


Social contagion

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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Mathematical Epidemiology

The standard SIR model [28]

- = basic model of disease contagion
- Three states:
  1. S = Susceptible
  2. I = Infective/Infectious
  3. R = Recovered or Removed or Refractory
- $S(t) + I(t) + R(t) = 1$
- Presumes random interactions (mass-action principle)
- Interactions are independent (no memory)
- Discrete and continuous time versions

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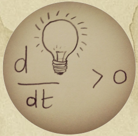

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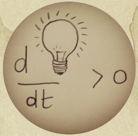

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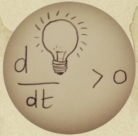

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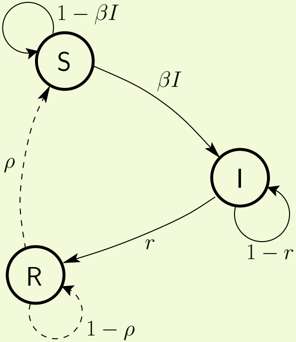

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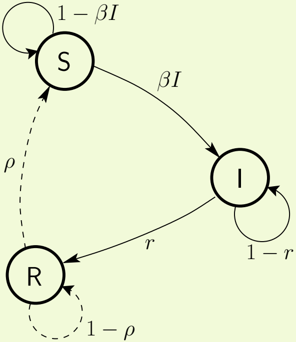
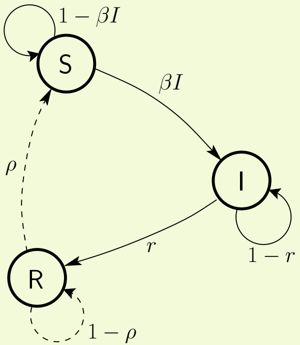


Transition Probabilities:

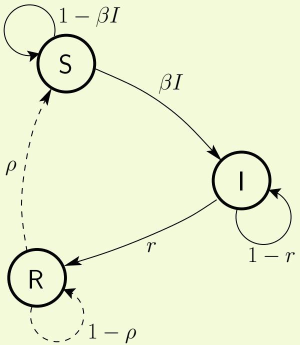
Discrete time automata example:



Transition Probabilities:

β for being infected given contact with infected

Discrete time automata example:



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Mathematical Epidemiology

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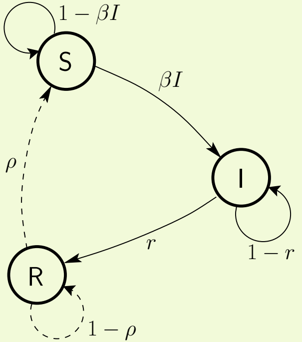

Transition Probabilities:

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ρ for loss of immunity

Original models attributed to

- 1920's: Reed and Frost
- 1920's/1930's: Kermack and McKendrick [23, 25, 24]
- Coupled differential equations with a mass-action principle

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Independent Interaction models

Differential equations for continuous model

$$\frac{\mathrm{d}}{\mathrm{d}t} S = -\beta IS + \rho R$$

$$\frac{\mathrm{d}}{\mathrm{d}t} I = \beta IS - rI$$

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β, r, and ρ are now rates.

Reproduction Number R_0:

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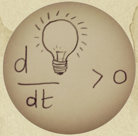

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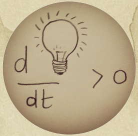

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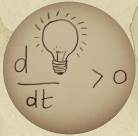

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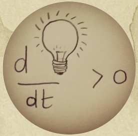

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- Set up: One Infective in a randomly mixing population of Susceptibles
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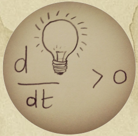

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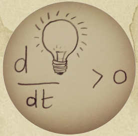

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For S_0 initial infectives ($1 - S_0 = R_0$ immune):

$$R_0 = S_0\beta/r$$

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- Second equation:

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- Number of infectives grows initially if

$$\beta S(0) - r > 0$$

- Same story as for discrete model.

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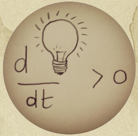

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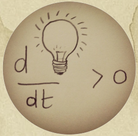

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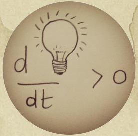

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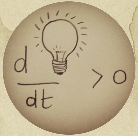

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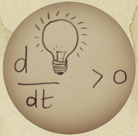

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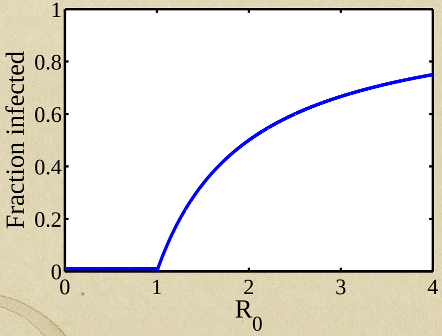

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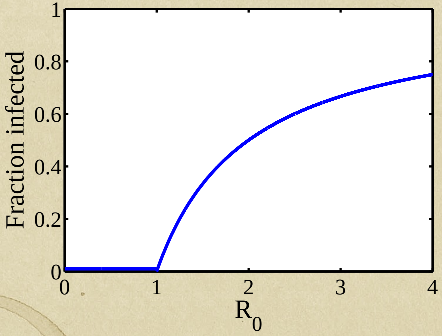

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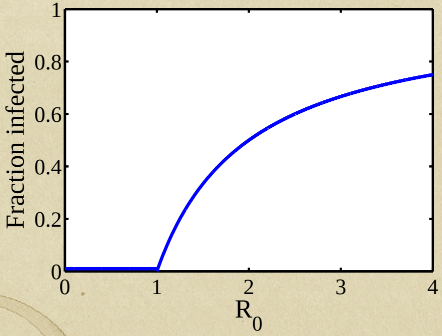

- Continuous phase transition.
- Fine idea from a simple model.

Independent Interaction models

Many variants of the SIR model:

- SIS: susceptible-infective-susceptible
- SIRS: susceptible-infective-recovered-susceptible
- compartment models (age or gender partitions)
- more categories such as 'exposed' (SEIRS)
- recruitment (migration, birth)

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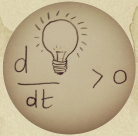

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Disease spreading models

For novel diseases:

1. Can we predict the size of an epidemic?
2. How important is the reproduction number R_0?

R_0 approximately same for all of the following:

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

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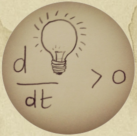

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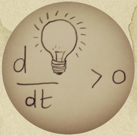


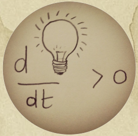
Size distributions

Size distributions are important elsewhere:

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

Really, what about epidemics?

- Simply hasn’t attracted much attention.
- Data not as clean as for other phenomena.



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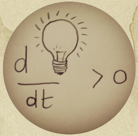

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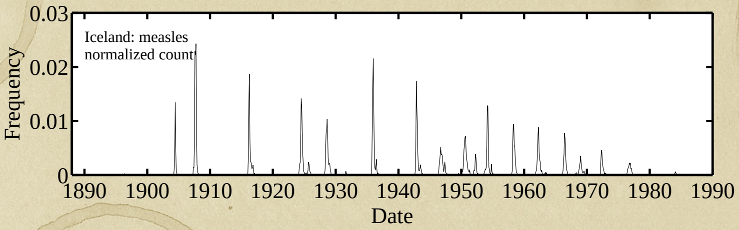
Feeling Ill in Iceland

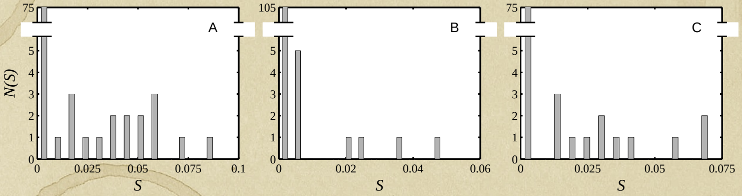
Caseload recorded monthly for range of diseases in Iceland, 1888-1990



- Treat outbreaks separated in time as 'novel' diseases.

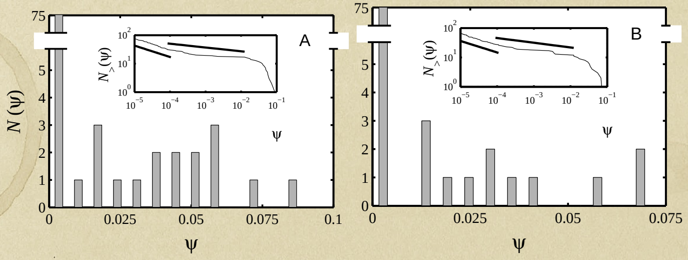
Really not so good at all in Iceland

Epidemic size distributions $N(S)$ for Measles, Rubella, and Whooping Cough.



Spike near $S = 0$, relatively flat otherwise.

Measles & Pertussis



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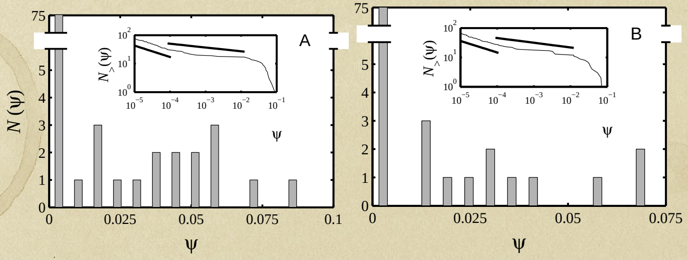

Insert plots:

Complementary cumulative frequency distributions:

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

Limited scaling with a possible break.

Power law distributions

Measured values of γ:

- measles: 1.40 (low Ψ) and 1.13 (high Ψ)
- pertussis: 1.39 (low Ψ) and 1.16 (high Ψ)

- Expect $2 \le \gamma < 3$ (finite mean, infinite variance)
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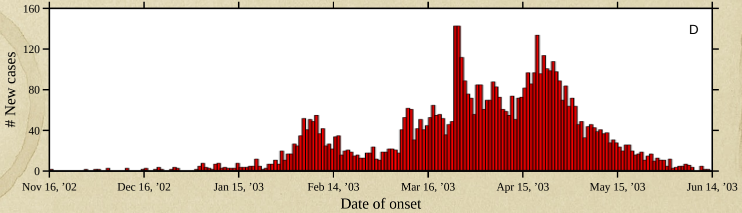
Resurgence—example of SARS



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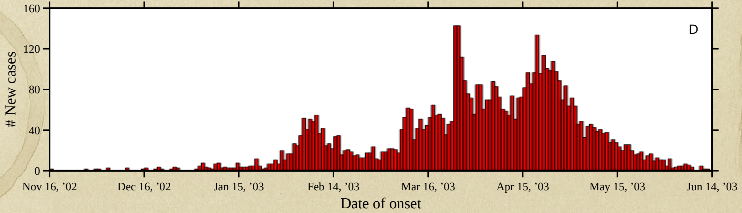

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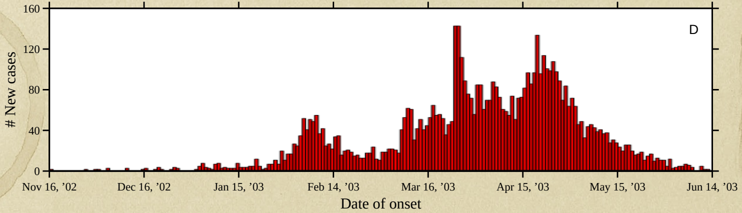

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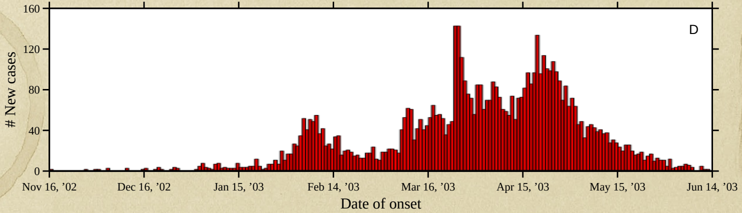

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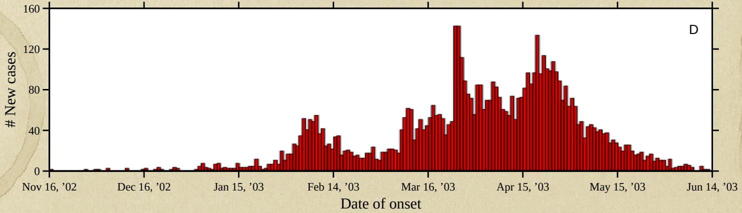

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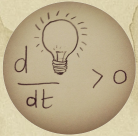
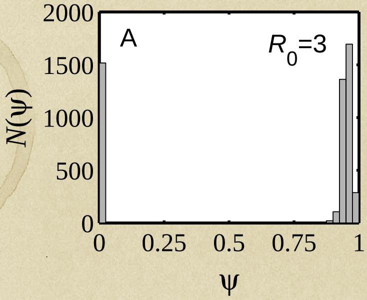


The challenge

So... can a simple model produce

1. broad epidemic distributions
   and
2. resurgence ?

Size distributions



Simple models typically produce bimodal or unimodal size distributions.

- This includes network models: random, small-world, scale-free, ...
- Exceptions:
  1. Forest fire models
  2. Sophisticated metapopulation models

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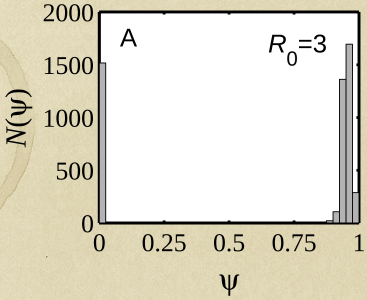

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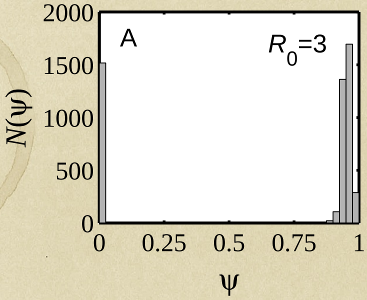

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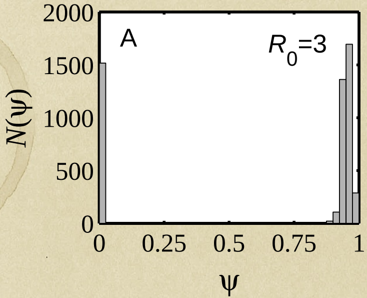

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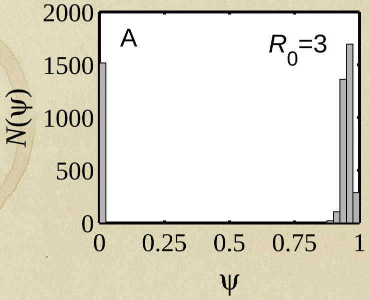

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Burning through the population

Forest fire models: [30]

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- The physicist's approach:
  "if it works for magnets, it'll work for people..."

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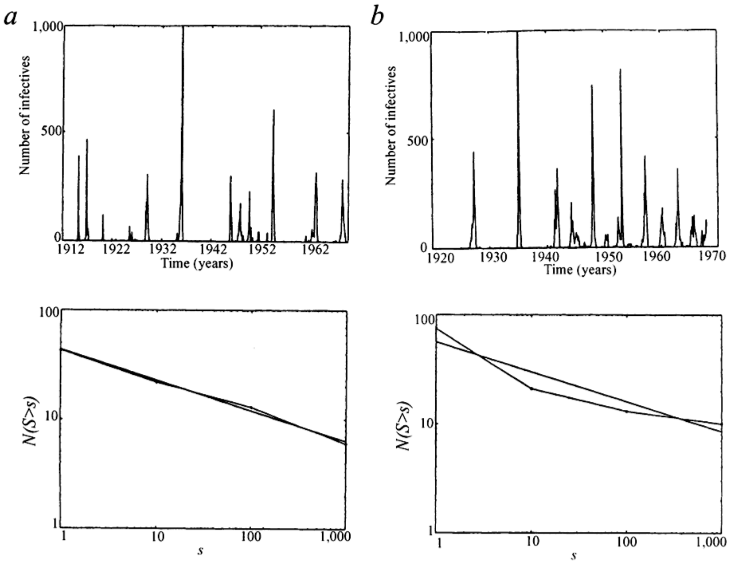

From Rhodes and Anderson, 1996.

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- Community based mixing: Longini (two scales).
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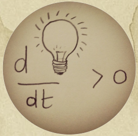

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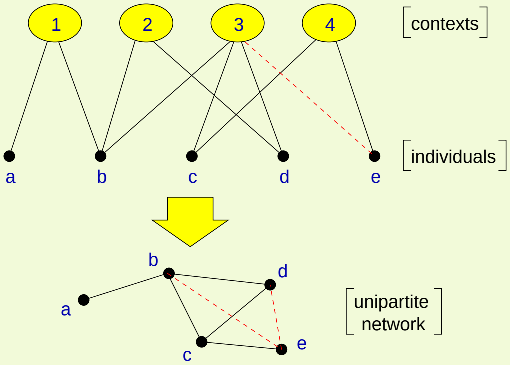
Improving simple models

Contexts and Identities—Bipartite networks



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- movies
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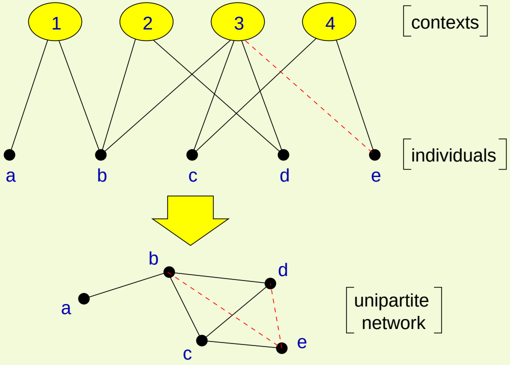

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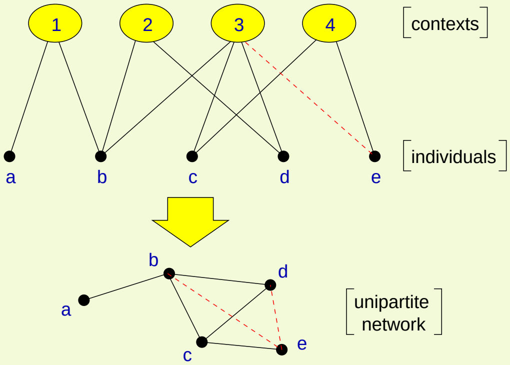

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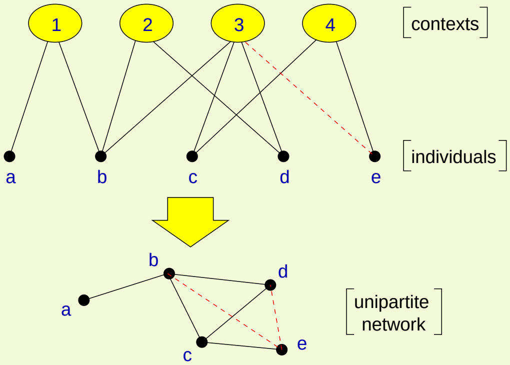

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Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

- Geographic location
- Type of employment
- Age
- Recreational activities

Groups are crucial...

- formed by people with at least one similar attribute
- Attributes $\Leftrightarrow$ Contexts $\Leftrightarrow$ Interactions $\Leftrightarrow$ Networks.[43]

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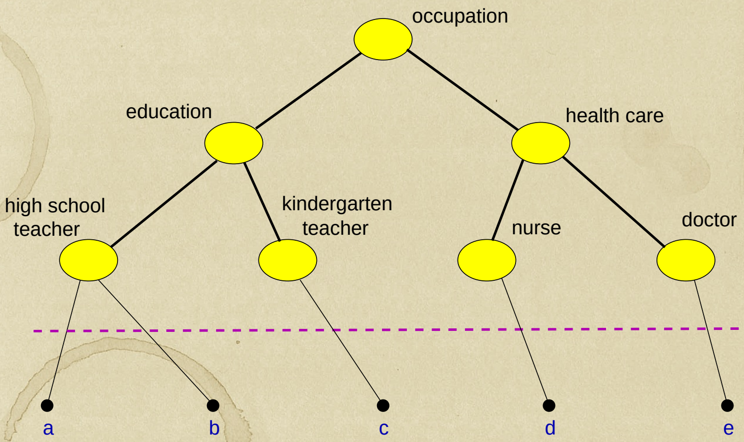
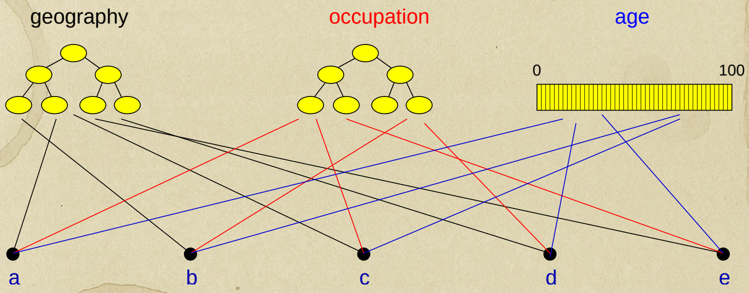
Infer interactions/network from identities



Distance makes sense in identity/context space.

Generalized context space



(Blau & Schwartz [6], Simmel [37], Breiger [7])

A toy agent-based model

Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- β = infection probability
- γ = recovery probability
- P = probability of travel
- Movement distance: $\Pr(d) \propto \exp(-d/\xi)$
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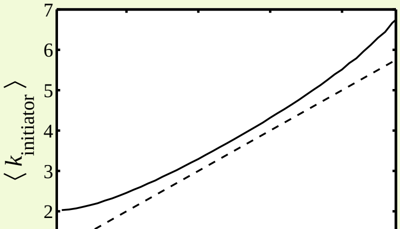
Schematic:



Model output

- Define P_0 = Expected number of infected individuals leaving initially infected context.
- Need $P_0 > 1$ for disease to spread (independent of R_0).
- Limit epidemic size by restricting frequency of travel and/or range.

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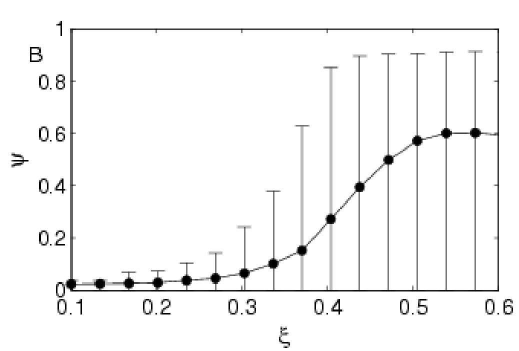

- Transition in expected final size based on typical movement distance

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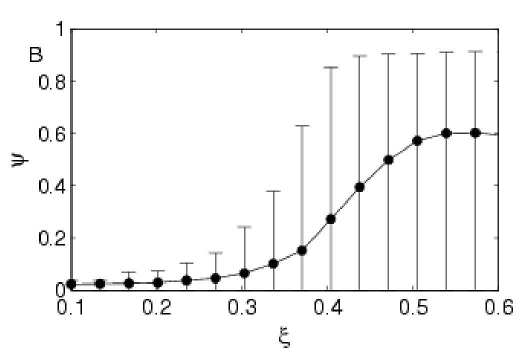
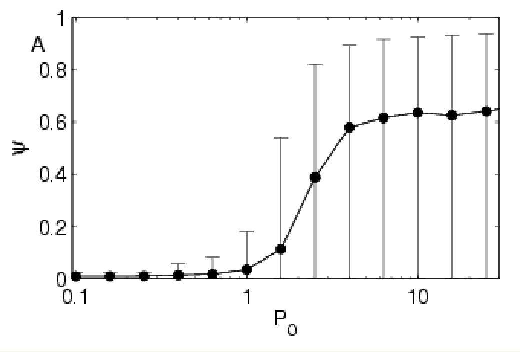


- Transition in expected final size based on typical movement distance (sensible)

Model output

Varying P_0:



- Transition in expected final size based on typical number of infectives leaving first group
- Travel advisories: ξ has larger effect than P_0.

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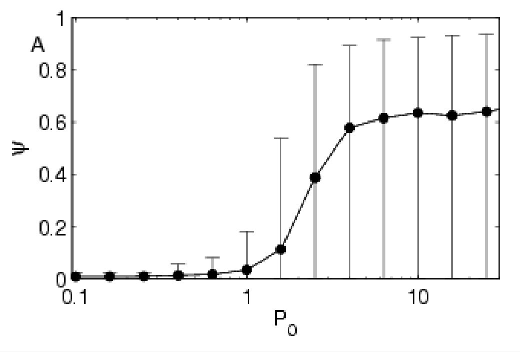

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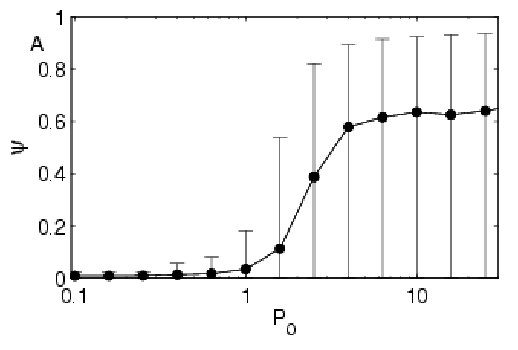

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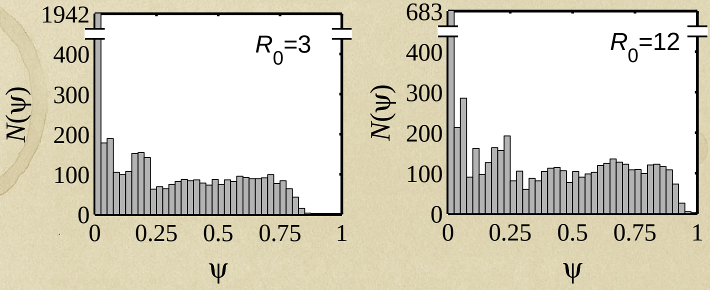

- Flat distributions are possible for certain ξ and P.
- Different R_0's may produce similar distributions
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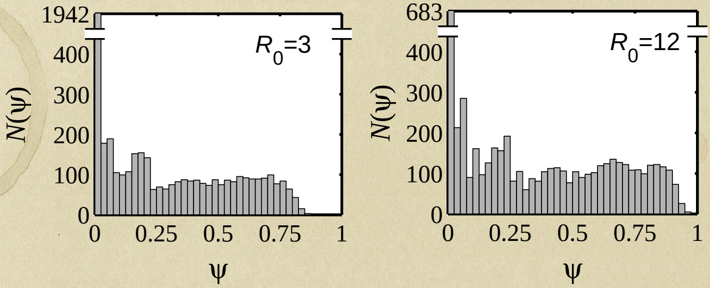

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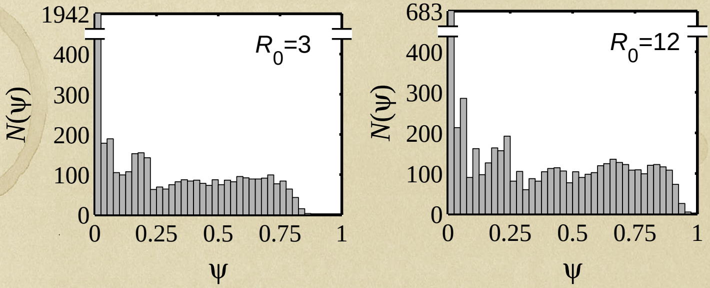

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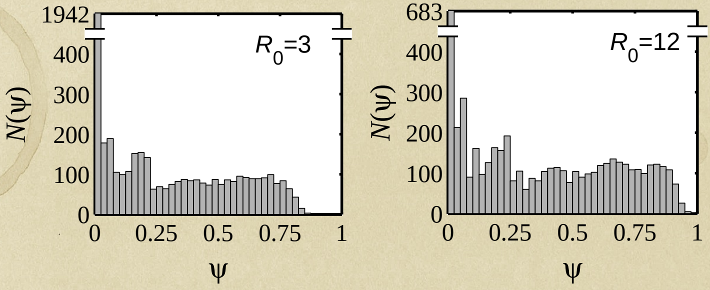

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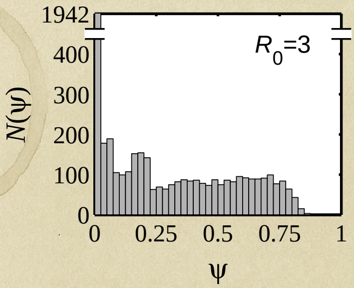
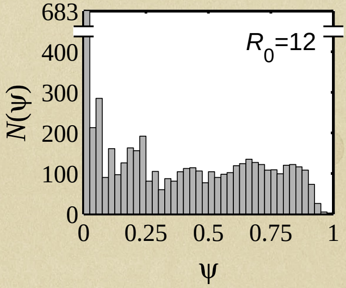
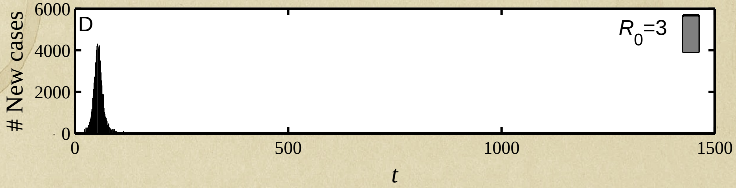




- Flat distributions are possible for certain ξ and P.
- Different R_0's may produce similar distributions
- Same epidemic sizes may arise from different R_0's

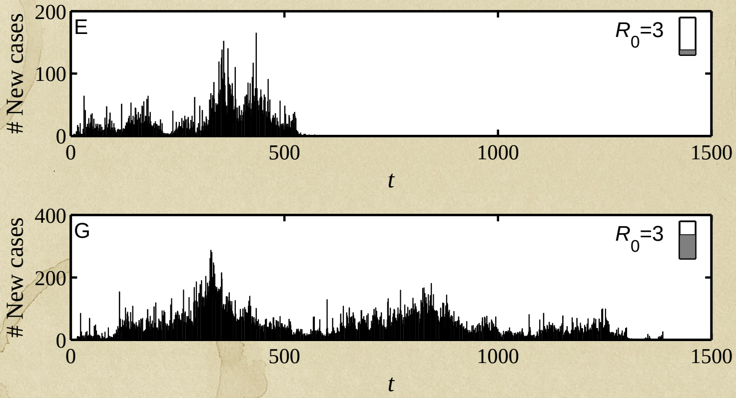
Model output—resurgence

Standard model:



Model output—resurgence

Standard model with transport:



The upshot

Simple multiscale population structure

The upshot

Simple multiscale population structure
+
stochasticity

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leads to

resurgence
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broad epidemic size distributions

Conclusions

- For this model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- The reproduction number R_0 is not terribly useful.
- R_0, however measured, is not informative about
  1. how likely the observed epidemic size was,
  2. and how likely future epidemics will be.
- Problem: R_0 summarises one epidemic after the fact and enfolds movement, the price of bananas, everything.

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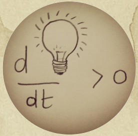
- Disease spread highly sensitive to population structure
- Rare events may matter enormously
- More support for controlling population movement



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What to do:

- Need to separate movement from disease
- R_0 needs a friend or two.
- Need $R_0 > 1$ and $P_0 > 1$ and ξ sufficiently large for disease to have a chance of spreading

More wondering:

- Exactly how important are rare events in disease spreading?
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Valiant attempts to use SIR and co. elsewhere:

- Adoption of ideas/beliefs (Goffman & Newell, 1964) [18]
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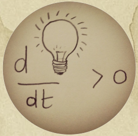

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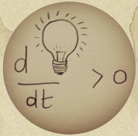

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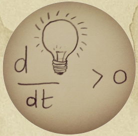

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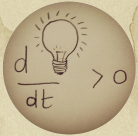

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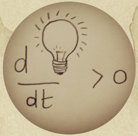

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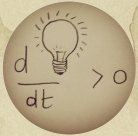

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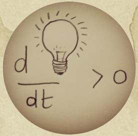

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