Biological Contagion

Principles of Complex Systems | @pocsvox
CSYS/MATH 300, Fall, 2015 | #FallPoCS2015

Prof. Peter Dodds | @peterdodds

Dept. of Mathematics & Statistics | Vermont Complex Systems Center
Vermont Advanced Computing Core | University of Vermont

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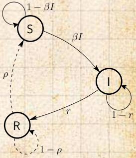
What's the Story?



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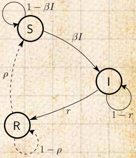
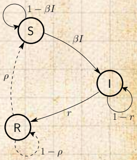
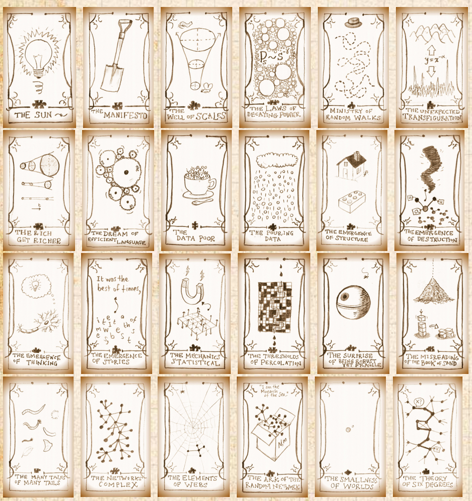
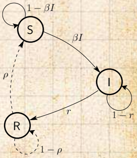


Outline




THE SUN
THE MANIFESTO
THE WELL OF SCALES
THE LAWS OF DECAYING POWER
MINISTRY OF RANDOM WALKS
THE UNEXPECTED TRANSFIGURATION
THE RICH GET RICHER
THE DREAM OF EFFICIENT LANGUAGE
THE DATA POOR
THE POURING DATA
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
THE EMERGENCE OF THINKING
It was the best of times,
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE SURPRISE OF BEING ROBUST YET FRAGILE
THE MISREADING OF THE BOOK OF SAND
THE MANY TALES OF MANY TAILS
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE ARK OF THE RANDOM NETWORK
THE SMALLNESS OF WORLDS
THE THEORY OF SIX DEGREES


THE NETWORKS FREE OF SCALE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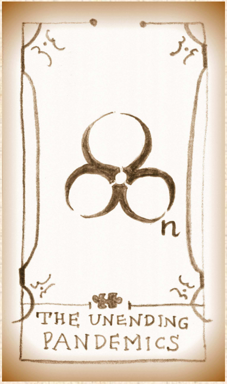
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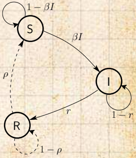
THE UNENDING PANDEMICS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- An awful recording: Wikipedia's list of epidemics from 430 BC on.

List of epidemics

From Wikipedia, the free encyclopedia

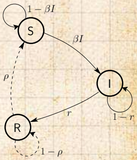
This article is a **list of epidemics** of infectious disease. Widespread and chronic complaints such as heart disease and allergy are not included if they are not thought to be infectious.

This list is incomplete; you can help by expanding it.

Death toll (estimate)	Location	Date	Comment	Disease	Reference
ca. 75,000 - 100,000	Greece	429–426 BC	Known as Plague of Athens, because it was primarily in Athens.	unknown, similar to typhoid	
ca. 30% of population	Europe, Western Asia, Northern Africa	165–180	Known as Antonine Plague, due to the name of the Roman emperor in power at the time.	unknown, symptoms similar to smallpox	
	Europe	250-266 AD	Know as the Plague of Cyprian named after St. Cyprian Bishop of Carthage.	unknown, possibly smallpox	
ca. 40% of population	Europe	541–542	Known as Plague of Justinian, due to the Byzantine emperor in power at the time.	Bubonic plague	[1]
30% to 70% of population	Europe	1346–1350	Known as "Black Death" or Second plague pandemic, first return of the plague to Europe after the Justinianic plague of the 6th century.	plague	[2]
5-15 million (80% of population)	Mexico	1545-1548	Cocoliztli	viral hemorrhagic fever	[3][4][5]
2 - 2.5 million (50% of population)	Mexico	1576	Cocoliztli	viral hemorrhagic fever	[6][7][8]
	Seneca nation	1592–1596		measles	[9]


Plague panel with the triumph of death. 1607–35, Deutsches Historisches Museum Berlin


An artistic portrayal of cholera which was epidemic in the 19th century

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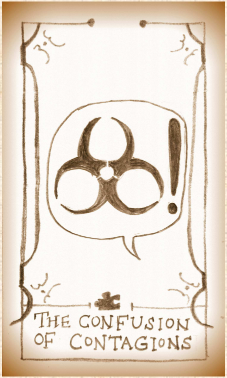
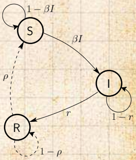

THE CONFUSION OF CONTAGIONS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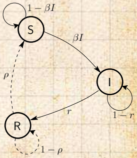
Contagion



A confusion of contagions:

- Is Harry Potter some kind of virus?
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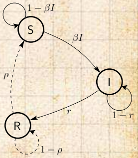

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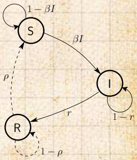

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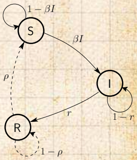

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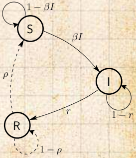

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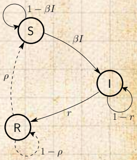

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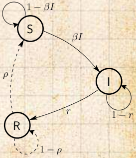

Contagion

Naturomorphisms

- "The feeling was contagious."
- "The news spread like wildfire."
- "Freedom is the most contagious virus known to man."
  —Hubert H. Humphrey, Johnson's vice president
- "Nothing is so contagious as enthusiasm."
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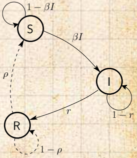
Optimism according to Ambrose Bierce

The doctrine that everything is beautiful, including what is ugly, everything good, especially the bad, and everything right that is wrong. ...



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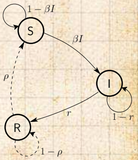

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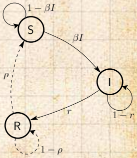

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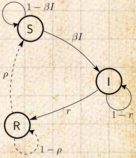

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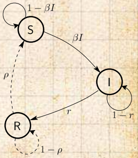

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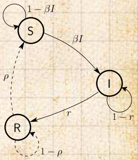

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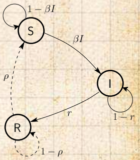
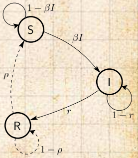


Social contagion

Eric Hoffer, 1902–1983

There is a grandeur in the uniformity of the mass.

- Hoffer was an interesting fellow...



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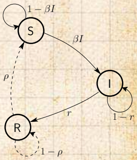

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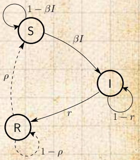

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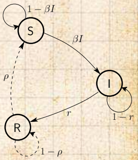

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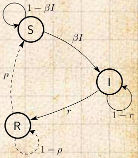

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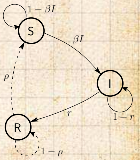

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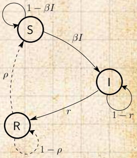

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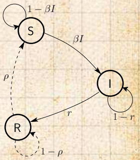
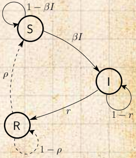


The spread of fanaticism

Hoffer's most famous work: "The True Believer: Thoughts On The Nature Of Mass Movements" (1951)[11]

Aphorisms-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."
- "Where freedom is real, equality is the passion of the masses. Where equality is real, freedom is the passion of a small minority."



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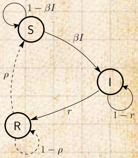

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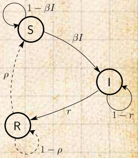

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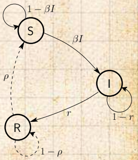

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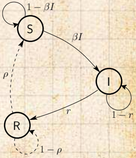
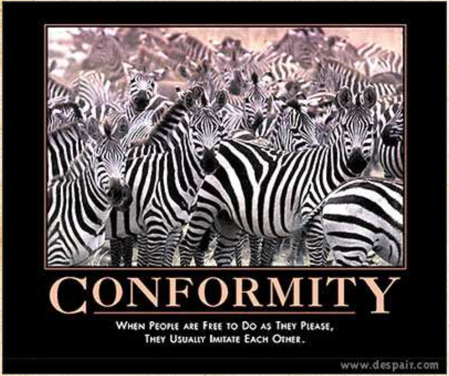


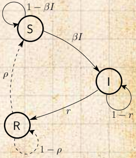
Imitation



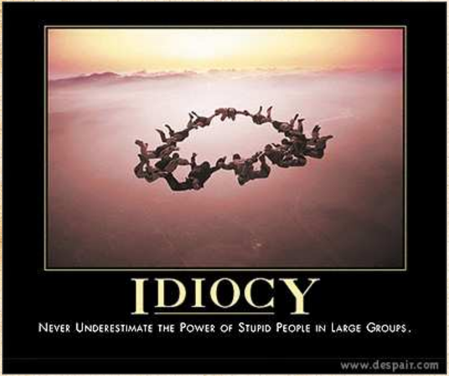
despair.com

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

—Eric Hoffer
"The Passionate State of Mind" [12]

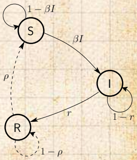


The collective...



despair.com

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

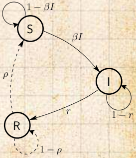


Examples of non-disease spreading:

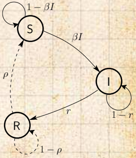
Interesting infections:

- Spreading of certain buildings in the US:

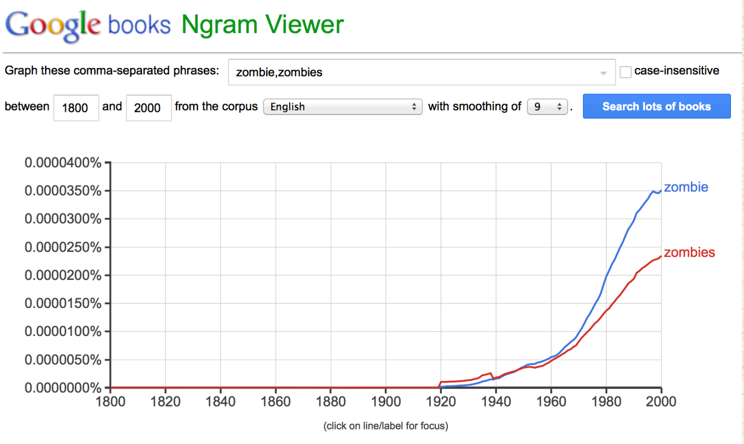
- 2008 Viral get-out-the-vote video.

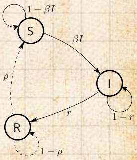


Marbleization of the US:

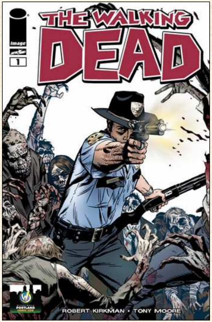


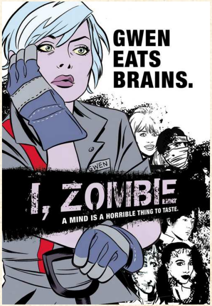
The most terrifying contagious outbreak?



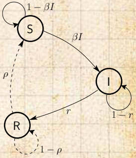



THE
WALKING DEAD


THE WALKING
DEAD
image
1
ROBERT KIRKMAN • TONY MOORE


GWEN EATS BRAINS.
GWEN
I, ZOMBIE
A MIND IS A HORRIBLE THING TO TASTE.


iZOMBiE


S
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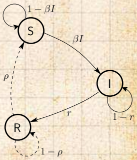
R
$1-\beta I$
βI
ρ
r
$1-r$
$1-\rho$

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.'
- Contagion has unpleasant overtones...
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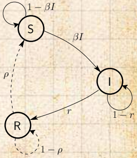

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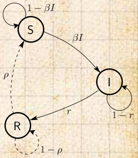

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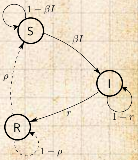

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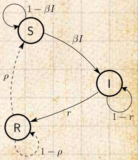

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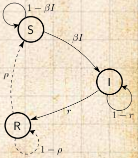

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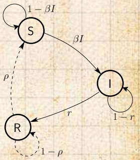
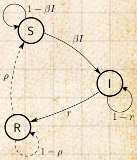


Contagions

Two main classes of contagion

1. Infectious diseases

2. Social contagion



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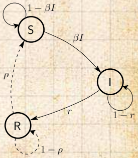
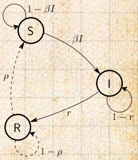


Contagions



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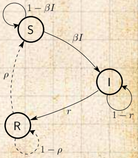

Two main classes of contagion

1. Infectious diseases:
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2. Social contagion:
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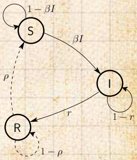
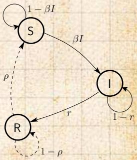
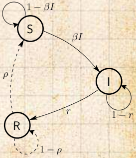


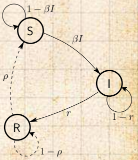
Archival footage from the Black Plague



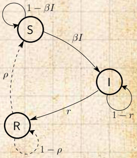
An awful recording: Wikipedia's list of epidemics from 430 BC on.



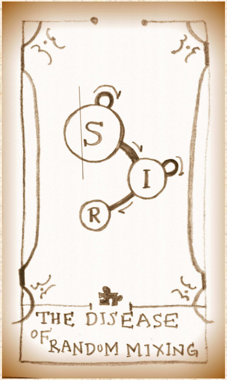
Community—S2E6: Epidemiology

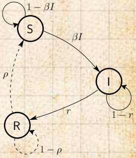


Outline




THE SUN
THE MANIFESTO
THE WELL OF SCALES
THE LAWS OF DECAYING POWER
MINISTRY OF RANDOM WALKS
THE UNEXPECTED TRANSFIGURATION
THE RICH GET RICHER
THE DREAM OF EFFICIENT LANGUAGE
THE DATA POOR
THE POURING DATA
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
THE EMERGENCE OF THINKING
THE EMERGENCE OF STORIES
THE MECHANICS STATISTICAL
THE THRESHOLDS OF PERCOLATION
THE SURPRISE OF BEING ROBUST YET FRAGILE
THE MISREADING OF THE BOOK OF SAND
THE MANY TALES OF MANY TAILS
THE NETWORKS COMPLEX
THE ELEMENTS OF WEBS
THE ARK OF THE RANDOM NETWORK
THE SMALLNESS OF WORLDS
THE THEORY OF SIX DEGREES
THE NETWORKS FREE OF SCALE
THE CONFUSION OF CONTAGIONS
THE UNENDING PANDEMICS


S
I
R
THE DISEASE OF RANDOM MIXING


S
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Mathematical Epidemiology

The standard SIR model [17]

- = basic model of disease contagion
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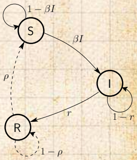

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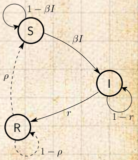

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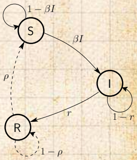

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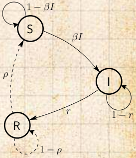

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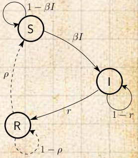

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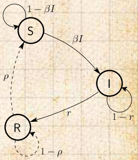

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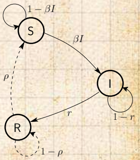

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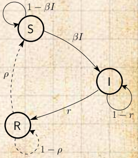

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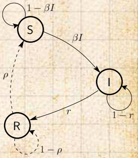

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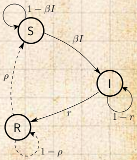

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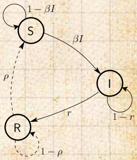
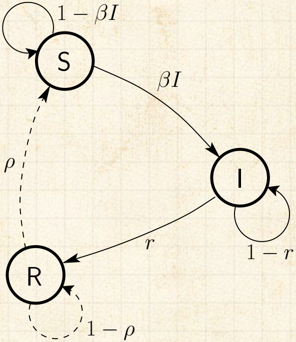
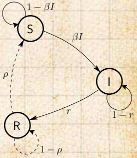


Mathematical Epidemiology

Discrete time automata example:





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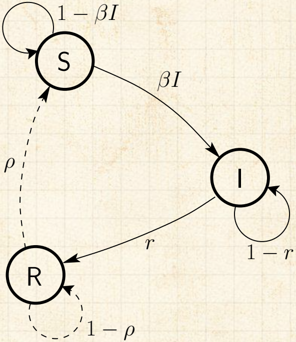

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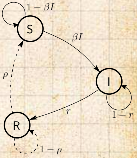

Mathematical Epidemiology

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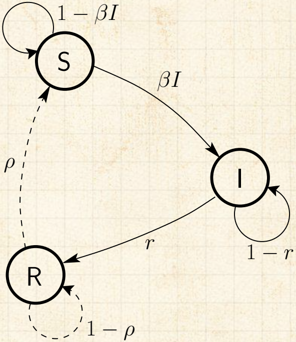
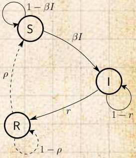


Transition Probabilities:

β for being infected given contact with infected



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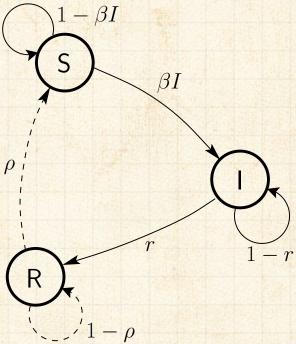

Transition Probabilities:

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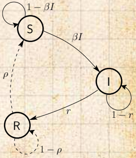
r for recovery



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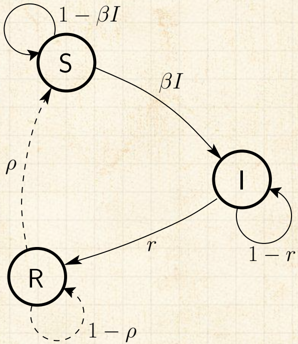
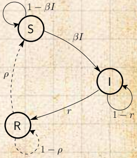


Transition Probabilities:

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



Mathematical Epidemiology

Original models attributed to

- 1920's: Reed and Frost
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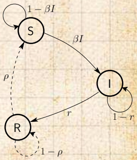
- Coupled differential equations with a mass-action principle



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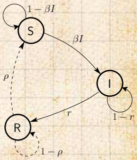

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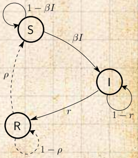

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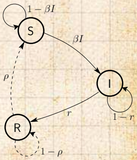


Independent Interaction models

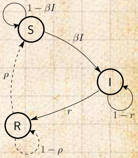
Differential equations for continuous model

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

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

$$\frac{\mathsf{d}}{\mathsf{d}t}R = rI - \rho R$$

β, r, and ρ are now rates.



Reproduction Number R_0

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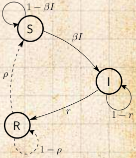
- R_0 = expected number of infected individuals resulting from a single initial infective
- Epidemic threshold: If $R_0 > 1$, 'epidemic' occurs.
- Exponential take off: R_0^n where n is the number of generations.
- Fantastically awful notation convention: R_0 and the R in SIR.



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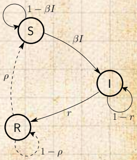

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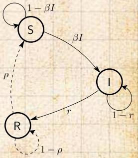

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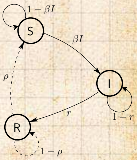

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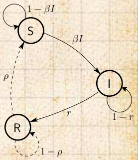

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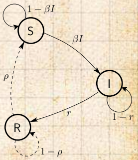
Discrete version:

- Set up: One Infective in a randomly mixing population of Susceptibles
- At time $t = 0$, single infective random bumps into a Susceptible
- Probability of transmission = β
- At time $t = 1$, single Infective remains infected with probability $1 - r$
- At time $t = k$, single Infective remains infected with probability $(1 - r)^k$



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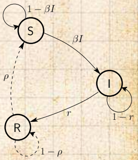

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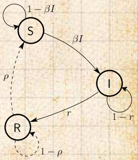

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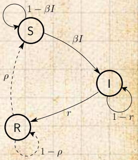

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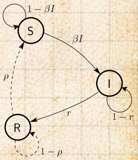

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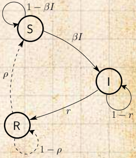
- Expected number infected by original infective:

$$R_0 = \beta + (1-r)\beta + (1-r)^2\beta + (1-r)^3\beta + \dots$$



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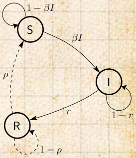

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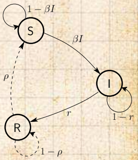

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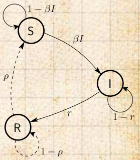

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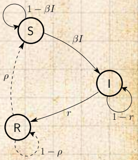
For $S(0) \simeq 1$ initial susceptibles
($1 - S(0) = R(0)$ = fraction initially immune):

$$R_0 = S(0)\beta/r$$



Independent Interaction models

For the continuous version

- Second equation:

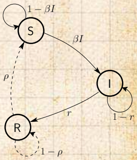
$$\frac{\mathrm{d}}{\mathrm{d}t} I = \beta S I - r I$$

- Number of infectives grows initially if

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

where $S(0) \simeq 1$.

- Same story as for discrete model.



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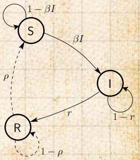

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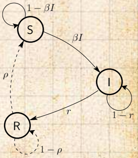

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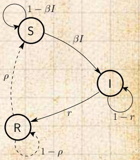

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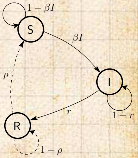

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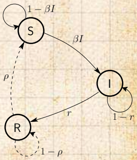
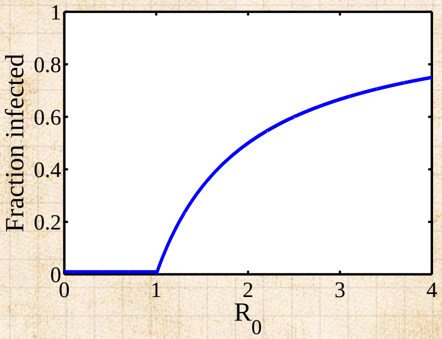
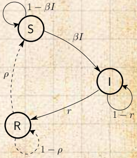


Independent Interaction models

Example of epidemic threshold:





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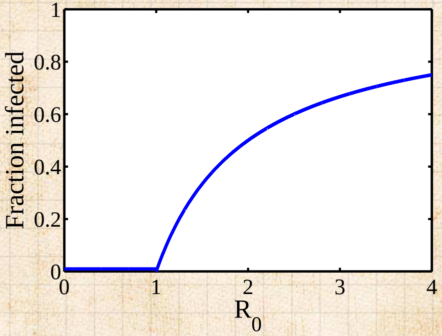
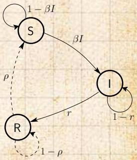


- Continuous phase transition.



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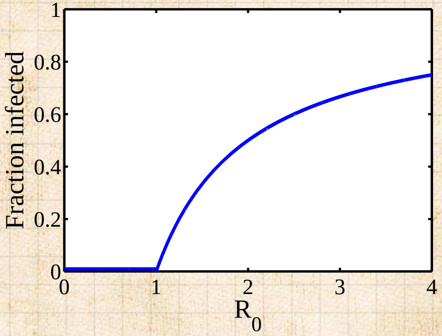
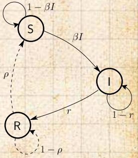


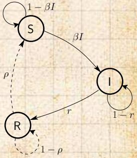
- Continuous phase transition.
- Fine idea from a simple model.



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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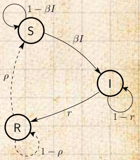

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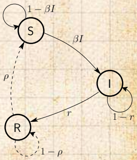

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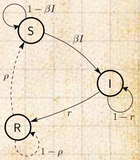

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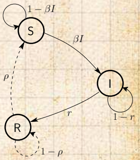

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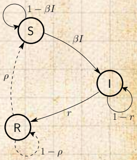
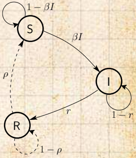
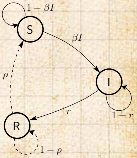


Watch someone else pretend to save the world:

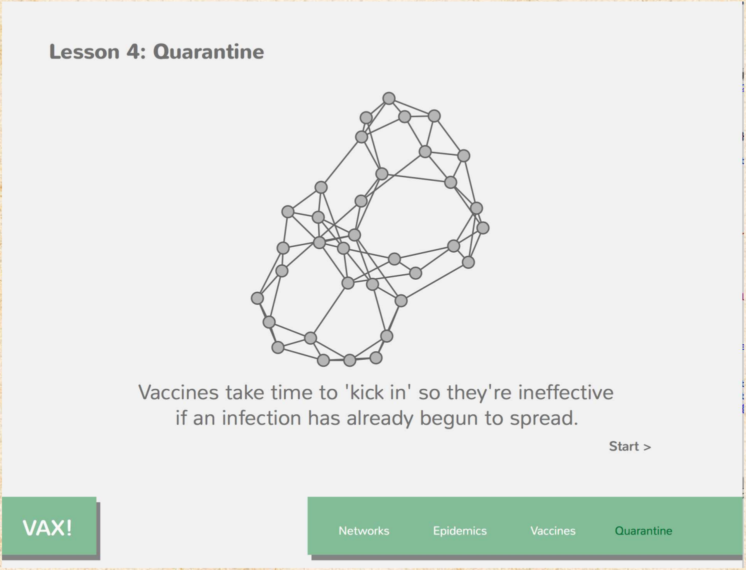


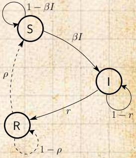
Save the world yourself:

- And you can be the virus.
- Also contagious?: Cooperative games ...



Neural reboot—Save another pretend world with Vax:



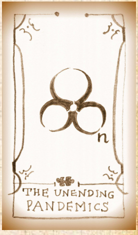


Outline

Introduction

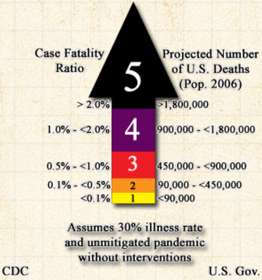
Simple disease spreading models
- Background
- Prediction
- More models
- Toy metapopulation models
- Model output
- Nutshell
- Other kinds of prediction
- Next

References

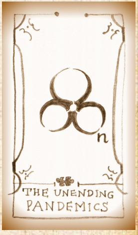


Pandemic severity index (PSI)

- Classification during/post pandemic:



- Category based.
- 1–5 scale.
- Modeled on the Saffir-Simpson hurricane scale.

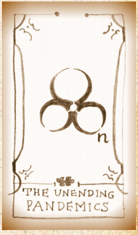


For novel diseases:

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" $\sim$ 75,000,000 world-wide, 500,000 deaths in US.
- 1957-58 "Asian Flu" $\sim$ 2,000,000 world-wide, 70,000 deaths in US.
- 1968-69 "Hong Kong Flu" $\sim$ 1,000,000 world-wide, 34,000 deaths in US.
- 2003 "SARS Epidemic" $\sim$ 800 deaths world-wide.



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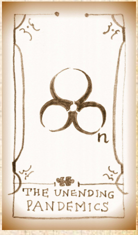

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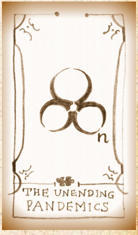

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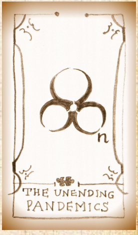

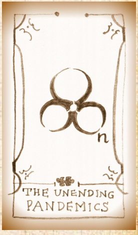

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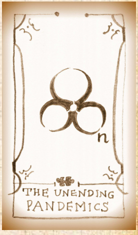

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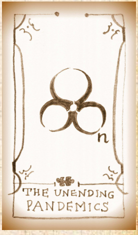

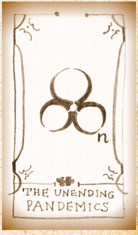

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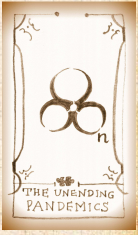

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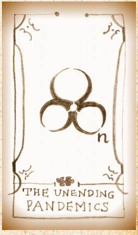

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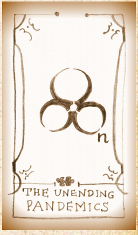

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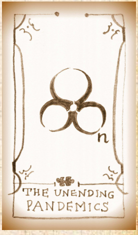

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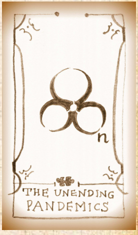

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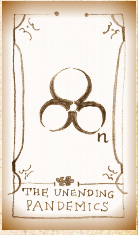

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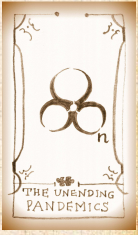

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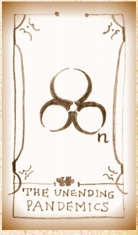

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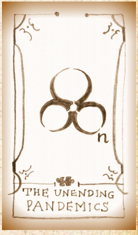

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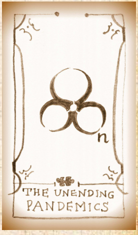

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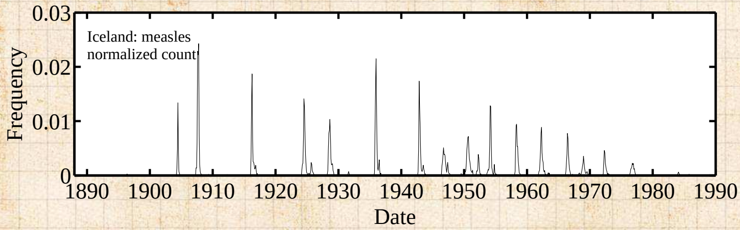
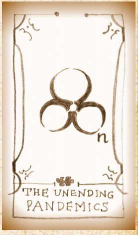
Feeling Ill in Iceland

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

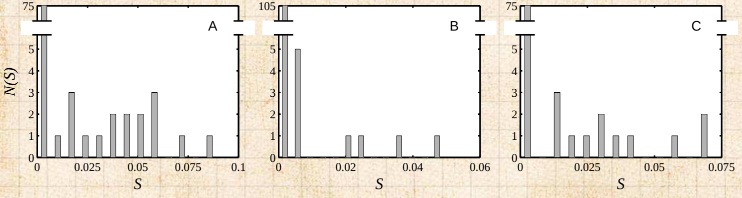


- Treat outbreaks separated in time as 'novel' diseases.

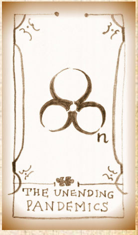


Really not so good at all in Iceland

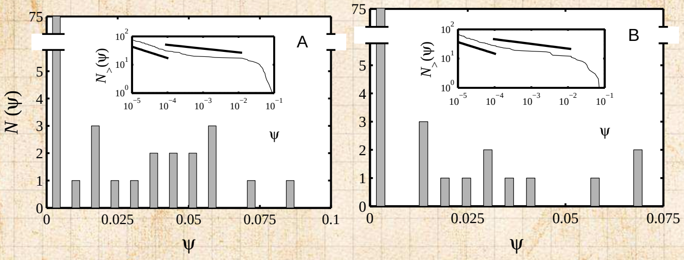
Epidemic size distributions $N(S)$ for Measles, Rubella, and Whooping Cough.

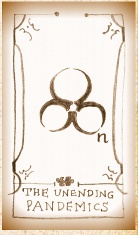


Spike near $S = 0$, relatively flat otherwise.



Measles & Pertussis





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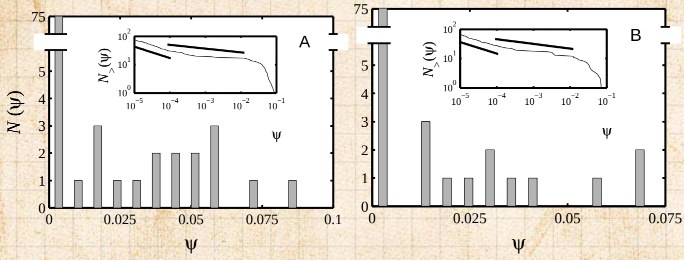
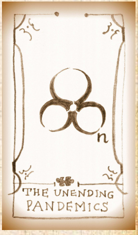


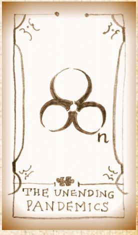
Insert plots:
Complementary cumulative frequency distributions:

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

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)
- When $\gamma < 1$, can't normalize
- Distribution is quite flat.

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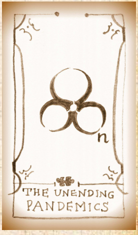

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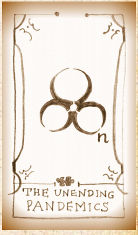

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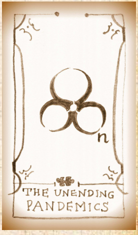

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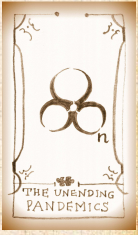

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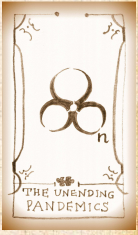

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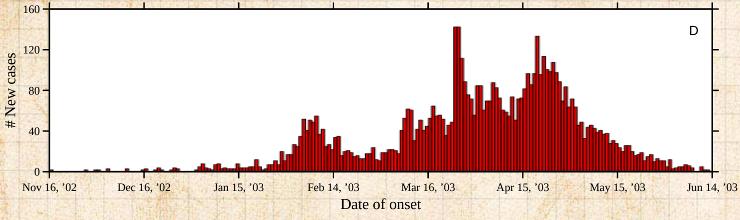
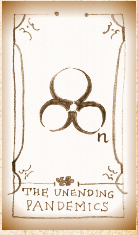


- Epidemic slows...
- Epidemic discovers new 'pools' of susceptibles: Resurgence.
- Importance of rare, stochastic events.



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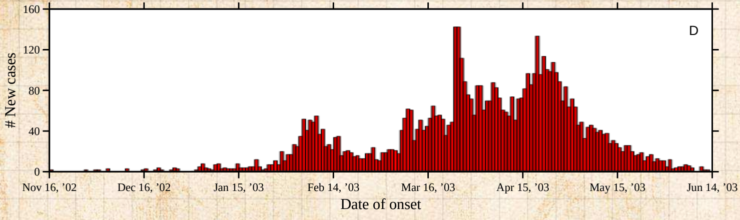

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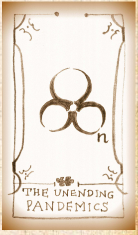

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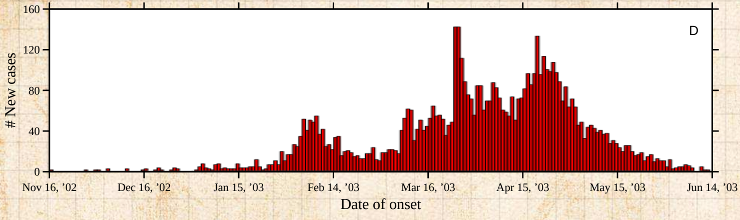

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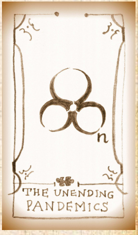

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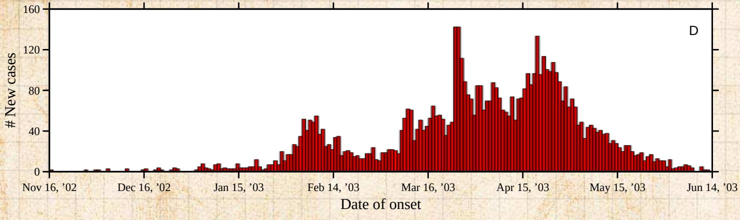

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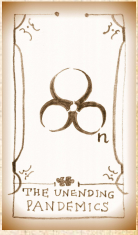

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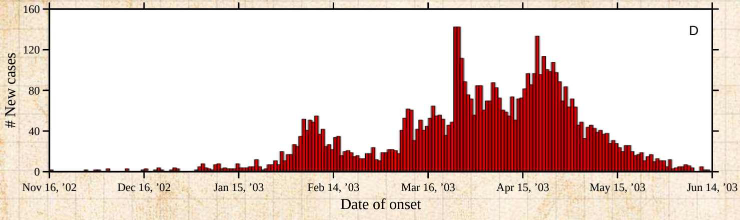

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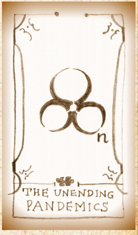
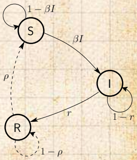


Community—S2E6: Epidemiology

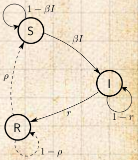
Outline



The challenge

So... can a simple model produce

1. broad epidemic distributions and
2. resurgence ?



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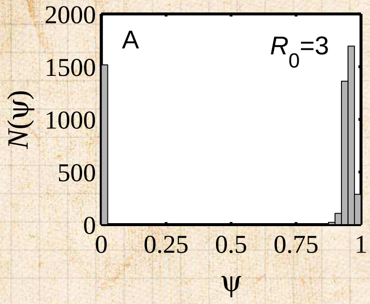
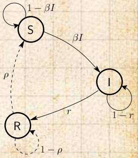


Simple models typically produce bimodal or unimodal size distributions.

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



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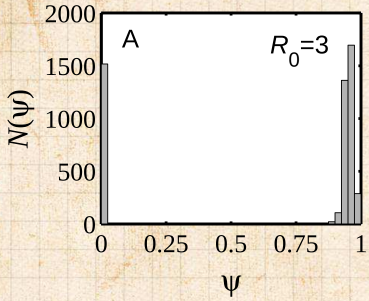

Simple models typically produce bimodal or unimodal size distributions.

- This includes network models: random, small-world, scale-free, ...
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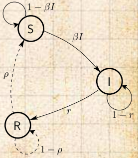

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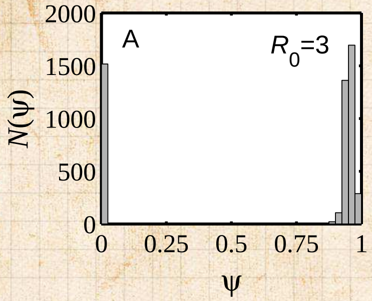

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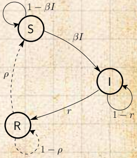

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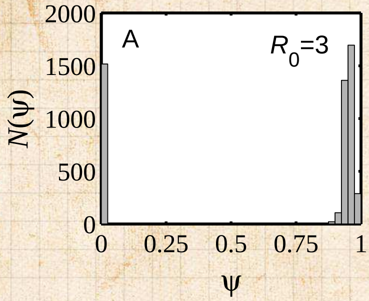

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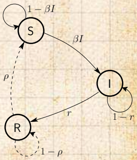

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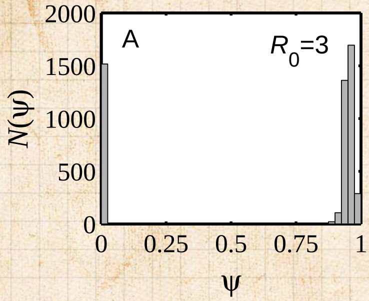

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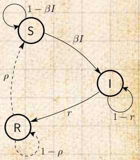

Burning through the population

Forest fire models: [18]

- Rhodes & Anderson, 1996
- The physicist's approach:
  "if it works for magnets, it'll work for people..."

A bit of a stretch:

1. Epidemics ≡ forest fires spreading on 3-d and 5-d lattices.
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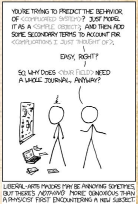

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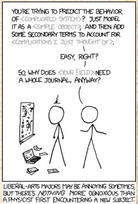

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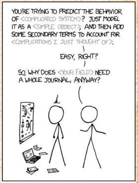

LIBERAL-ARTS MAJORS MAY BE ANNOYING SOMETIMES, BUT THERE'S NOTHING MORE OBNOXIOUS THAN A PHYSICIST FIRST ENCOUNTERING A NEW SUBJECT.

The UNIVERSITY of VERMONT

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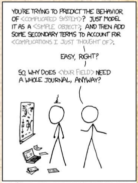

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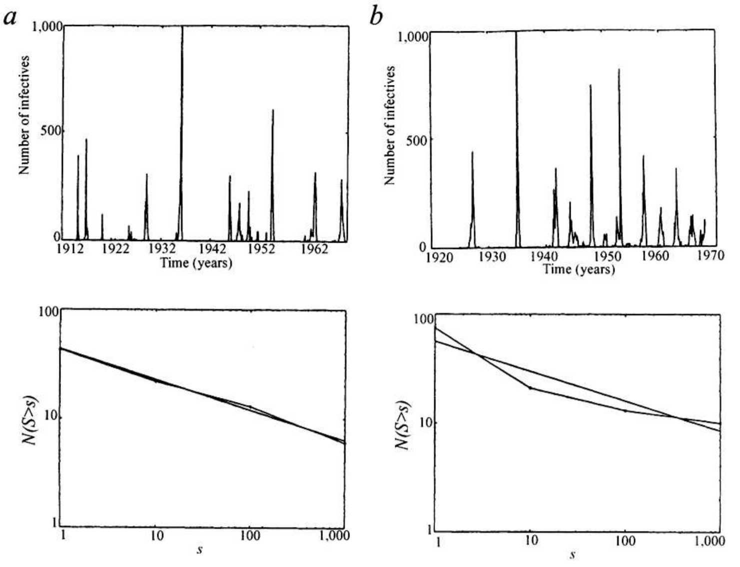
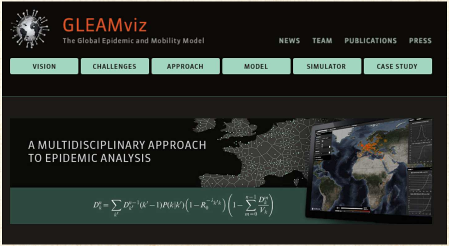


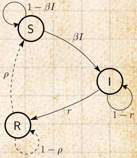
From Rhodes and Anderson, 1996.

Sophisticated metapopulation models:

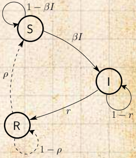
- Multiscale models suggested earlier by others but not formalized (Bailey [1], Cliff and Haggett [5], Ferguson et al.)
- Community based mixing (two scales)—Longini. [16]
- Eubank et al.'s EpiSims/TRANSIMS—city simulations. [8]
- Spreading through countries—Airlines: Germann et al., Colizza et al. [6]



- GLEAM: Global pandemic simulations by Vespignani et al.



Community—S2E6: Epidemiology



Size distributions

- Vital work but perhaps hard to generalize from...
- $\Rightarrow$ Create a simple model involving multiscale travel
- Very big question: What is N?
- Should we model SARS in Hong Kong as spreading in a neighborhood, in Hong Kong, Asia, or the world?
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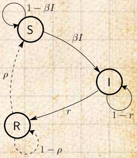

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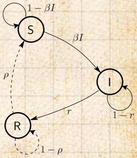

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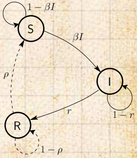

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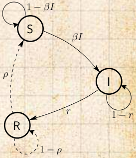

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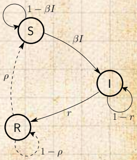
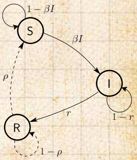
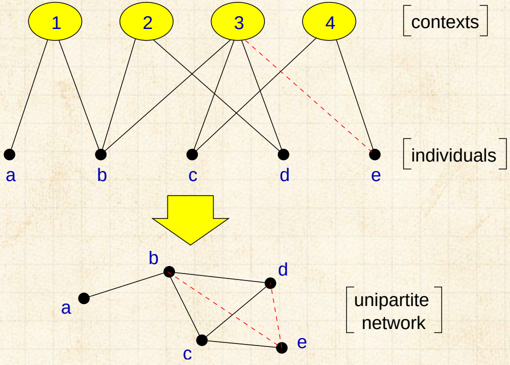


Outline



Improving simple models

Contexts and Identities—Bipartite networks



- boards of directors
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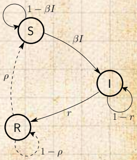

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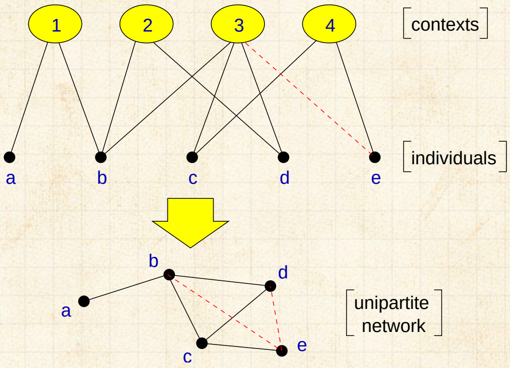

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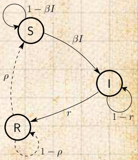

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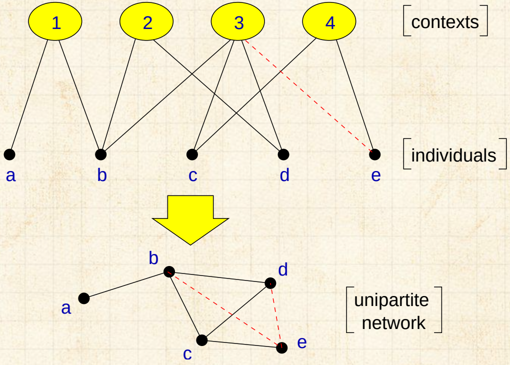

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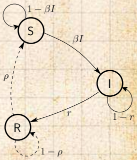

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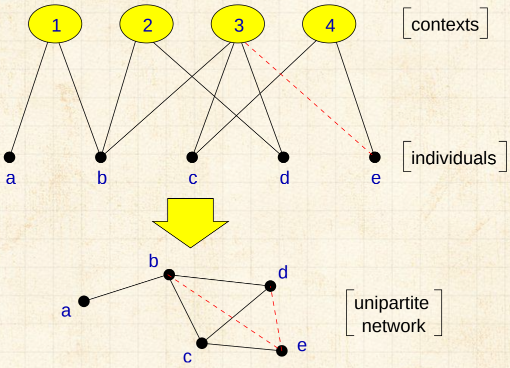

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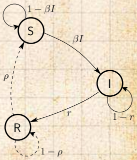

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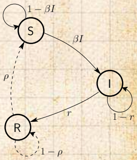
Idea for social networks: incorporate identity

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 ⇔ Contexts ⇔ Interactions ⇔ Networks. [22]



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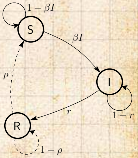

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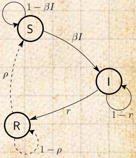

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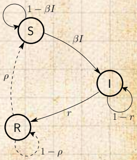

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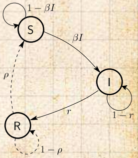

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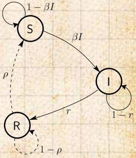

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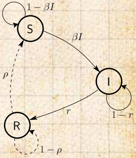

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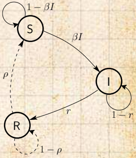

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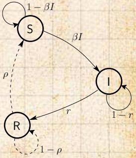
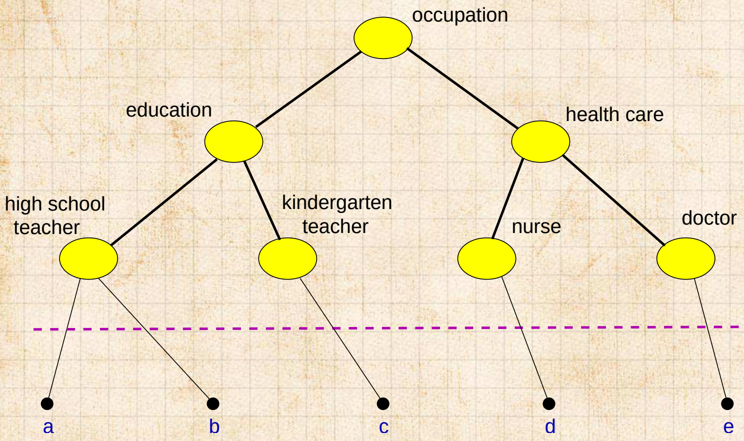
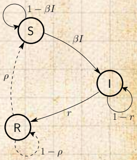


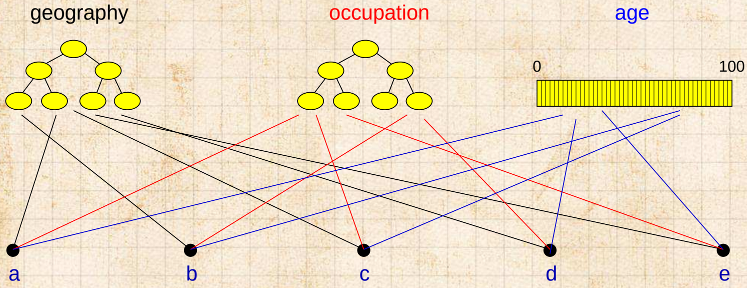
Infer interactions/network from identities



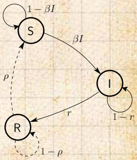
Distance makes sense in identity/context space.



Generalized context space



(Blau & Schwartz [3], Simmel [19], Breiger [4])



A toy agent-based model:

"Multiscale, resurgent epidemics in a hierarchcial metapopulation model"
Watts et al.,
Proc. Natl. Acad. Sci., **102**, 11157–11162, 2005. [23]

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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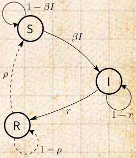

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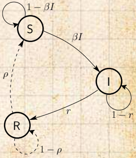

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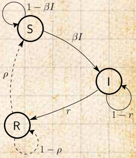

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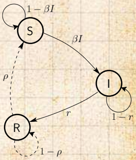

A toy agent-based model:

"Multiscale, resurgent epidemics in a hierarchcial metapopulation model"
Watts et al.,
Proc. Natl. Acad. Sci., **102**, 11157–11162, 2005. [23]

Geography: allow people to move between contexts

- Locally: standard SIR model with random mixing
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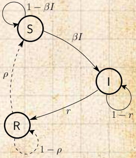

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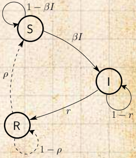

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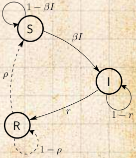

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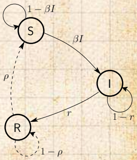

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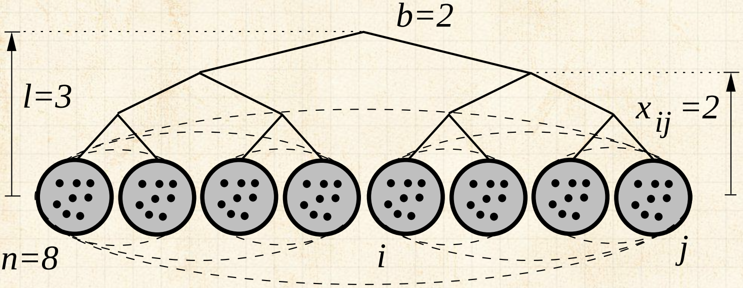

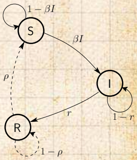

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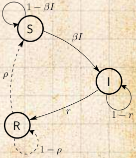
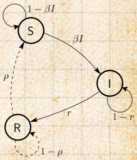


Model output

- 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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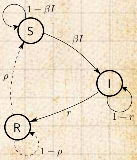

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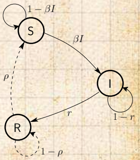
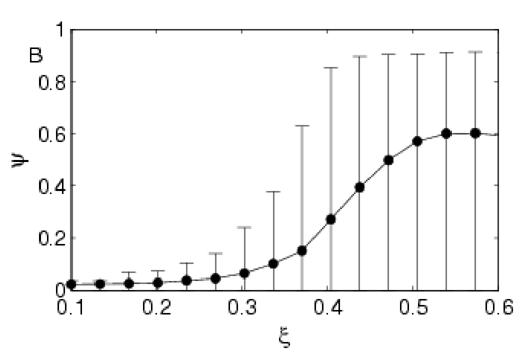
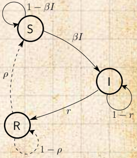


Model output

Varying ξ:



- Transition in expected final size based on typical movement distance



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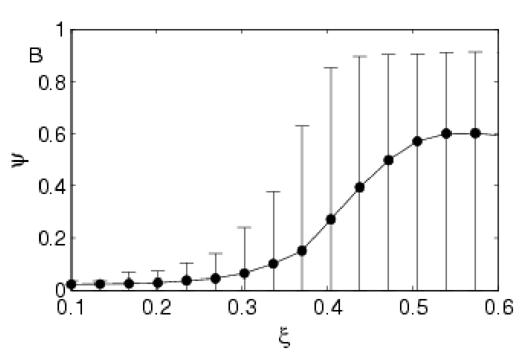
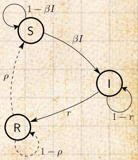
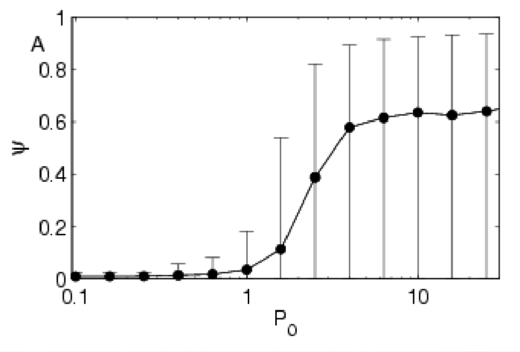


- Transition in expected final size based on typical movement distance (sensible)

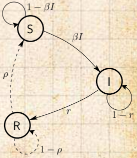


Model output

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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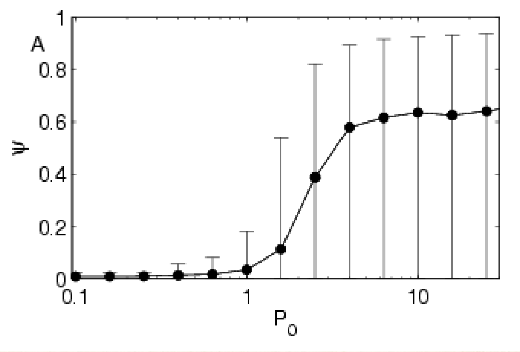

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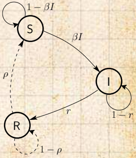

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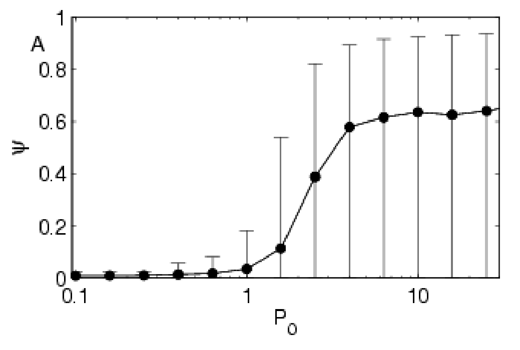

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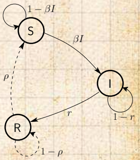
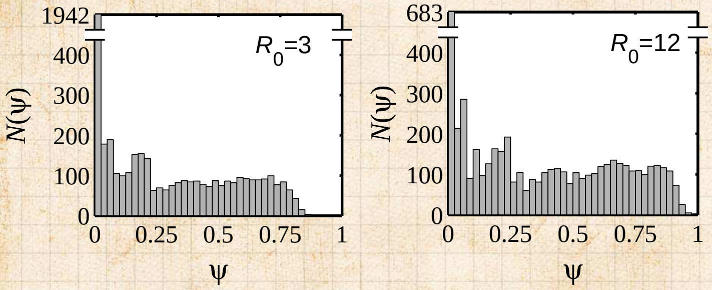
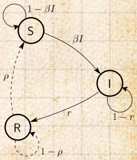


Example model output: size distributions



- 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



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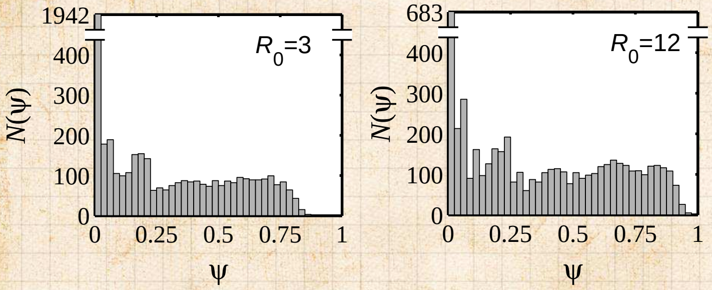

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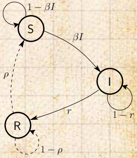

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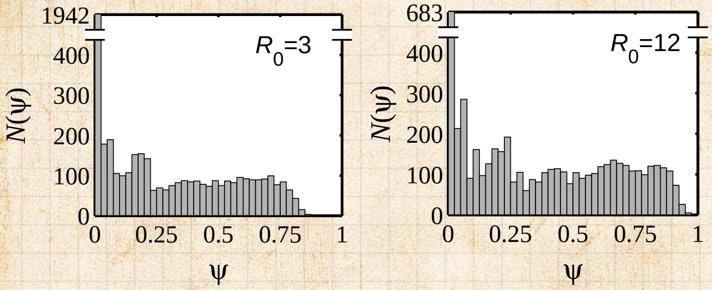

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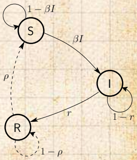

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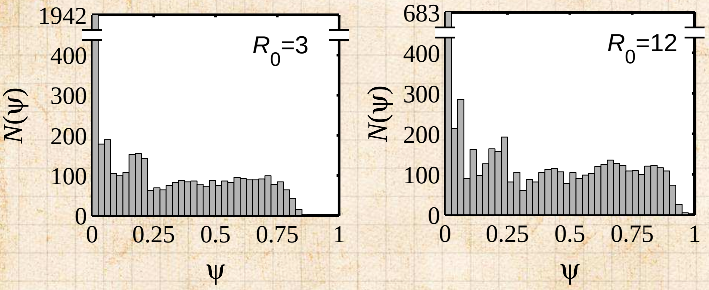

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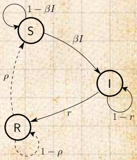

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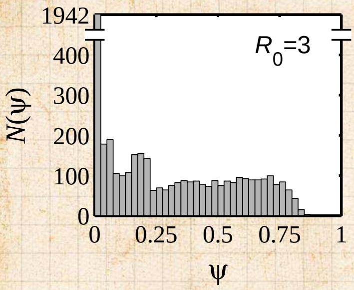

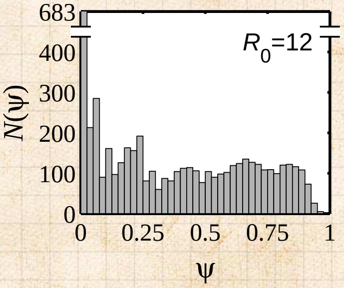

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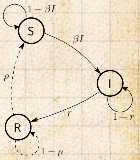
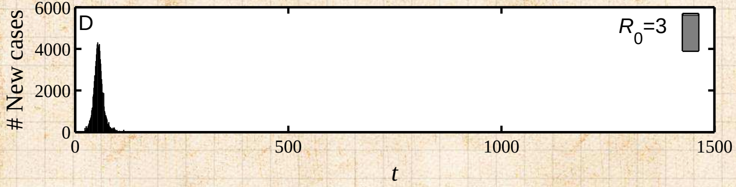
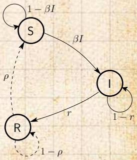


Model output—resurgence

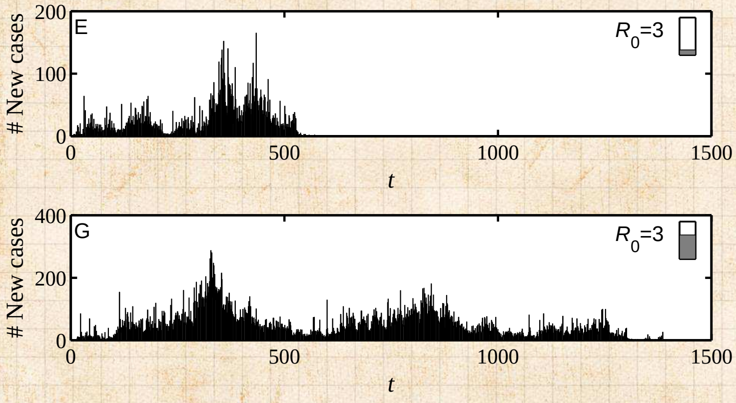
Standard model:

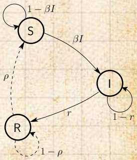




Model output—resurgence

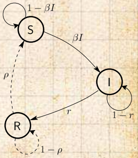
Standard model with transport:





The upshot

Simple multiscale population structure



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Simple multiscale population structure

+

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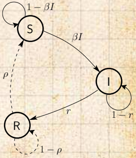
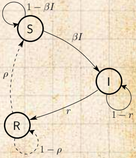


The upshot

Simple multiscale population structure
+
stochasticity

leads to

resurgence
+
broad epidemic size distributions

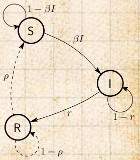


Outline

Introduction

Simple disease spreading models
- Background
- Prediction
- More models
- Toy metapopulation models
- Model output
- Nutshell
- Other kinds of prediction
- Next

References



Nutshelling

- For the hierarchical movement 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,
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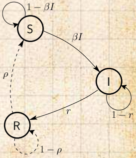
- Problem: R_0 summarises one epidemic after the fact and enfolds movement, the price of bananas, everything.



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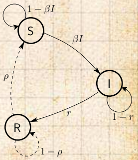

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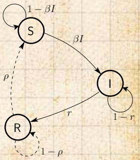

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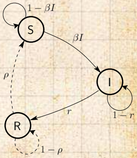

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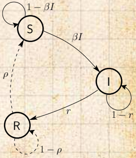

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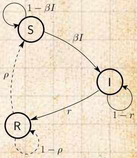

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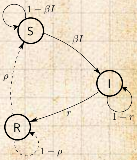

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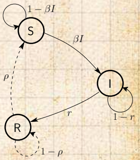

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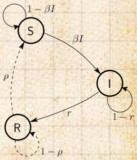
- Disease's spread is highly sensitive to population structure.
- Rare events may matter enormously.
- More support for controlling population movement.



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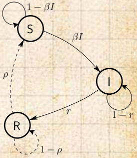

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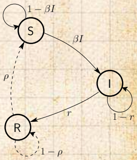

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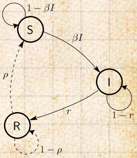

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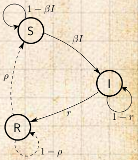
- More support for controlling population movement:
  e.g., travel advisories, quarantine



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What to do:

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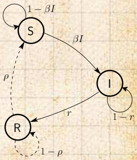
- R_0 needs a friend or two.
- Need $R_0 > 1$ and $P_0 > 1$ and ξ sufficiently large for disease to have a chance of spreading
- And in general: keep building up the kitchen sink models.

More wondering:

- Exactly how important are rare events in disease spreading?
- Again, what is N?



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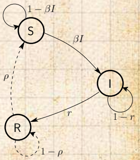

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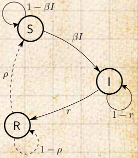

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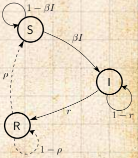

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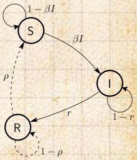

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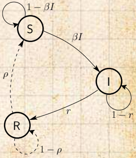

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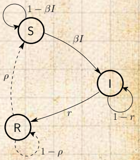

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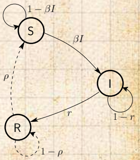


THE SUN
THE MANIFESTO
THE WELL OF SCALES
THE LAWS OF DECAYING POWER
MINISTRY OF RANDOM WALKS
THE UNEXPECTED TRANSFIGURATION
THE RICH GET RICHER
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THE DATA POOR
THE POURING DATA
THE EMERGENCE OF STRUCTURE
THE EMERGENCE OF DESTRUCTION
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THE NETWORKS COMPLEX
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THE SMALLNESS OF WORLDS
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THE NETWORKS FREE OF SCALE
THE UNENDING PANDEMICS
THE CONFUSION OF CONTAGIONS
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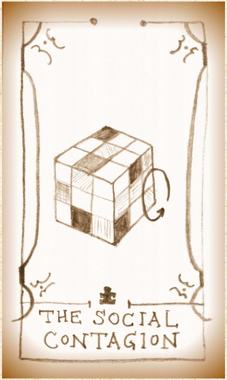
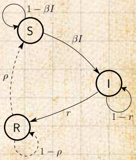

THE SOCIAL CONTAGION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Outline

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

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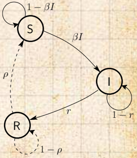

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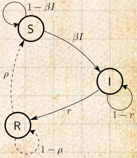

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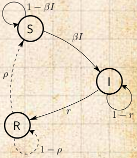

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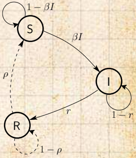

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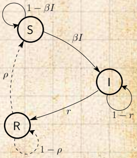

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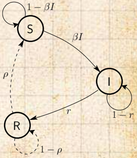

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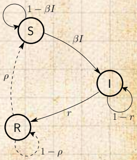

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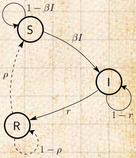

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Alan Greenspan (September 18, 2007):

"I've been dealing with these big mathematical models of forecasting the economy ...

If I could figure out a way to determine whether or not people are more fearful or changing to more euphoric,

I don't need any of this other stuff.

I could forecast the economy better than any way I know."

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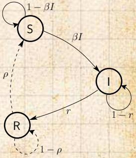

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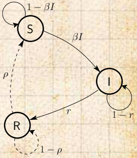

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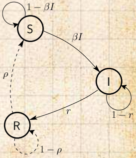

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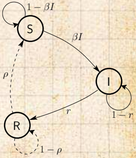

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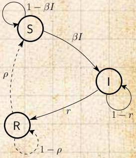

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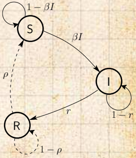

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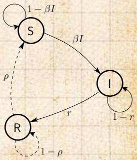

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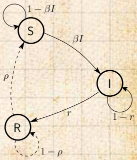

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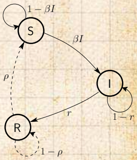

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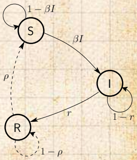

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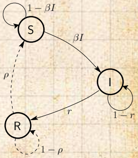

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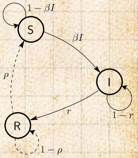

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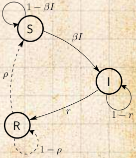
Jon Stewart:

"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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"Greenspan Concedes Error on Regulation"

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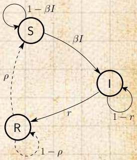
New York Times, October 23, 2008



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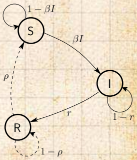

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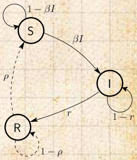

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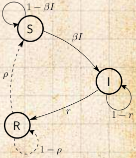

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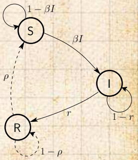

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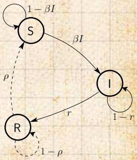

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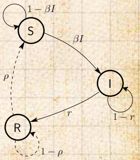

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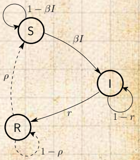

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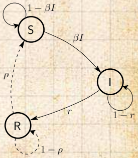

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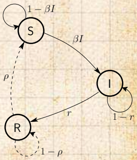

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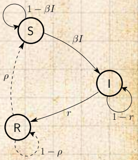

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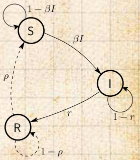

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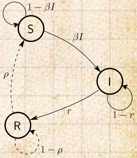

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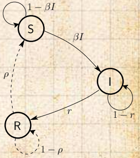

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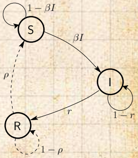

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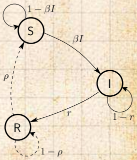

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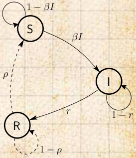

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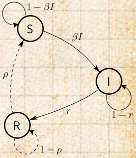

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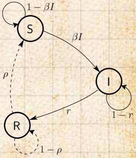

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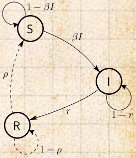

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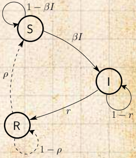

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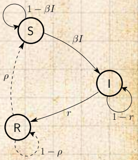

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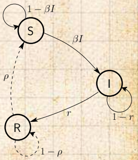

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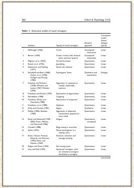

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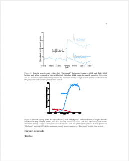

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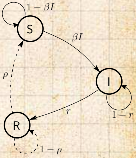

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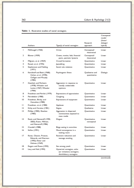

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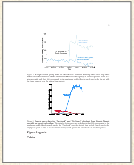

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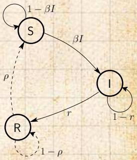

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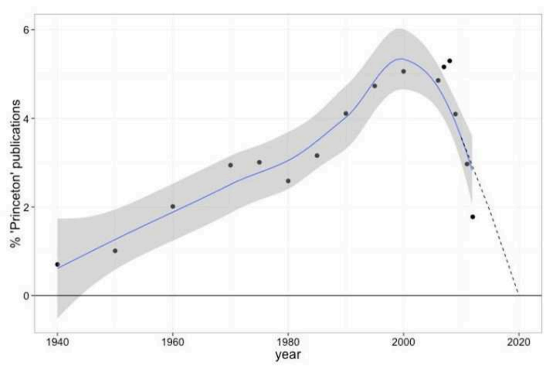
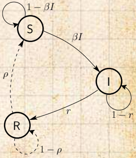


- Mike Develin, Lada Adamic, and Sean Taylor.



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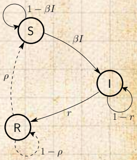

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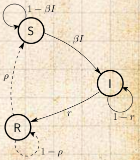

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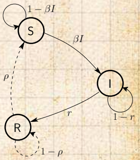

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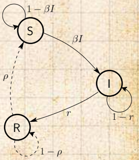

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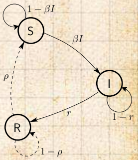

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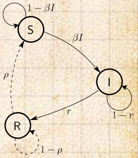

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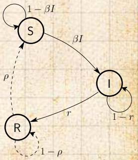

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