

# Biological Contagion

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Principles of Complex Systems, Vols. 1 & 2  
CSYS/MATH 300 and 303, 2021-2022 | @pocsvox

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Computational Story Lab | Vermont Complex Systems Center  
Vermont Advanced Computing Core | University of Vermont



The PoCVerse  
Biological  
Contagion  
1 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

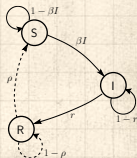
Model output

Nutshell

Other kinds of prediction

Next

References



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The PoCSverse  
Biological  
Contagion  
2 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

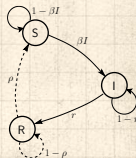
Nutshell

Other kinds of prediction

Next

References

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The PoCSverse  
Biological  
Contagion  
3 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

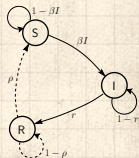
Model output



Nutshell

Other kinds of prediction

Next

References



 On Instagram at [pratchett\\_the\\_cat](https://www.instagram.com/pratchett_the_cat) 

# Outline

## Introduction

## Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

## References

The PoCSverse  
Biological  
Contagion  
4 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

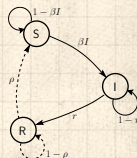
Model output

Nutshell

Other kinds of prediction

Next

References









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

## Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

## References



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## 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.*

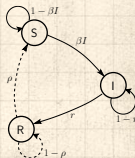
Death toll (estimate)	Location	Date	Comment	Disease	Reference
ca. 75,000 - 100,000	Greece	429–426 BC	Known as <b>Plague of Athens</b> , because it was primarily in Athens.	unknown, similar to typhoid	
ca. 30% of population	Europe, Western Asia, Northern Africa	165–180	Known as <b>Antonine Plague</b>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

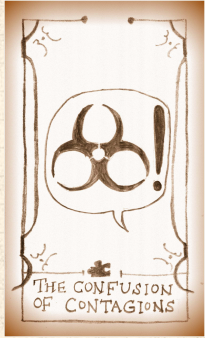


Plague panel with the triumph of death, 1607–35, Deutsches Historisches Museum Berlin



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







# Contagion

The PoCSverse  
Biological  
Contagion  
9 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

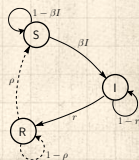
Nutshell

Other kinds of prediction

Next

## References

A confusion of contagions:



# Contagion

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell

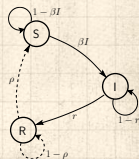
Other kinds of prediction

Next

## References

A confusion of contagions:

 Did Harry Potter spread like a virus?



# Contagion

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction

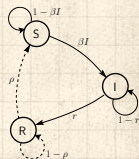
Next

## References

A confusion of contagions:

 Did Harry Potter spread like a virus?

 Can disinformation be “infectious”?



# Contagion

## Introduction

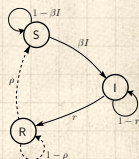
### Simple disease spreading models

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

## References

## A confusion of contagions:

- Did Harry Potter spread like a virus?
- Can disinformation be “infectious”?
- Suicide, violence?



# Contagion

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

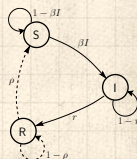
Other kinds of prediction

Next

References

A confusion of contagions:

- Did Harry Potter spread like a virus?
- Can disinformation be “infectious”?
- Suicide, violence?
- Morality? Evil? Laziness? Stupidity? Happiness?



# Contagion

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

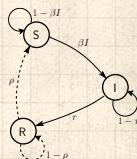
Other kinds of prediction

Next

References

## A confusion of contagions:

- Did Harry Potter spread like a virus?
- Can disinformation be “infectious”?
- Suicide, violence?
- Morality? Evil? Laziness? Stupidity? Happiness?
- Religion?



# Contagion

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

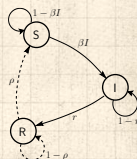
Other kinds of prediction

Next

References

## A confusion of contagions:

- Did Harry Potter spread like a virus?
- Can disinformation be “infectious”?
- Suicide, violence?
- Morality? Evil? Laziness? Stupidity? Happiness?
- Religion?
- Democracy ...?



# Contagion

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

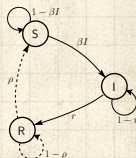
Other kinds of prediction

Next

References

## A confusion of contagions:

- Did Harry Potter spread like a virus?
- Can disinformation be “infectious”?
- Suicide, violence?
- Morality? Evil? Laziness? Stupidity? Happiness?
- Religion?
- Democracy ...?
- Language? The alphabet? <sup>[10]</sup>





# Contagion

## Introduction

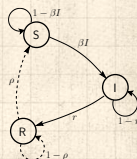
### Simple disease spreading models

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

### References

## A confusion of contagions:

- Did Harry Potter spread like a virus?
- Can disinformation be “infectious”?
- Suicide, violence?
- Morality? Evil? Laziness? Stupidity? Happiness?
- Religion?
- Democracy ...?
- Language? The alphabet? <sup>[10]</sup>
- Stories?



# Contagion

## Naturomorphisms

The PoCSverse  
Biological  
Contagion  
10 of 97

### Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

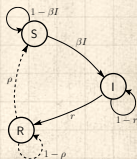
Model output

Nutshell

Other kinds of prediction


Next

References



# Contagion

## Naturomorphisms

 "The feeling was contagious."

The PoCSverse  
Biological  
Contagion  
10 of 97

### Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

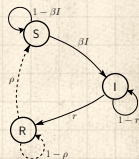
Model output

Nutshell

Other kinds of prediction


Next


### References



# Contagion

## Naturomorphisms

 "The feeling was contagious."

 "The news spread like wildfire."

### Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

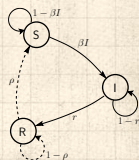
Model output

Nutshell

Other kinds of prediction

Next

### References



# 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

### Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

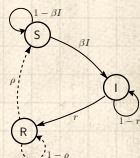
Model output

Nutshell

Other kinds of prediction

Next

### References



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## Naturomorphisms

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- “Nothing is so contagious as enthusiasm.”  
—Samuel Taylor Coleridge

### Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

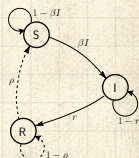
Model output

Nutshell

Other kinds of prediction

Next

### References



# Contagion

## Naturomorphisms



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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. ...

### Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

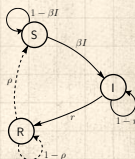
Model output

Nutshell

Other kinds of prediction

Next

### References



# Contagion

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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. ... **It is hereditary, but fortunately not contagious.**

### Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

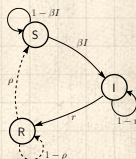
Model output

Nutshell

Other kinds of prediction

Next

### References





# Social contagion

Eric Hoffer, 1902–1983

There is a grandeur in the uniformity of the mass.

The PoCSverse  
Biological  
Contagion  
11 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

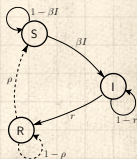
Model output

Nutshell

Other kinds of prediction

Next

## References



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There is a grandeur in the uniformity of the mass.  
When a fashion, a dance, a song, a slogan or a joke

The PoCSverse  
Biological  
Contagion  
11 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

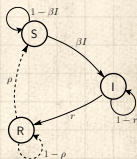
Model output

Nutshell

Other kinds of prediction

Next

## References



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When a fashion, a dance, a song, a slogan or a joke  
sweeps like **wildfire** from one end of the continent to  
the other,

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

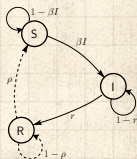
Model output

Nutshell

Other kinds of prediction

Next

References



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When a fashion, a dance, a song, a slogan or a joke  
sweeps like **wildfire** from one end of the continent to  
the other, and a hundred million people roar with  
laughter,

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

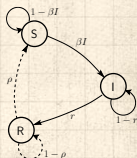
Model output

Nutshell

Other kinds of prediction

Next

References



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sweeps like **wildfire** from one end of the continent to  
the other, and a **hundred million people roar with  
laughter**, sway their bodies in unison,

The PoCSverse  
Biological  
Contagion  
11 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

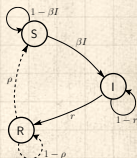
Model output

Nutshell

Other kinds of prediction

Next

References



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## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

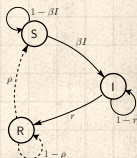
Model output

Nutshell

Other kinds of prediction

Next

References



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## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

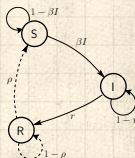
Model output

Nutshell

Other kinds of prediction

Next



References



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 Hoffer  was an interesting fellow...

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

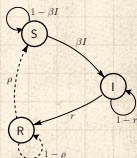
Model output

Nutshell

Other kinds of prediction

Next

References





# The spread of fanaticism

Hoffer's most famous work: "**The True Believer:**  
Thoughts On The Nature Of Mass Movements"  
(1951)<sup>[12]</sup>

Aphorisms-aplenty:

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

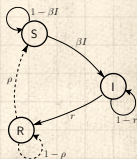
Model output

Nutshell

Other kinds of prediction

Next


## References



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Aphorisms-aplenty:

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we do not understand."

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

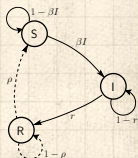
Model output

Nutshell

Other kinds of prediction

Next

References



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(1951)<sup>[12]</sup>

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."

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

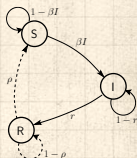
Model output

Nutshell

Other kinds of prediction

Next

References



# The spread of fanaticism

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

Next

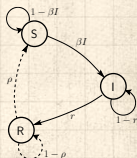
References

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## 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."

"



# The spread of fanaticism

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

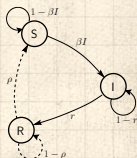
Next

References

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## 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."



# Imitation

The PoCSverse  
Biological  
Contagion  
13 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

Next

References



## CONFORMITY

WHEN PEOPLE ARE FREE TO DO AS THEY PLEASE,  
THEY USUALLY IMITATE EACH OTHER.

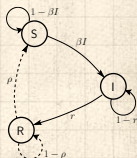
www.despair.com

despair.com

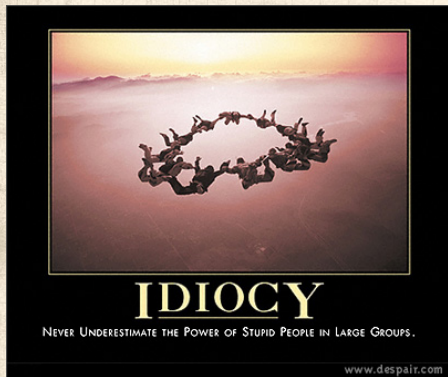
“When people are free to do as they please, they usually imitate each other.”

—Eric Hoffer

“The Passionate State of Mind” [13]



# The collective...



despair.com

“Never Underestimate the Power of Stupid People in Large Groups.”

The PoCSverse  
Biological Contagion  
14 of 97

## Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

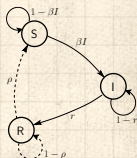
Model output

Nutshell

Other kinds of prediction


Next

References



# Examples of non-disease spreading:

## Interesting infections:

 Spreading of certain buildings in the US:

### Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

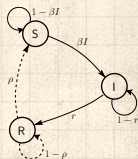
Model output

Nutshell

Other kinds of prediction

Next

### References



<http://www.youtube.com/watch?v=EGzHBtoVvpc?rel=0>



## Marbleization of the US:

### Introduction

#### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation  
models

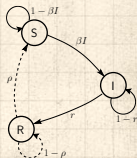
Model output

Nutshell

Other kinds of prediction

Next

### References



<http://www.youtube.com/watch?v=9ihSeStoXOw?rel=0>

# The most terrifying contagious outbreak?

The PoCSverse  
Biological  
Contagion  
17 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

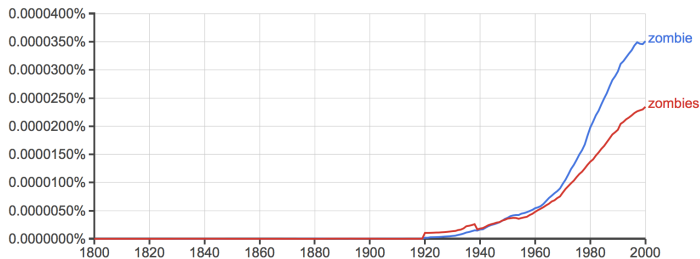
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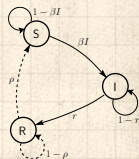
Google books Ngram Viewer

Graph these comma-separated phrases:   case-insensitive

between  and  from the corpus  with smoothing of  [Search lots of books](#)



(click on line/label for focus)



## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

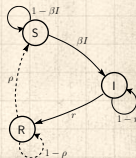
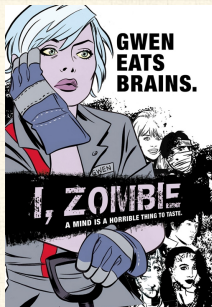
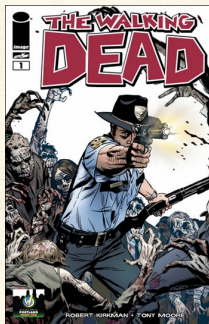
Model output

Nutshell

Other kinds of prediction

Next

## References



# Contagion

The PoCSverse  
Biological  
Contagion  
19 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

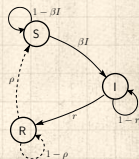
Nutshell

Other kinds of prediction

Next

## References

## Definitions



## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

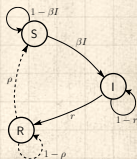
Next

## References

## Definitions



(1) The spreading of a quality or quantity between individuals in a population.



# Contagion

## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output



Nutshell

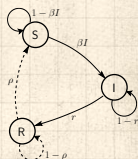
Other kinds of prediction

Next

## References

## 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, ...



## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output




Nutshell

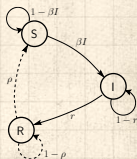
Other kinds of prediction

Next

## References

## 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* = 'with' + *tangere* 'to touch.'



## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output





Nutshell

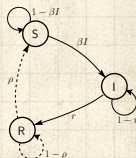
Other kinds of prediction

Next

## References

## 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* = 'with' + *tangere* 'to touch.'
-  Contagion has unpleasant overtones...





## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output


Nutshell


Other kinds of prediction


Next


### References


## Definitions

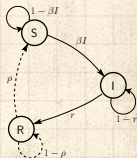
 (1) The spreading of a quality or quantity between individuals in a population.

 (2) A disease itself:  
the plague, a blight, the dreaded lurgi, ...

 from Latin: *con* = 'with' + *tangere* 'to touch.'

 Contagion has unpleasant overtones...

 Just **Spreading** might be a more neutral word



# Contagion

## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

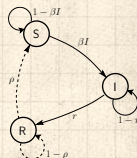
Other kinds of prediction

Next

### References

## 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* = 'with' + *tangere* 'to touch.'
- 🧱 Contagion has unpleasant overtones...
- 🧱 Just **Spreading** might be a more neutral word
- 🧱 But contagion is kind of exciting...



# Contagions

The PoCSverse  
Biological  
Contagion  
20 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

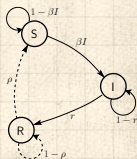
Nutshell

Other kinds of prediction

Next

## References

Two main classes of contagion



# Contagions

The PoCSverse  
Biological  
Contagion  
20 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

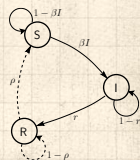
Other kinds of prediction

Next

References

Two main classes of contagion

## 1. Infectious diseases



# Contagions

The PoCSverse  
Biological  
Contagion  
20 of 97

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

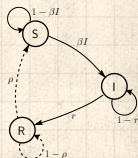
Next

References

Two main classes of contagion

1. Infectious diseases

2. Social contagion



# Contagions

## Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

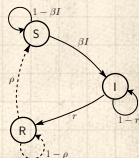
Other kinds of prediction

Next

References

## Two main classes of contagion

1. **Infectious diseases:**  
tuberculosis, HIV, ebola, SARS, influenza,  
zombification, ...
2. **Social contagion**



# Contagions

## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

Next

## References

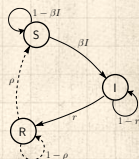
## Two main classes of contagion

### 1. Infectious diseases:

tuberculosis, HIV, ebola, SARS, influenza,  
zombification, ...

### 2. Social contagion:

fashion, word usage, rumors, uprisings, religion,  
stories about zombies, ...



# Archival footage from the Black Plague

## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

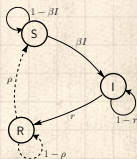
Nutshell

Other kinds of prediction

Next

## References

<http://www.youtube.com/watch?v=GU0d8kpybVg?rel=0>





## Community—S2E6: Epidemiology

### Introduction

#### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation  
models

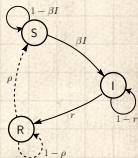
Model output

Nutshell

Other kinds of prediction

Next

### References



# Outline

## Introduction

## Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

## References

The PoCSverse  
Biological  
Contagion  
23 of 97

Introduction

Simple disease  
spreading models

**Background**

Prediction

More models

Toy metapopulation  
models

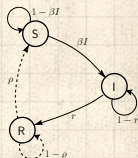
Model output

Nutshell

Other kinds of prediction

Next

References





# Mathematical Epidemiology

The PoCSverse  
Biological  
Contagion  
25 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

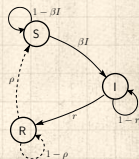
Nutshell

Other kinds of prediction

Next


References

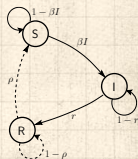
The standard SIR model [18]



# Mathematical Epidemiology

The standard SIR model <sup>[18]</sup>

 = basic model of disease contagion



# Mathematical Epidemiology

The PoCSverse  
Biological  
Contagion  
25 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction

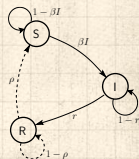
Next

References

The standard **SIR model** [18]

 = basic model of disease contagion

 Three states:



# Mathematical Epidemiology

The PoCSverse  
Biological  
Contagion  
25 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction

Next

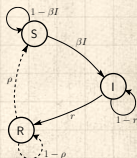
References

The standard **SIR model** <sup>[18]</sup>

 = basic model of disease contagion

 Three states:

1.  $S$  = Susceptible



# Mathematical Epidemiology

The PoCSverse  
Biological  
Contagion  
25 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction

Next

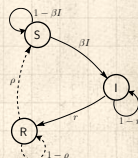
References

The standard **SIR model** [18]

 = basic model of disease contagion

 Three states:


1. S = Susceptible
2. I = Infective/Infectious






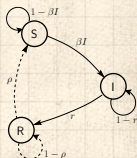
# Mathematical Epidemiology

## The standard SIR model <sup>[18]</sup>

 = basic model of disease contagion

 Three states:

1. S = Susceptible
2. I = Infective/Infectious
3. R = Recovered



# Mathematical Epidemiology

The PoCSverse  
Biological  
Contagion  
25 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction

Next

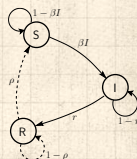
References

The standard **SIR model** <sup>[18]</sup>

 = basic model of disease contagion


 Three states:


1. S = Susceptible
2. I = Infective/Infectious
3. R = Recovered or Removed or Refractory




# Mathematical Epidemiology

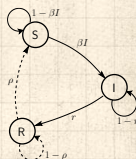
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 = basic model of disease contagion


 Three states:


1. S = Susceptible
2. I = Infective/Infectious
3. R = Recovered or Removed or Refractory

  $S(t) + I(t) + R(t) = 1$





## The standard SIR model <sup>[18]</sup>

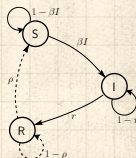
 = basic model of disease contagion

 Three states:

1. S = Susceptible
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3. R = Recovered or Removed or Refractory


  $S(t) + I(t) + R(t) = 1$


 Presumes random interactions (mass-action principle)




# Mathematical Epidemiology


## The standard SIR model <sup>[18]</sup>


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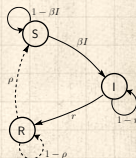
 Three states:

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 Presumes random interactions (mass-action principle)

 Interactions are independent (no memory)





## The standard SIR model <sup>[18]</sup>


 = basic model of disease contagion


 Three states:

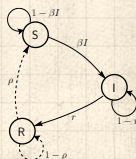
1. S = Susceptible
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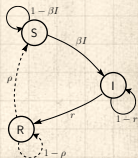
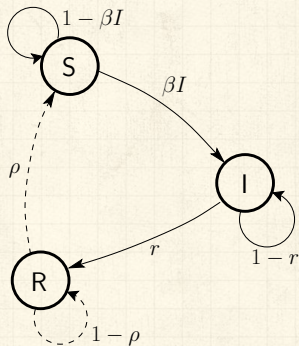
 Presumes random interactions (mass-action principle)

 Interactions are independent (no memory)

 Discrete and continuous time versions

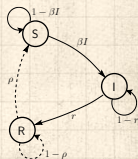
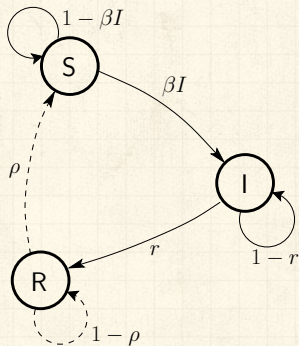


## Discrete time automata example:



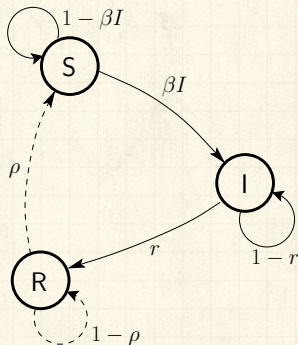
## Discrete time automata example:

Transition Probabilities:



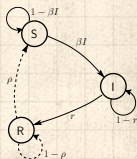


## Discrete time automata example:

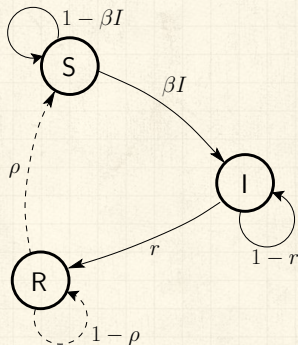


Transition Probabilities:

$\beta$  for being infected given contact with infected

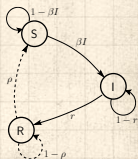


## Discrete time automata example:

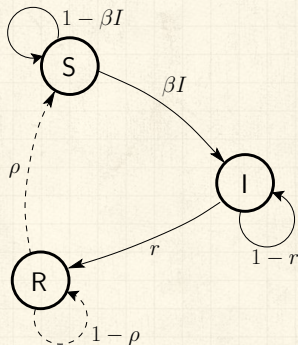


Transition Probabilities:

$\beta$  for being infected given  
contact with infected  
 $r$  for recovery



## Discrete time automata example:

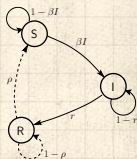


## Transition Probabilities:

$\beta$  for being infected given  
contact with infected

$r$  for recovery

$\rho$  for loss of immunity



# Mathematical Epidemiology

The PoCSverse  
Biological  
Contagion  
27 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

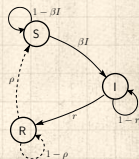
Nutshell

Other kinds of prediction

Next

References

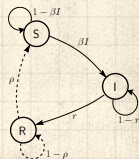
Original models attributed to



Original models attributed to



1920's: Reed and Frost



# Mathematical Epidemiology

The PoCSverse  
Biological  
Contagion  
27 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction

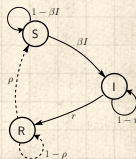
Next

References




Original models attributed to

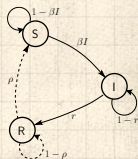
 1920's: Reed and Frost

 1920's/1930's: Kermack and McKendrick [14, 16, 15]



## Original models attributed to

-  1920's: Reed and Frost
-  1920's/1930's: Kermack and McKendrick [14, 16, 15]
-  Coupled differential equations with a mass-action principle



# Independent Interaction models

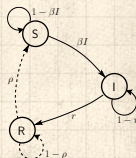
## Differential equations for continuous model

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

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

$$\frac{d}{dt}R = rI - \rho R$$

$\beta$ ,  $r$ , and  $\rho$  are now **rates**.





# Reproduction Number $R_0$

The PoCSverse  
Biological  
Contagion  
29 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

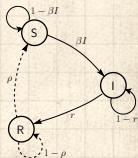
Nutshell

Other kinds of prediction

Next


References

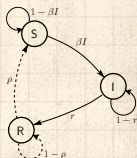
Reproduction Number  $R_0$  ↗



# Reproduction Number $R_0$


## Reproduction Number $R_0$


  $R_0$  = expected number of infected individuals resulting from a single initial infective

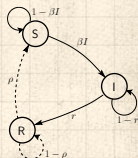


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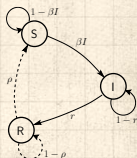
 Epidemic threshold: If  $R_0 > 1$ , 'epidemic' occurs.



# Reproduction Number $R_0$





## Reproduction Number $R_0$

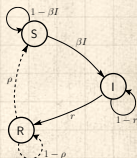
-   $R_0$  = expected number of infected individuals resulting from a single initial infective
-  Epidemic threshold: If  $R_0 > 1$ , 'epidemic' occurs.
-  Exponential take off:  $R_0^n$  where  $n$  is the number of generations.



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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  $SIR$ .

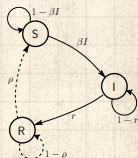


# Reproduction Number $R_0$

## Discrete version:



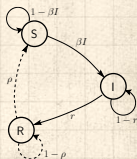
Set up: One Infective in a randomly mixing population of Susceptibles



# Reproduction Number $R_0$

## Discrete version:

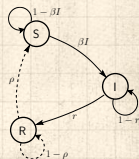
- Set up: One Infective in a randomly mixing population of Susceptibles
- At time  $t = 0$ , single infective random bumps into a Susceptible



# Reproduction Number $R_0$

## 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 =  $\beta$

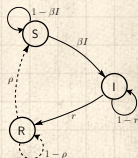




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## Discrete version:

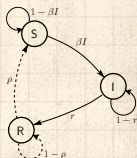
- Set up: One Infective in a randomly mixing population of Susceptibles
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# Reproduction Number $R_0$


## 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 =  $\beta$
- At time  $t = 1$ , single Infective remains infected with probability  $1 - r$
- At time  $t = k$ , single Infective remains infected with probability  $(1 - r)^k$

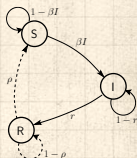


# Reproduction Number $R_0$

Discrete version:


 Expected number infected by original infective:

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



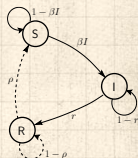
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$$R_0 = \beta + (1 - r)\beta + (1 - r)^2\beta + (1 - r)^3\beta + \dots$$

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



# Reproduction Number $R_0$

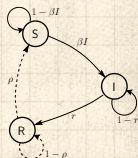
Discrete version:

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


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

$$= \beta \frac{1}{1 - (1 - r)}$$



# Reproduction Number $R_0$

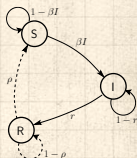
Discrete version:

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

$$= \beta \frac{1}{1 - (1 - r)} = \beta/r$$



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Discrete version:

 Expected number infected by original infective:

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

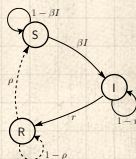
$$= \beta(1 + (1 - r) + (1 - r)^2 + (1 - r)^3 + \dots)$$

$$= \beta \frac{1}{1 - (1 - r)} = \beta/r$$

For  $S(0) \simeq 1$  initial susceptibles

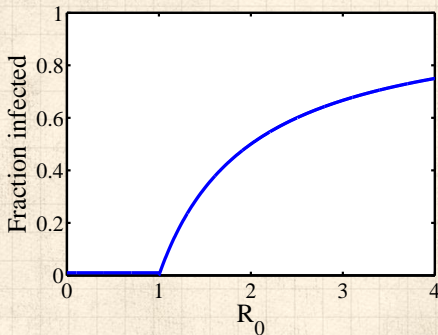
$(1 - S(0) = R(0) =$  fraction initially immune):

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



# Independent Interaction models

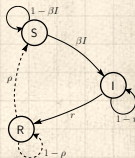
Example of epidemic threshold:



Continuous phase transition.



Fine idea from a simple model.






# Independent Interaction models

The PoCVerse  
Biological  
Contagion  
33 of 97

For the continuous version

 Second equation:

$$\frac{d}{dt}I = \beta SI - rI$$

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

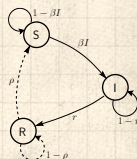
Model output

Nutshell

Other kinds of prediction


Next

References



# Independent Interaction models

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 Second equation:

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$$\frac{d}{dt}I = (\beta S - r)I$$

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

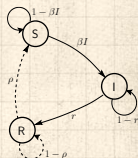
Model output

Nutshell

Other kinds of prediction


Next

References




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 Number of infectives grows initially if

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

where  $S(0) \simeq 1$ .

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

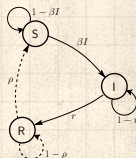
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Nutshell

Other kinds of prediction


Next

References




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Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

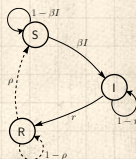
Model output

Nutshell

Other kinds of prediction


Next

References




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Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

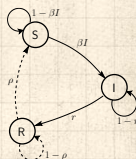
Model output

Nutshell

Other kinds of prediction


Next

References




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$$\frac{d}{dt}I = (\beta S - r)I$$

 Number of infectives grows initially if

$$\beta S(0) - r > 0 \Rightarrow \beta S(0) > r \Rightarrow \beta S(0)/r > 1$$

where  $S(0) \simeq 1$ .

 Same story as for discrete model.

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

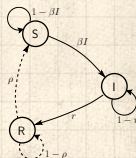
Model output

Nutshell

Other kinds of prediction

Next

References



# Independent Interaction models

The PoCSverse  
Biological  
Contagion  
34 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

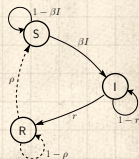
Nutshell

Other kinds of prediction

Next

References

Many variants of the SIR model:



# Independent Interaction models

The PoCSverse  
Biological  
Contagion  
34 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell

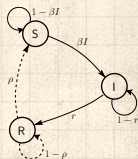
Other kinds of prediction

Next

References

Many variants of the SIR model:


 **SIS**: susceptible-infective-susceptible




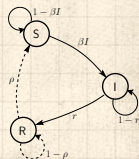


# Independent Interaction models

Many variants of the SIR model:

 **SIS**: susceptible-infective-susceptible

 **SIRS**: susceptible-infective-recovered-susceptible



# Independent Interaction models

Many variants of the SIR model:



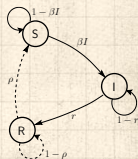
**SIS**: susceptible-infective-susceptible



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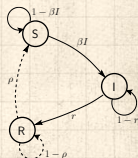
compartment models (age or gender partitions)



# Independent Interaction models






Many variants of the SIR model:

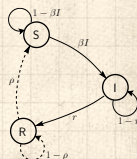
-  **SIS**: susceptible-infective-susceptible
-  **SIRS**: susceptible-infective-recovered-susceptible
-  compartment models (age or gender partitions)
-  more categories such as 'exposed' (**SEIRS**)



# 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)



Watch someone else pretend to save the world:

The PoCSverse  
Biological  
Contagion  
35 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

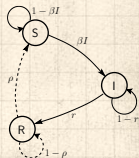
Model output

Nutshell

Other kinds of prediction

Next

References



Save the world yourself: 



The PoCSverse  
Biological  
Contagion  
36 of 97

Introduction

Simple disease  
spreading models

**Background**

Prediction

More models

Toy metapopulation  
models

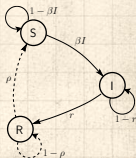
Model output



Nutshell


Other kinds of prediction

Next

References



 And you can be the virus. 

 Also contagious?: Cooperative games ...

# Neural reboot—Save another pretend world with

Vax: 

The PoCSverse  
Biological  
Contagion  
37 of 97

Introduction

Simple disease  
spreading models

**Background**

Prediction

More models

Toy metapopulation  
models

Model output

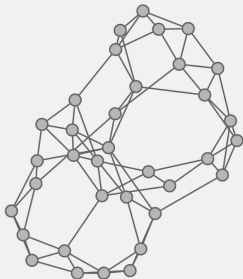
Nutshell

Other kinds of prediction

Next

References

## Lesson 4: Quarantine



Vaccines take time to 'kick in' so they're ineffective if an infection has already begun to spread.

Start >

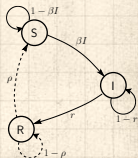
VAX!

Networks

Epidemics

Vaccines

Quarantine



# Outline

## Introduction

## Simple disease spreading models

Background

**Prediction**

More models

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

## References

The PoCSverse  
**Biological  
Contagion**  
38 of 97

Introduction

Simple disease  
spreading models

Background

**Prediction**

More models

Toy metapopulation  
models

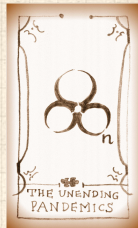
Model output

Nutshell

Other kinds of prediction

Next

References

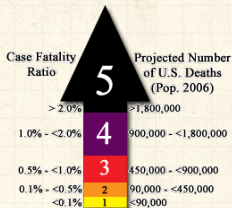




## Pandemic severity index (PSI)



Classification during/post pandemic:



Assumes 30% illness rate  
and unmitigated pandemic  
without interventions

CDC

U.S. Gov.




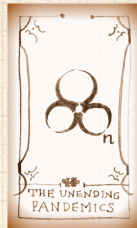
Category based.



1-5 scale.



Modeled on the  
Saffir-Simpson hurricane  
scale 



For novel diseases:

The PoCSverse  
Biological  
Contagion  
40 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

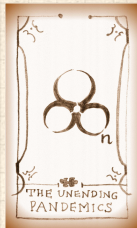
Model output

Nutshell

Other kinds of prediction

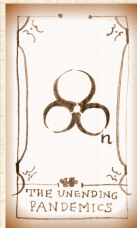
Next

References



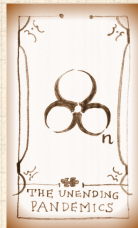
For novel diseases:

1. Can we predict the size of an epidemic?



For novel diseases:

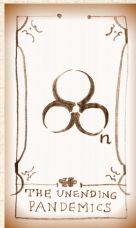
1. Can we predict the size of an epidemic?
2. How important is the reproduction number  $R_0$ ?



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$R_0$  approximately same for all of the following:



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$R_0$  approximately same for all of the following:



 1918-19 "Spanish Flu" ~ 75,000,000 world-wide,  
500,000 deaths in US.

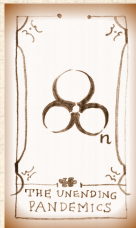


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-  1957-58 "Asian Flu" ~ 2,000,000 world-wide, 70,000 deaths in US.

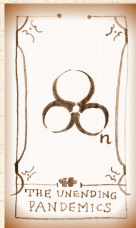


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-  2003 "SARS Epidemic" ~ 800 deaths world-wide.



# Size distributions

As we know, heavy-tailed size distributions are somewhat prevalent in complex systems:

The PoCSverse  
Biological  
Contagion  
41 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction


Next

References



# Size distributions

As we know, heavy-tailed size distributions are somewhat prevalent in complex systems:

 earthquakes (Gutenberg-Richter law)

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

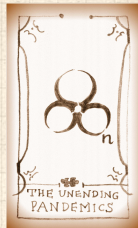
Model output

Nutshell

Other kinds of prediction


Next


References

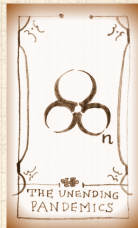


# Size distributions

As we know, heavy-tailed size distributions are somewhat prevalent in complex systems:




 earthquakes (Gutenberg-Richter law)

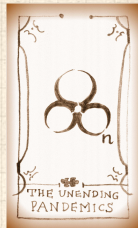
 city sizes, forest fires, war fatalities



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-  **Epidemics?**



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Power law distributions are common but not obligatory...





# Size distributions

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-  **Epidemics?**






Power law distributions are common but not obligatory...

Really, what about epidemics?




# Size distributions

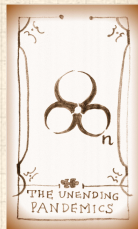
As we know, heavy-tailed size distributions are somewhat prevalent in complex systems:

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-  wealth distributions
-  'popularity' (books, music, websites, ideas)
-  **Epidemics?**

Power law distributions are common but not obligatory...

Really, what about epidemics?

-  Simply hasn't attracted much attention.



# Size distributions

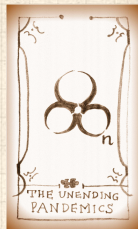
As we know, heavy-tailed size distributions are somewhat prevalent in complex systems:

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- 'popularity' (books, music, websites, ideas)
- Epidemics?**

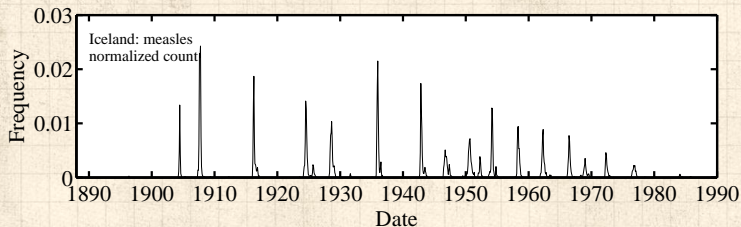
Power law distributions are common but not obligatory...

Really, what about epidemics?

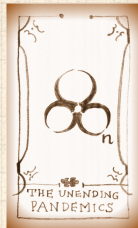
- Simply hasn't attracted much attention.
- Data not as clean as for other phenomena.



## 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

The PoCVerse  
Biological  
Contagion  
43 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

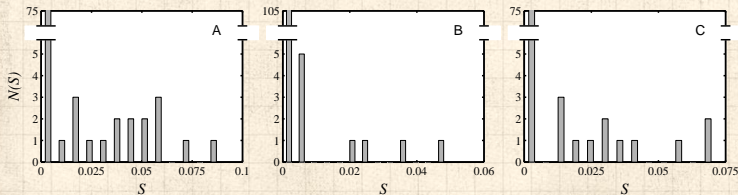
Nutshell

Other kinds of prediction

Next

References

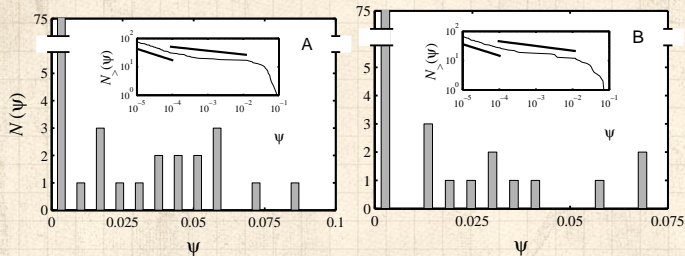
Epidemic size distributions  $N(S)$  for  
Measles, Rubella, and Whooping Cough.



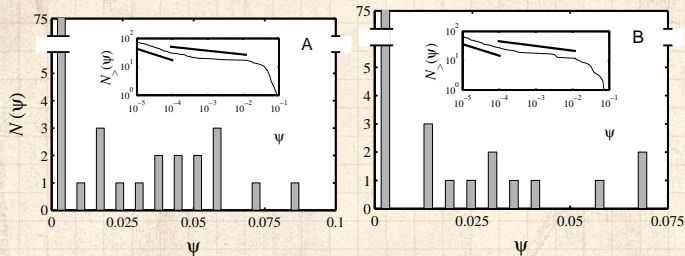
Spike near  $S = 0$ , relatively flat otherwise.



# Measles & Pertussis



# Measles & Pertussis

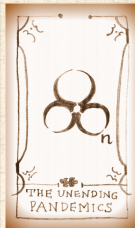


Insert plots:

Complementary cumulative frequency distributions:

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

Limited scaling with a possible break.



# Power law distributions

Measured values of  $\gamma$ :

The PoCSverse  
Biological  
Contagion  
45 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

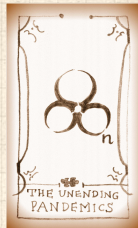
Model output

Nutshell

Other kinds of prediction

Next

References





# Power law distributions

The PoCSverse  
Biological  
Contagion  
45 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell

Other kinds of prediction

Next

References

Measured values of  $\gamma$ :

 measles: 1.40 (low  $\Psi$ ) and 1.13 (high  $\Psi$ )



# Power law distributions

The PoCSverse  
Biological  
Contagion  
45 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction

Next

References

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 measles: 1.40 (low  $\Psi$ ) and 1.13 (high  $\Psi$ )

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 Expect  $2 \leq \gamma < 3$  (finite mean, infinite variance)



# Power law distributions

The PoCSverse  
Biological  
Contagion  
45 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction


Next


References

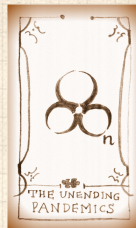
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 measles: 1.40 (low  $\Psi$ ) and 1.13 (high  $\Psi$ )

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 When  $\gamma < 1$ , can't normalize





# Power law distributions


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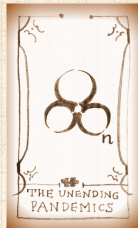
 measles: 1.40 (low  $\Psi$ ) and 1.13 (high  $\Psi$ )

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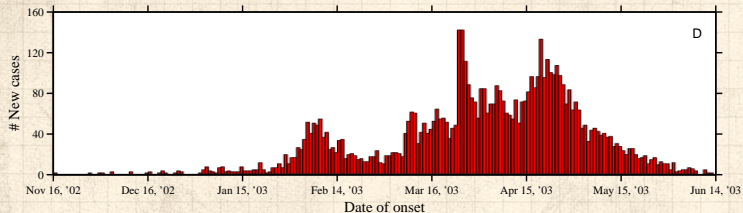
 Expect  $2 \leq \gamma < 3$  (finite mean, infinite variance)

 When  $\gamma < 1$ , can't normalize

 Distribution is quite flat.



# Resurgence—example of SARS



The PoCVerse  
Biological  
Contagion  
46 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

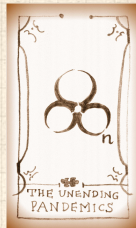
Model output

Nutshell

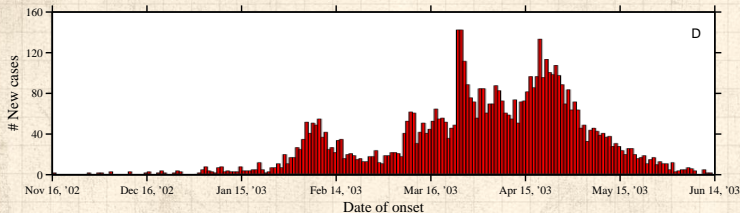
Other kinds of prediction

Next

References



# Resurgence—example of SARS



Epidemic slows...

The PoCVerse  
Biological  
Contagion  
46 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

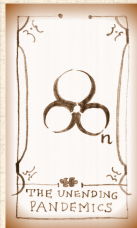
Model output

Nutshell

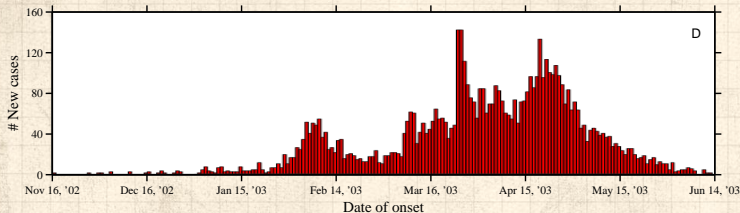
Other kinds of prediction

Next

References



# Resurgence—example of SARS



Epidemic slows...  
then an infective moves to a new context.

The PoCVerse  
Biological  
Contagion  
46 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

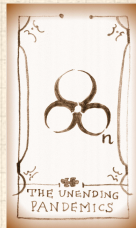
Model output

Nutshell

Other kinds of prediction

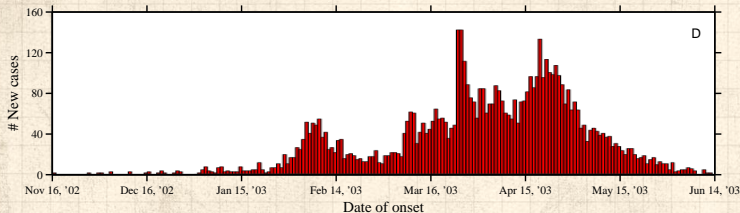
Next

References





# Resurgence—example of SARS



Epidemic slows...  
then an infective moves to a new context.



Epidemic discovers new 'pools' of susceptibles:  
**Resurgence.**

The PoCVerse  
Biological  
Contagion  
46 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

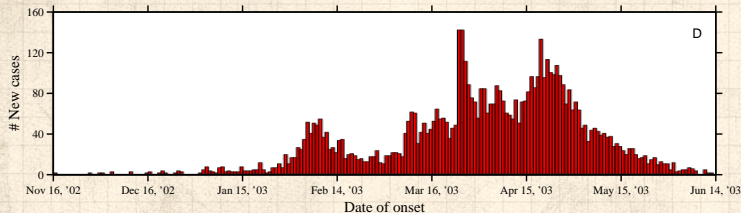
Other kinds of prediction

Next

References



# Resurgence—example of SARS



Epidemic slows...  
then an infective moves to a new context.



Epidemic discovers new 'pools' of susceptibles:  
**Resurgence.**



**Importance of rare, stochastic events.**

The PoCVerse  
Biological  
Contagion  
46 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

Next

References



# Community—S2E6: Epidemiology

The PoCSverse  
**Biological  
Contagion**  
47 of 97

Introduction

Simple disease  
spreading models

Background

**Prediction**

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

Next

References



# Outline

## Introduction

## Simple disease spreading models

Background

Prediction

**More models**

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

## References

The PoCSverse  
**Biological  
Contagion**  
48 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

**More models**

Toy metapopulation  
models

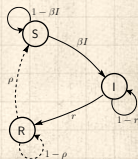
Model output

Nutshell

Other kinds of prediction

Next

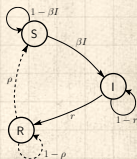
References



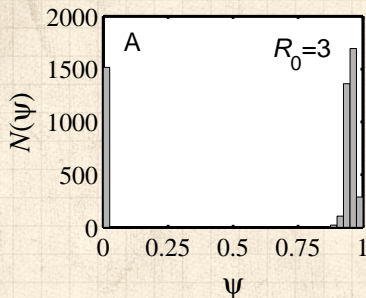
# The challenge

So... can a simple model produce

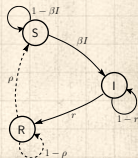
1. **broad epidemic distributions**  
and
2. **resurgence ?**



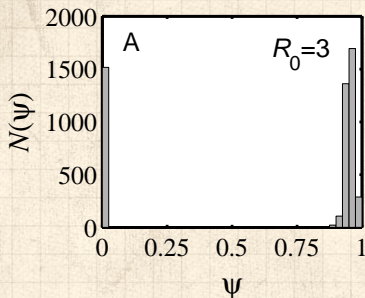
# Size distributions



Simple models typically produce **bimodal** or **unimodal** size distributions.



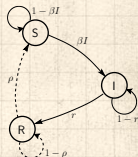
# Size distributions



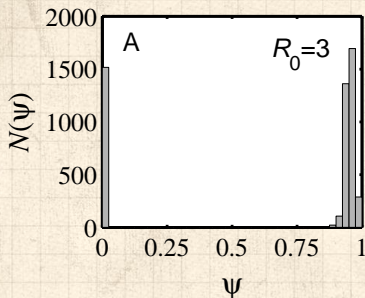
Simple models  
typically produce  
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This **includes** network models:  
random, small-world, scale-free, ...




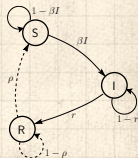
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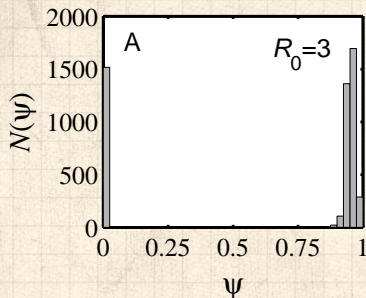
 This **includes** network models:  
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 Exceptions:







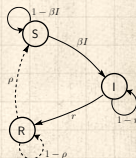
# Size distributions



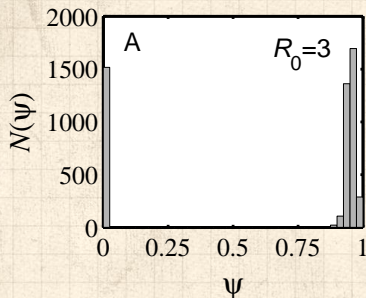
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1. Forest fire models




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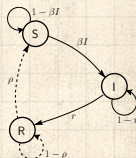


Simple models  
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size distributions.

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

 Exceptions:

1. Forest fire models
2. Sophisticated metapopulation models



# Burning through the population

Forest fire models: <sup>[19]</sup>

The PoCVerse  
Biological  
Contagion  
51 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

Next

References



# Burning through the population

The PoCVerse  
Biological  
Contagion  
51 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell

Other kinds of prediction

Next

References

Forest fire models: <sup>[19]</sup>

 Rhodes & Anderson, 1996



# Burning through the population

The PoCVerse  
Biological  
Contagion  
51 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output


Nutshell


Other kinds of prediction

Next

References

Forest fire models: <sup>[19]</sup>

 Rhodes & Anderson, 1996


 The physicist's approach:


**"if it works for magnets, it'll work for people..."**



# Burning through the population

## Forest fire models: <sup>[19]</sup>

 Rhodes & Anderson, 1996

 The physicist's approach:


**"if it works for magnets, it'll work for people..."**


A bit of a stretch:



# Burning through the population

## Forest fire models: <sup>[19]</sup>

 Rhodes & Anderson, 1996

 The physicist's approach:

**"if it works for magnets, it'll work for people..."**


## A bit of a stretch:


1. Epidemics  $\equiv$  forest fires spreading on 3-d and 5-d lattices.



# Burning through the population

## Forest fire models: <sup>[19]</sup>

 Rhodes & Anderson, 1996

 The physicist's approach:

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## A bit of a stretch:


1. Epidemics  $\equiv$  forest fires spreading on 3-d and 5-d lattices.
2. Claim Iceland and Faroe Islands exhibit power law distributions for outbreaks.






# Burning through the population

## Forest fire models: <sup>[19]</sup>

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 The physicist's approach:

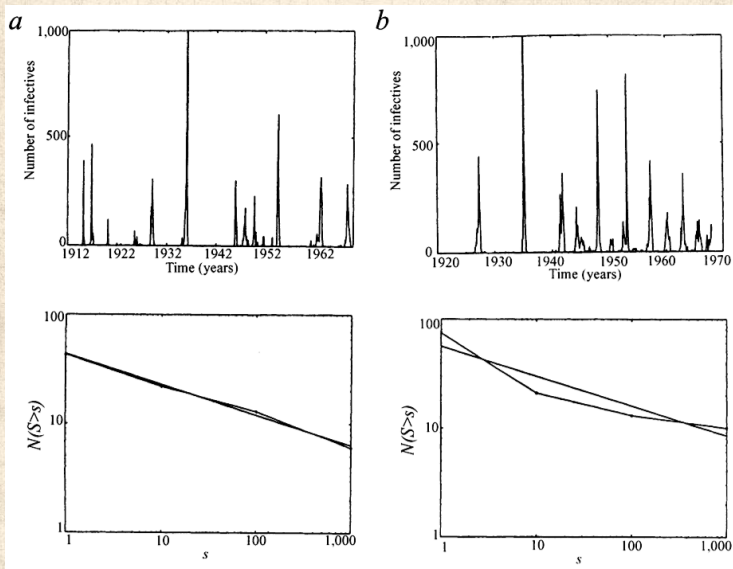
**"if it works for magnets, it'll work for people..."**

## A bit of a stretch:

1. Epidemics  $\equiv$  forest fires spreading on 3-d and 5-d lattices.
2. Claim Iceland and Faroe Islands exhibit power law distributions for outbreaks.
3. Original forest fire model not completely understood.




# Size distributions

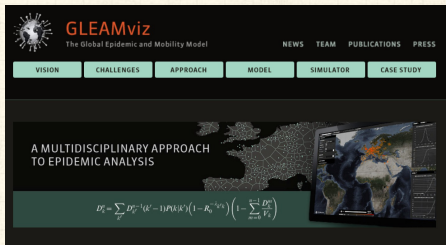


From Rhodes and Anderson, 1996.



# Sophisticated metapopulation models:

- ☰ Multiscale models suggested earlier by others but not formalized (Bailey <sup>[1]</sup>, Cliff and Haggett <sup>[6]</sup>, Ferguson et al.)
- ☰ Community based mixing (two scales)—Longini. <sup>[17]</sup>
- ☰ Eubank et al.'s EpiSims/TRANSIMS —city simulations. <sup>[9]</sup>
- ☰ Spreading through countries—Airlines: Germann et al., Colizza et al. <sup>[7]</sup>




**GLEAMviz**  
The Global Epidemic and Mobility Model

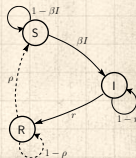
NEWS TEAM PUBLICATIONS PRESS

VISION CHALLENGES APPROACH MODEL SIMULATOR CASE STUDY


A MULTIDISCIPLINARY APPROACH TO EPIDEMIC ANALYSIS

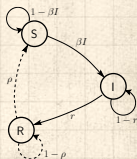
$$D_t^c = \sum_{k=1}^{K-1} D_t^{c(k)} (1 - R_0^{-k/\alpha}) \left( 1 - \sum_{i=1}^{k-1} \frac{D_t^c}{V_i} \right)$$

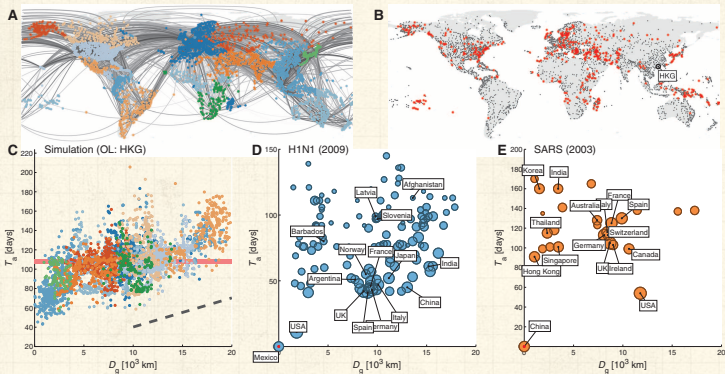
☰ **GLEAM** :  
Global pandemic simulations by Vespignani et al.





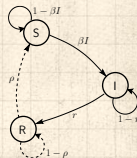
“The hidden geometry of complex,  
network-driven contagion phenomena”   
Brockmann and Helbing,  
Science, **342**, 1337–1342, 2013. [5]

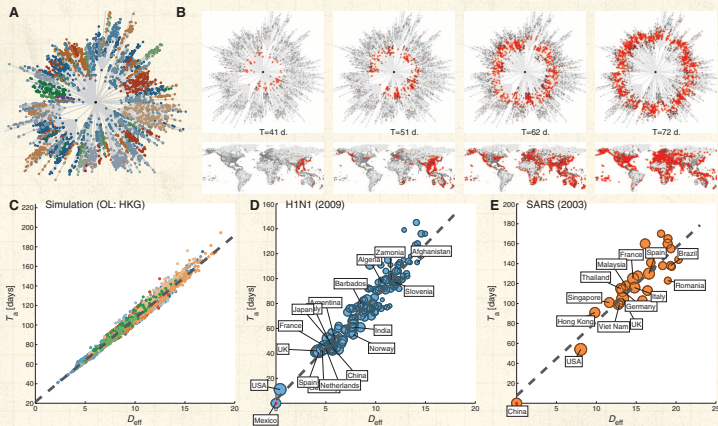




**Fig. 1. Complexity in global, network-driven contagion phenomena.** (A) The global mobility network (GMN). Gray lines represent passenger flows along direct connections between 4069 airports worldwide. Geographic regions are distinguished by color [classified according to network modularity maximization (39)]. (B) Temporal snapshot of a simulated global pandemic with initial outbreak location (OL) in Hong Kong (HKG). The simulation is based on the metapopulation model defined by Eq. 3 with parameters  $R_0 = 1.5$ ,  $\beta = 0.285 \text{ day}^{-1}$ ,  $\gamma = 2.8 \times 10^{-3} \text{ day}^{-1}$ ,  $\epsilon = 10^{-8}$ . Red symbols depict locations with epidemic arrival times in the time window 105 days  $\leq T_a \leq 110$  days. Because of the multiscale structure of the underlying network, the spatial distribution of disease prevalence (i.e., the fraction of infected individuals) lacks geometric coherence. No clear wave-front is visible, and based on this dynamic state, the OL cannot be easily deduced. (C) For the same simulation as in (B), the panel depicts arrival times  $T_a$  as a function of geographic distance  $D_g$  from the OL [nodes are colored according to geographic region as in (A)] for each of the 4069 nodes in the network. On a

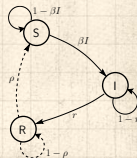
global scale,  $T_a$  weakly correlates with geographic distance  $D_g$  ( $R^2 = 0.34$ ). A linear fit yields an average global spreading speed of  $v_g = 331 \text{ km/day}$  (see also fig. S7). Using  $D_g$  and  $v_g$  to estimate arrival times for specific locations, however, does not work well owing to the strong variability of the arrival times for a given geographic distance. The red horizontal bar corresponds to the arrival time window shown in (B). (D) Arrival times versus geographic distance from the source (Mexico) for the 2009 H1N1 pandemic. Symbols represent 140 affected countries, and symbol size quantifies total traffic per country. Arrival times are defined as the date of the first confirmed case in a given country after the initial outbreak on 17 March 2009. As in the simulated scenario, arrival time and geographic distance are only weakly correlated ( $R^2 = 0.0394$ ). (E) In analogy to (D), the panel depicts the arrival times versus geographic distance from the source (China) of the 2003 SARS epidemic for 29 affected countries worldwide. Arrival times are taken from WHO published data (2). As in (C) and (D), arrival time correlates weakly with geographic distance.

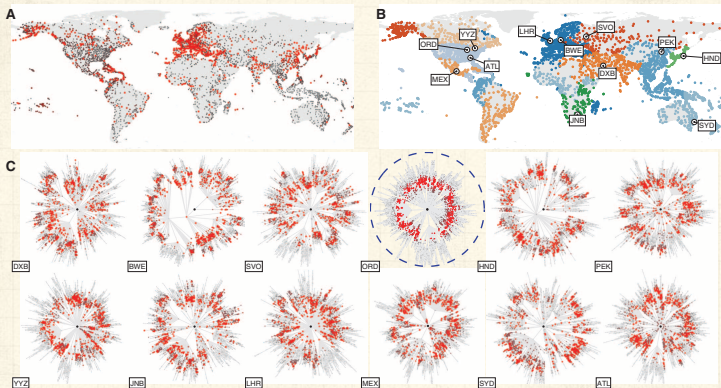




**Fig. 2. Understanding global contagion phenomena using effective distance.** (A) The structure of the shortest path tree (in gray) from Hong Kong (central node). Radial distance represents effective distance  $D_{\text{eff}}$  as defined by Eqs. 4 and 5. Nodes are colored according to the same scheme as in Fig. 1A. (B) The sequence (from left to right) of panels depicts the time course of a simulated model disease with initial outbreak in Hong Kong (HKG), for the same parameter set as used in Fig. 1B. Prevalence is reflected by the redness of the symbols. Each panel compares the state of the system in the conventional geographic representation (bottom) with the effective distance representation (top). The complex spatial pattern in the conventional view is equivalent to a homoge-

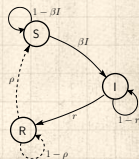
neous wave that propagates outwards at constant effective speed in the effective distance representation. (C) Epidemic arrival time  $T_a$  versus effective distance  $D_{\text{eff}}$  for the same simulated epidemic as in (B). In contrast to geographic distance (Fig. 1C), effective distance correlates strongly with arrival time ( $R^2 = 0.973$ ), i.e., effective distance is an excellent predictor of arrival times. (D and E) Linear relationship between effective distance and arrival time for the 2009 H1N1 pandemic (D) and the 2003 SARS epidemic (E). The arrival time data are the same as in Fig. 1, D and E. The effective distance was computed from the projected global mobility network between countries. As in the model system, we observe a strong correlation between arrival time and effective distance.





**Fig. 3. Qualitative outbreak reconstruction based on effective distance.** (A) Spatial distribution of prevalence  $j_n(t)$  at time  $T = 81$  days for OL Chicago (parameters  $\beta = 0.28 \text{ day}^{-1}$ ,  $R_0 = 1.9$ ,  $\gamma = 2.8 \times 10^{-3} \text{ day}^{-1}$ , and  $\epsilon = 10^{-4}$ ). After this time, it is difficult, if not impossible, to determine the correct OL from snapshots of the dynamics. (B) Candidate OLs chosen from different geographic regions. (C) Panels depict the state of the system shown in (A) from the

perspective of each candidate OL, using each OL's shortest path tree representation. Only the actual OL (ORD, circled in blue) produces a circular wavefront. Even for comparable North American airports [Atlanta (ATL), Toronto (YYZ), and Mexico City (MEX)], the wavefronts are not nearly as concentric. Effective distances thus permit the extraction of the correct OL, based on information on the mobility network and a single snapshot of the dynamics.



## Community—S2E6: Epidemiology

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

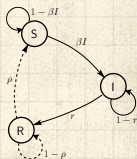
Model output

Nutshell

Other kinds of prediction


Next

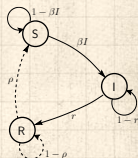
References







# Size distributions

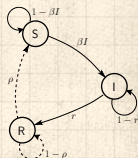
 Vital work but perhaps hard to generalize from...




# Size distributions


 Vital work but perhaps hard to generalize from...


  $\Rightarrow$  Create a simple model involving multiscale travel

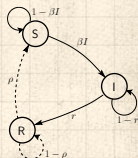


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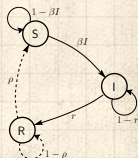
  $\Rightarrow$  Create a simple model involving multiscale travel

 Very big question: **What is  $N$ ?**



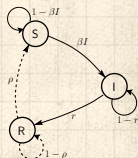
# Size distributions

- 🧱 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?



# 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?
- 🧱 For simple models, we need to know the final size beforehand...



# Outline

## Introduction

## Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

## References

The PoCSverse  
Biological  
Contagion  
60 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

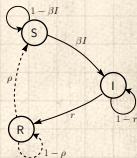
Model output

Nutshell

Other kinds of prediction

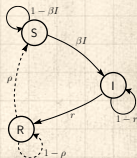
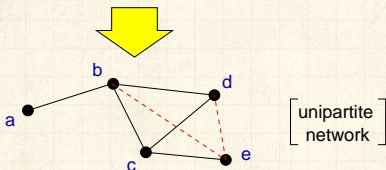
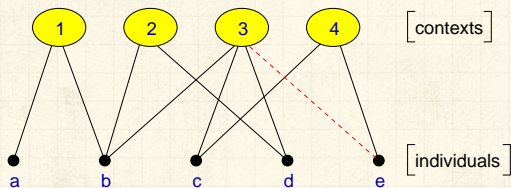
Next

References



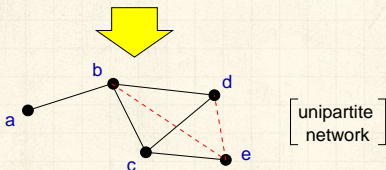
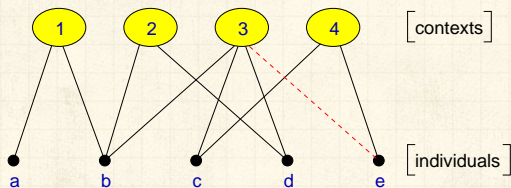
# Improving simple models

## Contexts and Identities—Bipartite networks

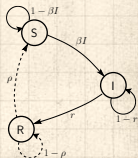


# Improving simple models

## Contexts and Identities—Bipartite networks



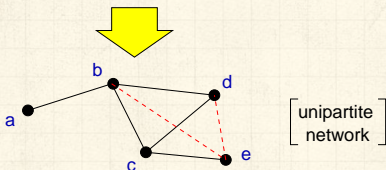
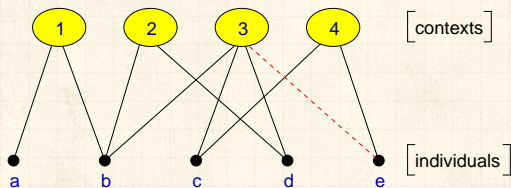
boards of directors





# Improving simple models

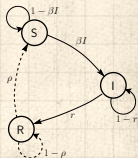
## Contexts and Identities—Bipartite networks



boards of directors

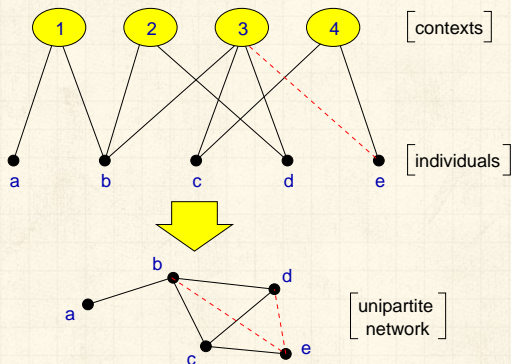





movies

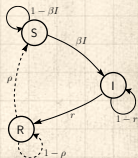


# Improving simple models

## Contexts and Identities—Bipartite networks



-  boards of directors
-  movies
-  transportation modes (subway)



# Improving simple models

Idea for social networks: incorporate identity

The PoCSverse  
Biological  
Contagion  
62 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

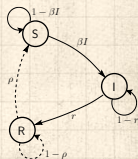
Model output

Nutshell

Other kinds of prediction

Next

References



# Improving simple models

Idea for social networks: incorporate identity

Identity is formed from attributes such as:

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

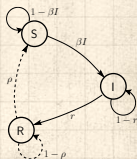
Model output

Nutshell

Other kinds of prediction

Next


References



# Improving simple models

Idea for social networks: incorporate identity

Identity is formed from attributes such as:

 Geographic location

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

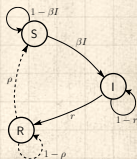
Model output

Nutshell

Other kinds of prediction

Next



References



# Improving simple models

Idea for social networks: incorporate identity

Identity is formed from attributes such as:

-  Geographic location
-  Type of employment

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

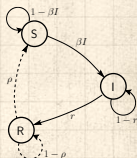
Model output

Nutshell

Other kinds of prediction

Next




References



# Improving simple models

Idea for social networks: incorporate identity

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-  Type of employment
-  Age

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

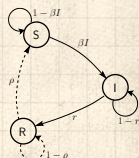
Model output

Nutshell

Other kinds of prediction

Next





References



# Improving simple models

Idea for social networks: incorporate identity

Identity is formed from attributes such as:

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-  Recreational activities

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

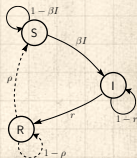
Model output

Nutshell

Other kinds of prediction

Next

References









# Improving simple models

Idea for social networks: incorporate identity

Identity is formed from attributes such as:

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Groups are crucial...

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

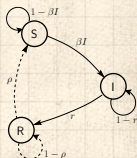
Model output

Nutshell

Other kinds of prediction

Next





References




# Improving simple models

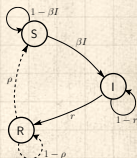
Idea for social networks: incorporate identity

Identity is formed from attributes such as:

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Groups are crucial...





-  formed by people with at least one similar attribute





# Improving simple models

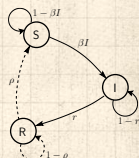
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Identity is formed from attributes such as:

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-  Type of employment
-  Age
-  Recreational activities

Groups are crucial...

-  formed by people with at least one similar attribute
-  Attributes  $\Leftrightarrow$  Contexts  $\Leftrightarrow$  Interactions  $\Leftrightarrow$  Networks. [23]



# Infer interactions/network from identities

The PoCSverse  
Biological  
Contagion  
63 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

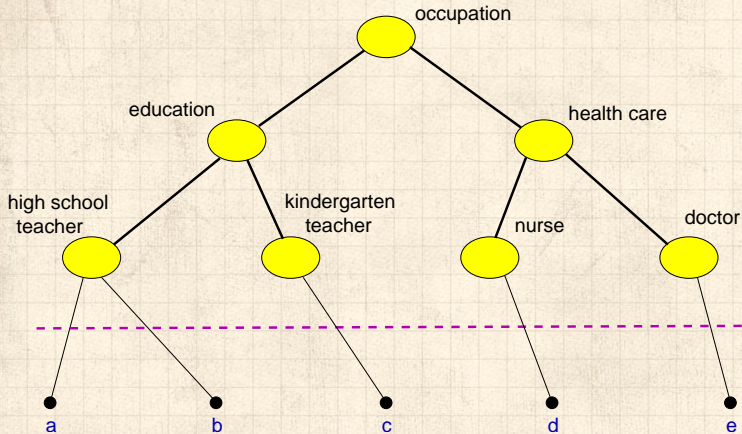
Model output

Nutshell

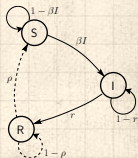
Other kinds of prediction

Next

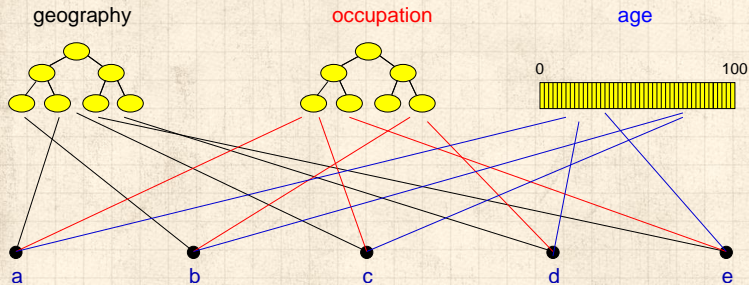
References



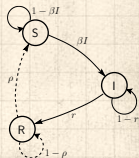
Distance makes sense in identity/context space.



# Generalized context space




(Blau & Schwartz <sup>[3]</sup>, Simmel <sup>[20]</sup>, Breiger <sup>[4]</sup>)



# A toy agent-based model:



“Multiscale, resurgent epidemics in a hierarchical metapopulation model” 

Watts et al.,

Proc. Natl. Acad. Sci., **102**, 11157–11162, 2005. [24]

Geography: allow people to move between contexts

The PoCSverse  
Biological  
Contagion  
65 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

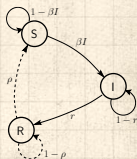
Model output

Nutshell

Other kinds of prediction


Next

References



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Geography: allow people to move between contexts

 Locally: standard SIR model with random mixing

The PoCSverse  
Biological  
Contagion  
65 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

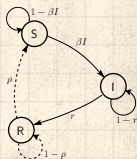
Model output

Nutshell

Other kinds of prediction


Next

References



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 Locally: standard SIR model with random mixing

 discrete time simulation

The PoCSverse  
Biological  
Contagion  
65 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

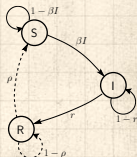
Model output

Nutshell

Other kinds of prediction

Next


References





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 Locally: standard SIR model with random mixing

 discrete time simulation

  $\beta$  = infection probability

The PoCSverse  
Biological  
Contagion  
65 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

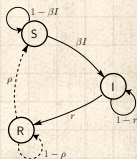
Model output

Nutshell

Other kinds of prediction


Next

References



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“Multiscale, resurgent epidemics in a hierarchical metapopulation model” 


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 Locally: standard SIR model with random mixing

 discrete time simulation

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  $\gamma$  = recovery probability

The PoCSverse  
Biological  
Contagion  
65 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

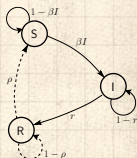
Model output

Nutshell

Other kinds of prediction


Next

References



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 discrete time simulation

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  $P$  = probability of travel

The PoCSverse  
Biological  
Contagion  
65 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

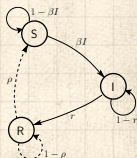
Model output

Nutshell

Other kinds of prediction


Next

References



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 **Movement distance:**  $\Pr(d) \propto \exp(-d/\xi)$

The PoCSverse  
Biological  
Contagion  
65 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

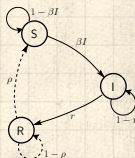
Model output

Nutshell

Other kinds of prediction


Next

References



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 **Movement distance:**  $\Pr(d) \propto \exp(-d/\xi)$

  $\xi$  = typical travel distance

The PoCSverse  
Biological  
Contagion  
65 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

**Toy metapopulation  
models**

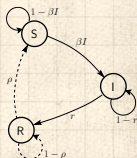
Model output

Nutshell

Other kinds of prediction

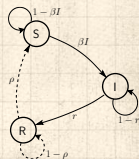
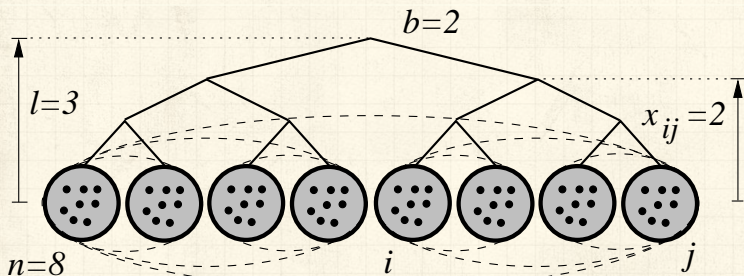
Next

References



# A toy agent-based model

Schematic:



# Outline

## Introduction

## Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

**Model output**

Nutshell

Other kinds of prediction

Next

## References

The PoCSverse  
**Biological  
Contagion**  
67 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

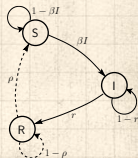
Model output

Nutshell

Other kinds of prediction

Next

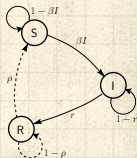
References



# Model output



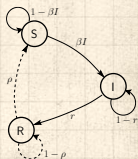
Define  $P_0$  = Expected number of infected individuals **leaving** initially infected context.





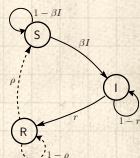
# Model output

- Define  $P_0$  = Expected number of infected individuals **leaving** initially infected context.
- Need  $P_0 > 1$  for disease to spread (independent of  $R_0$ ).



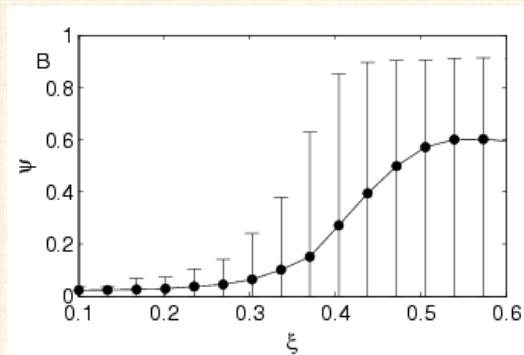
# Model output

- 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**

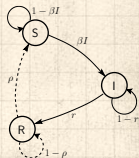


# Model output

Varying  $\xi$ :

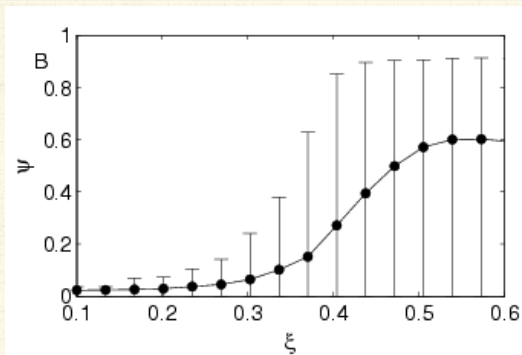


Transition in expected final size based on typical movement distance

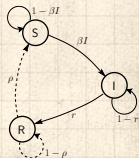


# Model output

Varying  $\xi$ :

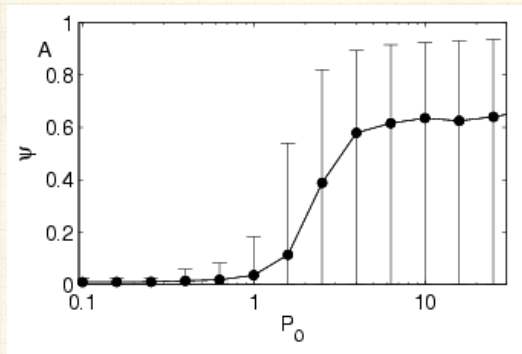


Transition in expected final size based on typical movement distance (**sensible**)



# Model output

Varying  $P_0$ :



Transition in expected final size based on typical number of infectives leaving first group

The PoCSverse  
Biological  
Contagion  
70 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

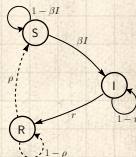
Model output

Nutshell

Other kinds of prediction

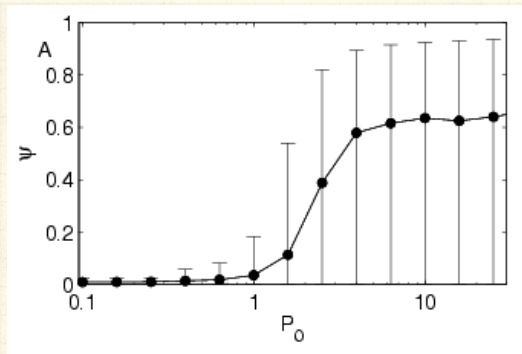
Next

References



# Model output

Varying  $P_0$ :



Transition in expected final size based on typical number of infectives leaving first group (also sensible)

The PoCSverse  
Biological  
Contagion  
70 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

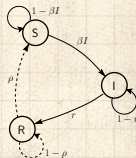
Model output

Nutshell

Other kinds of prediction

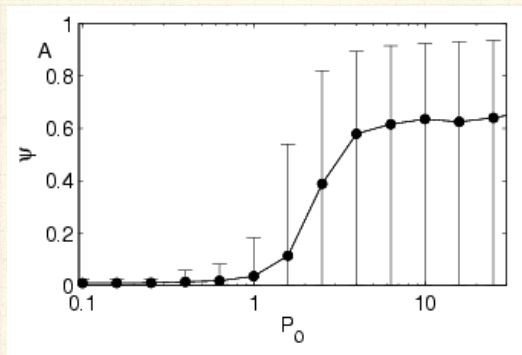
Next


References




# Model output

Varying  $P_0$ :



 Transition in expected final size based on typical number of infectives leaving first group (also sensible)

 Travel advisories:  $\xi$  has larger effect than  $P_0$ .

The PoCSverse  
Biological  
Contagion  
70 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

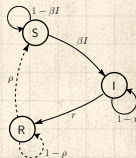
Model output

Nutshell

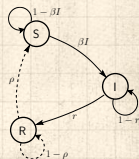
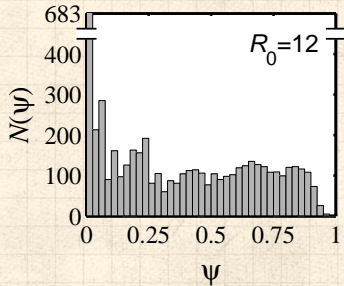
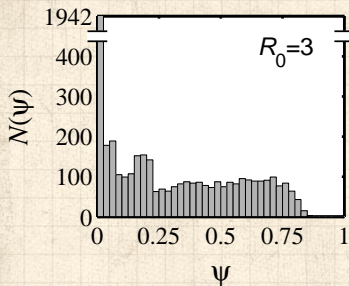
Other kinds of prediction

Next

References

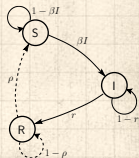
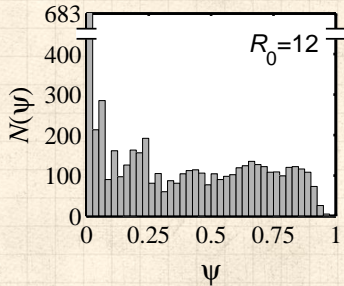
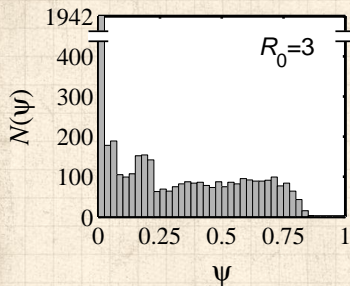


# Example model output: size distributions

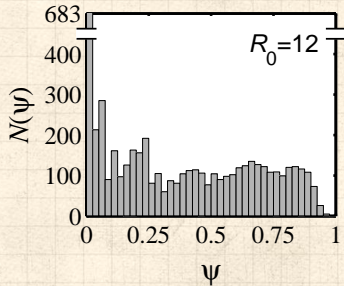
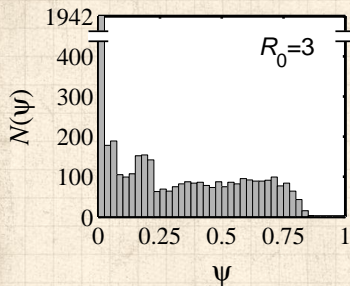





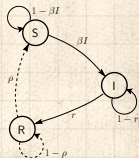
# Example model output: size distributions



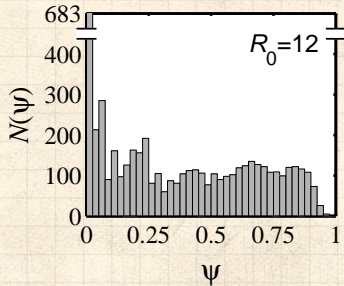
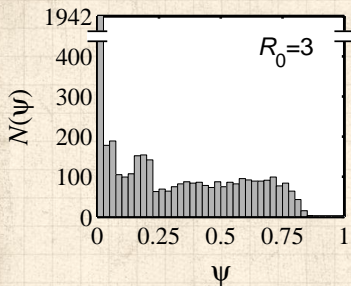
# Example model output: size distributions



 Flat distributions are possible for certain  $\xi$  and  $P$ .

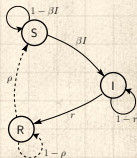


# Example model output: size distributions

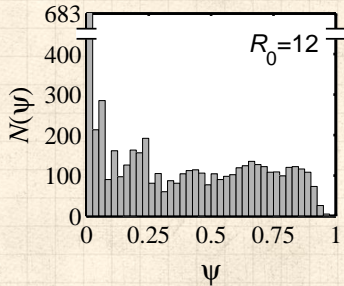
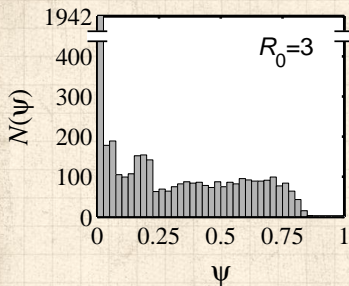


Flat distributions are possible for certain  $\xi$  and  $P$ .

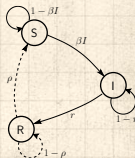
Different  $R_0$ 's may produce similar distributions



# Example model output: size distributions



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



# Model output—resurgence

The PoCSverse  
Biological  
Contagion  
72 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

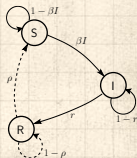
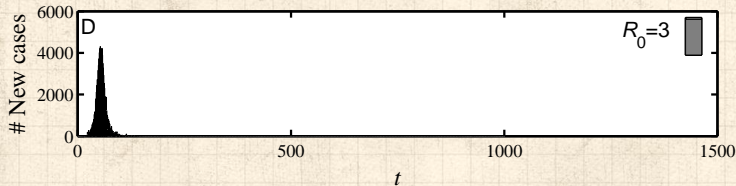
Nutshell

Other kinds of prediction

Next

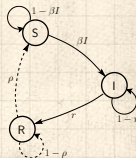
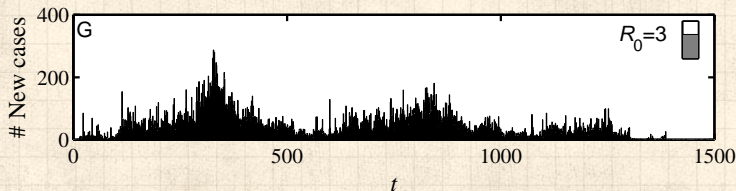
References

Standard model:



# Model output—resurgence

## Standard model with transport:



# The upshot

The PoCSverse  
Biological  
Contagion  
74 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

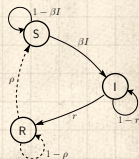
Nutshell

Other kinds of prediction

Next

References

## Simple multiscale population structure



# The upshot

Simple multiscale population structure  
+  
stochasticity

The PoCSverse  
Biological  
Contagion  
74 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

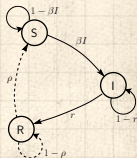
Model output

Nutshell

Other kinds of prediction

Next

References





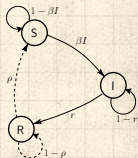
# The upshot

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

The PoCSverse  
Biological  
Contagion  
75 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

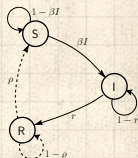
Model output

**Nutshell**

Other kinds of prediction

Next

References



# Nutshelling



For the hierarchical movement model, epidemic size is highly unpredictable

The PoCSverse  
Biological  
Contagion  
76 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

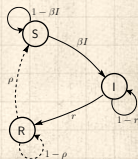
Model output

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.

## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

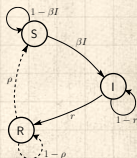
Model output

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.

## Introduction

### Simple disease spreading models

Background

Prediction

More models

Toy metapopulation  
models

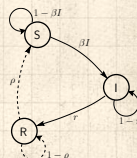
Model output

Nutshell

Other kinds of prediction

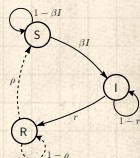
Next

## References



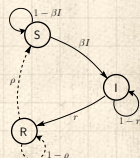
# Nutshelling

- 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.



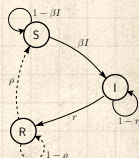
# Nutshelling

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- $R_0$ , however measured, is not informative about



# Nutshelling

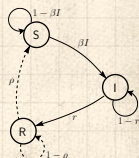
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- Model is more complicated than SIR but still simple.
- We haven't even included normal social responses such as travel bans and self-quarantine.
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- $R_0$ , however measured, is not informative about
  - how likely the observed epidemic size was,





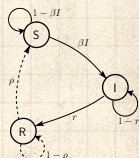
# Nutshelling

- For the hierarchical movement model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple.
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  - how likely the observed epidemic size was,
  - and how likely future epidemics will be.



# 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
  - how likely the observed epidemic size was,
  - and how likely future epidemics will be.
- Problem:  $R_0$  summarises **one** epidemic after the fact and enfolds movement, the price of bananas, everything.



# Conclusions



Disease's spread is highly sensitive to population structure.

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

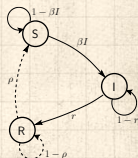
Model output

Nutshell

Other kinds of prediction

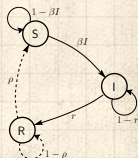
Next

References



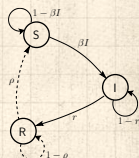
# Conclusions

- 🧱 Disease's spread is highly sensitive to population structure.
- 🧱 Rare events may matter enormously:



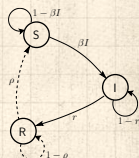
# Conclusions

- 🧱 Disease's spread is highly sensitive to population structure.
- 🧱 Rare events may matter enormously: e.g., an infected individual taking an international flight.



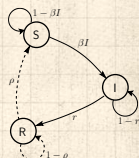
# Conclusions

- 🧱 Disease's spread is highly sensitive to population structure.
- 🧱 Rare events may matter enormously: e.g., an infected individual taking an international flight.
- 🧱 More support for controlling population movement:



# Conclusions

- 🧱 Disease's spread is highly sensitive to population structure.
- 🧱 Rare events may matter enormously: e.g., an infected individual taking an international flight.
- 🧱 More support for controlling population movement:  
e.g., travel advisories, quarantine



# Nutshelling

What to do:

The PoCSverse  
Biological  
Contagion  
78 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

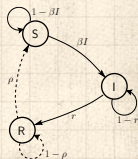
Model output

Nutshell

Other kinds of prediction

Next

References






# Nutshelling

The PoCSverse  
Biological  
Contagion  
78 of 97

What to do:

 Need to separate movement from disease

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

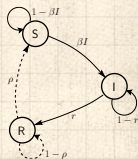
Model output

Nutshell

Other kinds of prediction


Next


References

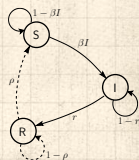


# Nutshelling

What to do:

 Need to separate movement from disease

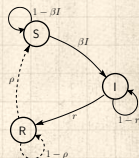
  $R_0$  needs a friend or two.



# Nutshelling

## What to do:

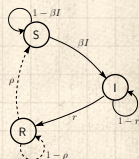
- Need to separate movement from disease
- $R_0$  needs a friend or two.
- Need  $R_0 > 1$  and  $P_0 > 1$  and  $\xi$  sufficiently large for disease to have a chance of spreading



# Nutshelling

## What to do:

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

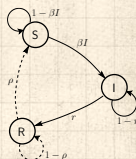


# Nutshelling

## What to do:

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

## More wondering:



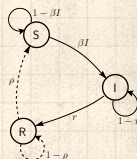
# Nutshelling

## What to do:

- Need to separate movement from disease
- $R_0$  needs a friend or two.
- Need  $R_0 > 1$  and  $P_0 > 1$  and  $\xi$  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?



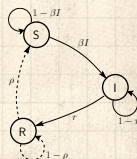
# Nutshelling

## What to do:

- Need to separate movement from disease
- $R_0$  needs a friend or two.
- Need  $R_0 > 1$  and  $P_0 > 1$  and  $\xi$  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  $N$ ?







# Outline

## Introduction

## Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

## References

The PoCSverse  
Biological  
Contagion  
80 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

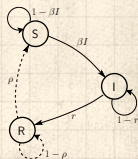
Model output

Nutshell

**Other kinds of prediction**

Next

References



Krugman, 1998: "Why most economists' predictions are wrong."



Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

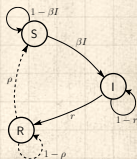
Model output

Nutshell

**Other kinds of prediction**

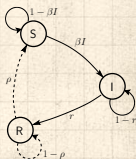
Next

References



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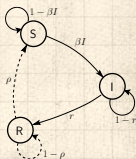
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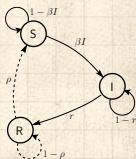


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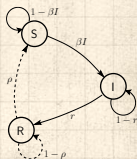
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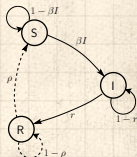
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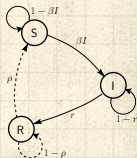
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<sup>1</sup><http://www.redherring.com/mag/issue55/economics.html>



# Economics, Schmeconomics

The PoCSverse  
Biological  
Contagion  
82 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

**Other kinds of prediction**

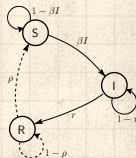
Next

References

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<http://wikipedia.org>



# Economics, Schmeconomics

The PoCSverse  
Biological  
Contagion  
82 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

**Other kinds of prediction**

Next

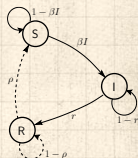
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# Economics, Schmeconomics

The PoCSverse  
Biological  
Contagion  
82 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

**Other kinds of prediction**

Next

References

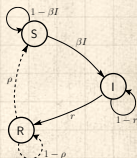
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The PoCSverse  
Biological  
Contagion  
82 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

**Other kinds of prediction**

Next

References

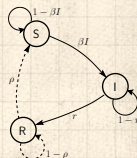
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The PoCSverse  
Biological  
Contagion  
82 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

**Other kinds of prediction**

Next

References

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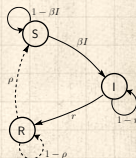
If I could figure out a way to determine whether or not people are more fearful or changing to more euphoric,

I don't need any of this other stuff.

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



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# Economics, Schmeconomics

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The PoCSverse  
Biological  
Contagion  
83 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

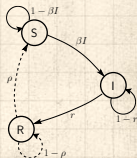
Model output

Nutshell

**Other kinds of prediction**

Next

References



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Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

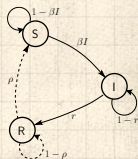
Model output

Nutshell

**Other kinds of prediction**

Next

References



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The PoCSverse  
Biological  
Contagion  
83 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

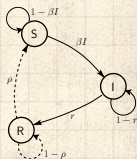
Model output

Nutshell

**Other kinds of prediction**

Next

References

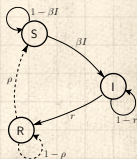




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Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

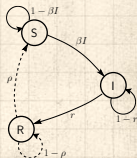
Model output

Nutshell

Other kinds of prediction

Next

References



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Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

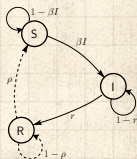
Model output

Nutshell

Other kinds of prediction

Next

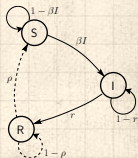
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Jon Stewart:

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



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Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

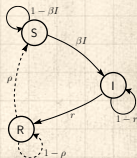
Model output

Nutshell

Other kinds of prediction

Next

References



From the Daily Show  (September 18, 2007)



The full episode is here:

<http://www.cc.com/video-clips/cenrt5/the-daily-show-with-jon-st>

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"Greenspan Concedes Error on Regulation"

The PoCSverse  
Biological  
Contagion  
84 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

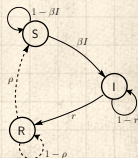
Model output

Nutshell

**Other kinds of prediction**

Next

References



New York Times, October 23, 2008 

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The PoCSverse  
Biological  
Contagion  
84 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

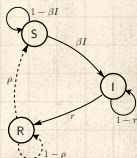
Model output

Nutshell

**Other kinds of prediction**

Next

References



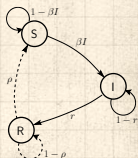
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Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

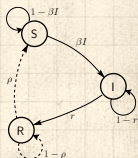
Model output

Nutshell

Other kinds of prediction

Next

References



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Rep. Henry A. Waxman: "Do you feel that your ideology pushed you to make decisions that you wish you had not made?"

Mr. Greenspan conceded: "Yes, I've found a flaw. I don't know how significant or permanent it is. But I've been very distressed by that fact."

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

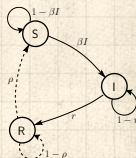
Model output

Nutshell

Other kinds of prediction

Next

References



# Economics, Schmeconomics

James K. Galbraith:

The PoCSverse  
Biological  
Contagion  
85 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

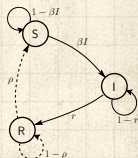
Model output

Nutshell

**Other kinds of prediction**

Next

References



From the [New York Times, 11/02/2008](#)

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The PoCSverse  
Biological  
Contagion  
85 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

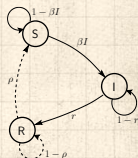
Model output

Nutshell

**Other kinds of prediction**

Next

References



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# Economics, Schmeconomics

The PoCSverse  
Biological  
Contagion  
85 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

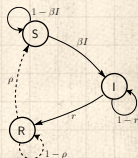
Other kinds of prediction

Next

References

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# Economics, Schmeconomics

The PoCSverse  
Biological  
Contagion  
85 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

Model output

Nutshell

Other kinds of prediction

Next

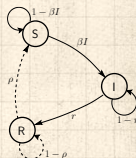
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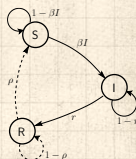
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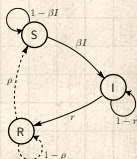
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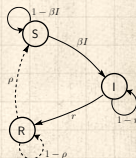
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# Outline

## Introduction

## Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Nutshell

Other kinds of prediction

Next

## References

The PoCSverse  
Biological  
Contagion  
86 of 97

Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

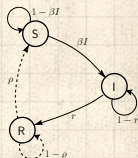
Model output

Nutshell

Other kinds of prediction

Next

References



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Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

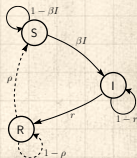
Model output

Nutshell


Other kinds of prediction

Next

References



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Introduction

Simple disease  
spreading models

Background

Prediction

More models

Toy metapopulation  
models

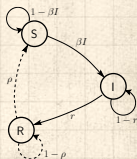
Model output

Nutshell

Other kinds of prediction

Next

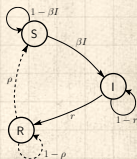
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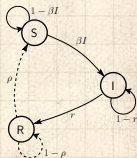


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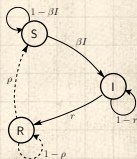
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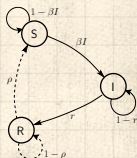
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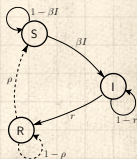




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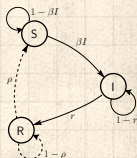


## Other attempts to use SIR and co. elsewhere:

- Adoption of ideas/beliefs (Goffman & Newell, 1964)<sup>[11]</sup>
- Spread of rumors (Daley & Kendall, 1965)<sup>[8]</sup>
- Diffusion of innovations (Bass, 1969)<sup>[2]</sup>
- Spread of fanatical behavior (Castillo-Chávez & Song, 2003)
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## Social contagion:

- SIR may apply sometimes ...

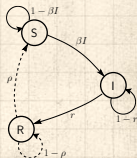


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## Social contagion:

- SIR may apply sometimes ...
- But we need new fundamental models.

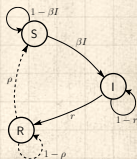


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## Social contagion:

- SIR may apply sometimes ...
- But we need new fundamental models.
- Next up: Thresholds.

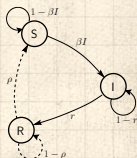


# We really should know social contagion is different but ...




"It's contagious: Rethinking a metaphor dialogically" 

Warren and Power,  
Culture & Psychology, **21**, 359–379,  
2015. [22]




# We really should know social contagion is different but ...

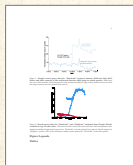



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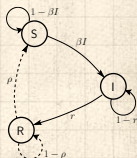


"Facebook will lose 80% of users by 2017, say Princeton researchers"  (Guardian, 2014)

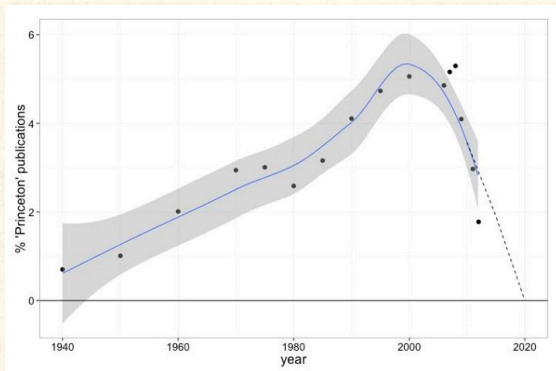


"Epidemiological modeling of online social network dynamics" 

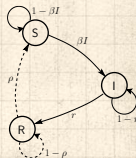
Spechler and Cannarella,  
Available online at  
<http://arxiv.org/abs/1401.4208>, 2014. [21]





## The Facebook Data Science team's response

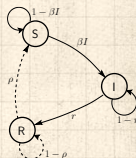


Mike Develin, Lada Adamic, and Sean Taylor.



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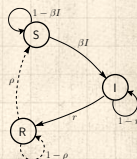
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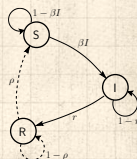
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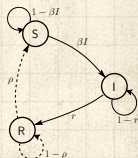
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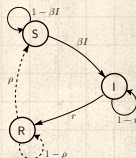
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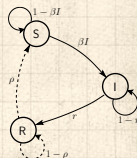
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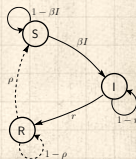
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