Biological Contagion

Principles of Complex Systems CSYS/MATH 300, Fall, 2011

Prof. Peter Dodds

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















Licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 3.0 License.

Biological Contagion

Introductio

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

D II II

catastrophe







Outline

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Conclusions

Predicting social catastrophe

References

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions

Predicting soci





A confusion of contagions:

- ▶ Was Harry Potter some kind of virus?
- ▶ What about the Da Vinci Code?
- ▶ Did Sudoku spread like a disease?
- ▶ Language?
- ► Religion?
- ▶ Democracy...?

Biological Contagion

Introduction

Simple disease spreading models

Background

Frediction

Tov metapopulation models

Model output

Prodicting soci

catastrophe







A confusion of contagions:

- Was Harry Potter some kind of virus?
- What about the Da Vinci Code?
- ▶ Did Sudoku spread like a disease?
- ▶ Language?
- ► Religion?
- ► Democracy...?

Biological Contagion

Introduction

Simple disease spreading models

Background

More model

Tov metapopulation models

Model output

Predicting socia





A confusion of contagions:

- Was Harry Potter some kind of virus?
- What about the Da Vinci Code?
- ▶ Did Sudoku spread like a disease?
- ▶ Language?
- ► Religion?
- ► Democracy...?

Biological Contagion

Introduction

Simple disease spreading models

Background

More model

Toy metapopulation models

Model output

Dradiating and

catastrophe





A confusion of contagions:

- Was Harry Potter some kind of virus?
- What about the Da Vinci Code?
- Did Sudoku spread like a disease?
- Language?
- ► Religion?
- ► Democracy...?

Biological Contagion

Introduction

Simple disease spreading models

Background

Frediction

Toy metapopulation models

Model output

D II II

catastrophe





A confusion of contagions:

- Was Harry Potter some kind of virus?
- What about the Da Vinci Code?
- Did Sudoku spread like a disease?
- Language?
- ► Religion?
- ► Democracy...?

Biological Contagion

Introduction

Simple disease spreading models

Background

Managed

Tov metapopulation models

Model output

D " · ·

catastrophe





A confusion of contagions:

- Was Harry Potter some kind of virus?
- What about the Da Vinci Code?
- ▶ Did Sudoku spread like a disease?
- Language?
- ▶ Religion?
- ► Democracy...?

Biological Contagion

Introduction

Simple disease spreading models

Background

Managed

Toy metapopulation models

Model output

Conclusions

catastrophe





A confusion of contagions:

- Was Harry Potter some kind of virus?
- What about the Da Vinci Code?
- ▶ Did Sudoku spread like a disease?
- Language?
- ▶ Religion?
- ► Democracy...?

Biological Contagion

Introduction

Simple disease spreading models

Background

Managed

Toy metapopulation models

Model output

D II II

catastrophe





Naturomorphisms

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions

catastrophe







Naturomorphisms

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Managed

Tov metapopulation models

Model output

Conclusions

catastrophe





Naturomorphisms

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions

Predicting soci





Naturomorphisms

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Frediction

Tov metapopulation models

Model output

Conclusions

catastrophe





Naturomorphisms

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Frediction

Toy metanonulation models

Model output

Conclusions

catastrophe





Introduction

Biological

Contagion

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

Predicting soci

References

Optimism according to Ambrose Bierce: (H)

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





Contagion

Biological

Simple disease spreading models

Background

More models

Toy metapopulation models

Conclusions

Poforonoos

Optimism according to Ambrose Bierce: (H)

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.





Eric Hoffer, 1902-1983

There is a grandeur in the uniformity of the mass.

► Hoffer (⊞) was an interesting fellow.

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Predicting soci







Eric Hoffer, 1902–1983

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

Catastrophie

References







Biological Contagion

Eric Hoffer, 1902-1983

There is a grandeur in the uniformity of the mass. 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

More mode

Tov metapopulation models

Model output

Deadiating again

References





Biological Contagion

Eric Hoffer, 1902–1983

There is a grandeur in the uniformity of the mass. 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

Tov metapopulation models

Model output

Description

catastropne

References





Biological Contagion

Eric Hoffer, 1902-1983

There is a grandeur in the uniformity of the mass. 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, sway their bodies in unison.

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

Predicting soc

References





Biological Contagion

Eric Hoffer, 1902-1983

There is a grandeur in the uniformity of the mass. 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, sway their bodies in unison, hum one song or break forth in anger and denunciation,

Introduction

Simple disease spreading models Background

Prediction

Tov metapopulation models

Model output

Conclusions





Eric Hoffer, 1902–1983

There is a grandeur in the uniformity of the mass. 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, sway their bodies in unison, hum one song or break forth in anger and denunciation, there is the overpowering feeling that in this country we have come nearer the brotherhood of man than ever before.

► Hoffer (⊞) was an interesting fellow

Introduction

Simple disease spreading models

Prediction

Tov metapopulation models

Model output

Predicting so





Eric Hoffer, 1902-1983

There is a grandeur in the uniformity of the mass. 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, sway their bodies in unison, hum one song or break forth in anger and denunciation, there is the overpowering feeling that in this country we have come nearer the brotherhood of man than ever before.

► Hoffer (⊞) was an interesting fellow...

Introduction

Simple disease spreading models Background

Prediction

Toy metapopulation mode

Model output

Predicting soc





The spread of fanaticism

Biological Contagion

Hoffer's acclaimed work: "The True Believer:

Thoughts On The Nature Of Mass Movements" (1951) [3]

Quotes-aplenty:

- "We can be absolutely certain only about things we do not understand."
- "Mass movements can rise and spread without belief in a God, but never without belief in a devil."
- "Where freedom is real, equality is the passion of the masses. Where equality is real, freedom is the passion of a small minority."

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Conclusions

Poforonoos





The spread of fanaticism

Biological Contagion

Hoffer's acclaimed work: "The True Believer:

Thoughts On The Nature Of Mass Movements" (1951) [3]

Quotes-aplenty:

- "We can be absolutely certain only about things we do not understand."
- "Mass movements can rise and spread without belief in a God, but never without belief in a devil."
- "Where freedom is real, equality is the passion of the masses. Where equality is real, freedom is the passion of a small minority."

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

Deferences





The spread of fanaticism

Biological Contagion

Hoffer's acclaimed work: "The True Believer:

Thoughts On The Nature Of Mass Movements" (1951) [3]

Quotes-aplenty:

- "We can be absolutely certain only about things we do not understand."
- "Mass movements can rise and spread without belief in a God, but never without belief in a devil."
- "Where freedom is real, equality is the passion of the masses. Where equality is real, freedom is the

nassion of a small minority"

Introduction

Simple disease spreading models

Background

Prediction

Toy metanonulation models

Model output

Dradicting each





Thoughts On The Nature Of Mass Movements" (1951) [3]

Quotes-aplenty:

- "We can be absolutely certain only about things we do not understand."
- "Mass movements can rise and spread without belief in a God, but never without belief in a devil."
- "Where freedom is real, equality is the passion of the masses. Where equality is real, freedom is the passion of a small minority."

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Predicting soci





do not understand."

Quotes-aplenty:

Hoffer's acclaimed work: "The True Believer:

spreading models

Background

Simple disease

"Mass movements can rise and spread without belief in a God, but never without belief in a devil."

"We can be absolutely certain only about things we

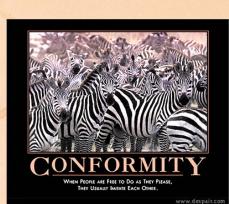
Thoughts On The Nature Of Mass Movements" (1951) [3]

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





Imitation



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

—Eric Hoffer
"The Passionate State
of Mind" [4]

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

More models

Toy metapopulation models

onclusions

Predicting soci catastrophe

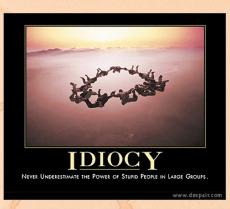
References



despair.com



The collective...



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

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

FIEUICIOII

Toy metapopulation models

Conclusions

Predicting socia

References



despair.com



Biological Contagion

Definitions

- ► (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself: the plague, a blight, the dreaded lurgi, ...
- ▶ from Latin: *con* = 'together with' + *tangere* 'to touch.'
- ► Contagion has unpleasant overtones...
- Just Spreading might be a more neutral word
- But contagion is kind of exciting...

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Predicting soc







Biological Contagion

Definitions

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself: the plague, a blight, the dreaded lurgi, ...
- ▶ from Latin: *con* = 'together with' + *tangere* 'to touch.'
- ► Contagion has unpleasant overtones...
- Just Spreading might be a more neutral word
- But contagion is kind of exciting...

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Predicting soc





Definitions

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself: the plague, a blight, the dreaded lurgi, ...
- ▶ from Latin: *con* = 'together with' + *tangere* 'to touch.'
- ► Contagion has unpleasant overtones...
- Just Spreading might be a more neutral word
- ▶ But contagion is kind of exciting...

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Predicting soc





Definitions

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself: the plague, a blight, the dreaded lurgi, ...
- from Latin: con = 'together with' + tangere 'to touch.'
- Contagion has unpleasant overtones..
- Just Spreading might be a more neutral word
- ▶ But contagion is kind of exciting...

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Predicting soci

Poforoncos







Definitions

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself: the plague, a blight, the dreaded lurgi, ...
- from Latin: con = 'together with' + tangere 'to touch.'
- ► Contagion has unpleasant overtones...
- Just Spreading might be a more neutral word
- But contagion is kind of exciting...

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation mode

Model output

Desdisting

catastrophe





Definitions

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself: the plague, a blight, the dreaded lurgi, ...
- from Latin: con = 'together with' + tangere 'to touch.'
- Contagion has unpleasant overtones...
- Just Spreading might be a more neutral word
- But contagion is kind of exciting...

Introduction

Simple disease spreading models Background

Prediction

More mode

Toy metapopulation mo

Model output

Predicting soc





Definitions

- (1) The spreading of a quality or quantity between individuals in a population.
- (2) A disease itself: the plague, a blight, the dreaded lurgi, ...
- from Latin: con = 'together with' + tangere 'to touch.'
- Contagion has unpleasant overtones...
- Just Spreading might be a more neutral word
- But contagion is kind of exciting...

Introduction

Simple disease spreading models

Background

More mode

Toy metapopulation model

Model output

Predicting so





Examples of non-disease spreading:

Interesting infections:

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



► Viral get-out-the-vote video. (⊞)

Biological Contagion

Introduction

Simple disease spreading models

Background

Toy metapopulation models







Examples of non-disease spreading:

Interesting infections:

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



➤ Viral get-out-the-vote video. (⊞)

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models Model output

Conclusions

Predicting social







Two main classes of contagion

- 1 Infectious diseases
- 2. Social contagion

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

Predicting soc







Two main classes of contagion

- 1. Infectious diseases
- 2. Social contagion

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

Predicting so







Two main classes of contagion

- 1. Infectious diseases
- 2. Social contagion

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Predicting soc







Two main classes of contagion

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

Biological Contagion

Introduction

Simple disease spreading models

Background

1 Toulction

Tov metapopulation models

Model output

Conclusions

Predicting soc





Introduction

Biological

Contagion

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Predicting so

References

Two main classes of contagion

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





Outline

Introduction

Simple disease spreading models Background

Prediction

More models

Toy metapopulation models

Model output

Complisions

Predicting social catastrophe

References

Biological Contagion

Introduction

Simple disease spreading models

Toy metapopulation models

Background

Prediction

More models

Administration of

Conclusions

Predicting socia







The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

iviouei output

Predicting social





The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Toy metapopulation models

Background

Prediction

More models

Conclusions

Predicting social







The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Toy metapopulation models

Background

Prediction

More models

Model output

Conclusions







The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Predicting social







The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Predicting socia

Deferences





The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Predicting socia







The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Conclusions

catastrophe







The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Prodicting social







The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Conclusions





The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Dradiating agai

Deference







The standard SIR model [8]

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More model

And all and and

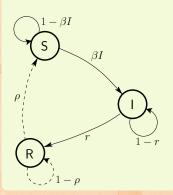
Conclusions

catastrophe





Discrete time automata example:



Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More mode

Toy metapopulation models

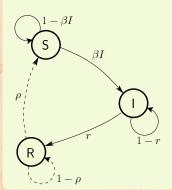
Model output

Predicting so





Discrete time automata example:



Transition Probabilities:

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

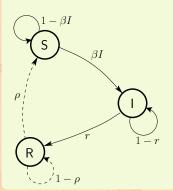
odidoliopilo







Discrete time automata example:



Transition Probabilities:

 β for being infected given contact with infected

Biological Contagion

Simple disease spreading models

Toy metapopulation models

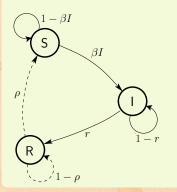
Background







Discrete time automata example:



Transition Probabilities:

β for being infected given contact with infected r for recovery

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More mode

Toy metapopulation models

Conclusions

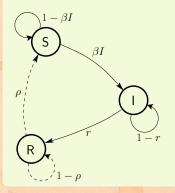
catastrophe







Discrete time automata example:



Transition Probabilities:

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

Biological Contagion

Introduction

Simple disease spreading models

Toy metapopulation models

Background

Prediction

More models

Madal autaut

Conclusions

Deferences







Original models attributed to

- ▶ 1920's: Reed and Frost
- ▶ 1920's/1930's: Kermack and McKendrick [5, 7, 6]
- Coupled differential equations with a mass-action principle

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More mode

Toy metapopulation models

Model output

Conclusions

catastrophe







Original models attributed to

- ▶ 1920's: Reed and Frost
- ▶ 1920's/1930's: Kermack and McKendrick [5, 7, 6]
- Coupled differential equations with a mass-action principle

Biological Contagion

Introduction

Simple disease spreading models

Background

More mode

Toy metapopulation models

Model output

Conclusions

Predicting soc







Original models attributed to

- ▶ 1920's: Reed and Frost
- ▶ 1920's/1930's: Kermack and McKendrick [5, 7, 6]
- Coupled differential equations with a mass-action principle

Biological Contagion

Introduction

Simple disease spreading models

Background

More mode

Tov metapopulation models

Model output

Conclusions

catastrophe







Original models attributed to

- ▶ 1920's: Reed and Frost
- ▶ 1920's/1930's: Kermack and McKendrick [5, 7, 6]
- Coupled differential equations with a mass-action principle

Biological Contagion

Introduction

Simple disease spreading models

Background

More mode

Toy metanonulation mode

Model output

Predicting soci





Differential equations for continuous model

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

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

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

 β , r, and ρ are now rates.

Reproduction Number R_0 :

▶ R₀ = expected number of infected individuals resulting from a single initial infective
 ▶ Epidemic threshold: If R₀ > 1, 'epidemic' occur

Biological Contagion

Introduction

Simple disease spreading models

Background

Frediction

Tov metapopulation models

Model output

Desdistance

- (









Differential equations for continuous model

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

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

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

 β , r, and ρ are now rates.

Reproduction Number R_0 :

- ► R₀ = expected number of infected individuals resulting from a single initial infective
- ▶ Epidemic threshold: If $R_0 > 1$, 'epidemic' occurs.

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation model

Model output

Predicting soci

odidotroprio







Differential equations for continuous model

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

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

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

 β , r, and ρ are now rates.

Reproduction Number R_0 :

- ► R₀ = expected number of infected individuals resulting from a single initial infective
- ▶ Epidemic threshold: If $R_0 > 1$, 'epidemic' occurs.

Biological Contagion

Introduction

Simple disease spreading models

Background

More mode

Tourse de la constante de la c

Model output

Predicting soci

D-6----







Differential equations for continuous model

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

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

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

 β , r, and ρ are now rates.

Reproduction Number R_0 :

- R₀ = expected number of infected individuals resulting from a single initial infective
- ▶ Epidemic threshold: If $R_0 > 1$, 'epidemic' occurs.

Biological Contagion

Introduction

Simple disease spreading models

Background

Managed

More models

Model output

Conclusion







Reproduction Number R₀

Discrete version:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Prodicting soc

catastrophe





Reproduction Number R₀

Discrete version:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More mede

Tou motopopulation mode

Model output

Prodicting eaci





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

- At time t = 0, single infective random bumps into a Susceptible
- ▶ Probability of transmission = β
- At time t = 1, single Infective remains infected with probability 1 - r
- At time t = k, single Infective remains infected with probability $(1 r)^k$

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Conclusions





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

Introduction

Simple disease spreading models

Background

Managed

More models

Model output

Conclusions

catastrophe





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

- At time t = 0, single infective random bumps into a Susceptible
- ▶ Probability of transmission = β
- At time t = 1, single Infective remains infected with probability 1 r
- At time t = k, single Infective remains infected with probability $(1 r)^k$

Introduction

Simple disease spreading models

Background

More med

Tou motopopulation ma

Model output

Desdistances





Reproduction Number Ro

Discrete version:

Expected number infected by original Infective:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Frediction

Toy metapopulation models

Model output

Predicting socia





Discrete version:

Expected number infected by original Infective:

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

$$=\beta\left(1+(1-r)+(1-r)^2+(1-r)^3+\ldots\right)$$

Introductio

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions





Reproduction Number Ro

Discrete version:

Expected number infected by original Infective:

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

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

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

Predicting social







Reproduction Number Ro

Discrete version:

► Expected number infected by original Infective:

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

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

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Panalusiana

Predicting socia





Discrete version:

Expected number infected by original Infective:

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

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

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

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

$$R_0 = S_0 \beta / r$$

Introductio

Simple disease spreading models

Background

More model:

Toy metapopulation models

Conclusions

Predicting social







For the continuous version

► Second equation:

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

Number of infectives grows initially if

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

Same story as for discrete model.

Biological Contagion

Introduction

Simple disease spreading models

Toy metapopulation models

Background

Prediction

More models

Model output

Dradicting soc





For the continuous version

Second equation:

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

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

Number of infectives grows initially if

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

Same story as for discrete model.

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Conclusions

Predicting socia







For the continuous version

► Second equation:

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

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

Number of infectives grows initially if

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

Same story as for discrete model.

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More model

Toy metapopulation models

Conclusions

Predicting social





For the continuous version

Second equation:

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

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

Number of infectives grows initially if

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

Same story as for discrete model.

Biological Contagion

Introduction

Simple disease spreading models

Toy metapopulation models

Background

Prediction

More models

Model output

Conclusions







For the continuous version

Second equation:

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

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

Number of infectives grows initially if

$$\beta S(0) - r > 0 \Rightarrow \beta S(0) > r \Rightarrow \frac{\beta S(0)}{r} > 1$$

Same story as for discrete model.

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More mode

Toy metapopulation models

Conclusions

Predicting social







For the continuous version

Second equation:

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

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

Number of infectives grows initially if

$$\beta S(0) - r > 0 \Rightarrow \beta S(0) > r \Rightarrow \frac{\beta S(0)}{r} > 1$$

Same story as for discrete model.

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More model

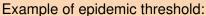
Toy metapopulation models

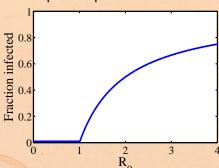
Conclusions

Predicting social









Biological Contagion

Simple disease spreading models

Background

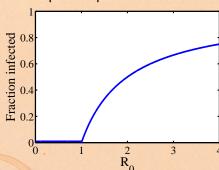
Toy metapopulation models







Example of epidemic threshold:



Continuous phase transition.

Biological Contagion

Simple disease spreading models

Background

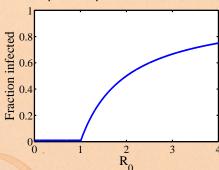
Toy metapopulation models







Example of epidemic threshold:



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

Biological Contagion

Introduction

Simple disease spreading models

Background

More model

to inclupope

Conclusion

redicting social







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)

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Onnel output

Predicting socia







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)

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Predicting socia







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)

Biological Contagion

Introduction

Simple disease spreading models

Background

More mode

Toy metanonulation mode

Conclusions

Predicting socia





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)

Biological Contagion

Introduction

Simple disease spreading models

Background

More mod

To a contract of the contract of

Model output

Predicting soc





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)

Biological Contagion

Introduction

Simple disease spreading models

Background

More mod

ioy metapopulation i

Conclusions

Predicting socia





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)

Biological Contagion

Introduction

Simple disease spreading models

Background

More mod

Toy metapopulation mode

Model output

Predicting soc





Outline

Simple disease spreading models

Prediction

Biological Contagion

Simple disease spreading models

Background

Prediction

Toy metapopulation models







For novel diseases:

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

R_0 approximately same for all of the following:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions







For novel diseases:

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

R_0 approximately same for all of the following:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Description





For novel diseases:

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

R_0 approximately same for all of the following:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclus

Predicting soci





For novel diseases:

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

R_0 approximately same for all of the following:

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

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

Prediction

Toy metapopulation models

Model outpi

Predicting soc





For novel diseases:

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

R_0 approximately same for all of the following:

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

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

More models

Toy metapopulation models

Model output

Predicting soc





For novel diseases:

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

R_0 approximately same for all of the following:

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

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

More models

Model output

Predicting soc





For novel diseases:

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

R_0 approximately same for all of the following:

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

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

More models

Toy metapopulation models

Model output

Predicting soci





For novel diseases:

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

R_0 approximately same for all of the following:

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

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

Toy metapopulation models

Model output

Predicting so





Size distributions are important elsewhere:

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

Really, what about epidemics?

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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Predicting soci







Biological Contagion

Size distributions are important elsewhere:

- earthquakes (Gutenberg-Richter law)
- wealth distributions
- ► Epidemics?

Simple disease spreading models

Background

Prediction

Toy metapopulation models







Biological Contagion

Size distributions are important elsewhere:

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

macadonon

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

catastropne

References

Really, what about epidemics?

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







Biological Contagion

Size distributions are important elsewhere:

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

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

Predicting soc catastrophe

References

Really, what about epidemics?

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







Biological Contagion

Size distributions are important elsewhere:

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

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Predicting so

References

Really, what about epidemics?

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







Biological Contagion

Size distributions are important elsewhere:

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

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Predicting e

References

Really, what about epidemics?

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







Biological Contagion

Size distributions are important elsewhere:

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

Power laws distributions are common but not obligatory...

Really, what about epidemics?

Simply hasn't attracted much attention.

Data not as clean as for other phenomena.

Introduction

Simple disease spreading models

Background

Prediction

Toursette and the second

Model output

Predicting s

catastrophe





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

Power laws distributions are common but not obligatory...

Really, what about epidemics?

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

Introduction

Simple disease spreading models

Background

Prediction

Toy metanonulation mode

Model output

Predicting so





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

Power laws distributions are common but not obligatory...

Really, what about epidemics?

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

Introduction

Simple disease spreading models

Background

Prediction

Tou motonopulation made

Model output

Predicting so





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

Power laws distributions are common but not obligatory...

Really, what about epidemics?

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

Simple disease

spreading models

Prediction

Toy metapopulation mode

Model output

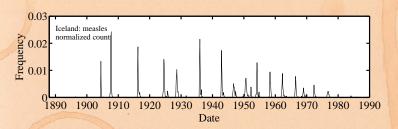
Predicting so





Feeling III in Iceland

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



 Treat outbreaks separated in time as 'novel' diseases.

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

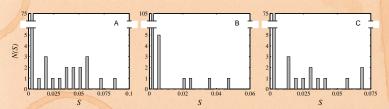
Conclusions





Really not so good at all in Iceland

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



Spike near S=0, relatively flat otherwise.

Biological Contagion

Simple disease spreading models

Background

Prediction

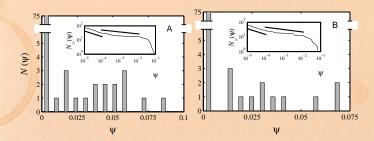
Toy metapopulation models







Measles & Pertussis



Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models Model output

Conclusions

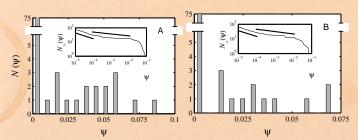
Predicting so







Measles & Pertussis



Insert plots:

Complementary cumulative frequency distributions:

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

Limited scaling with a possible break.

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

Prediction

Tov metapopulation models

Model output

Predicting so

catastrophe





Measured values of γ :

- pertussis: 1.39 (low Ψ) and 1.16 (high Ψ)

Biological Contagion

Simple disease spreading models Background

Prediction

Toy metapopulation models







Measured values of γ :

- measles: 1.40 (low Ψ) and 1.13 (high Ψ)

Biological Contagion

Simple disease spreading models Background

Prediction

Toy metapopulation models







Measured values of γ :

► measles: 1.40 (low Ψ) and 1.13 (high Ψ)

pertussis: 1.39 (low Ψ) and 1.16 (high Ψ)

- Expect 2 < ~ < 3 (finite mean, infinite variance)
- ➤ When > < 1, can't normalize
- Distribution is quite flat

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

catastrophe





Measured values of γ :

- measles: 1.40 (low Ψ) and 1.13 (high Ψ)
- pertussis: 1.39 (low Ψ) and 1.16 (high Ψ)
- Expect $2 \le \gamma < 3$ (finite mean, infinite variance)
- ▶ When ¬ < 1, can't normalize</p>
- Distribution is quite flat

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusio

Predicting soci catastrophe







Measured values of γ :

- ► measles: 1.40 (low Ψ) and 1.13 (high Ψ)
- pertussis: 1.39 (low Ψ) and 1.16 (high Ψ)
- Expect $2 \le \gamma < 3$ (finite mean, infinite variance)
- When γ < 1, can't normalize
- Distribution is quite flat

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

Prediction

Toy metapopulation models

Model output

Desdistance

Catastrophie





Measured values of γ :

- measles: 1.40 (low Ψ) and 1.13 (high Ψ)
- pertussis: 1.39 (low Ψ) and 1.16 (high Ψ)
- Expect $2 \le \gamma < 3$ (finite mean, infinite variance)
- ▶ When γ < 1, can't normalize
- Distribution is quite flat.

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

Prediction

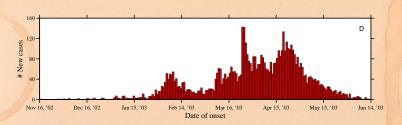
Toy metapopulation models

Model output

Conclusions







- Epidemic slows.
- Epidemic discovers new 'pools' of susceptibles.

 Resurgence.
- ► Importance of rare, stochastic events

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

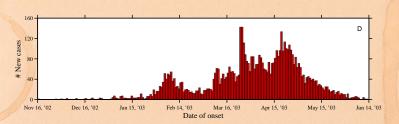
Conclusions

Predicting social catastrophe









- Epidemic slows...

Biological Contagion

Simple disease spreading models

Background

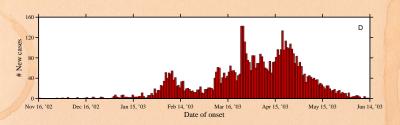
Prediction

Toy metapopulation models









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

Biological Contagion

Simple disease spreading models Background

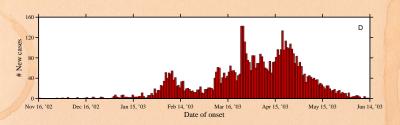
Prediction

Toy metapopulation models









- Epidemic slows... then an infective moves to a new context.
- Epidemic discovers new 'pools' of susceptibles: Resurgence.
- Importance of rare, stochastic events

Biological Contagion

Introduction

Simple disease spreading models

Prediction

Prediction More mode

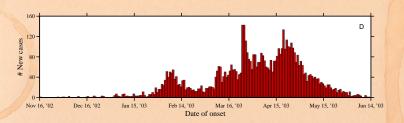
Toy metapopulation models

Model output

Predicting socia







- Epidemic slows... then an infective moves to a new context.
- ► Epidemic discovers new 'pools' of susceptibles: Resurgence.
- Importance of rare, stochastic events.

Biological Contagion

Introduction

Simple disease spreading models

Prediction

Prediction

Tov metapopulation models

Model output

Prodicting soc







Outline

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Madal output

Complians

Predicting social catastrophe

References

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models Toy metapopulation models

Model output

Conclusions

Predicting soci







The challenge

So... can a simple model produce

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

Biological Contagion

Introduction

Simple disease spreading models

Background

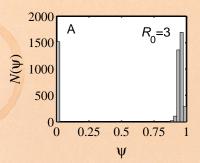
More models Toy metapopulation models

Model output

Conclusions







Simple models typically produce bimodal or unimodal size distributions.

I his includes network models

random, small-world, scale-free

- 1. Forest fire models
- 2. Sophisticated metapopulation models

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

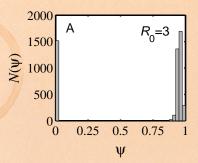
Predicting so

Deferences









Simple models typically produce bimodal or unimodal size distributions.

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

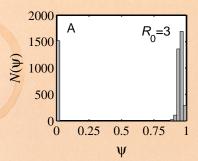
Model output

Predicting so









Simple models typically produce bimodal or unimodal size distributions.

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

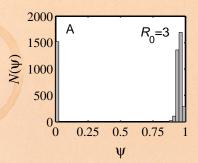
Toy metapopulation models

Model output

Predicting socia







Simple models typically produce bimodal or unimodal size distributions.

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

2. Sophisticated metapopulation models

Biological Contagion

Introduction

Simple disease spreading models

Prediction

More models

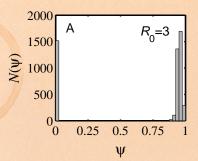
Toy metapopulation models

O---Ividen

Predicting so







Simple models typically produce bimodal or unimodal size distributions.

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Conclusions

Predicting soc





Forest fire models: [9]

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

A bit of a stretch:

- Epidemics = 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.

Biological Contagion

Introduction

Simple disease spreading models

Background

More models Toy metapopulation models

Model output Conclusions

Predicting soc







Forest fire models: [9]

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

A bit of a stretch:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models Toy metapopulation models

Model output

Predicting so







Forest fire models: [9]

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

A bit of a stretch:

- spreading on 3-d and 5-d lattice
- Claim Iceland and Faroe Islands exhibit power law distributions for outbreaks.
- 3. Original forest fire model not completely understood

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models Model output

Conclusions

catastrophe







Forest fire models: [9]

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

A bit of a stretch:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

Predicting soc







Forest fire models: [9]

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

A bit of a stretch:

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models Toy metapopulation models

Model output

Predicting soc







Forest fire models: [9]

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

A bit of a stretch:

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

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

More models Toy metapopulation models

Model output

Predicting soc





Forest fire models: [9]

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

A bit of a stretch:

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

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

More models

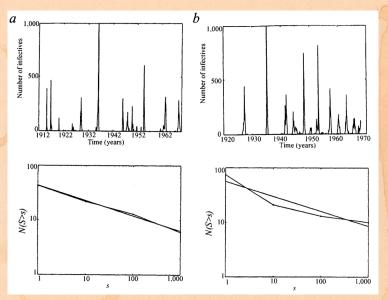
Toy metapopulation models

Model output

Predicting soc







From Rhodes and Anderson, 1996.

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

Predicting so

References







2 9 € 35 of 65

- Community based mixing: Longini (two scales).
- Eubank et al.'s EpiSims/TRANSIMS—city simulations.
- Spreading through countries—Airlines: Germann et al., Corlizza et al.
- ▶ Vital work but perhaps hard to generalize from...
- ► ⇒ Create a simple model involving multiscale travel
- ► Multiscale models suggested by others but not formalized (Bailey, Cliff and Haggett, Ferguson et al.)

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

More models Toy metapopulation models

Model output

Predicting social







Biological Contagion

intioddotton

Simple disease spreading models Background

Prediction

More models Toy metapopulation models

Conclusions

Predicting social

- Community based mixing: Longini (two scales).
- Eubank et al.'s EpiSims/TRANSIMS—city simulations.
- Spreading through countries—Airlines: Germann et al., Corlizza et al.
- ▶ Vital work but perhaps hard to generalize from...
- ► ⇒ Create a simple model involving multiscale travel
- Multiscale models suggested by others but not formalized (Bailey, Cliff and Haggett, Ferguson et al.





Biological Contagion

Community based mixing: Longini (two scales).

- Eubank et al.'s EpiSims/TRANSIMS—city simulations.
- Spreading through countries—Airlines: Germann et al., Corlizza et al.
- ▶ Vital work but perhaps hard to generalize from...
- ➤ ⇒ Create a simple model involving multiscale travel
- Multiscale models suggested by others but not formalized (Bailey, Cliff and Haggett, Ferguson et al.)

Introduction

Simple disease spreading models

Background

Prediction

More models Toy metapopulation models

Conclusions

Predicting social





Biological Contagion

Community based mixing: Longini (two scales).

- Eubank et al.'s EpiSims/TRANSIMS—city simulations.
- Spreading through countries—Airlines: Germann et al., Corlizza et al.
- Vital work but perhaps hard to generalize from...
- ➤ ⇒ Create a simple model involving multiscale travel
- Multiscale models suggested by others but not formalized (Bailey, Cliff and Haggett, Ferguson et al.)

Introduction

Simple disease spreading models Background

Prediction

More models

Toy metapopulation models

Conclusions

Predicting social catastrophe





Biological Contagion

Community based mixing: Longini (two scales).

Eubank et al.'s EpiSims/TRANSIMS—city simulations.

- Spreading through countries—Airlines: Germann et al., Corlizza et al.
- Vital work but perhaps hard to generalize from...
- ► ⇒ Create a simple model involving multiscale travel
- Multiscale models suggested by others but not formalized (Bailey, Cliff and Haggett, Ferguson et al.)

Introduction

Simple disease spreading models Background

More models

Toy metapopulation models

Conclusions

Predicting soc





More models Toy metapopulation models

Conclusions

Predicting soc catastrophe

- Community based mixing: Longini (two scales).
- Eubank et al.'s EpiSims/TRANSIMS—city simulations.
- Spreading through countries—Airlines: Germann et al., Corlizza et al.
- Vital work but perhaps hard to generalize from...
- ➤ ⇒ Create a simple model involving multiscale travel
- Multiscale models suggested by others but not formalized (Bailey, Cliff and Haggett, Ferguson et al.)





Size distributions

Biological Contagion

Introduction

Simple disease spreading models

Background

More models Toy metapopulation models

Model output

Predicting soc

- 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...







Size distributions

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

catastrophe

- ► 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





Size distributions

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

Conclusions

Predicting socia

- ► 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

/Backgrounc

Prediction

More models

Toy metapopulation models

Model output

Canadosiens

Predicting social catastrophe

References

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

O----

D. II II

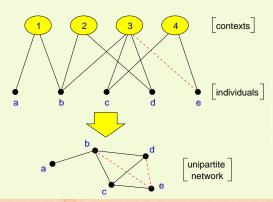
catastrophe







Contexts and Identities—Bipartite networks



Biological Contagion

Simple disease spreading models

Background

Toy metapopulation models

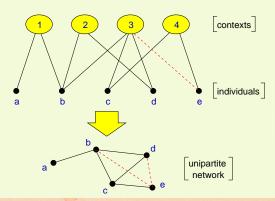








Contexts and Identities—Bipartite networks



boards of directors

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

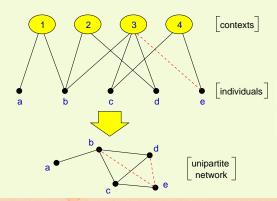
Predicting so







Contexts and Identities—Bipartite networks



- boards of directors
- movies

Biological Contagion

Introduction

Simple disease spreading models

Background

Fiediction

Toy metapopulation models

Model output

Prodicting ed

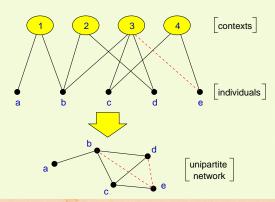
Deferences







Contexts and Identities—Bipartite networks



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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

Predicting so







Idea for social networks: incorporate identity.

Identity is formed from attributes such as

- Geographic location
- ▶ Type of employmen
- ► Age
- ▶ Recreational activities

Groups are crucial...

- formed by people with at least one similar attribute
- ▶ Attributes ⇔ Contexts ⇔ Interactions ⇔ Networks [11]

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Predicting so

catastrophe







Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

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

Groups are crucial...

- formed by people with at least one similar attribute
- Attributes

 Contexts

 Interactions

 Networks. [11]

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Conclusions

Predicting social





Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

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

Biological Contagion

Simple disease spreading models

Background

Toy metapopulation models







Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

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

Groups are crucial...

- formed by people with at least one similar attribute
- Attributes

 Contexts

 Interactions

 Networks. [11]

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

More medale

Toy metapopulation models

Conclusions

Predicting soc





Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

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

Groups are crucial...

- formed by people with at least one similar attribute
- ▶ Attributes ⇔ Contexts ⇔ Interactions ⇔ Networks [11]

Biological Contagion

Introduction

Simple disease spreading models

Prediction

More models

Toy metapopulation models

Conclusions

Predicting soc







Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

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

Groups are crucial...

- formed by people with at least one similar attribute
- ► Attributes ⇔ Contexts ⇔ Interactions ⇔

Biological Contagion

Introduction

Simple disease spreading models

Background

More model

Toy metapopulation models

Conclusions

Predicting so







Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

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

Groups are crucial...

- formed by people with at least one similar attribute
- ► Attributes ⇔ Contexts ⇔ Interactions ⇔ Networks. [11]

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

More model

Toy metapopulation models

Conclusions

Predicting soc







Idea for social networks: incorporate identity.

Identity is formed from attributes such as:

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

Groups are crucial...

- formed by people with at least one similar attribute
- ► Attributes ⇔ Contexts ⇔ Interactions ⇔ Networks. [11]

Biological Contagion

Introduction

Simple disease spreading models

Background

Managed

Toy metapopulation models

Conclusions

Predicting soci







Identity is formed from attributes such as:

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

Groups are crucial...

- formed by people with at least one similar attribute
- ► Attributes ⇔ Contexts ⇔ Interactions ⇔ Networks. [11]

Introduction

Simple disease spreading models

Background

Frediction

Toy metapopulation models

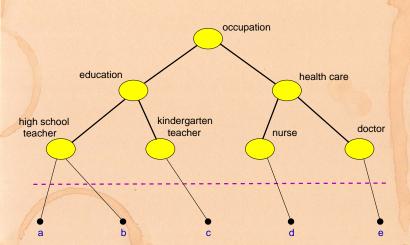
Conclusions

Predicting soci





Infer interactions/network from identities



Distance makes sense in identity/context space.

Biological Contagion

Introduction

Simple disease spreading models

Background

Mara madala

Toy metapopulation models

del output

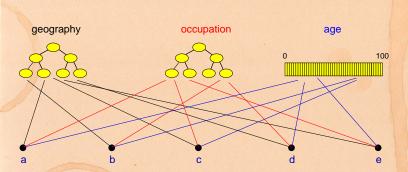
Predicting soci







Generalized context space



(Blau & Schwartz [1], Simmel [10], Breiger [2])

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

More models

Toy metapopulation models

Conclusions

Predicting son





Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- \triangleright β = infection probability
- $ightharpoonup \gamma = recovery probability$
- ► *P* = probability of travel
- ▶ Movement distance: $Pr(d) \propto exp(-d/\xi)$
- \blacktriangleright ξ = typical travel distance

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Conclusions

catastrophe







Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- $\triangleright \beta = \text{infection probability}$
- $ightharpoonup \gamma = recovery probability$
- ► *P* = probability of travel
- ▶ Movement distance: $Pr(d) \propto exp(-d/\xi)$
- \blacktriangleright ξ = typical travel distance

Biological Contagion

Introduction

Simple disease spreading models

Background

Fiediction

Toy metapopulation models

Model output

Predicting sor

catastrophe







Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- \triangleright β = infection probability
- $ightharpoonup \gamma = recovery probability$
- \triangleright P = probability of travel
- ▶ Movement distance: $Pr(d) \propto exp(-d/\xi)$
- \blacktriangleright ξ = typical travel distance

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Predicting son







Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- $\triangleright \beta = infection probability$
- $ightharpoonup \gamma = recovery probability$
- ► *P* = probability of travel
- ▶ Movement distance: $Pr(d) \propto exp(-d/\xi)$
- \blacktriangleright ξ = typical travel distance

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Conclusions

Predicting social catastrophe







Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- $\triangleright \beta = infection probability$
- $ightharpoonup \gamma$ = recovery probability
- ► *P* = probability of travel
- ▶ Movement distance: $Pr(d) \propto exp(-d/\xi)$
- \blacktriangleright ξ = typical travel distance

Biological Contagion

Introduction

Simple disease spreading models

Background

Mara madal

Toy metapopulation models

Model output Conclusions

Predicting soci







Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- $\triangleright \beta = infection probability$
- $ightharpoonup \gamma$ = recovery probability
- ► P = probability of travel
- ▶ Movement distance: $Pr(d) \propto exp(-d/\xi)$
- \blacktriangleright ξ = typical travel distance

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Conclusions

catastropne







Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- $\triangleright \beta = infection probability$
- $ightharpoonup \gamma$ = recovery probability
- ► P = probability of travel
- ▶ Movement distance: $Pr(d) \propto exp(-d/\xi)$
- \triangleright ξ = typical travel distance

Biological Contagion

Introduction

Simple disease spreading models

Background

Managed

Toy metapopulation models

lodel output

Predicting soci





Geography—allow people to move between contexts:

- Locally: standard SIR model with random mixing
- discrete time simulation
- $\triangleright \beta = infection probability$
- $ightharpoonup \gamma$ = recovery probability
- ► P = probability of travel
- ▶ Movement distance: $Pr(d) \propto exp(-d/\xi)$
- \triangleright ξ = typical travel distance

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

More models

Toy metapopulation models

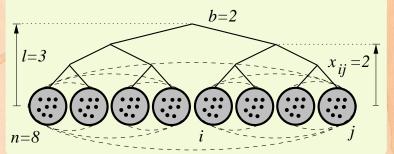
Conclusion

Predicting social catastrophe





Schematic:



Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Conclusions







Outline

Introduction

Simple disease spreading models

/Background

Prediction

More model:

Toy metapopulation models

Model output

Campingians

Predicting social catastrophe

References

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions

eredicting social







Model output

- Define P_0 = Expected number of infected individuals leaving initially infected context.
- ▶ Need P₀ > 1 for disease to spread (independent or
- ► Limit epidemic size by restricting frequency of travel and/or range

Biological Contagion

Introduction

Simple disease spreading models

Background

Toy metapopulation models

Model output

Predicting so





- 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

Biological Contagion

Introduction

Simple disease spreading models

Background

Tov metapopulation models

Model output

Predicting so





Interdication

Biological

Contagion

Simple disease spreading models

Background Prediction

Toy metapopulation mode

Model output

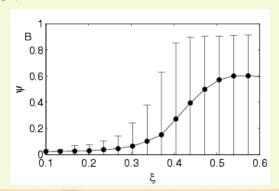
Predicting so

- 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





Varying ξ :



 Transition in expected final size based on typical movement distance

Biological Contagion

Introduction

Simple disease spreading models

Background

Tov metapopulation models

Model output

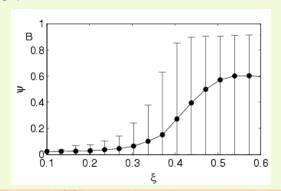
Predicting soc







Varying ξ :



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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Tov metapopulation models

Model output

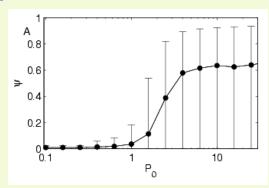
Conclusions







Varying P_0 :



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

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

Tov metapopulation models

Model output

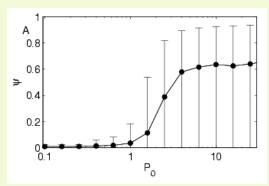
Predicting soc







Varying P_0 :



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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Tov metapopulation models

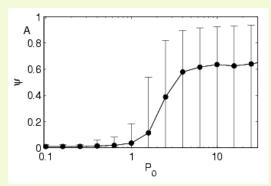
Model output

Predicting soc





Varying P_0 :



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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Tov metapopulation models

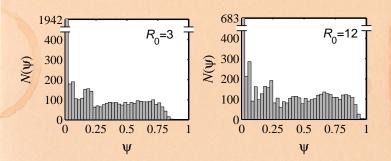
Model output

Predicting soc









Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

Toy metapopulation models

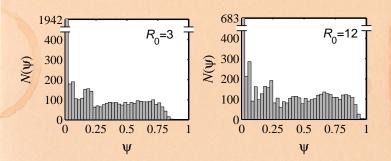
Model output

Predicting soc









Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

Toy metapopulation models

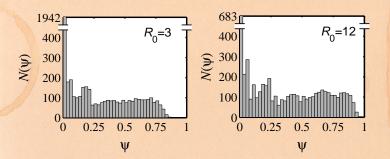
Model output

Predicting soc









Flat distributions are possible for certain ξ and P.

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

Toy metapopulation models

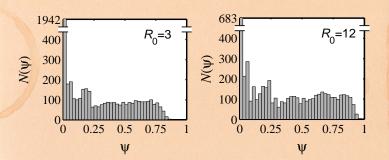
Model output

Predicting soc









- Flat distributions are possible for certain ξ and P.
- Different R₀'s may produce similar distributions

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

Toy metapopulation models

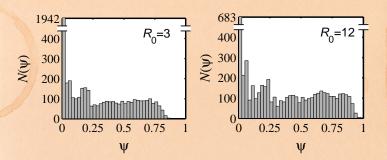
Model output

Predicting soc









- ▶ Flat distributions are possible for certain ξ and P.
- ► Different R₀'s may produce similar distributions
- Same epidemic sizes may arise from different R₀'s

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

Toy metapopulation models

Model output Conclusions

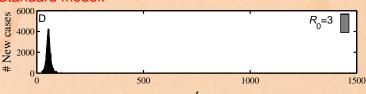
Predicting so catastrophe





Model output—resurgence

Standard model:



Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

1 rediction

Toy metapopulation mode

Model output

Conclusi

Predicting soci catastrophe

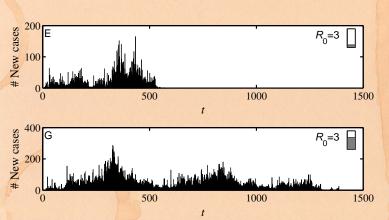






Model output—resurgence

Standard model with transport:



Biological Contagion

Simple disease spreading models

Background

Model output







The upshot

Simple multiscale population structure

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metanonulation mode

Model output

Conclusions

Predicting social catastrophe







The upshot

Simple multiscale population structure + stochasticity

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Tou metapopulation made

Model output

Conclusio

Predicting social catastrophe







The upshot

Simple multiscale population structure + stochasticity

leads to

resurgence

+

broad epidemic size distributions

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models Model output

Conclus

redicting social





Outline

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Conclusions

Predicting social catastrophe

References

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions

catastrophe







- For this model, epidemic size is highly unpredictable
- ▶ Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- The reproduction number n_0 is not terribly useful.
- ▶ R_h, however measured, is not informative about
 - 1. how likely the observed epidemic size was,
 - 2. and how likely future epidemics will be.

Problem: Ro summarises one epidemic after the fact and enfolds movement, the price of bananas.

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

Predicting soc





- For this model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple
- ➤ We haven't even included normal social response
 - such as travel bans and self-quarantine
- \blacktriangleright The reproduction number R_0 is not terribly useful.
- ▶ R₀, however measured, is not informative about
 - 1. how likely the observed epidemic size was,
 - 2. and how likely future epidemics will be.

s one epidemic after the fact

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions





- For this model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- \blacktriangleright The reproduction number H_0 is not terribly useful
 - z 145 nonovor mododrod, io not imornicario dol
 - how likely the observed epidemic size was,
 - 2. and how likely future epidemics will be.

one epidemic after the fact

Biological Contagion

Introduction

Simple disease spreading models

Dradiation

rieulction

Toy metapopulation models

Model output

Conclusions Predicting so

catastrophe





Biological Contagion

Simple disease

spreading models

Toy metapopulation models

- For this model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- ▶ The reproduction number R_0 is not terribly useful.
 - 1. how likely the observed epidemic size was
 - 2. and how likely future epidemics will be.

outdotroprio

References

Conclusions

ne epidemic after the fact





Biological Contagion

- For this model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- ▶ The reproduction number R_0 is not terribly useful.
- \triangleright R_0 , however measured, is not informative about

Introduction

Simple disease spreading models

Background

Prediction

More models

loy metapopulation mod

Model output

Conclusions Predicting so

catastropne







Biological Contagion

For this model, epidemic size is highly unpredictable

- Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- ▶ The reproduction number R_0 is not terribly useful.
- ▶ R₀, however measured, is not informative about
 - 1. how likely the observed epidemic size was,

introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation model:

Conclusions

Predicting so catastrophe





Biological Contagion

- For this model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- ▶ The reproduction number R_0 is not terribly useful.
- ▶ R₀, however measured, is not informative about
 - 1. how likely the observed epidemic size was,
 - 2. and how likely future epidemics will be.

Introduction

Simple disease spreading models

Background

Prediction

More models

Model output

Conclusions

Predicting sor catastrophe







- For this model, epidemic size is highly unpredictable
- Model is more complicated than SIR but still simple
- We haven't even included normal social responses such as travel bans and self-quarantine.
- ▶ The reproduction number R_0 is not terribly useful.
- ► R₀, however measured, is not informative about
 - 1. how likely the observed epidemic size was,
 - 2. and how likely future epidemics will be.
- Problem: R_0 summarises one epidemic after the fact and enfolds movement, the price of bananas, everything.

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation mode

Model output

Conclusions
Predicting so





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

▶ More support for controlling population movement

Biological Contagion

Introduction

Simple disease spreading models

Background

1 Tediction

Toy metapopulation models

Model output

Conclusions

catastrophe





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

▶ More support for controlling population movement

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions

catastrophe





- Disease spread 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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

catastrophe





- Disease spread 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

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation

Conclusions

Conclusions

catastrophe





- Disease spread 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)

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation mode

Model output

Conclusions

Predicting social catastrophe





What to do:

- Need to separate movement from disease
- $ightharpoonup R_0$ needs a friend or two.
- Need R₀ > 1 and P₀ > 1 and ξ sufficiently large for disease to have a chance of spreading

More wondering:

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

Biological Contagion

Introduction

Simple disease spreading models

Toy metapopulation models

Background

More models

Model output

Conclusions

Predicting soil catastrophe





Biological Contagion

What to do:

- Need to separate movement from disease
- R₀ needs a friend or two.
- Need R₀ > 1 and P₀ > 1 and ξ sufficiently large for disease to have a chance of spreading

More wondering:

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

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions

Predicting soil catastrophe





Biological Contagion

What to do:

- Need to separate movement from disease
- R₀ needs a friend or two.
- Need $R_0 > 1$ and $P_0 > 1$ and ξ sufficiently large for disease to have a chance of spreading

More wondering:

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

Simple disease

spreading models

Background

Prediction

Toy metapopulation models

Model output

Conclusions

Predicting soci





What to do:

- Need to separate movement from disease
- R₀ needs a friend or two.
- Need $R_0 > 1$ and $P_0 > 1$ and ξ sufficiently large for disease to have a chance of spreading

More wondering:

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

Simple disease

spreading models

Prediction

More models

Model output

Conclusions

Predicting sor





Need to separate movement from disease

- R₀ needs a friend or two.
- Need $R_0 > 1$ and $P_0 > 1$ and ξ sufficiently large for disease to have a chance of spreading

More wondering:

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

Introduction

Simple disease spreading models

Background

More models

Model output

Conclusions

Predicting soci

Deferences





Valiant attempts to use SIR and co. elsewhere:

- Adoption of ideas/beliefs (Goffman & Newell, 1964)
- ► Spread of rumors (Daley & Kendall, 1965)
- ▶ Diffusion of innovations (Bass, 1969)
- Spread of fanatical behavior (Castillo-Chávez & Song, 2003)
- Spread of Feynmann diagrams (Bettencourt et al., 2006)

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Conclusions

Predicting soci







Valiant attempts to use SIR and co. elsewhere:

- Adoption of ideas/beliefs (Goffman & Newell, 1964)
- ► Spread of rumors (Daley & Kendall, 1965)
- ▶ Diffusion of innovations (Bass, 1969)
- Spread of fanatical behavior (Castillo-Chávez & Song, 2003)
- Spread of Feynmann diagrams (Bettencourt et al., 2006)

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Conclusions

Predicting soo





Valiant attempts to use SIR and co. elsewhere:

- Adoption of ideas/beliefs (Goffman & Newell, 1964)
- Spread of rumors (Daley & Kendall, 1965)
- Diffusion of innovations (Bass, 1969)
- Spread of fanatical behavior (Castillo-Chávez & Song, 2003)
- Spread of Feynmann diagrams (Bettencourt et al., 2006)

Biological Contagion

Introduction

Simple disease spreading models Background

Prodiction

Prediction

Toy metapopulation models

Model output

Conclusions

Deferences





Valiant attempts to use SIR and co. elsewhere:

- Adoption of ideas/beliefs (Goffman & Newell, 1964)
- Spread of rumors (Daley & Kendall, 1965)
- ▶ Diffusion of innovations (Bass, 1969)
- Spread of fanatical behavior (Castillo-Chávez & Song, 2003)
- Spread of Feynmann diagrams (Bettencourt et al., 2006)

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

FIGUICION

Toy metapopulation mode

Model output

Conclusions

Predicting so catastrophe





Valiant attempts to use SIR and co. elsewhere:

- Adoption of ideas/beliefs (Goffman & Newell, 1964)
- ► Spread of rumors (Daley & Kendall, 1965)
- ▶ Diffusion of innovations (Bass, 1969)
- Spread of fanatical behavior (Castillo-Chávez & Song, 2003)
- Spread of Feynmann diagrams (Bettencourt et al., 2006)

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

Prediction

Toy metapopulation mode

Model output

Conclusions Predicting se

catastrophe





Biological Contagion

Introduction

Simple disease spreading models Background

Prodiction

Prediction

Toy metapopulation mode

Model output

Conclusions

catastropne

References

Valiant attempts to use SIR and co. elsewhere:

- Adoption of ideas/beliefs (Goffman & Newell, 1964)
- Spread of rumors (Daley & Kendall, 1965)
- ▶ Diffusion of innovations (Bass, 1969)
- Spread of fanatical behavior (Castillo-Chávez & Song, 2003)
- Spread of Feynmann diagrams (Bettencourt et al., 2006)





Outline

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Model output

Predicting social catastrophe

References

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Predicting social catastrophe





Predicting social catastrophe isn't easy...

"Greenspan Concedes Error on Regulation"

- ...humbled Mr. Greenspan admitted that he had put too much faith in the self-correcting power of free markets...
- "Those of us who have looked to the self-interest of lending institutions to protect shareholders' equity, myself included, are in a state of shocked disbelief"
- ▶ 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."

New York Times, October 23, 2008 (⊞)

Biological Contagion

Introduct

Simple disease spreading models Background

Prediction More models

Toy metapopulation models Model output

Predicting social catastrophe







Biological Contagion

"Greenspan Concedes Error on Regulation"

- ... humbled Mr. Greenspan admitted that he had put too much faith in the self-correcting power of free markets
- "Those of us who have looked to the self-interest of
- ▶ Rep. Henry A. Waxman: "Do you feel that your
- Mr. Greenspan conceded: "Yes, I've found a flaw. I

New York Times, October 23, 2008 (⊞)

Simple disease spreading models Background

Toy metapopulation models

Predicting social







"Greenspan Concedes Error on Regulation"

- ... humbled Mr. Greenspan admitted that he had put too much faith in the self-correcting power of free markets...
- "Those of us who have looked to the self-interest of lending institutions to protect shareholders' equity, myself included, are in a state of shocked disbelief"
- ▶ 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."

New York Times, October 23, 2008 (⊞)

Introduc

Simple disease spreading models Background

Prediction

Toy metapopulation mode

Conclusions

Predicting social catastrophe







"Greenspan Concedes Error on Regulation"

- ... humbled Mr. Greenspan admitted that he had put too much faith in the self-correcting power of free markets
- "Those of us who have looked to the self-interest of lending institutions to protect shareholders' equity, myself included, are in a state of shocked disbelief"
- 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

Simple disease spreading models

Predicting social







"Greenspan Concedes Error on Regulation"

- ... humbled Mr. Greenspan admitted that he had put too much faith in the self-correcting power of free markets ...
- "Those of us who have looked to the self-interest of lending institutions to protect shareholders' equity, myself included, are in a state of shocked disbelief"
- ▶ 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

Toy metapopulation model

Conclusions
Predicting social

catastropne





Alan Greenspan (September 18, 2007):

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

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

I don't need any of this other stuff.

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



http://wikipedia.org

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Tov metapopulation models

Model output

Predicting social





Biological Contagion

Alan Greenspan (September 18, 2007):

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



http://wikipedia.org

Simple disease spreading models

Background

Toy metapopulation models

Predicting social





Biological Contagion

Alan Greenspan (September 18, 2007):

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

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

I don't need any of this other stuff.

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



http://wikipedia.org

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation mode

Model output

Predicting social catastrophe





Biological Contagion

Alan Greenspan (September 18, 2007):

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

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

I don't need any of this other stuff.

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



http://wikipedia.org

Introduction

Simple disease spreading models

Background

More models

Model output

Conclusions
Predicting social







Biological Contagion

Alan Greenspan (September 18, 2007):

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

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

I don't need any of this other stuff.

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



http://wikipedia.org

Introduction

Simple disease spreading models

Background

More models

Model output

Predicting social





Greenspan continues:

"The trouble is that we can't figure that out. I've been in the forecasting business for 50 years. I'm no better than I ever was, and nobody else is. Forecasting 50 years ago was as good or as bad as it is today. And the reason is that human nature hasn't changed. We can't improve ourselves."

Biological Contagion

Introduction

Simple disease spreading models

Background Prediction

More models

Toy metapopulation models

Model output

Predicting social catastrophe







Greenspan continues:

"The trouble is that we can't figure that out. I've been in the forecasting business for 50 years. I'm no better than I ever was, and nobody else is. Forecasting 50 years ago was as good or as bad as it is today. And the reason is that human nature hasn't changed. We can't improve ourselves."

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

More models

Toy metapopulation models

Model output

Predicting social catastrophe







Greenspan continues:

"The trouble is that we can't figure that out. I've been in the forecasting business for 50 years. I'm no better than I ever was, and nobody else is. Forecasting 50 years ago was as good or as bad as it is today. And the reason is that human nature hasn't changed. We can't improve ourselves."

Biological Contagion

Introduction

Simple disease spreading models Background

Prediction

More models

Tov metapopulation models

Model output

Predicting social catastrophe







Greenspan continues:

"The trouble is that we can't figure that out. I've been in the forecasting business for 50 years. I'm no better than I ever was, and nobody else is. Forecasting 50 years ago was as good or as bad as it is today. And the reason is that human nature hasn't changed. We can't improve ourselves."

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation models

Conclusions

Predicting social catastrophe







Greenspan continues:

"The trouble is that we can't figure that out. I've been in the forecasting business for 50 years. I'm no better than I ever was, and nobody else is. Forecasting 50 years ago was as good or as bad as it is today. And the reason is that human nature hasn't changed. We can't improve ourselves."

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

Toy metapopulation models

Conclusions

Predicting social catastrophe







Greenspan continues:

"The trouble is that we can't figure that out. I've been in the forecasting business for 50 years. I'm no better than I ever was, and nobody else is. Forecasting 50 years ago was as good or as bad as it is today. And the reason is that human nature hasn't changed. We can't improve ourselves."

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation mode

Conclusions

Predicting social catastrophe







Greenspan continues:

"The trouble is that we can't figure that out. I've been in the forecasting business for 50 years. I'm no better than I ever was, and nobody else is. Forecasting 50 years ago was as good or as bad as it is today. And the reason is that human nature hasn't changed. We can't improve ourselves."

Biological Contagion

Introduction

Simple disease spreading models

Background

Prediction

More models

Toy metapopulation mode

Conclusions

Predicting social catastrophe







Greenspan continues:

"The trouble is that we can't figure that out. I've been in the forecasting business for 50 years. I'm no better than I ever was, and nobody else is. Forecasting 50 years ago was as good or as bad as it is today. And the reason is that human nature hasn't changed. We can't improve ourselves."

Jon Stewart:

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



wildbluffmedia.com

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

Biological Contagion

Introduction

Simple disease spreading models

Prediction

More models

Toy metanopulation mode

Model output

Predicting social catastrophe





James K. Galbraith:

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

NYT What does that say about the field of economics, which claims to be a science?

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

Biological Contagion

Introduction

Simple disease spreading models

Background

More models

Toy metapopulation models

Model output

Predicting social catastrophe





Biological Contagion

James K. Galbraith:

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

NYT What does that say about the field of economics, which claims to be a science? Introduction

Simple disease spreading models

Background

More model

Toy metapopulation models

Model output

Predicting social catastrophe

References



Biological Contagion

James K. Galbraith:

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

[JKG] Ten or 12 would be closer than two or three.

NYT What does that say about the field of economics, which claims to be a science?

Introduction

Simple disease spreading models

Prediction

More models

Toy metapopulation models

Model output

Predicting social

References





Biological Contagion

James K. Galbraith:

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

[JKG] Ten or 12 would be closer than two or three.

NYT What does that say about the field of economics, which claims to be a science?

Introduction

Simple disease spreading models

Prediction

Toy metapopulation mode

Model output

Predicting social

References



Biological Contagion

James K. Galbraith:

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

[JKG] Ten or 12 would be closer than two or three.

NYT What does that say about the field of economics, which claims to be a science? [JKG] It's an enormous blot on the reputation of the profession.

Introduction

Simple disease spreading models

Prediction

Toy metanopulation mode

Model output

Predicting social catastrophe

References



loted

James K. Galbraith:

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

[JKG] Ten or 12 would be closer than two or three.

NYT What does that say about the field of economics, which claims to be a science? [JKG] It's an enormous blot on the reputation of the profession. There are thousands of economists. Most of them teach.

Biological Contagion

Introduction

Simple disease spreading models

Prediction

Toy metanopulation mode

Model output

Predicting social

References



James K. Galbraith:

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

[JKG] Ten or 12 would be closer than two or three.

NYT What does that say about the field of economics, which claims to be a science? [JKG] It's an enormous blot on the reputation of the profession. There are thousands of economists. Most of them teach. And most of them teach a theoretical framework that has been shown to be fundamentally useless.

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

Introduction

Simple disease spreading models

Prodiction

More models

Model output

Predicting social





References I

- [1] P. M. Blau and J. E. Schwartz. Crosscutting Social Circles. Academic Press, Orlando, FL, 1984.
- R. L. Breiger. [2] The duality of persons and groups. Social Forces, 53(2):181–190, 1974. pdf (⊞)
- [3] E. Hoffer. The True Believer: On The Nature Of Mass Movements. Harper and Row, New York, 1951.
- [4] E. Hoffer. The Passionate State of Mind: And Other Aphorisms. Buccaneer Books, 1954.

Biological Contagion

Simple disease spreading models

Background







References II

[5] W. O. Kermack and A. G. McKendrick. A contribution to the mathematical theory of epidemics.

Proc. R. Soc. Lond. A, 115:700-721, 1927. pdf (⊞)

[6] W. O. Kermack and A. G. McKendrick. A contribution to the mathematical theory of epidemics. III. Further studies of the problem of endemicity.

Proc. R. Soc. Lond. A, 141(843):94–122, 1927. pdf (⊞)

[7] W. O. Kermack and A. G. McKendrick.
Contributions to the mathematical theory of epidemics. II. The problem of endemicity.

Proc. R. Soc. Lond. A, 138(834):55–83, 1927.

pdf (⊞)

Biological Contagion

Introduction

Simple disease spreading models

Prediction

More models

Toy metapopulation models

Model output

Dradiating age





References III

- J. D. Murray.
 Mathematical Biology.
 Springer, New York, Third edition, 2002.
- [9] C. J. Rhodes and R. M. Anderson. Power laws governing epidemics in isolated populations. Nature, 381:600–602, 1996. pdf (⊞)
- [10] G. Simmel. The number of members as determining the sociological form of the group. I. American Journal of Sociology, 8:1–46, 1902.
- [11] D. J. Watts, P. S. Dodds, and M. E. J. Newman. Identity and search in social networks.

 Science, 296:1302–1305, 2002. pdf (H)

Biological Contagion

Introduction

Simple disease spreading models

Prediction

Prediction

Toy metapopulation models

Conclusions

Predicting social



