Biological Contagion

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

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Outline

Introduction

Simple disease spreading models
  Background
  Prediction
  More models
  Toy metapopulation models
  Model output
  Conclusions
  Predicting social catastrophe

References
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...?
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Naturomorphisms

▶ “The feeling was contagious.”
▶ “The news spread like wildfire.”
▶ “Freedom is the most contagious virus known to man.”
   —Hubert H. Humphrey, Johnson’s vice president
▶ “Nothing is so contagious as enthusiasm.”
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Social contagion

Optimism according to Ambrose Bierce: (❑)
The doctrine that everything is beautiful, including what is ugly, everything good, especially the bad, and everything right that is wrong. ...
Social contagion

Optimism according to Ambrose Bierce: (叕)
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.
Social contagion

Eric Hoffer, 1902–1983

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Hoffer was an interesting fellow...
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The spread of fanaticism


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.”
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Imitation

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

—Eric Hoffer

The collective...

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

www.despair.com
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
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Examples of non-disease spreading:

Interesting infections:

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

- Viral get-out-the-vote video. (rectangle)
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Contagions

Two main classes of contagion

1. Infectious diseases

2. Social contagion
Contagions

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1. Infectious diseases
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1. Infectious diseases:
   tuberculosis, HIV, ebola, SARS, influenza, ...

2. Social contagion
Two main classes of contagion

1. **Infectious diseases**: tuberculosis, HIV, ebola, SARS, influenza, ...

2. **Social contagion**: fashion, word usage, rumors, riots, religion, ...
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- Three states:
  1. \( S = \text{Susceptible} \)
  2. \( I = \text{Infective/Infectious} \)
  3. \( R = \text{Recovered or Removed or Refractory} \)
- \( S(t) + I(t) + R(t) = 1 \)
- Presumes random interactions (mass-action principle)
- Interactions are independent (no memory)
- Discrete and continuous time versions
Mathematical Epidemiology

The standard SIR model \cite{8}

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Discrete time automata example:

Transition Probabilities:
- $\beta I$ for being infected given contact with infected
- $r$ for recovery
- $\rho$ for loss of immunity
Discrete time automata example:

Transition Probabilities:

- $1 - \beta I$ from $S$ to $S$
- $\beta I$ from $S$ to $I$
- $\rho$ from $I$ to $S$
- $r$ from $I$ to $R$
- $1 - r$ from $I$ to $I$
- $1 - \rho$ from $R$ to $R$
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$S \xrightarrow{1-\beta I} S \xrightarrow{\beta I} I \xrightarrow{r} R \xrightarrow{1-r} I \xrightarrow{\rho} S \xrightarrow{1-\rho} R$
Mathematical Epidemiology

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**Independent Interaction models**

**Differential equations for continuous model**

\[
\begin{align*}
\frac{d}{dt} S &= -\beta IS + \rho R \\
\frac{d}{dt} I &= \beta IS - rI \\
\frac{d}{dt} R &= rI - \rho R
\end{align*}
\]

\(\beta, r, \text{ and } \rho\) are now rates.

**Reproduction Number \(R_0\):**

- \(R_0 = \) expected number of infected individuals resulting from a single initial infective
- Epidemic threshold: If \(R_0 > 1\), ‘epidemic’ occurs.
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Reproduction Number $R_0$

Discrete version:

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

- Expected number infected by original Infective:

$$R_0 = \beta + (1 - r)\beta + (1 - r)^2\beta + (1 - r)^3\beta + \ldots$$
Reproduction Number $R_0$

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- Expected number infected by original Infective:

\[
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= \beta \left(1 + (1 - r) + (1 - r)^2 + (1 - r)^3 + \ldots\right)
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For $S_0$ initial infectives ($1 - S_0 = R_0$ immune):

\[
R_0 = S_0 \frac{\beta}{r}
\]
For the continuous version

- Second equation:

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

- Number of infectives grows initially if

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

- Same story as for discrete model.
Independent Interaction models

For the continuous version

- Second equation:
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  \[
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Example of epidemic threshold:

Fraction infected

0 0.2 0.4 0.6 0.8 1

R0

0 1 2 3 4

Continuous phase transition. Fine idea from a simple model.
Independent Interaction models

Example of epidemic threshold:

- Continuous phase transition.
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Many variants of the SIR model:

- **SIS**: susceptible-infective-susceptible
- **SIRS**: susceptible-infective-recovered-susceptible
- compartment models (age or gender partitions)
- more categories such as ‘exposed’ (SEIRS)
- recruitment (migration, birth)
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- **SIS**: susceptible-infective-susceptible
- **SIRS**: susceptible-infective-recovered-susceptible
- compartment models (age or gender partitions)
- more categories such as ‘exposed’ (**SEIRS**)
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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
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- earthquakes (Gutenberg-Richter law)
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- wealth distributions
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Feeling Ill in Iceland

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

- Treat outbreaks separated in time as ‘novel’ diseases.
Really not so good at all in Iceland

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

Spike near $S = 0$, relatively flat otherwise.
# Measles & Pertussis

<table>
<thead>
<tr>
<th>$N(\psi)$</th>
<th>$\psi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.025</td>
</tr>
<tr>
<td>1</td>
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<tr>
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<td>0.075</td>
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<tr>
<td>3</td>
<td>0.1</td>
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### Graphs A and B

**Graph A**
- Complementary cumulative frequency distributions: $N(\psi)$ vs. $\psi$
- Graph shows $N(\psi)$ as a function of $\psi$ with bars indicating frequency distribution.

**Graph B**
- Similar graph as Graph A with a different scale and data set.

---

**References**

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**Biological Contagion**

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Measles & Pertussis

Insert plots:
Complementary cumulative frequency distributions:

\[ N(\psi' > \psi) \propto \psi^{-\gamma + 1} \]

Limited scaling with a possible break.
Power law distributions

Measured values of $\gamma$:

- measles: $1.40$ (low $\Psi$) and $1.13$ (high $\Psi$)
- pertussis: $1.39$ (low $\Psi$) and $1.16$ (high $\Psi$)

- Expect $2 \leq \gamma < 3$ (finite mean, infinite variance)
- When $\gamma < 1$, can’t normalize
- Distribution is quite flat.
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Resurgence—example of SARS

- Epidemic slows...
- Epidemic discovers new ‘pools’ of susceptibles: Resurgence.
- Importance of rare, stochastic events.
Resurgence—example of SARS

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- Epidemic slows...
- Then an infective moves to a new context.
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The challenge

So... can a simple model produce

1. broad epidemic distributions
   and

2. resurgence?
Simple disease spreading models

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Size distributions

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

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

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:

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Improving simple models

Contexts and Identities—Bipartite networks

- boards of directors
- movies
- transportation modes (subway)
Improving simple models

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▶ contexts
▶ individuals
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Identity is formed from attributes such as:

- Geographic location
- Type of employment
- Age
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Groups are crucial...

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Infer interactions/network from identities

Distance makes sense in identity/context space.
Generalized context space

(Blau & Schwartz [1], Simmel [10], Breiger [2])
A toy agent-based model

Geography—allow people to move between contexts:

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

\[ x_{ij} = 2 \]

\[ b = 2 \]

\[ n = 8 \]

\[ l = 3 \]
Simple disease spreading models

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Define \( P_0 \) = Expected number of infected individuals leaving initially infected context.

- Need \( P_0 > 1 \) for disease to spread (independent of \( R_0 \)).
- Limit epidemic size by restricting frequency of travel and/or range.
Model output

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Varying $\xi$:

- Transition in expected final size based on typical movement distance
Model output

Varying $\xi$:

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

Varying $P_0$:

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

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- Flat distributions are possible for certain $\zeta$ and $P$.
- Different $R_0$'s may produce similar distributions.
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Model output—resurgence

Standard model:

\[ R_0 = 3 \]
Model output—resurgence

Standard model with transport:

- **E** (Standard model with transport: $R_0=3$)
  - # New cases vs. $t$
  - Peaks and troughs over time

- **G** (Standard model with transport: $R_0=3$)
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The upshot

Simple multiscale population structure
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- 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.
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Jon Stewart:

“You just bummed the @*!# out of me.”

- From the Daily Show ( september 18, 2007)
- The full interview is here (here).
James K. Galbraith:

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References I


References II


References III


