

# Mathematical Modelling of Infectious Diseases

**Barry Rowlingson**



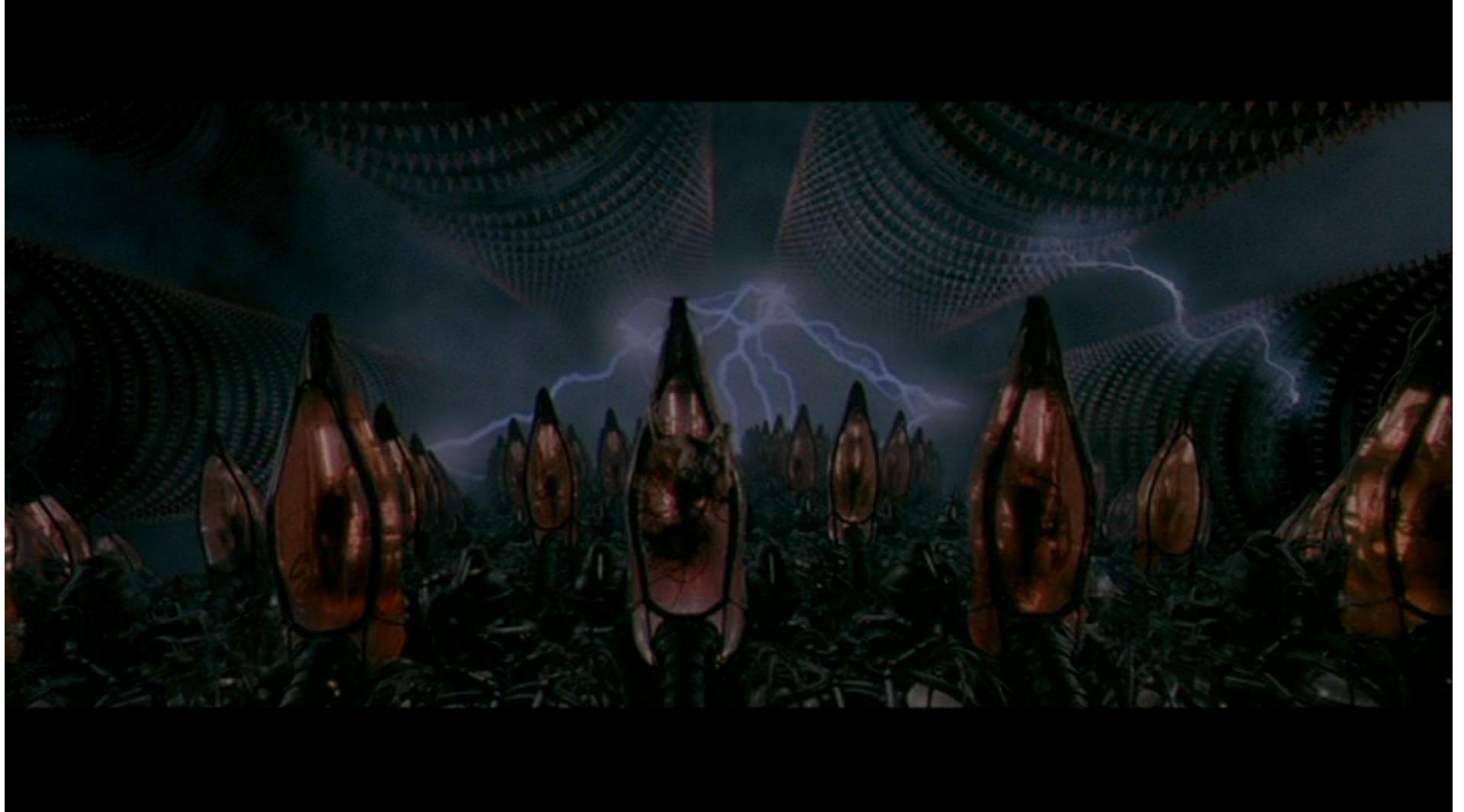
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Flickr: monosv7

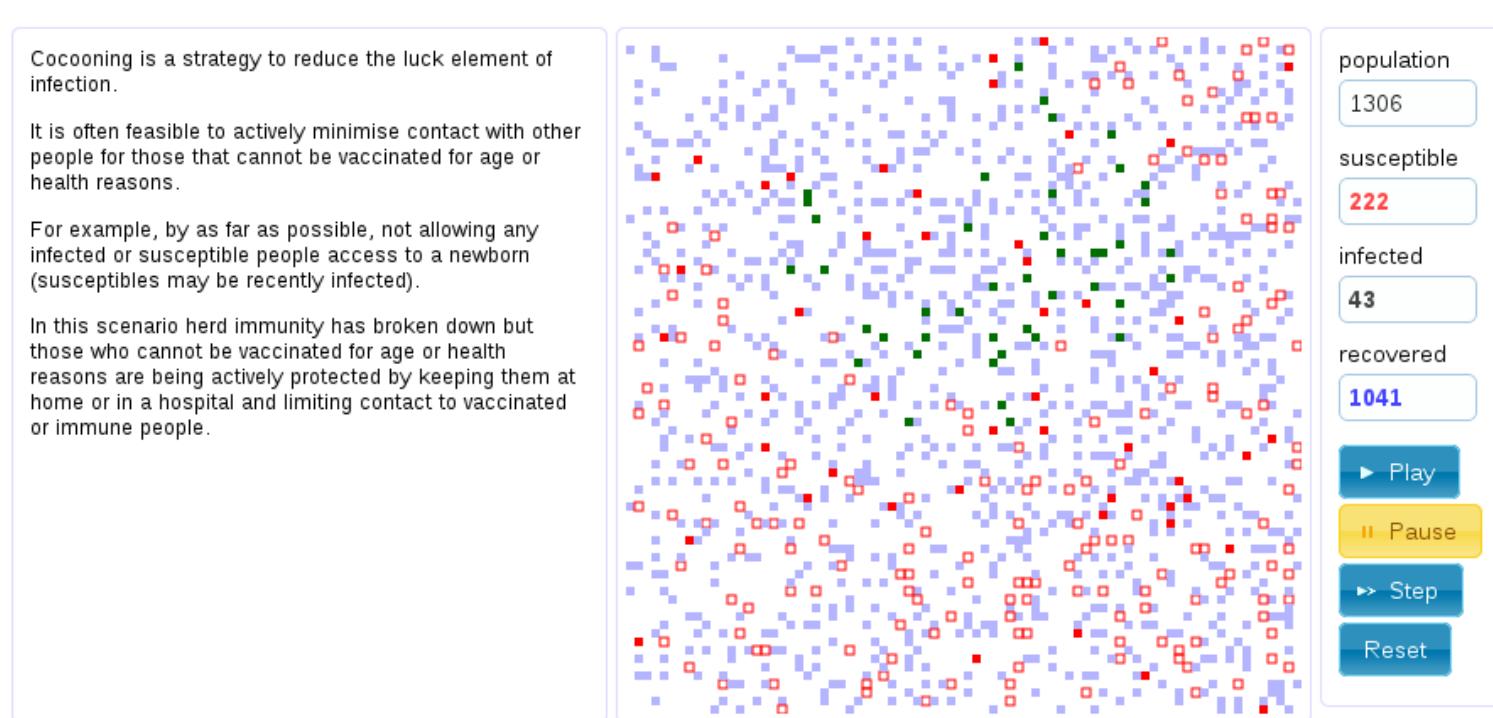


# If We Had That Much Computing Power We Could...

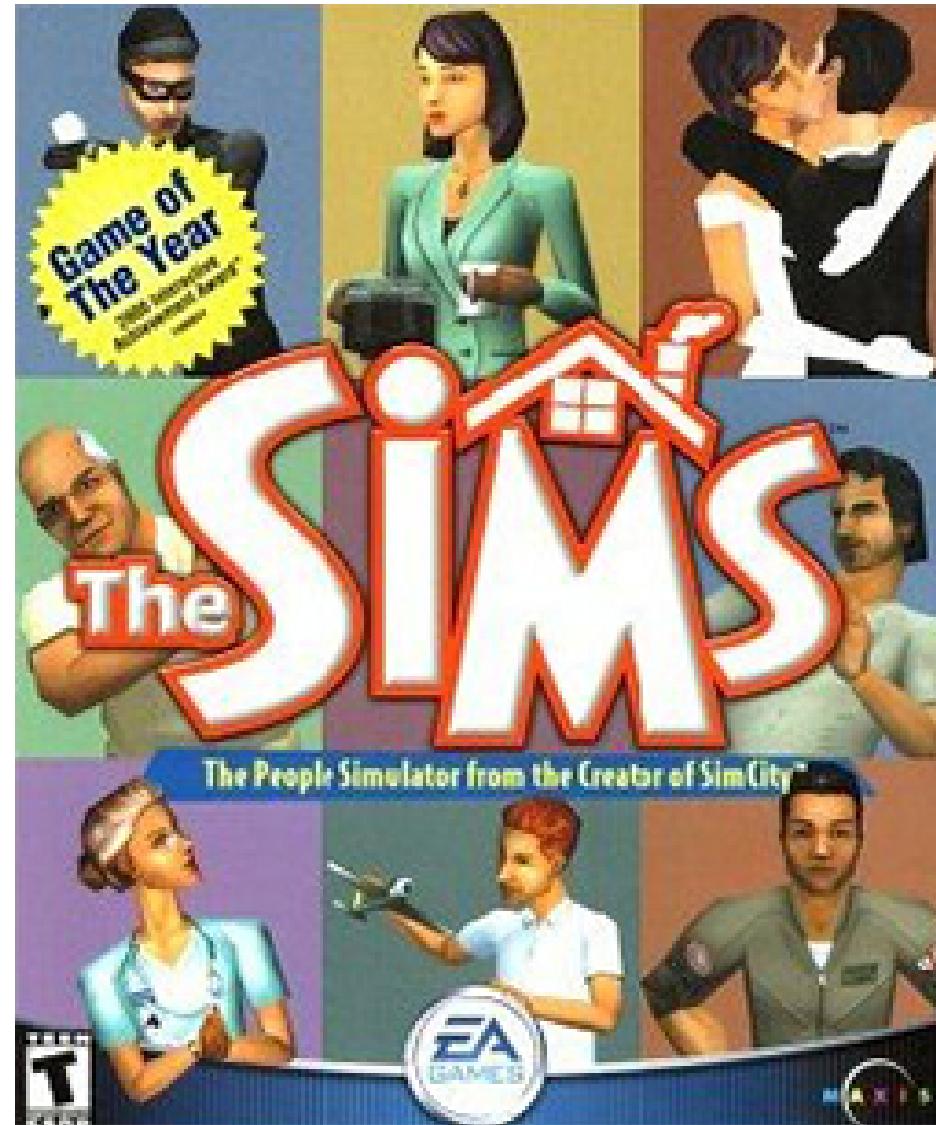
- ▶ Run infection experiments
- ▶ Infect “people”
- ▶ Change behaviour
- ▶ Change the environment
- ▶ Observe the impact on the disease process
- ▶ But we don’t have that much computing power. Yet.

# How Simple Can We Make This?

► <http://op12no2.me/toys/herd/>



- People are squares on a grid
- Illustrates transmission and immunity



# “Guinea Pig Disease”



# “Guinea Pig Disease”



▶ Example of a  
“Zoonosis”

# Dysentery



...can be passed on to other sims

# Agent-based Modelling

- ▶ Smallest modelled unit is an individual
- ▶ Mathematical model of agent behaviour
- ▶ Multiple simulations to get probabilistic answers to “if” questions.
- ▶ Found in other disciplines, eg traffic modelling, finance

*But what if we have too many agents to model?*



# Numerical Models

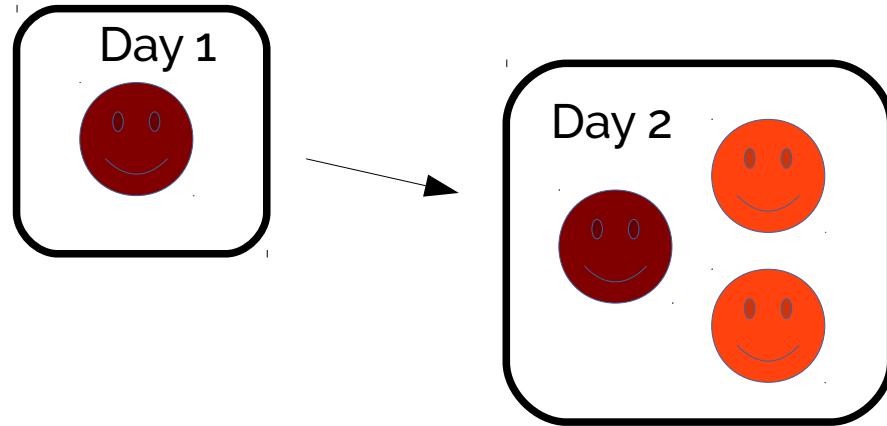
- ▶ Start with one infectious person
- ▶ Each day, every infectious person infects two more people
- ▶ People are infectious for two days
- ▶ What happens?

# Infectious Model

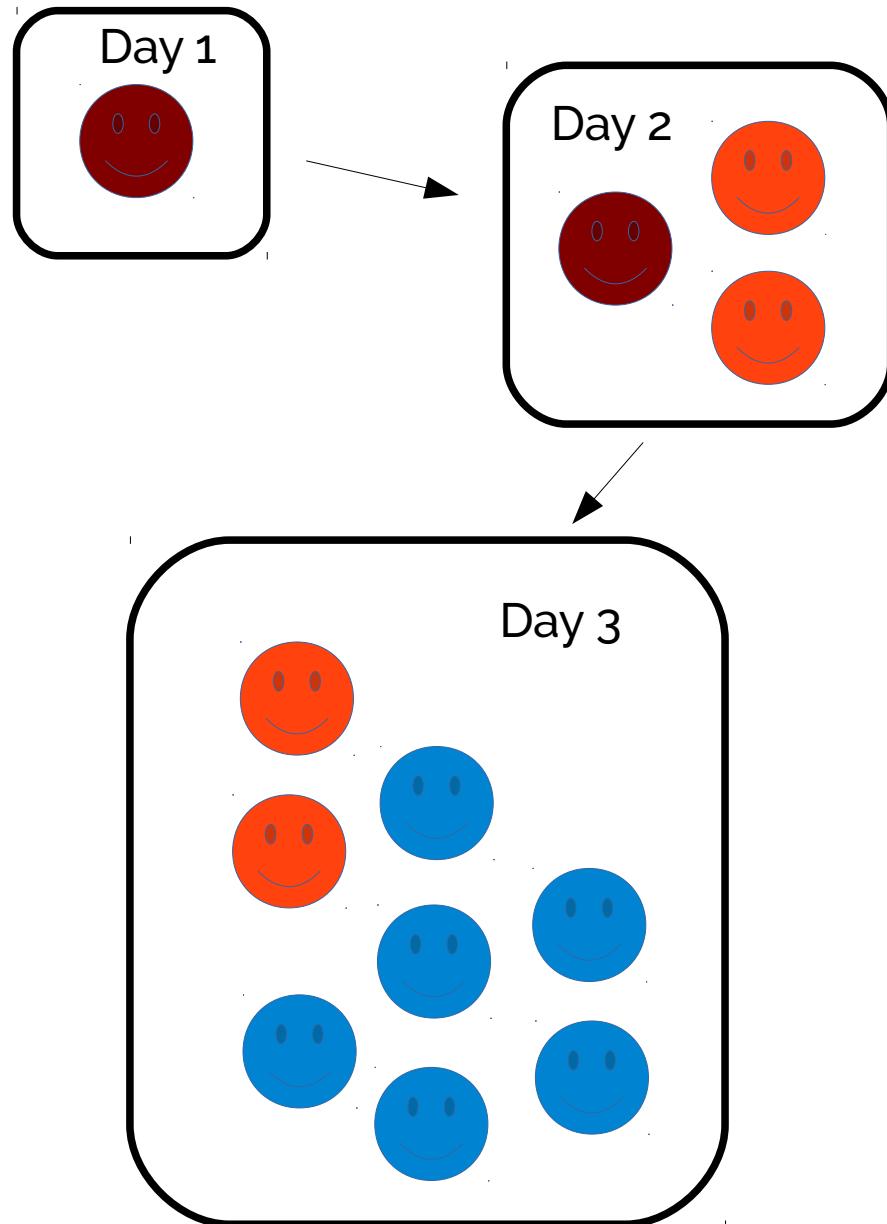
Day 1



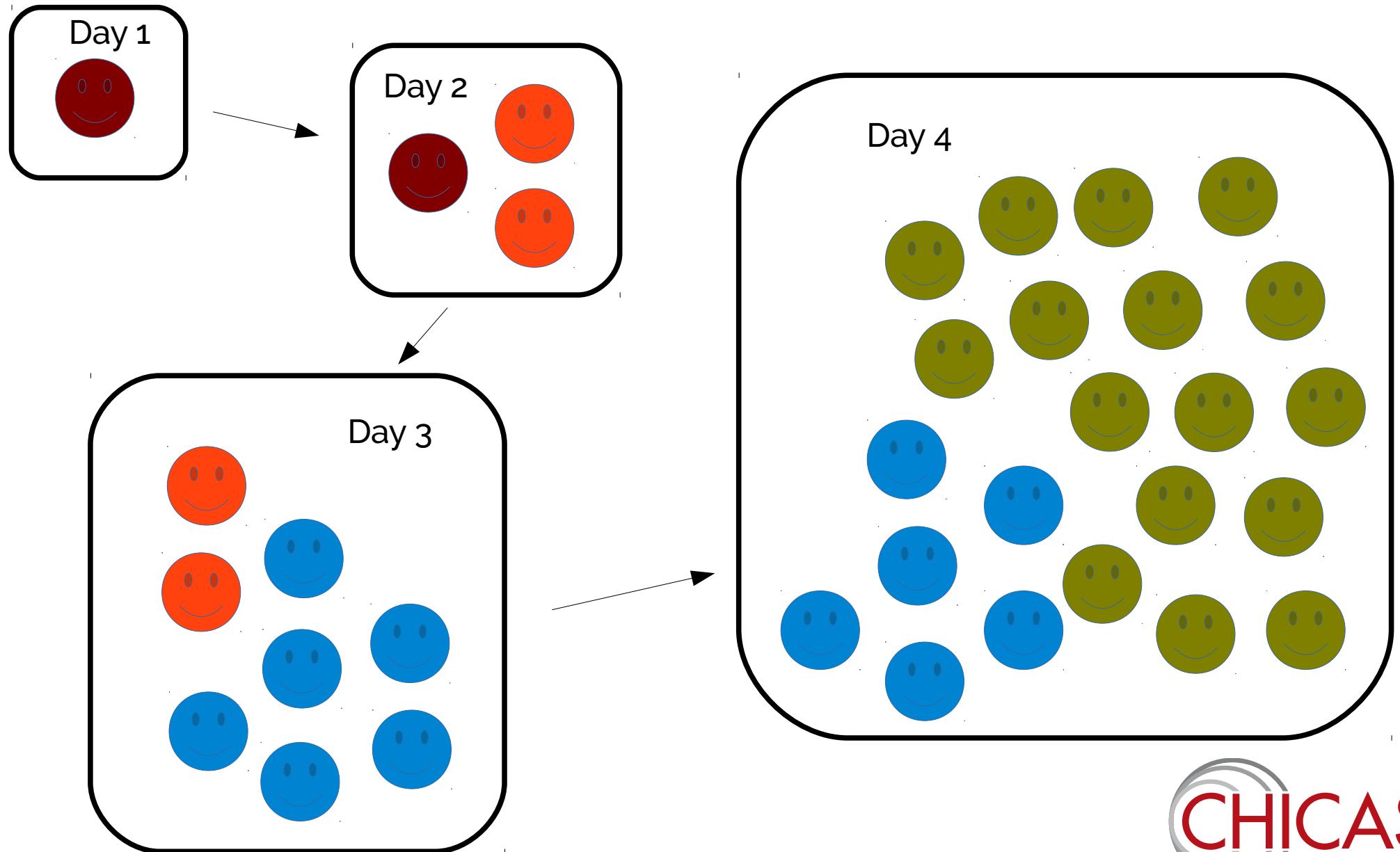
# Infectious Model



# Infectious Model

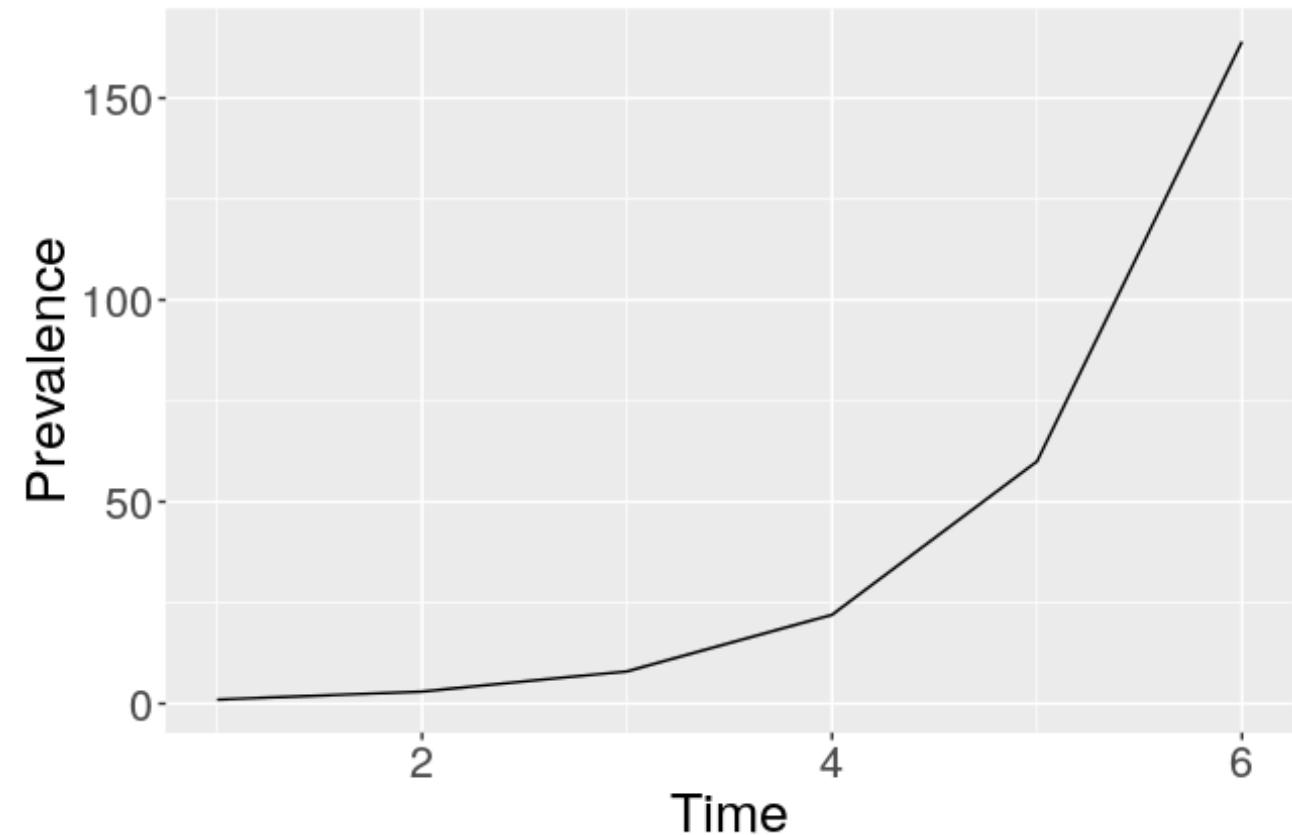


# Infectious Model



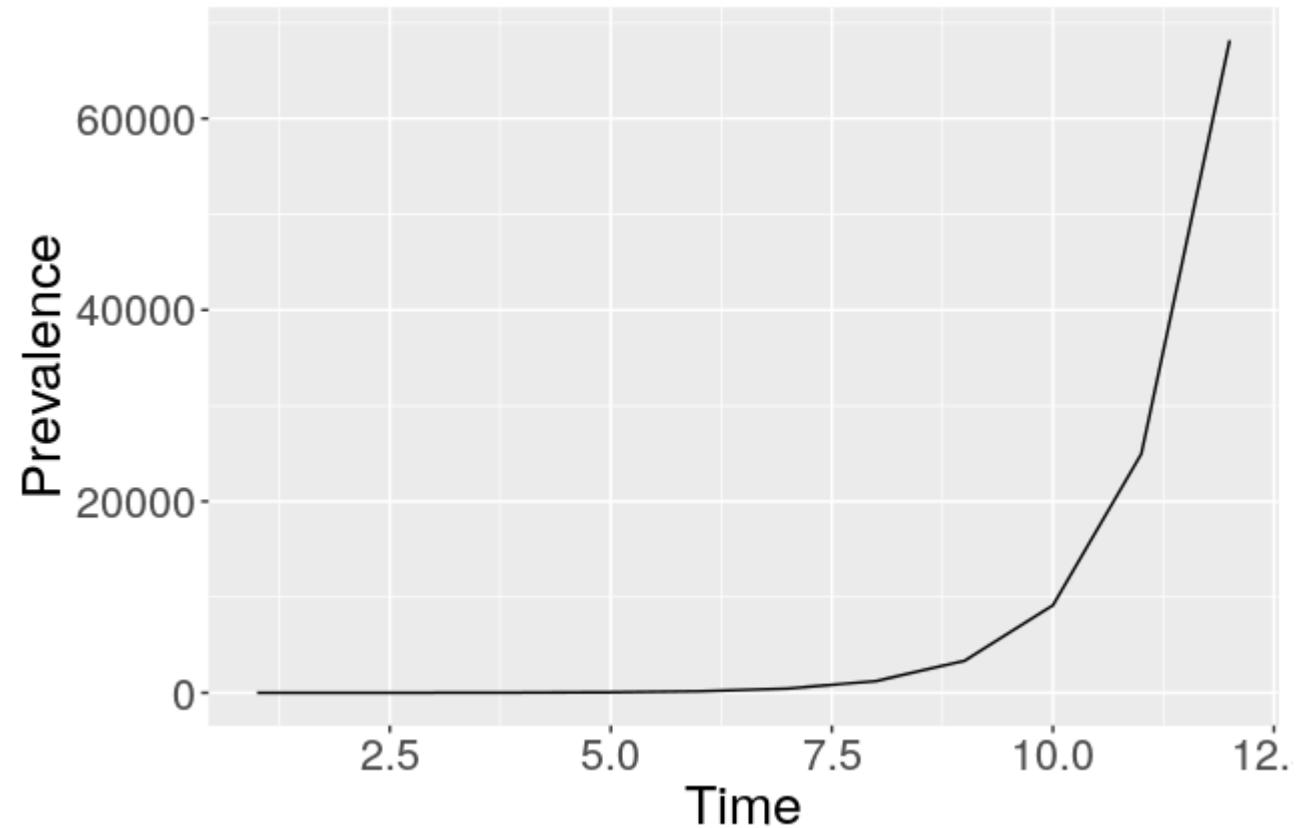
# Rapid Growth

Time	Prevalence
1	1
2	3
3	8
4	22
5	60
6	164

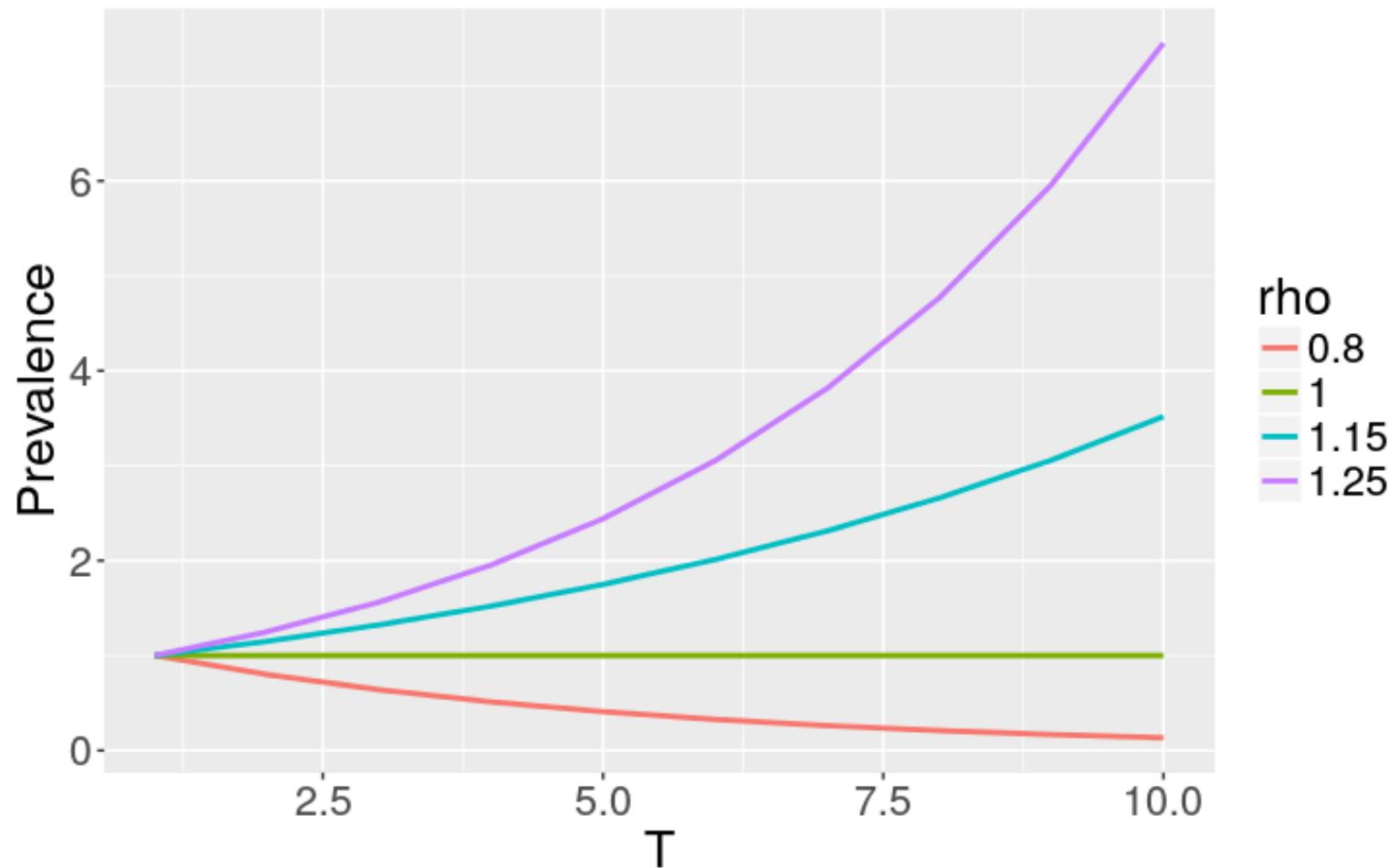


# Rapid Growth.....

Time	Prevalence
1	1
2	3
3	8
4	22
5	60
6	164
...	...
12	68192
...	...
24	11 billion



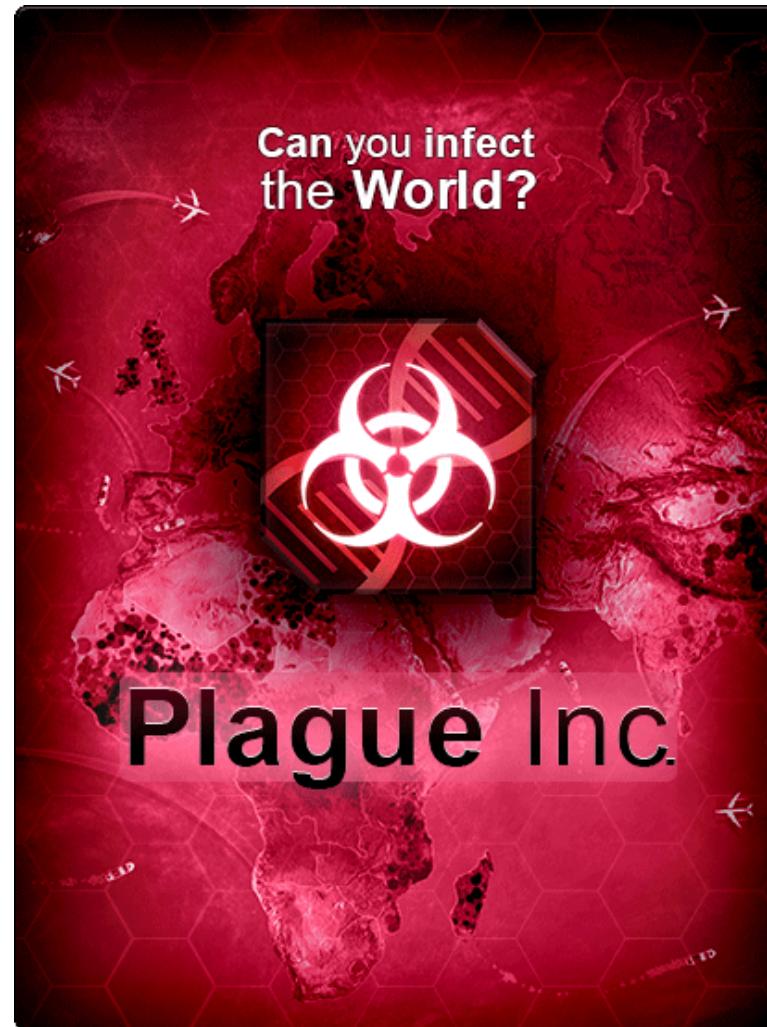
# Reproduction number



# Is Exponential Growth Valid?

- ▶ Yes, when:
  - ▶ Initial Stages of an Infection
  - ▶ Large Susceptible Population
  - ▶ Thorough Mixing of Infectious Cases
- ▶ No, when:
  - ▶ Finite Population
  - ▶ Few Susceptible Population
  - ▶ Poor Mixing of Infectious Cases and Population

# Finite Population



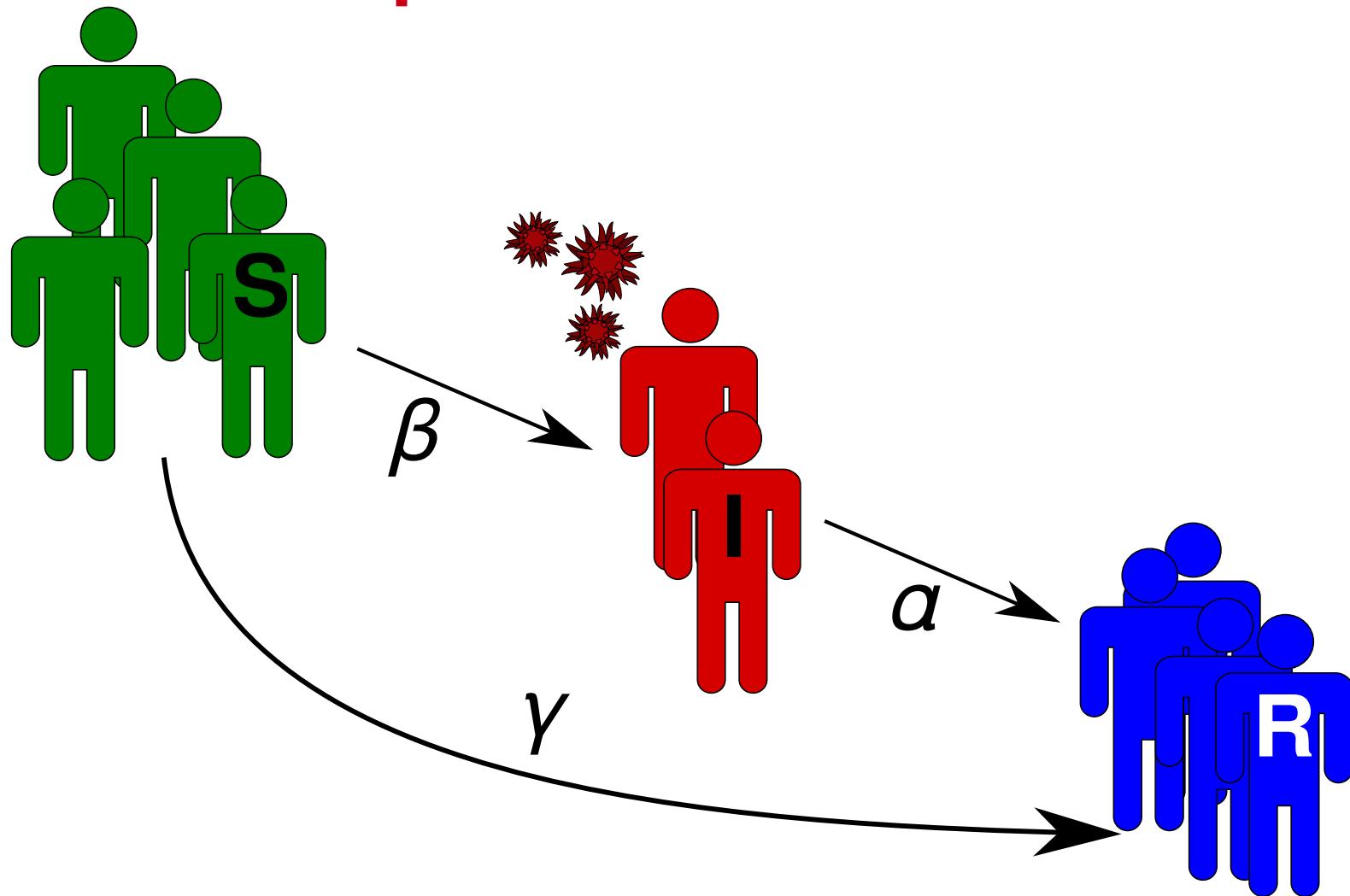
<http://www.ndemiccreations.com/en/>



# Aggregate Infection Tables

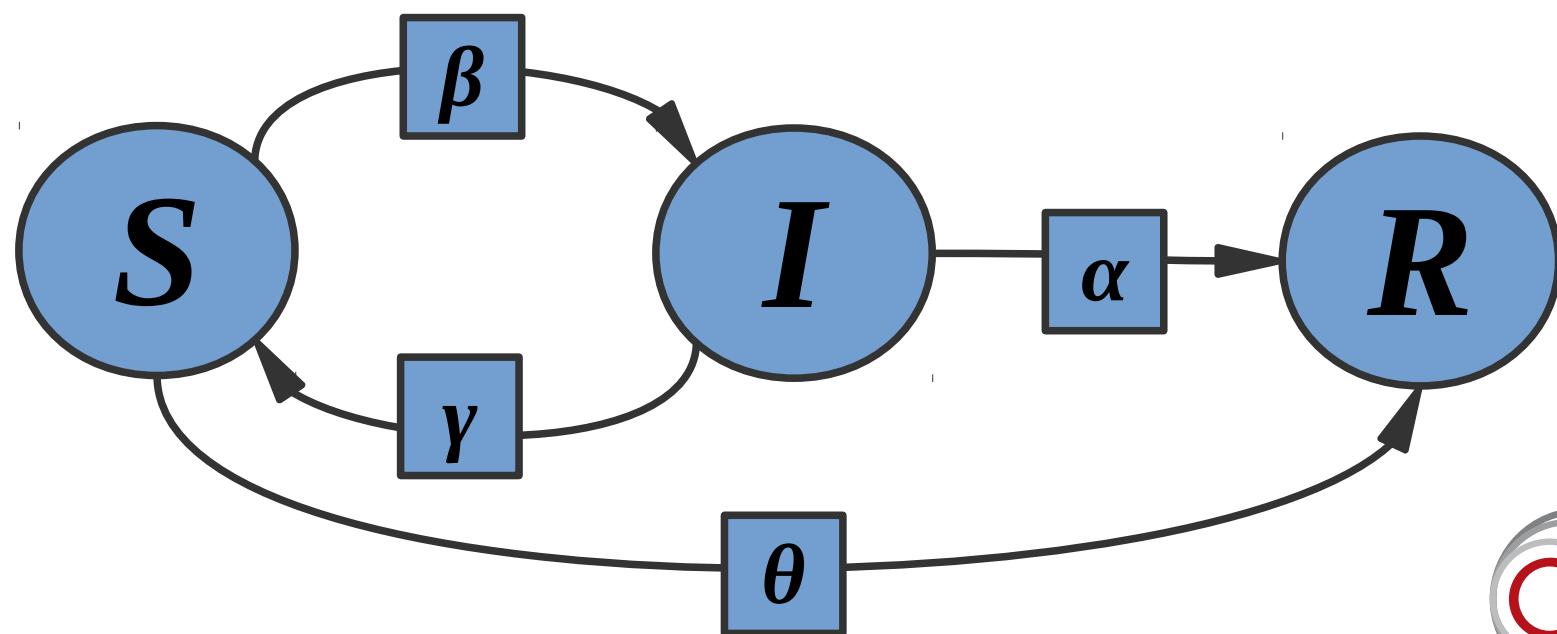
Country	Uninfected	Infectious	Dead
China	903,452,543	1,063,345	8,365
USA	325,753,342	0	1,20546
Brazil	180,537,623	20,663,634	7,653,634
Nigeria	191,836,451	0	0
...			
Pitcairn Islands	0	0	57

# Compartment Model



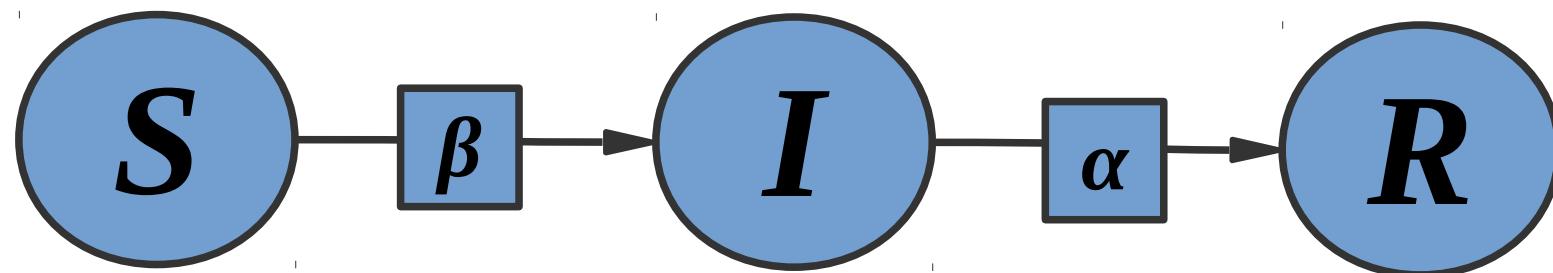
# Compartment Model Diagram

- ▶  $S$  = #Susceptible
- ▶  $I$  = #Infectious
- ▶  $R$  = #Removed or Recovered
- ▶ Greek letters are parameters
- ▶ Control rates of change

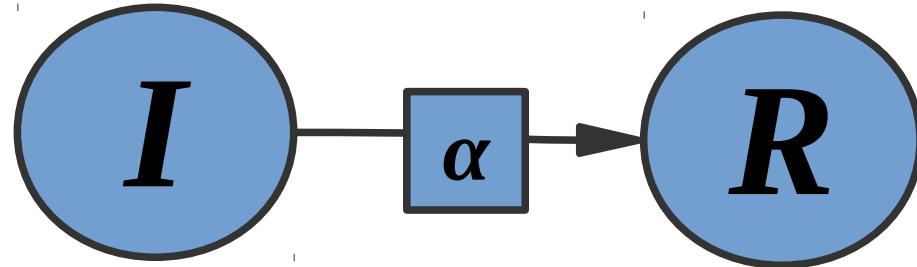


# SIR Compartment Model

- ▶ Three states
- ▶ Two parameters
- ▶ No re-infection (no arrows back to  $S$ )
- ▶ Ignore other causes of death (no  $S \rightarrow R$ )



# Removal/Death Rate



▶ Suppose today:

▶  $I = \underline{1000}$ ,  $R = \underline{0}$

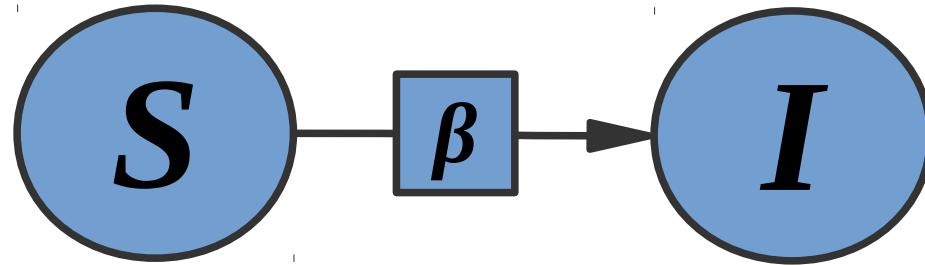
▶  $\alpha = 0.01$

▶ Then tomorrow

▶  $I$  changes to  $1000 - 1000 \times \alpha = \underline{990}$

▶  $R$  changes to  $0 + 1000 \times \alpha = \underline{10}$

# Infection Rate

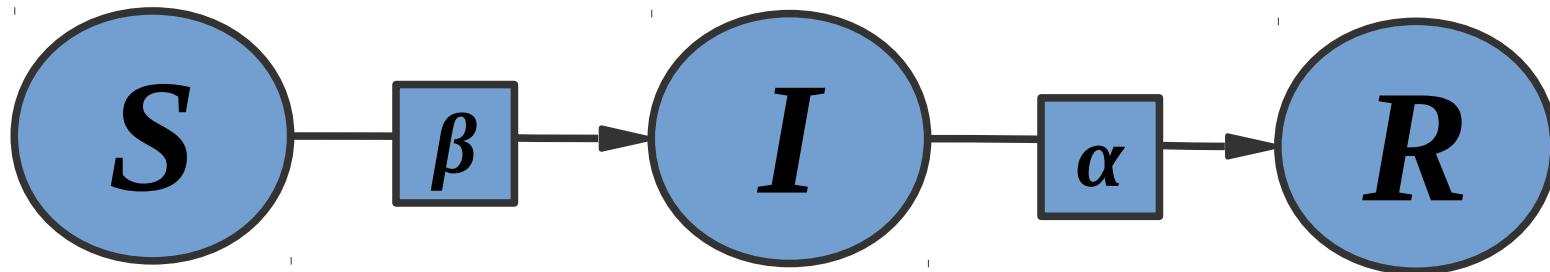


- ▶ Depends on number of infectious,  $I$
- ▶ Suppose today:
  - ▶  $S = \underline{1000}$ ,  $I = \underline{10}$
  - ▶  $\beta = 0.002$
- ▶ Then tomorrow:
  - ▶  $S$  becomes  $1000 - 10 \times 0.002 \times 1000 = \underline{980}$
  - ▶  $I$  becomes  $10 + 10 \times 0.002 \times 1000 = \underline{30}$

# Time Notation

- ▶  $S_1$  is the number of susceptibles on day 1
  - ▶ Could be week 1, month 1, year 1...
- ▶  $S_2$  is the number of susceptibles on day 2
- ▶  $S_t$  is the number on some day  $t$
- ▶  $S_{t+1}$  is number on the day after  $t$
- ▶ Time can start at  $t=0$

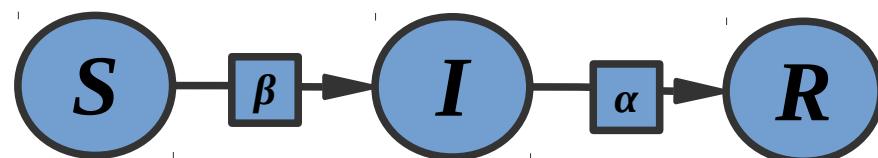
# Updating Steps



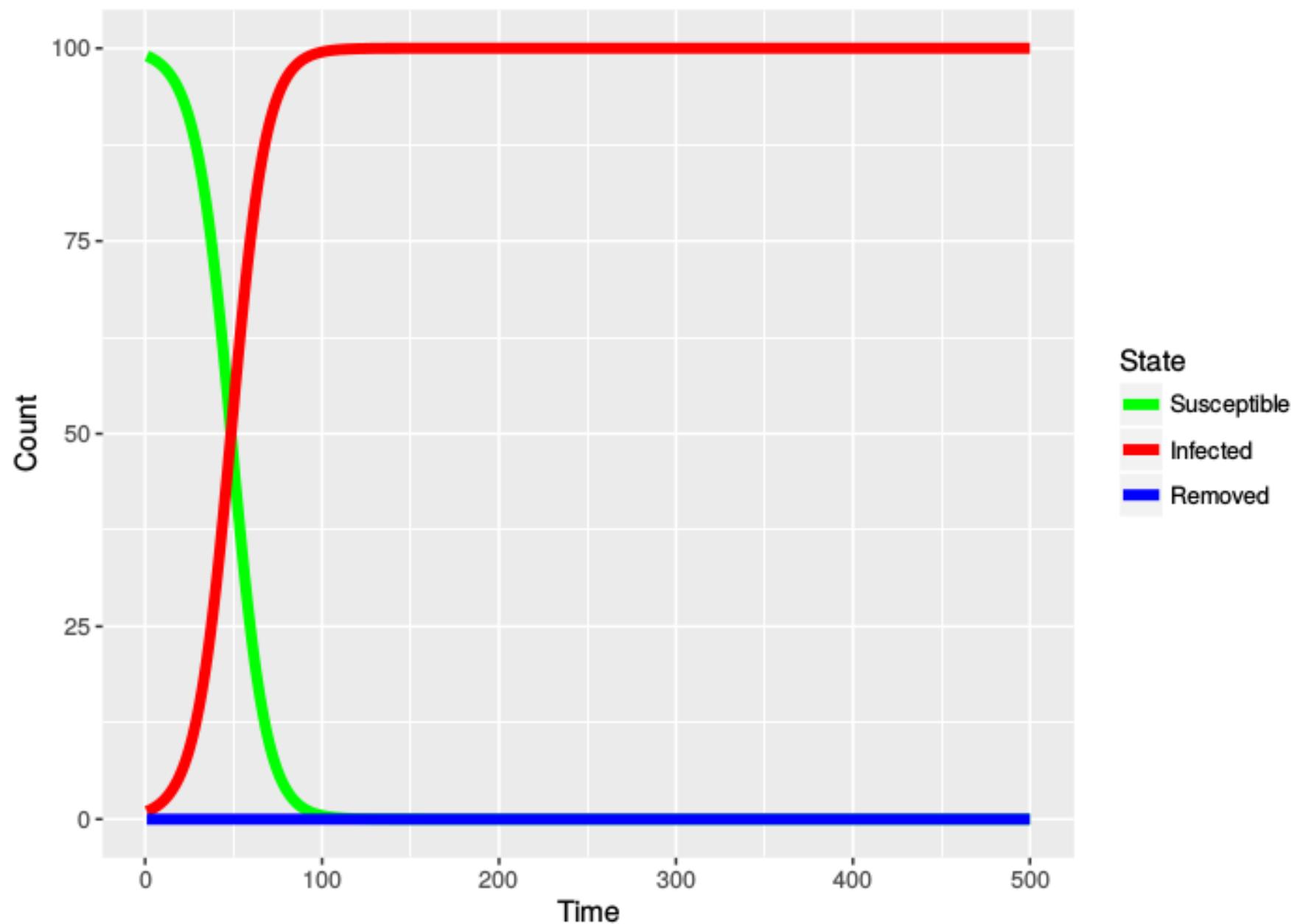
- ▶  $S_t - (\beta \times I_t \times S_t) \rightarrow S_{t+1}$
- ▶  $R_t + (\alpha \times I_t) \rightarrow R_{t+1}$
- ▶  $I_t - (\alpha \times I_t) + (\beta \times I_t \times S_t) \rightarrow I_{t+1}$
- ▶ Increase  $t$ , and repeat...

# Example 1

- ▶ 100 people in total
- ▶ Start with one infection
- ▶ 99 susceptibles
- ▶ Set  $\alpha=0$ 
  - ▶ Nobody recovers
  - ▶ Effectively an **SI** model
- ▶ Set  $\beta=0.001$

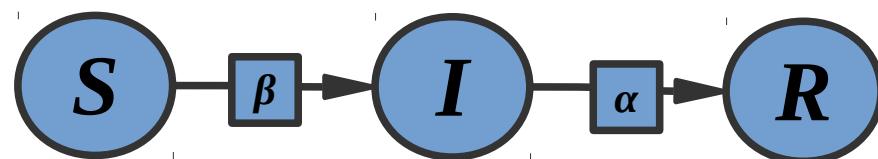


# Epidemic Chart

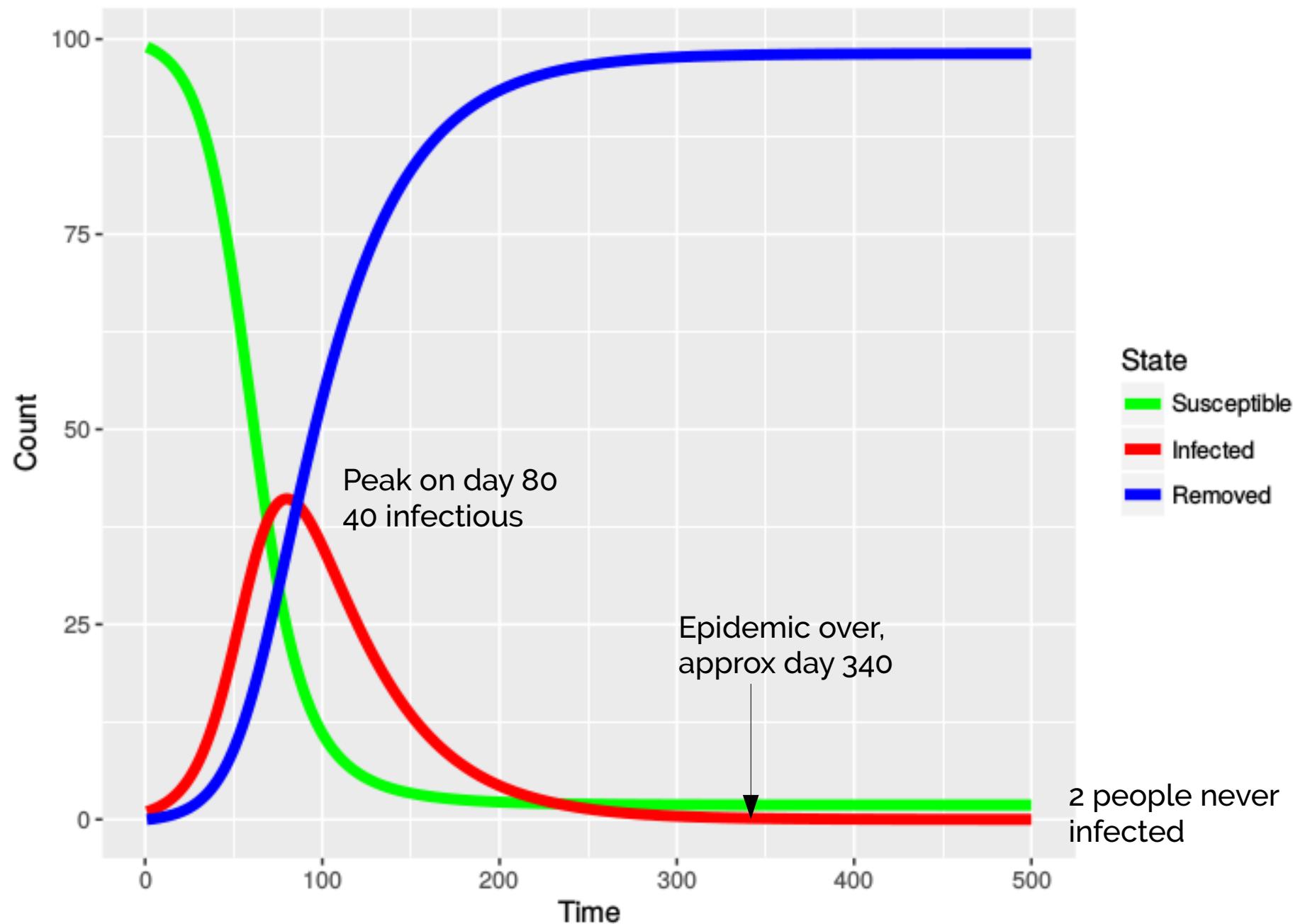


# Example 2 - recovery

- ▶ 100 people in total
- ▶ Start with one infection
- ▶ 99 susceptibles
- ▶ Set  $\alpha=0.025$ 
  - ▶ Some recovery
- ▶ Set  $\beta=0.001$

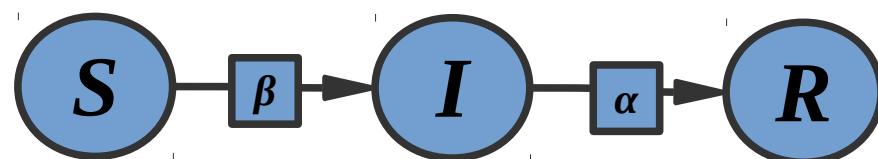


# Epidemic Chart

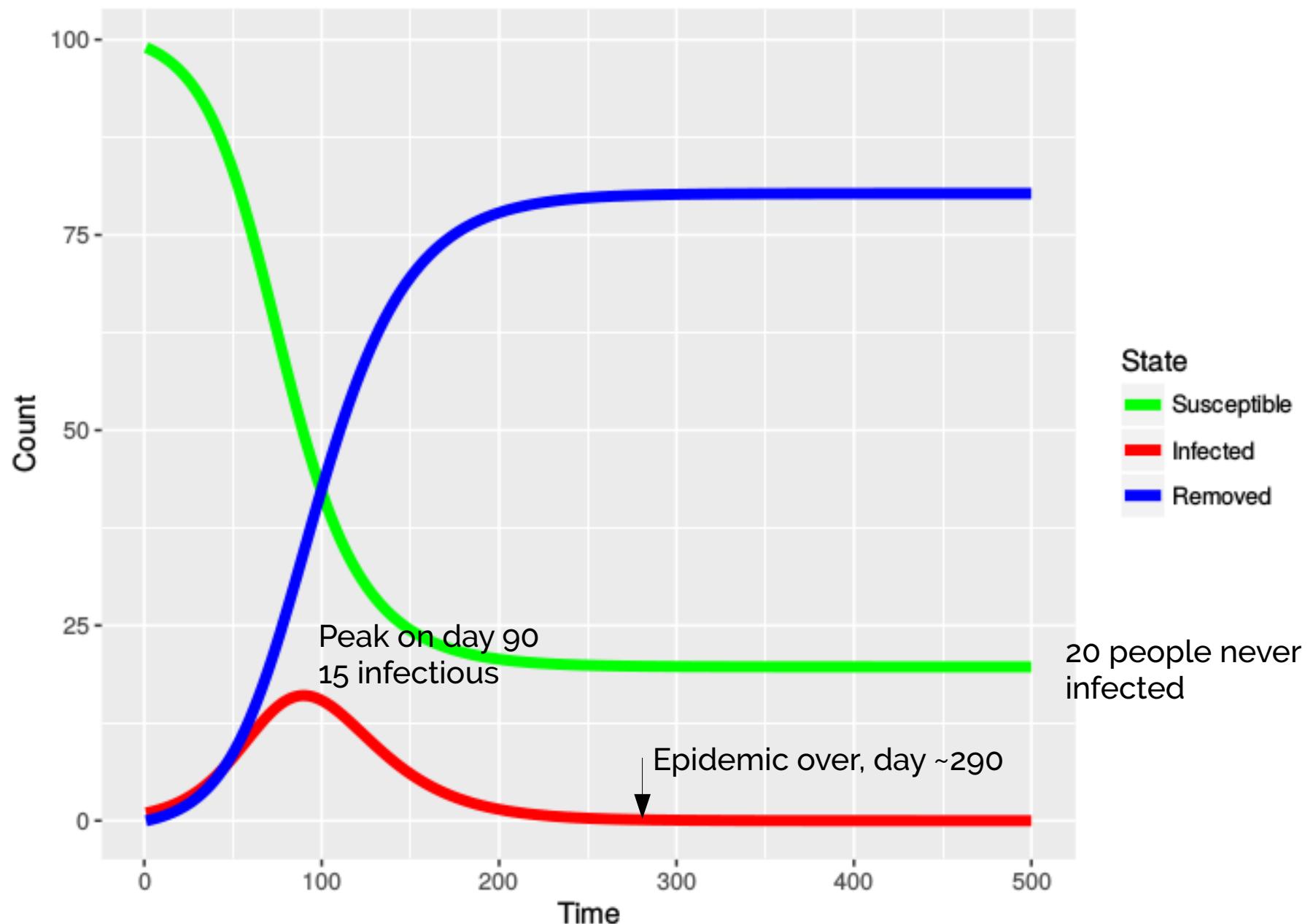


# Example 3 – faster recovery

- ▶ 100 people in total
- ▶ Start with one infection
- ▶ 99 susceptibles
- ▶ Set  $\alpha=0.050$ 
  - ▶ Double previous value
- ▶ Set  $\beta=0.001$

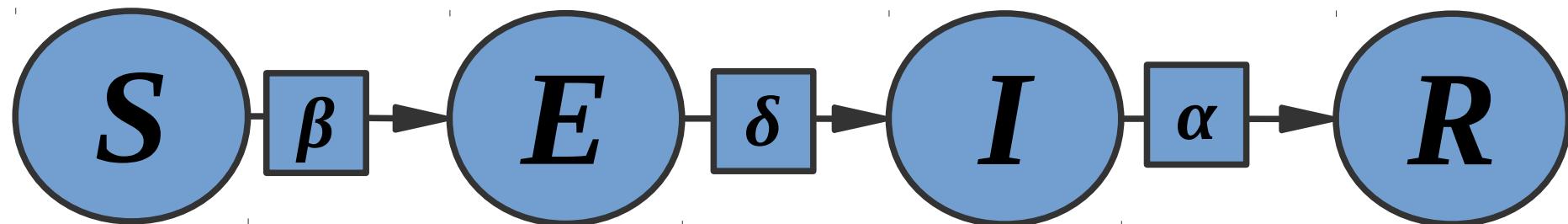


# Epidemic Chart



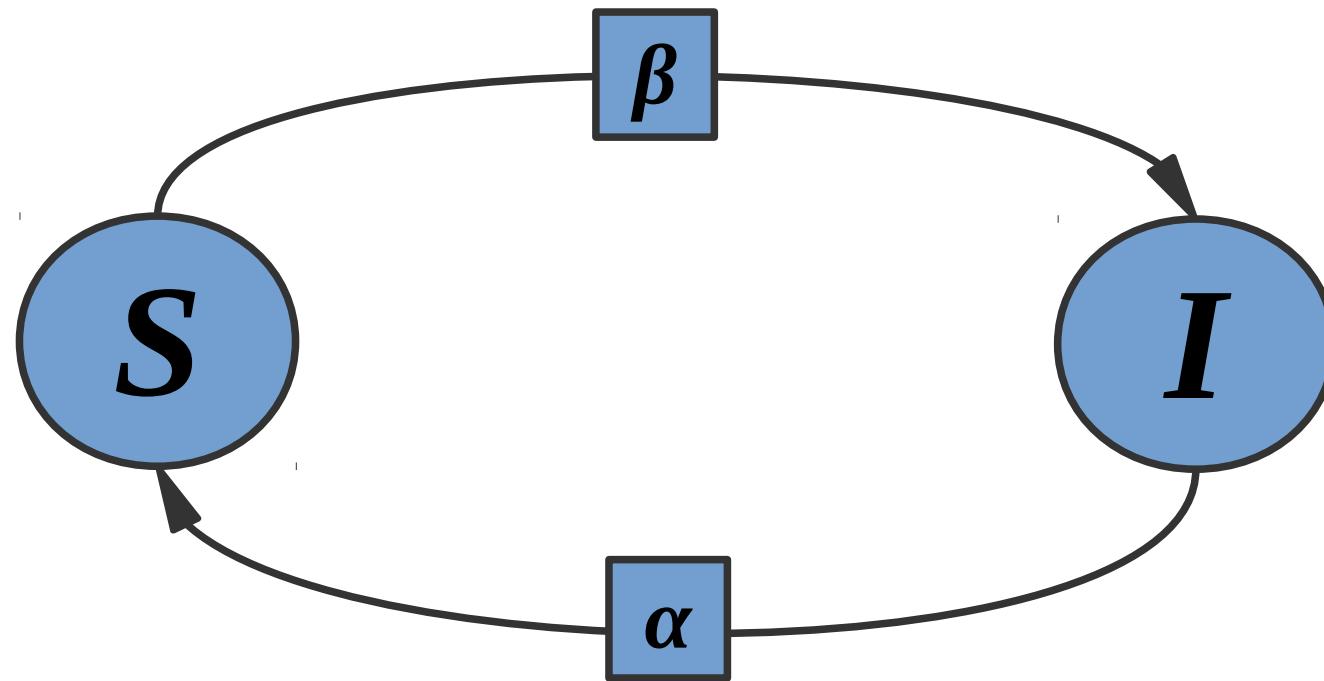
# More Complex Models

- ▶ Add a “Latent” infected state
- ▶ Infected, and will progress to infectious at some rate  $\delta$
- ▶ Usually “E”



# SIS Model

- ▶ Susceptible people become infectious
- ▶ Infected people recover
- ▶ How does the system end up?



# More Species

## Enzootic Cycle

New evidence strongly implicates bats as the reservoir hosts for ebolaviruses, though the means of local enzootic maintenance and transmission of the virus within bat populations remain unknown.

### Ebolaviruses:

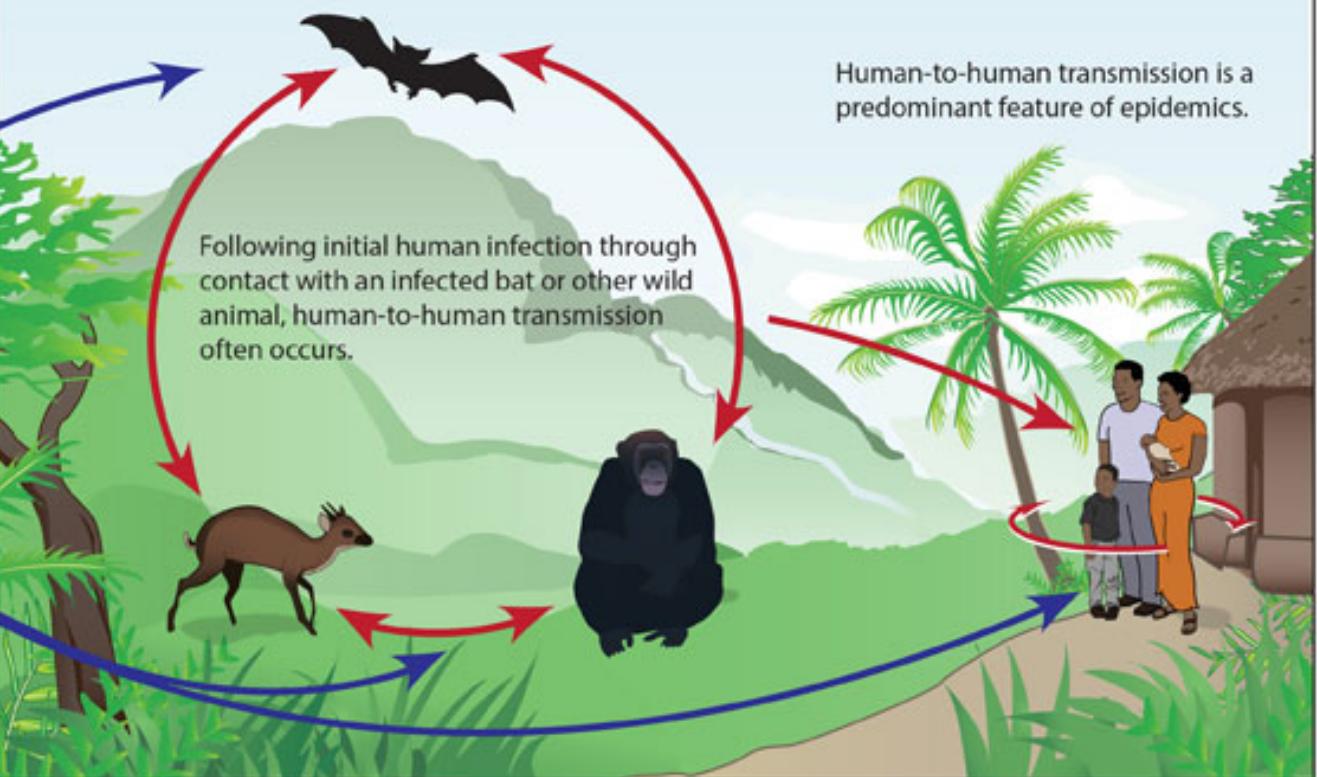
- Ebola virus (formerly Zaire virus)
- Sudan virus
- Tai Forest virus
- Bundibugyo virus
- Reston virus (non-human)



## Epizootic Cycle

Epizootics caused by ebolaviruses appear sporadically, producing high mortality among non-human primates and duikers and may precede human outbreaks. Epidemics caused by ebolaviruses produce acute disease among

humans, with the exception of Reston virus which does not produce detectable disease in humans. Little is known about how the virus first passes to humans, triggering waves of human-to-human transmission, and an epidemic.



# Human Ectoparasites

## Human ectoparasites and the spread of plague in Europe during the Second Pandemic



Katharine R. Dean, Fabienne Krauer, Lars Walløe, Ole Christian Lingjærde, Barbara Bramanti, Nils Chr. Stenseth, and Boris V. Schmid

PNAS 2018; published ahead of print January 16, 2018, <https://doi.org/10.1073/pnas.1715640115>

Contributed by Nils Chr. Stenseth, December 4, 2017 (sent for review September 4, 2017; reviewed by Xavier Didelot and Kenneth L. Gage)

- ▶ Can we blame the rats?

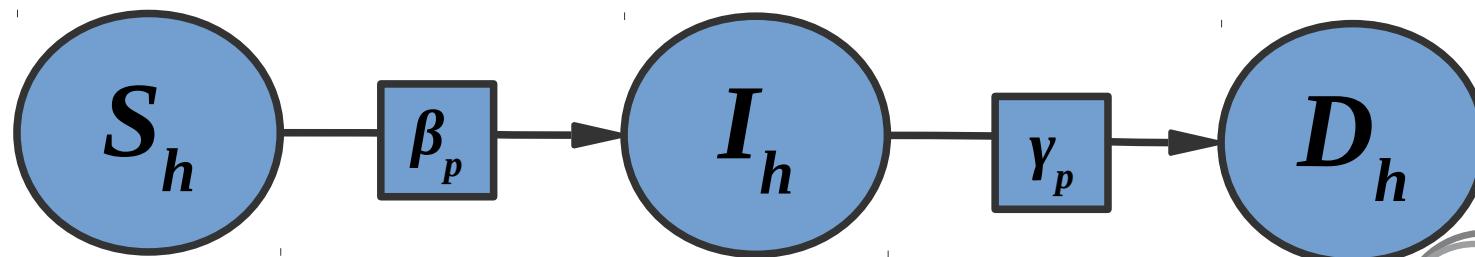
# Pneumonic Model

## ► Human-Human Transmission

$$\frac{dS_h}{dt} = -\beta_p \frac{S_h I_h}{N_h},$$

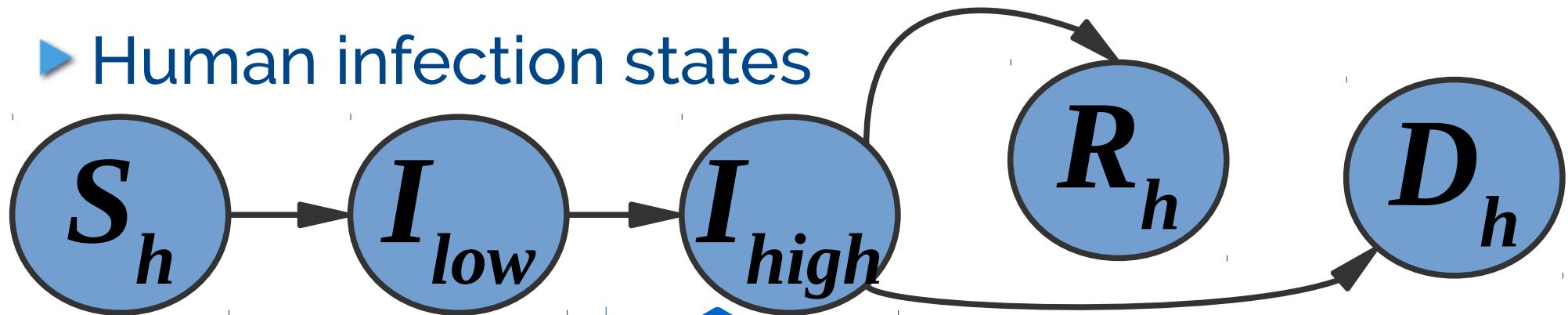
$$\frac{dI_h}{dt} = \beta_p \frac{S_h I_h}{N_h} - \gamma_p I_h,$$

$$\frac{dD_h}{dt} = \gamma_p I_h.$$



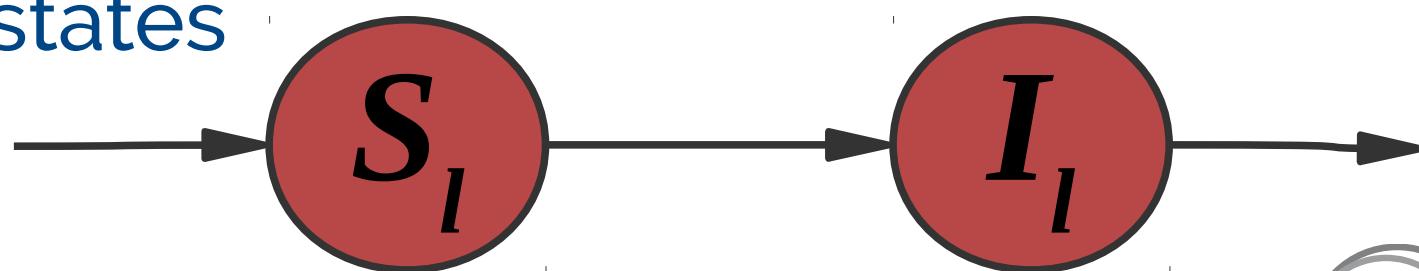
# Human Ectoparasites

- ▶ Human infection states



Coupled  
systems

- ▶ Flea states



# Human Ectoparasites

$$\frac{dS_h}{dt} = -\beta_l \frac{S_h I_l}{N_h},$$

$$\frac{dI_{\text{low}}}{dt} = \beta_l \frac{S_h I_l}{N_h} - \sigma_b I_{\text{low}},$$

$$\frac{dI_{\text{high}}}{dt} = (1 - g_h) \sigma_b I_{\text{low}} - \gamma_b I_{\text{high}},$$

$$\frac{dR_h}{dt} = g_h \sigma_b I_{\text{low}},$$

$$\frac{dD_h}{dt} = \gamma_b I_{\text{high}},$$

$$\frac{dS_l}{dt} = r_l S_l \left(1 - \frac{N_l}{K_l}\right) - \left[ (\beta_{\text{low}} I_{\text{low}} + \beta_{\text{high}} I_{\text{high}}) \frac{S_l}{N_h} \right],$$

$$\frac{dI_l}{dt} = \left[ (\beta_{\text{low}} I_{\text{low}} + \beta_{\text{high}} I_{\text{high}}) \frac{S_l}{N_h} \right] - \gamma_l I_l.$$

# Human/Rat/Flea Model

$$\frac{dS_r}{dt} = -\beta_r \frac{S_r F}{N_r} [1 - e^{-aN_r}],$$

$$\frac{dI_r}{dt} = \beta_r \frac{S_r F}{N_r} [1 - e^{-aN_r}] - \gamma_r I_r,$$

$$\frac{dR_r}{dt} = g_r \gamma_r I_r,$$

$$\frac{dD_r}{dt} = (1 - g_r) \gamma_r I_r,$$

$$\frac{dH}{dt} = r_f H \left(1 - \frac{H}{K_f}\right),$$

$$\frac{dF}{dt} = (1 - g_r) \gamma_r I_r H - d_f F,$$

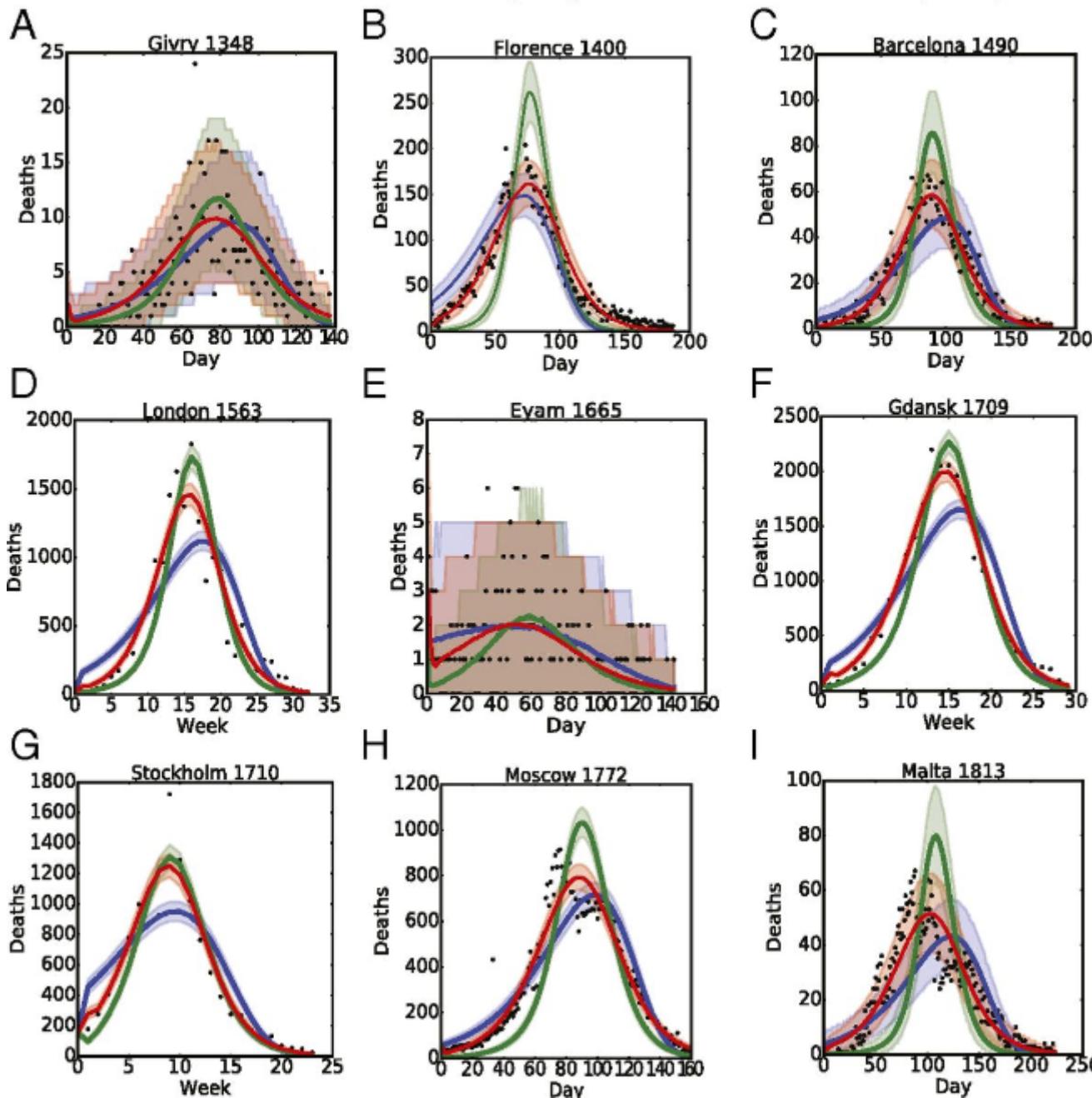
$$\frac{dS_h}{dt} = -\beta_h \frac{S_h F}{N_h} [e^{-aN_r}],$$

$$\frac{dI_h}{dt} = \beta_h \frac{S_h F}{N_h} [e^{-aN_r}] - \gamma_h I_h,$$

$$\frac{dR_h}{dt} = g_h \gamma_h I_h,$$

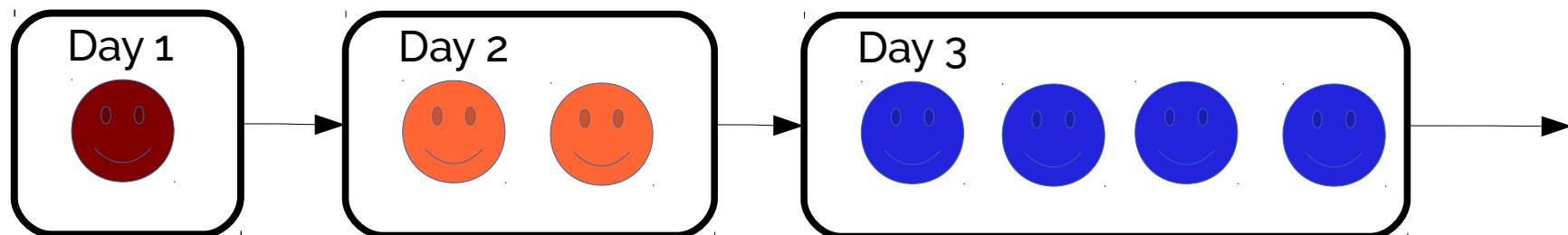
$$\frac{dD_h}{dt} = (1 - g_h) \gamma_h I_h.$$

— Human ectoparasite model (mean)  
— Pneumonic model (mean)  
— Rat and flea model (mean)  
■ Human ectoparasite model (95% CI)  
■ Pneumonic model (95% CI)  
■ Rat and flea model (95% CI)



# Deterministic

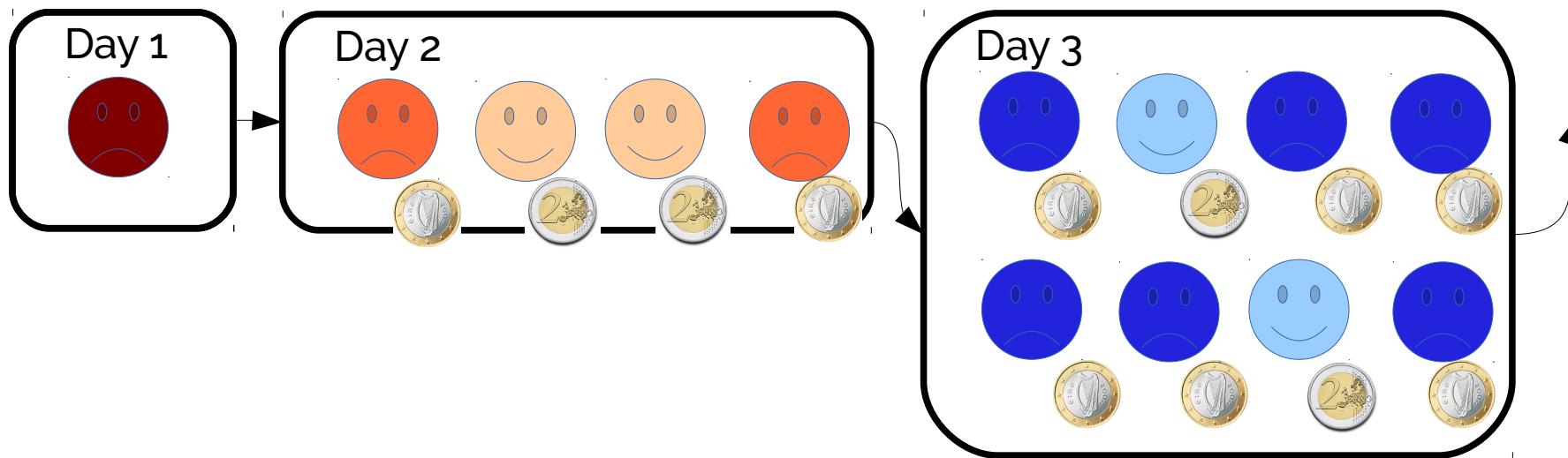
- ▶ Each infectious person infects 2 new people
- ▶ Infectious period is one day



Time	1	2	3	4	5	6	7	8
Count	1	2	4	8	16	32	64	128

# Stochastic

- ▶ Each infectious person → 4 new contacts
- ▶ Chance of new infection is  $\frac{1}{2}$



Time	1	2	3	4	5	6	7	8
Count	1	2	6	15	27	54	111	207

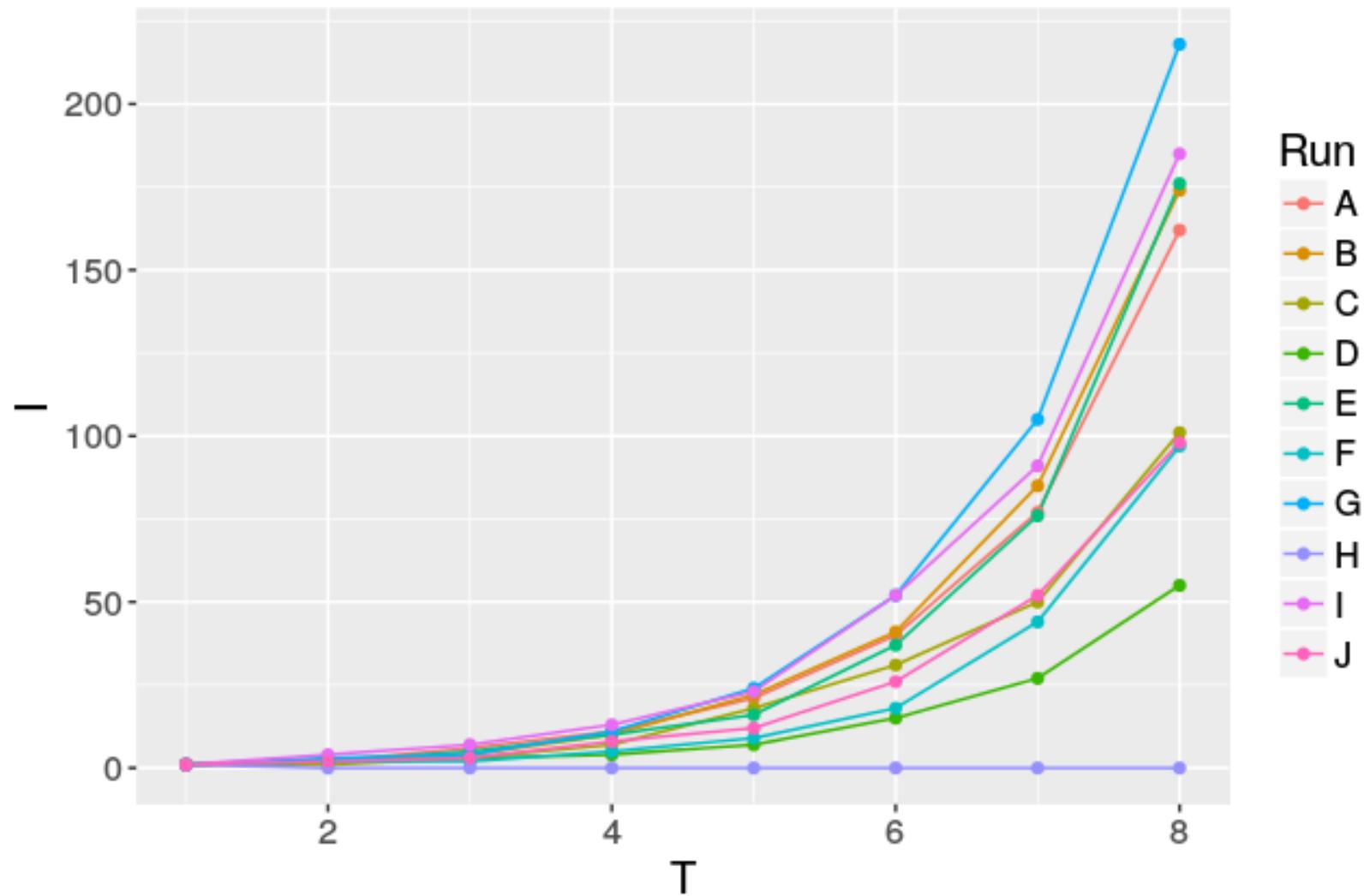
# Repeated Randomness

Time	1	2	3	4	5	6	7	8
	1	2	6	15	27	54	111	207
	1	3	9	16	31	68	120	250
	1	2	4	6	17	23	50	115
	1	1	2	1	0	0	0	0
	1	1	3	7	17	32	69	118
	1	3	6	12	26	43	83	156

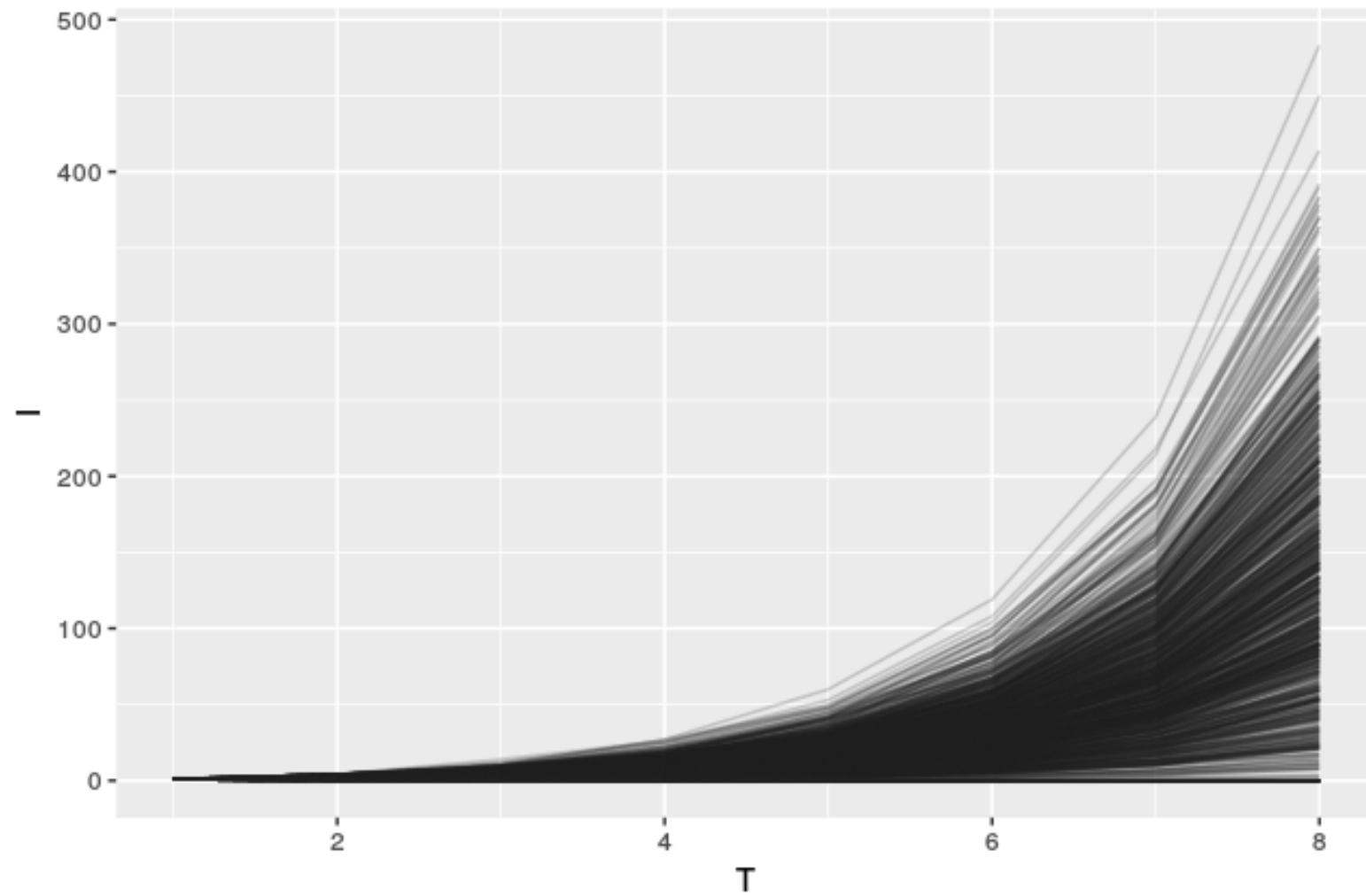
► Deterministic:

Time	1	2	3	4	5	6	7	8
Count	1	2	4	8	16	32	64	128

# Results



# More Results



# Randomness

- ▶ Previously...
  - ▶ Each infectious person → 4 new contacts
- ▶ Who meets the same number of people every day?
- ▶ The number of people you meet is the result of a *probability distribution*

# Probability Distributions

► Uniform

$$P = 1/2$$



$$P = 1/6$$

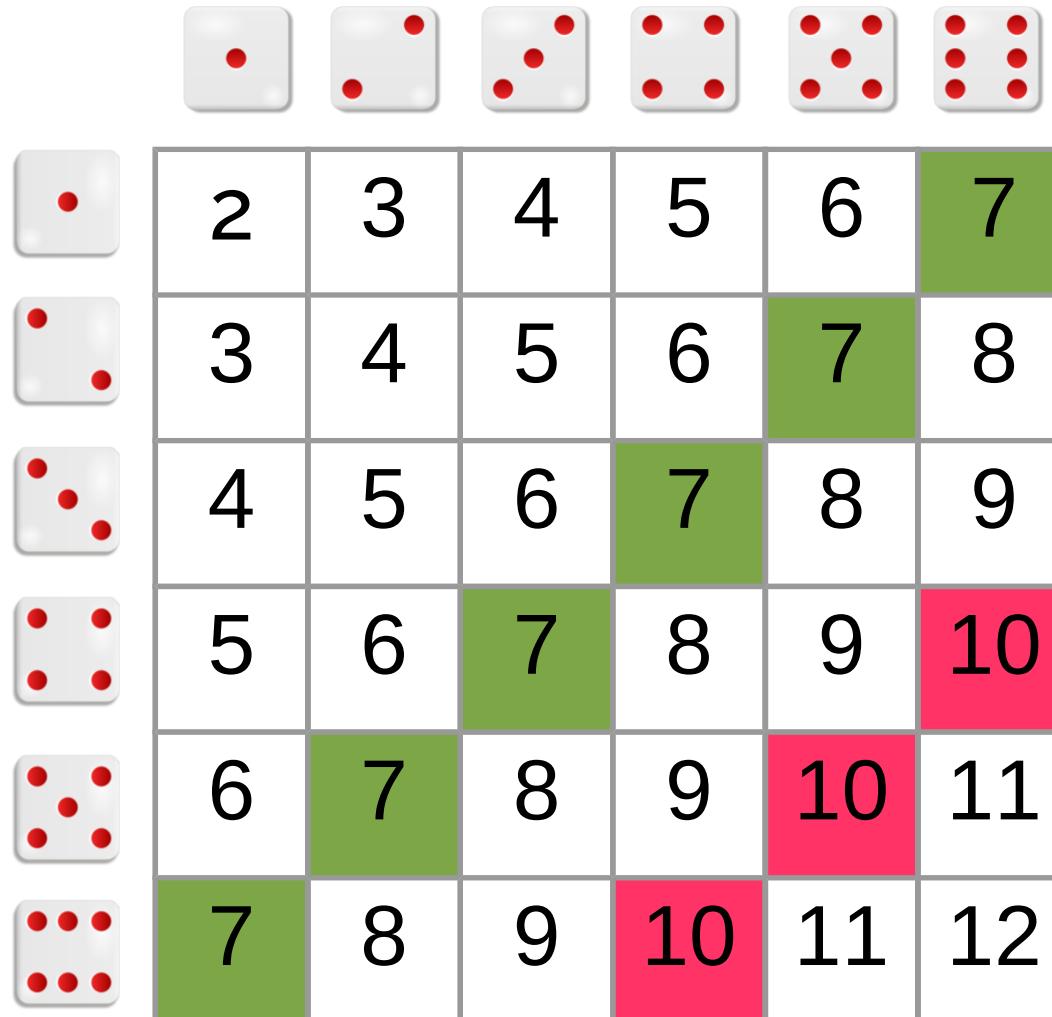


$$P = 1/10$$

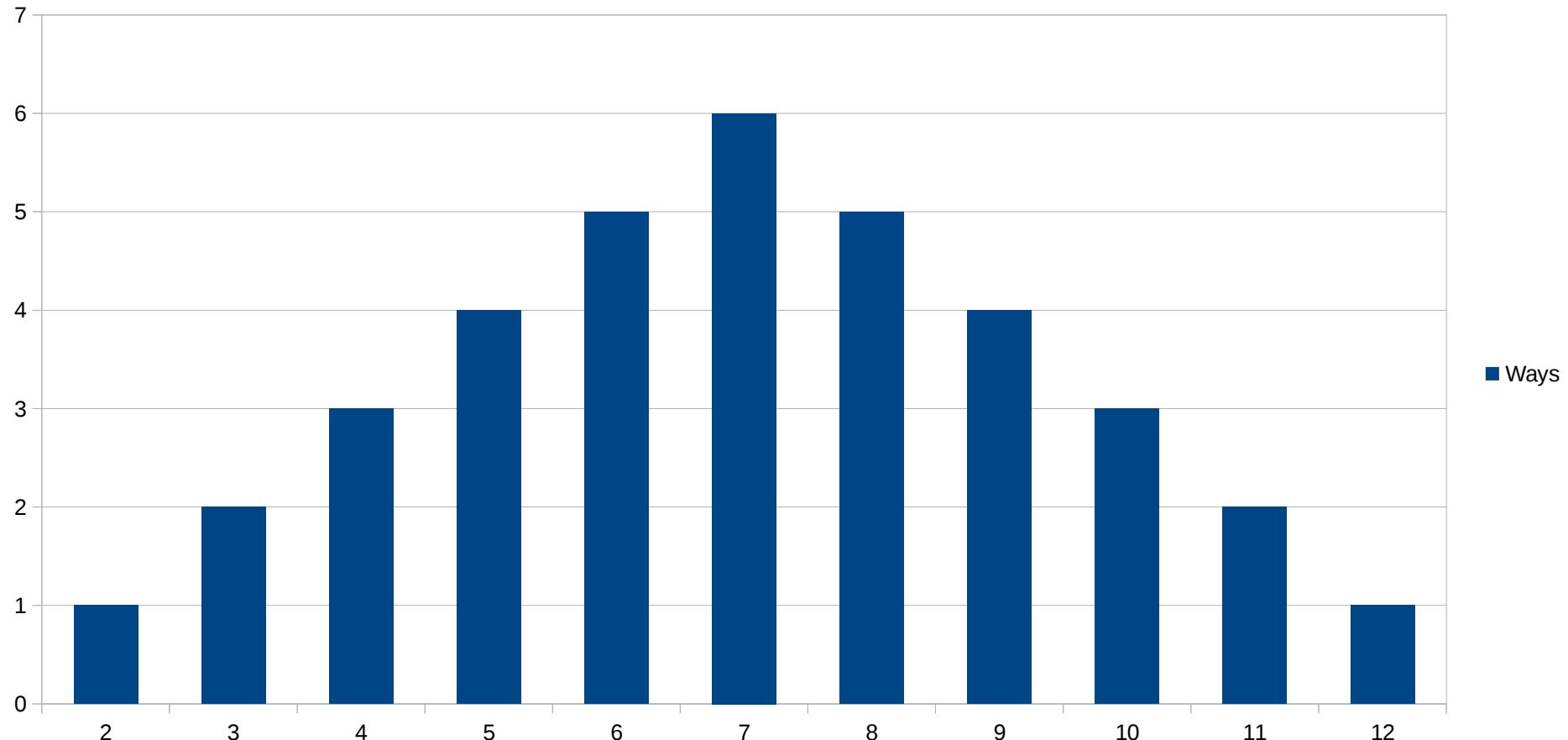
# Non-Uniform



# Non-Uniform



# Rolling Two Dice

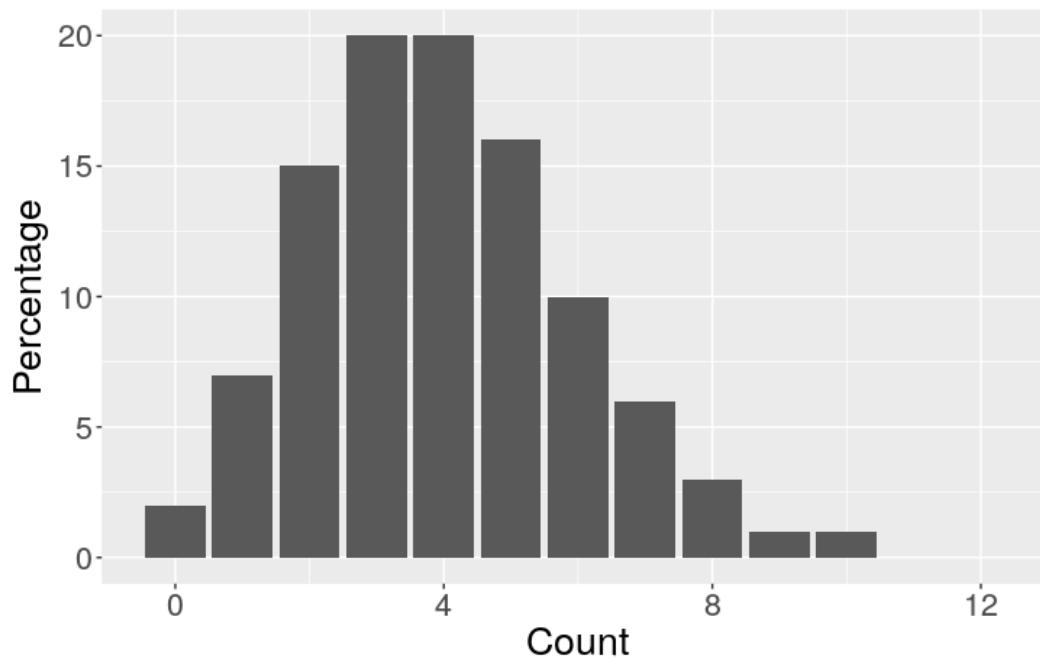


# Simple Count Distribution

- ▶ Need a distribution that:
  - ▶ Is always greater than or equal to zero
  - ▶ Has no upper bound
  - ▶ As few parameters as possible

# Poisson Distribution, mean=4

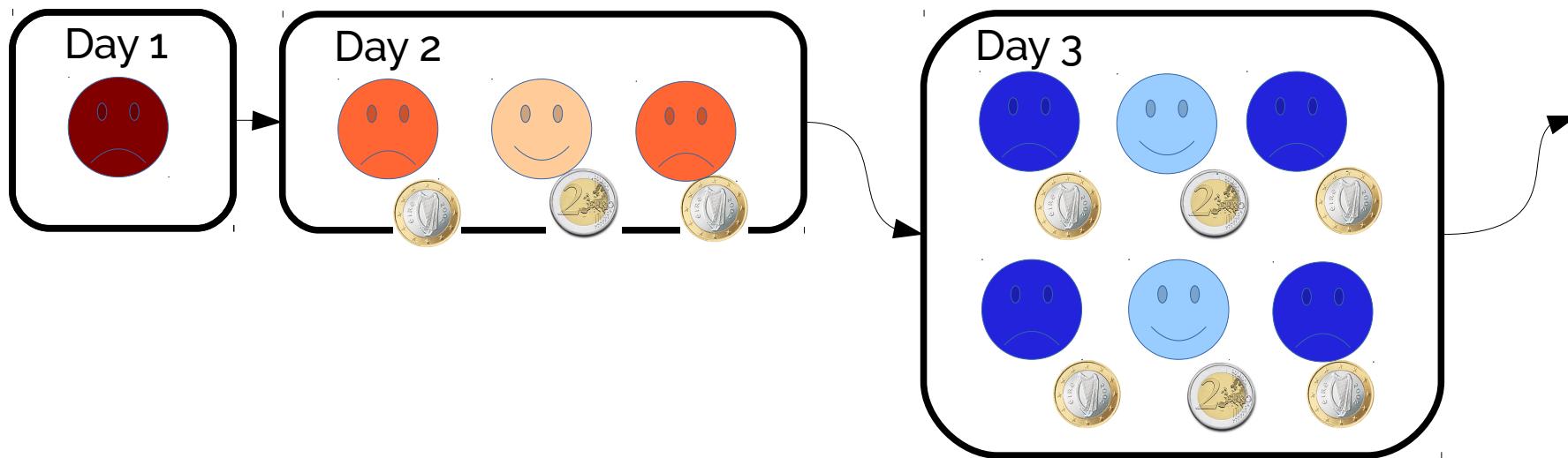
$$\frac{\lambda^k e^{-\lambda}}{k!}$$



Count	Percentage
0	2
1	7
2	15
3	20
4	20
5	16
6	10
7	6
8	3
9	1
10	1
11	0
12	0
...	0

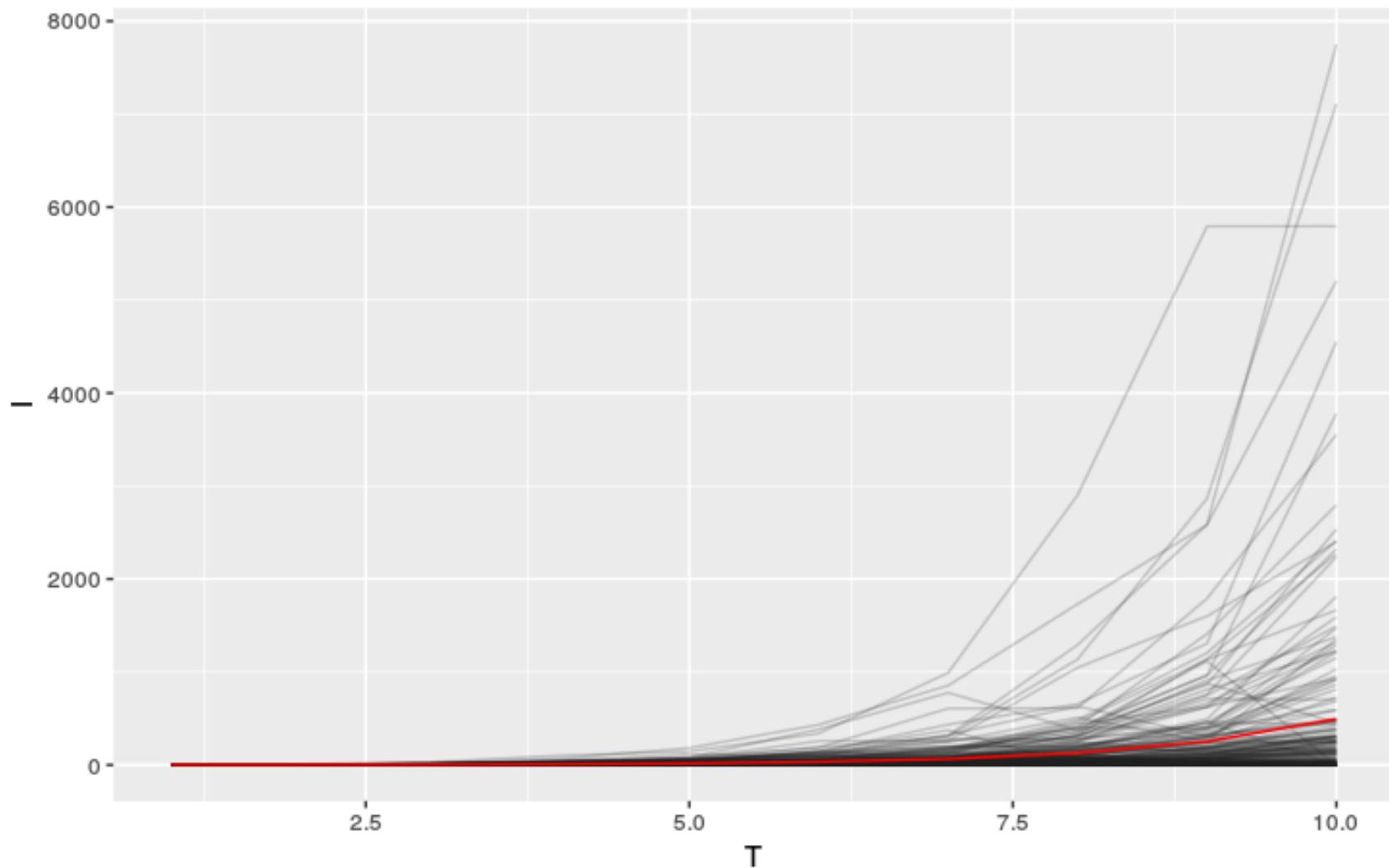
# Poisson Contacts

- ▶ Each infectious person → P(4) new contacts
- ▶ Chance of new infection is  $\frac{1}{2}$



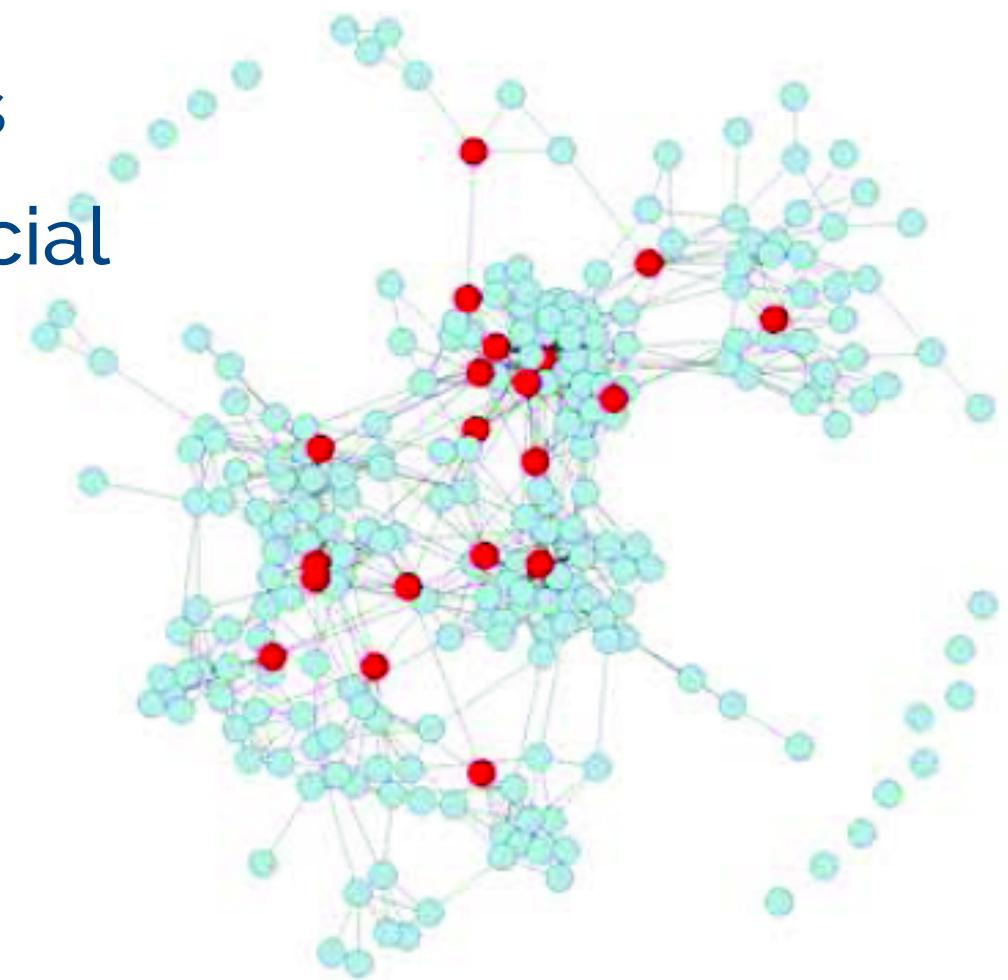
Time	1	2	3	...
Count	1	2	4	...

# t up to 10



# Network Model Analysis

- ▶ People interact with neighbours
- ▶ People group in cliques
- ▶ Some people highly social



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18 January 2015 Last updated at 00:03

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## Popular medical students 'should get flu jab first'

[COMMENTS \(168\)](#)

The government wants three-quarters of healthcare workers to be vaccinated

**Prioritising medical students with lots of friends for flu jabs could help increase the number of healthcare workers protected against the virus, say Lancaster University researchers.**

In a study in **The Lancet**, they calculated that vaccination rates would rise if people with large social networks influenced their peers.

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quits

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Can you stop them offending?



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The lines run to the sea



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Man battles pregnant wife



**Rodney**

Tactics for someone's



**Been and**

A pioneering photographic

# Conclusions

- ▶ Disease modelling helps understand the epidemic process
- ▶ Simple models can be useful
- ▶ Complex models give more insight, but take longer to compute