

# Time distributions and coronavirus control

Jonathan Dushoff, McMaster University

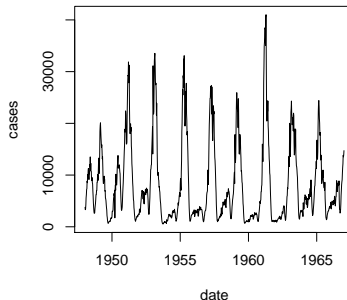
Cornell CAM Colloquium, Oct 2020



# What is dynamical modeling?



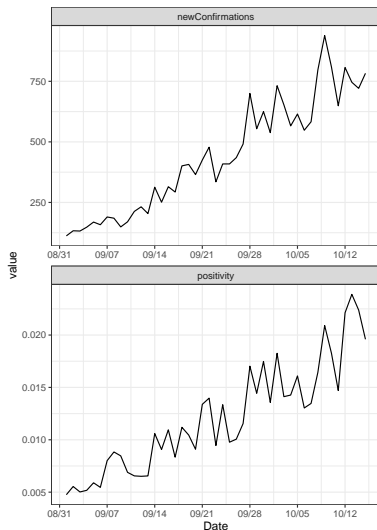
Measles reports from England and Wales



- ▶ A way to connect scales
- ▶ Start with rules about how things change in short time steps
  - ▶ Usually based on *individuals*
- ▶ Calculate results over longer time periods
  - ▶ Usually about *populations*

# Covid modeling questions

- ▶ How far and fast would it spread if unchecked?
- ▶ How hard is it to eliminate?
- ▶ How are we doing on control in a particular place and time?



<https://wzmli.github.io/COVID19-Canada>

# Outline

Modeling disease spread

Linking strength and speed

Estimating transmission intervals

- Generations through time

- Generations in space

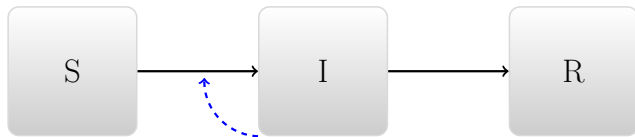
- Serial intervals

The speed paradigm

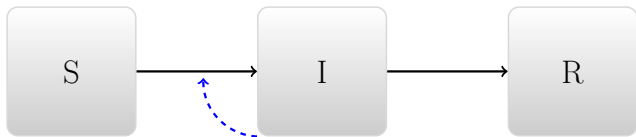
Real-time evaluation

# Simple dynamical models use compartments

Divide people into categories:

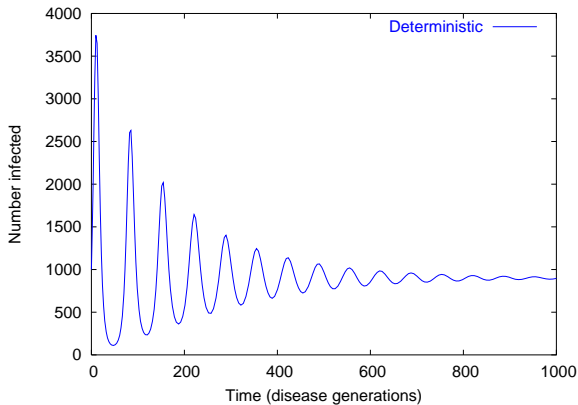


- ▶ Susceptible  $\rightarrow$  Infectious  $\rightarrow$  Recovered
- ▶ Individuals recover independently
- ▶ Individuals are infected by infectious people



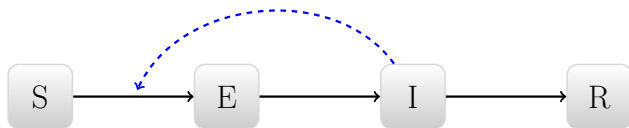
$$\begin{aligned}\frac{dS}{dt} &= \mu N - \beta \frac{SI}{N} - \mu S \\ \frac{dI}{dt} &= \beta \frac{SI}{N} - \gamma I - \mu I \\ \frac{dR}{dt} &= \gamma I - \mu R\end{aligned}$$

# Deterministic implementation

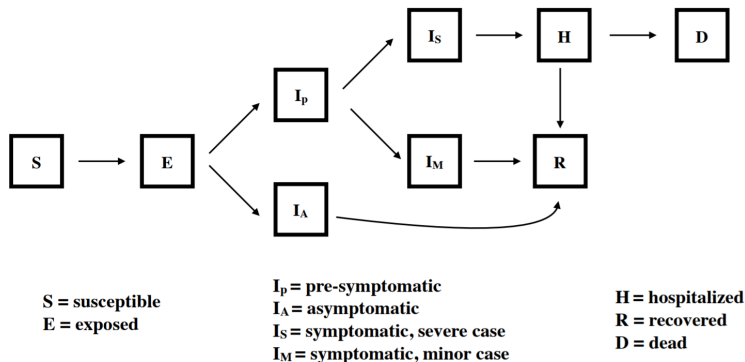




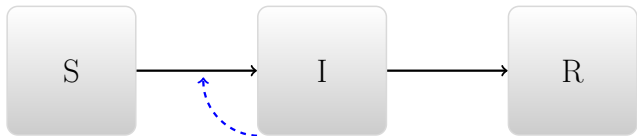
## Box models

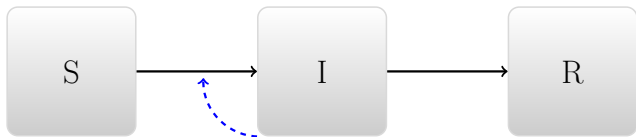


# More detailed dynamics

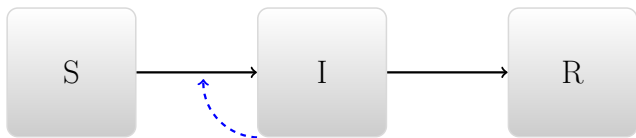


Childs et al., <http://covid-measures.stanford.edu/>



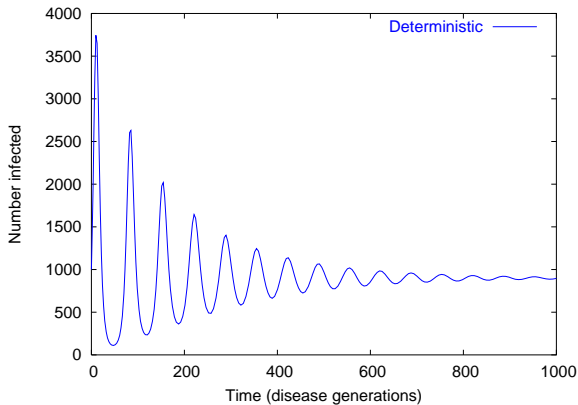


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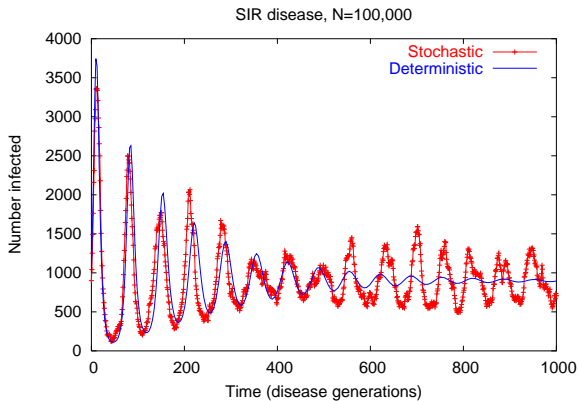


Event	transition	rate
Infection	$S \rightarrow I$	$R_0 SI/N$
Recovery	$I \rightarrow R$	$(1 - \rho)I$
Rebirth	$R \rightarrow S$	$\rho R$
Rebirth	$I \rightarrow S$	$\rho I$

# Deterministic implementation



# Individual-based implementation



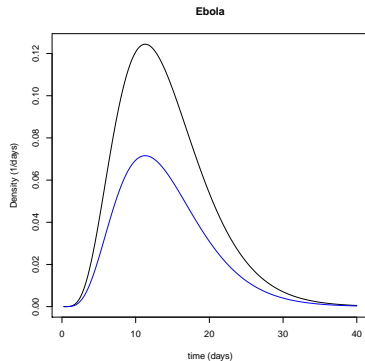
# Renewal equation

- ▶ A broad framework that covers a wide range of underlying models
- ▶  $i(t) = S(t) \int k(\tau) i(t - \tau) d\tau$ 
  - ▶  $i(t)$  is the *rate* of new infections (per-capita incidence)
  - ▶  $S(t)$  is the proportion of the population susceptible
  - ▶  $k(\tau)$  measures how infectious a person is (on average) at time  $\tau$  after becoming infected
- ▶ For invasion, treat  $S$  as constant

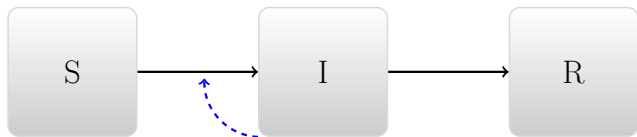


# Infection kernel

- ▶  $k(\tau)$  is the expected rate at which you infect at time  $\tau$  after being infected
- ▶  $\int_{\tau} k(\tau) d\tau$  is the expected number of people infected:
  - ▶  $\mathcal{R}$  the effective reproductive number
- ▶  $k(\tau)/\mathcal{R}$  is a distribution:
  - ▶  $g(\tau)$ , the *intrinsic* generation distribution

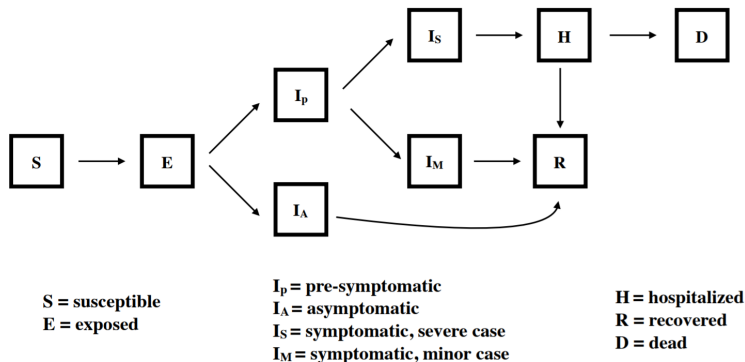


# Linear chain trick



- Create ODEs to follow a *cohort* of people infected at the same time

# Linear chain trick



Childs et al., <http://covid-measures.stanford.edu/>

How long until the bus comes?



# Mean of a self-weighted quantity

- ▶ Infectious period of an infector
- ▶ Activity level of an interactor
- ▶  $\mu(1 + \frac{\sigma^2}{\mu^2}) = \mu(1 + \kappa)$
- ▶ Time until bus comes:  $\mu(1 + \kappa)/2$

# Generation interval

- ▶ One generation:
  - ▶ Latent period (time until infectiousness) +
  - ▶ Infectious waiting time (time until infection)
- ▶ Infectious waiting time
  - ▶ Drawn at random from infectious period
  - ▶ Equal to infectious period *only* when we assume a Markovian process

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# Lessons from simple models

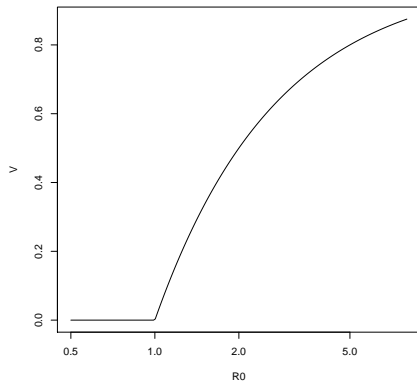
- ▶ Exponential invasion potential
- ▶ Tendency to oscillate
- ▶ Thresholds



# Strength

- ▶ We describe epidemic strength with big  $\mathcal{R}$
- ▶ Number of new cases per case
- ▶ Uncontrolled, initial value of  $\mathcal{R}$  is called  $\mathcal{R}_0$ .

# $\mathcal{R}$ and control



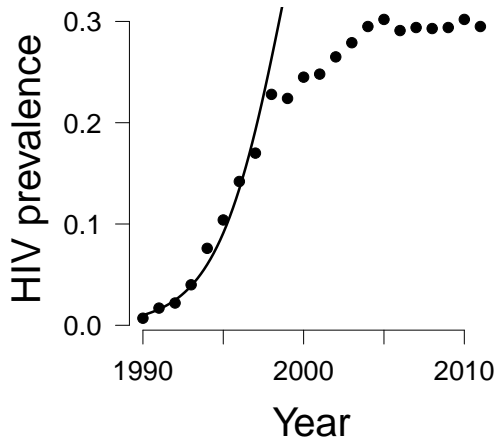
# Herd immunity

- ▶ If we have  $\mathcal{R}$  new cases per case when everyone is susceptible
- ▶ And 1 case per case (on average) at equilibrium:
  - ▶ Proportion susceptible at equilibrium is  $S = 1/\mathcal{R}$
  - ▶ Proportion affected at equilibrium is  $V = 1 - 1/\mathcal{R}$

# Speed

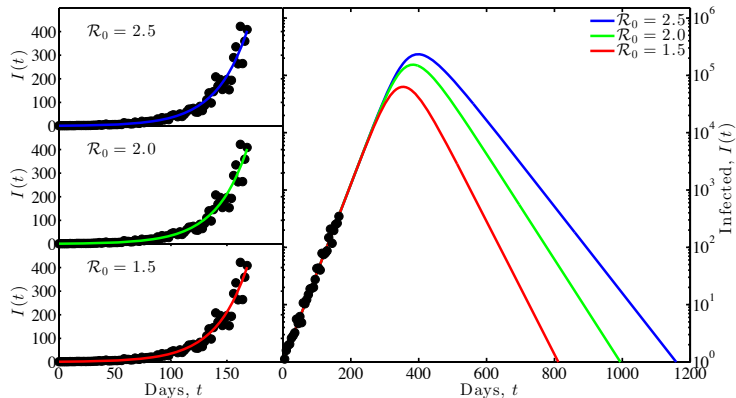
- ▶ We measure epidemic speed using little  $r$ :
  - ▶ The ratio of the *change* in disease impact to the *amount* of disease impact
  - ▶ *Units*: [1/time]
  - ▶ Disease increases like  $e^{rt}$
- ▶ Time scale is  $C = 1/r$

# HIV in sub-Saharan Africa



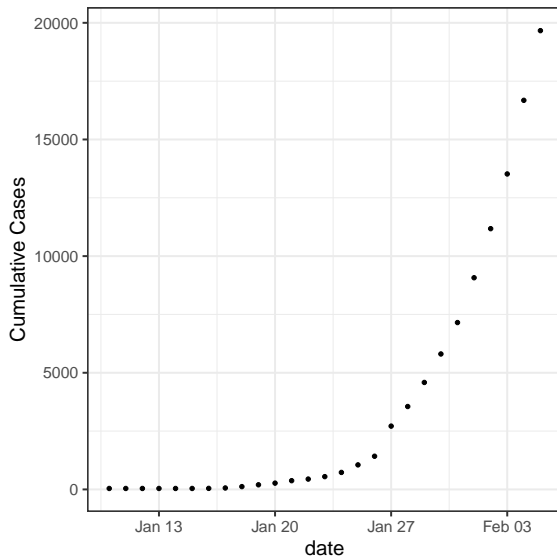
$C \approx 18$  month. Faster than expected.

# Ebola outbreak



$C \approx 1$  month. Slower than expected.

# Coronavirus speed



$C \approx 5$  day. Coronavirus!

# Coronavirus

- ▶ What we see clearly is  $r$
- ▶ What we rush to calculate is  $\mathcal{R}$
- ▶ How do we do this?
- ▶ *Why* do we do this?

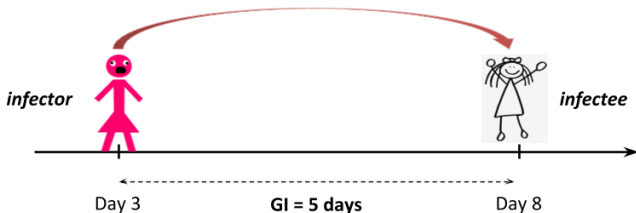


# How long is a disease generation? (present)

## Definition

### Generation Interval:

*Interval between the time that an individual is infected by an infector and the time this infector was infected*

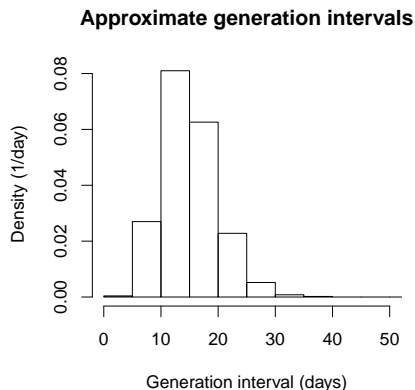


# Generation intervals



- ▶ Sort of the poor relations of disease-modeling world
- ▶ Ad hoc methods
- ▶ Error often not propagated

# Quickness: $g(\tau)$



- ▶ The generation distribution measures generations of the disease
  - ▶ Interval between “index” infection and resulting infection
- ▶ Does “quick” disease (short generations) mean more danger or less danger?

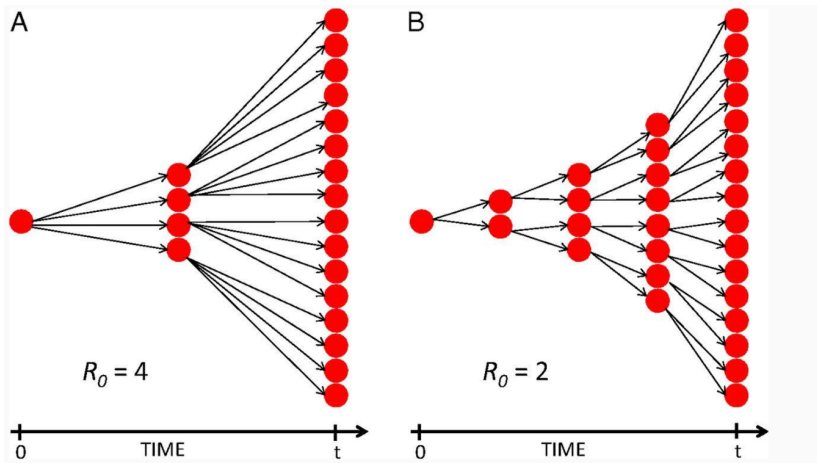
# Danger?



# Conditional effect of quickness

- ▶ *Given* the reproductive number  $\mathcal{R}$ 
  - ▶ quicker disease means faster growth rate  $r$
  - ▶ More danger
- ▶ *Given* the growth rate  $r$ 
  - ▶ quicker disease means *smaller*  $\mathcal{R}$
  - ▶ Less danger

# Generations and $\mathcal{R}$

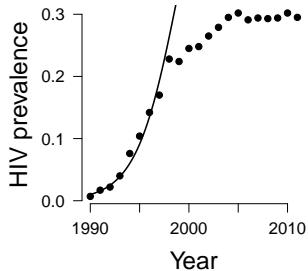


Powers et al., <https://www.pnas.org/content/111/45/15867>

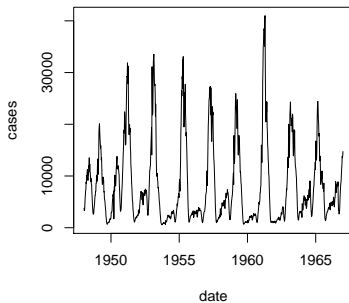
# Linking framework

- ▶ Epidemic speed ( $r$ ) is a *product*:
  - ▶ (something to do with) quickness  $\times$
  - ▶ (something to do with) epidemic strength
- ▶ Strength ( $\mathcal{R}$ ) is therefore (sort-of) a quotient
  - ▶ More quickness implies less strength
  - ▶ ... if speed is known

# Speed and strength



**Measles reports from England and Wales**



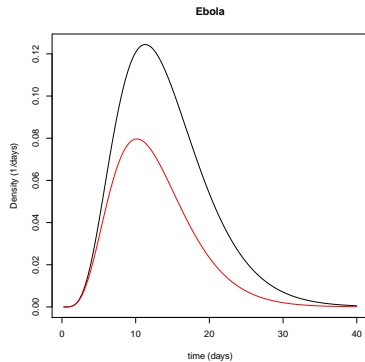


# Euler-Lotka equation

- ▶ If we neglect  $S$ , we expect exponential growth
- ▶  $1 = \int k(\tau) \exp(-r\tau) d\tau$ 
  - ▶ i.e., the total of *discounted* contributions is 1
- ▶  $1/\mathcal{R} = \int g(\tau) \exp(-r\tau) d\tau$
- ▶ Note that  $b(\tau) = k(\tau) \exp(-r\tau)$  is also a distribution
  - ▶ The initial “backwards” generation interval

# Interpretation: generating functions

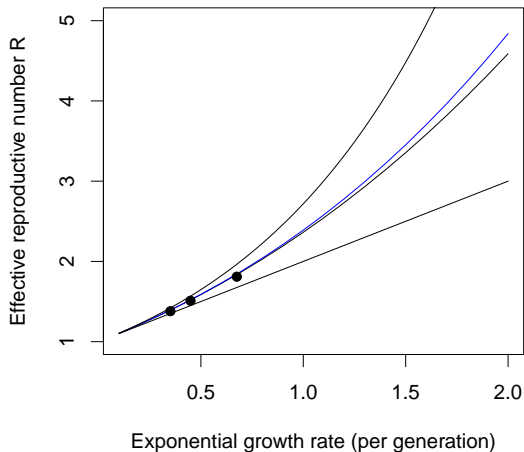
- ▶  $1/\mathcal{R} = \int g(\tau) \exp(-r\tau) d\tau$
- ▶  $\mathcal{R} = 1/M(-r)$
- ▶ *J Wallinga, M Lipsitch; DOI: 10.1098/rspb.2006.3754*



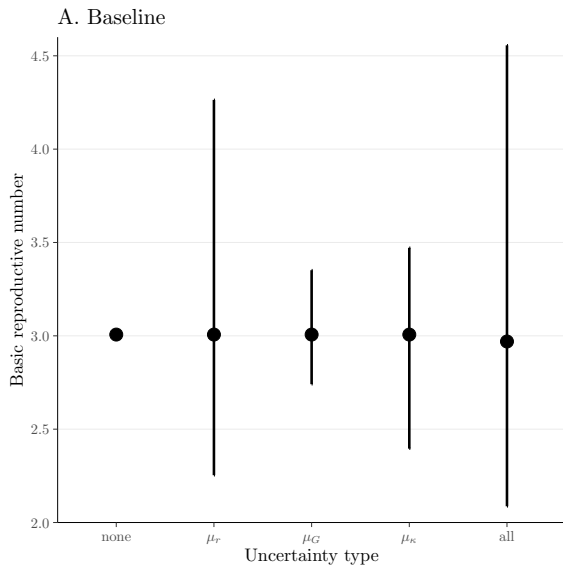
# Compound-interest interpretation

- ▶  $\mathcal{R} = (1 + r\kappa\bar{G})^{1/\kappa} \equiv X(r\bar{G}; 1/\kappa)$
- ▶  $\kappa$  is the 'effective dispersion'
  - ▶ Equal to the squared coefficient of variation when  $G$  is gamma-distributed
- ▶  $X$  is the compound-interest approximation to the exponential
  - ▶ Linear when  $\kappa = 1$  (i.e., when  $g$  is exponential)
  - ▶ Approaches exponential as  $\kappa \rightarrow 0$
- ▶ *Park et al., Epidemics DOI:10.1101/312397*

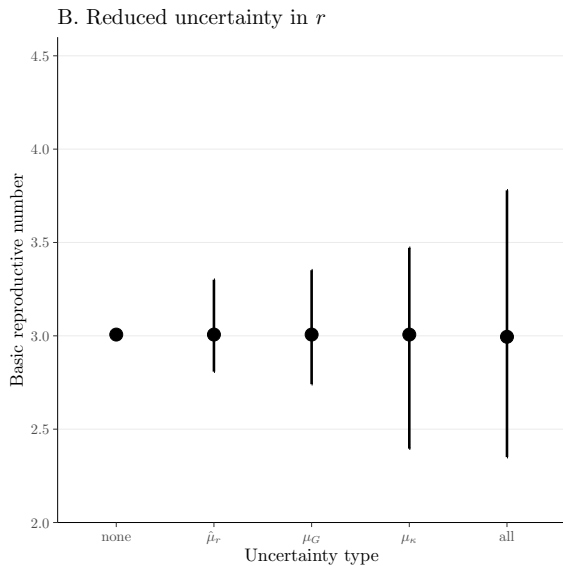
# Approximating the $r\mathcal{R}$ relationship



# Propagating error



# Propagating error



# Outline

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- Generations through time

- Generations in space

- Serial intervals

The speed paradigm

Real-time evaluation

# Estimating transmission intervals





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# Generations through time

- ▶ Generation intervals can be estimated by:
  - ▶ Observing patients:
    - ▶ How long does it take to become infectious?
    - ▶ How long does it take to recover?
    - ▶ What is the time profile of infectiousness/activity?
  - ▶ Contact tracing
    - ▶ Who (probably) infected whom?
    - ▶ When did each become infected?
    - ▶ — or ill (serial interval)?

# Which is the real interval?

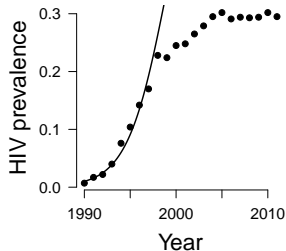
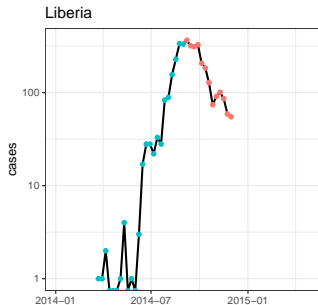
- ▶ Contact-tracing intervals look systematically different, depending on when you observe them.
- ▶ Observed in:
  - ▶ Real data, detailed simulations, simple model
- ▶ Also differ from intrinsic (infectior centered) estimates

# Types of interval

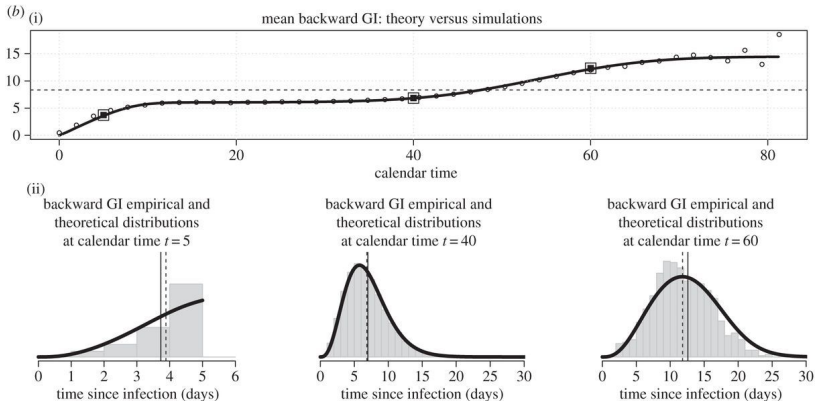
- ▶ Define:
  - ▶ *Intrinsic interval*: How infectious is a patient at time  $\tau$  after infection?
  - ▶ *Forward interval*: When will the people infected today infect others?
  - ▶ *Backward interval*: When did the people who infected people today themselves become infected?
  - ▶ *Censored interval*: What do all the intervals observed up until a particular time look like?
    - ▶ Like backward intervals, if it's early in the epidemic

# Growing epidemics

- ▶ Generation intervals look *shorter* at the beginning of an epidemic
  - ▶ A disproportionate number of people are infectious right now
  - ▶ They haven't finished all of their transmitting
  - ▶ We are biased towards observing faster events



# Backward intervals



*Champredon and Dushoff, 2015. DOI:10.1098/rspb.2015.2026*

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**Generations in space**

Serial intervals

The speed paradigm

Real-time evaluation

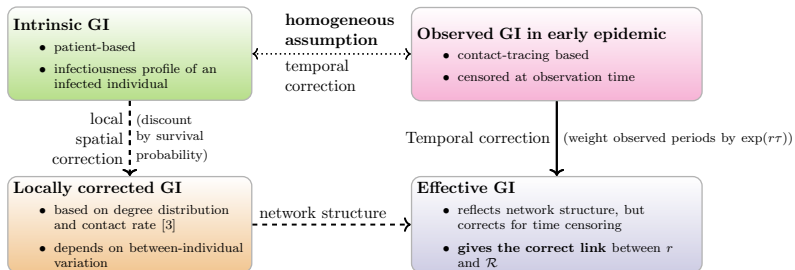




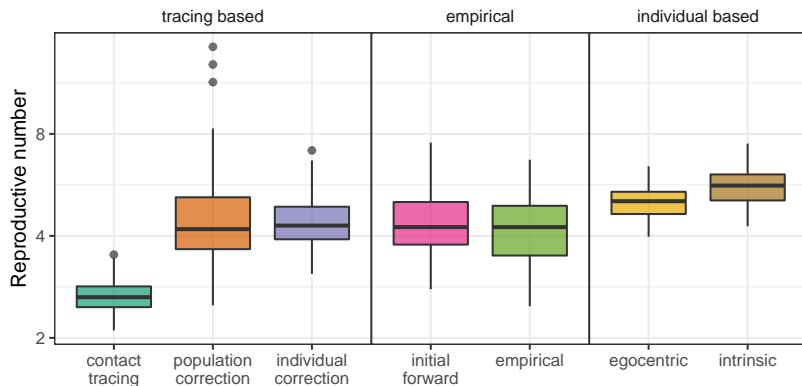
# Generation-interval perspective

- ▶ Modelers don't usually question the intrinsic generation interval
- ▶ But spatial network structure does change generation intervals:
  - ▶ Local interactions
  - ▶  $\implies$  wasted contacts
  - ▶  $\implies$  shorter generation intervals
  - ▶  $\implies$  smaller estimates of  $\mathcal{R}$ .

# Observed and estimated intervals



# Outbreak estimation



Park et al. JRSI, DOI: 10.1098/rsif.2019.0719

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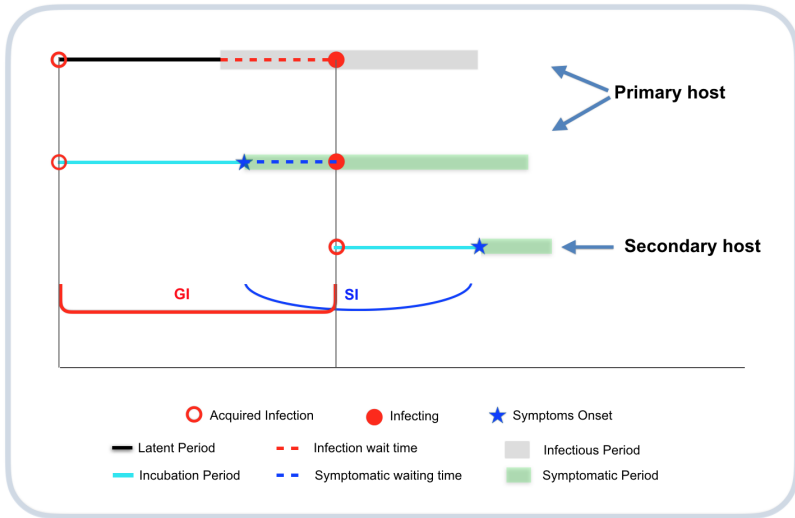
Generations in space

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# Serial intervals

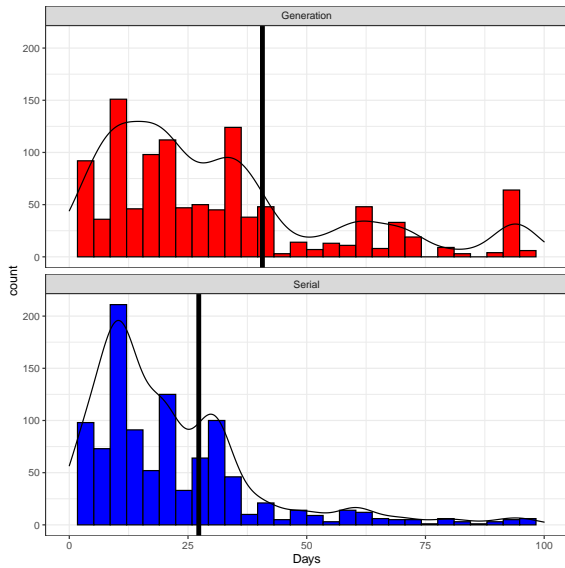


# Serial intervals

- ▶ Do serial intervals and generation intervals have the same distribution?
- ▶ It seems that they should: they describe generations of the same process
  - ▶ But serial intervals can be very different
  - ▶ Even negative! You might report to the clinic with flu before me, even though I infected you

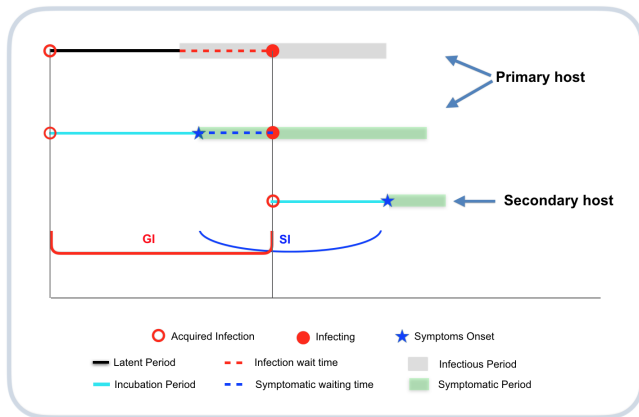
# Rabies

- ▶ If symptoms always start *before* infectiousness happens, then serial interval should equal generation interval:
  - ▶ incubation time + extra latent time + waiting time
  - ▶ extra latent time + waiting time + incubation time



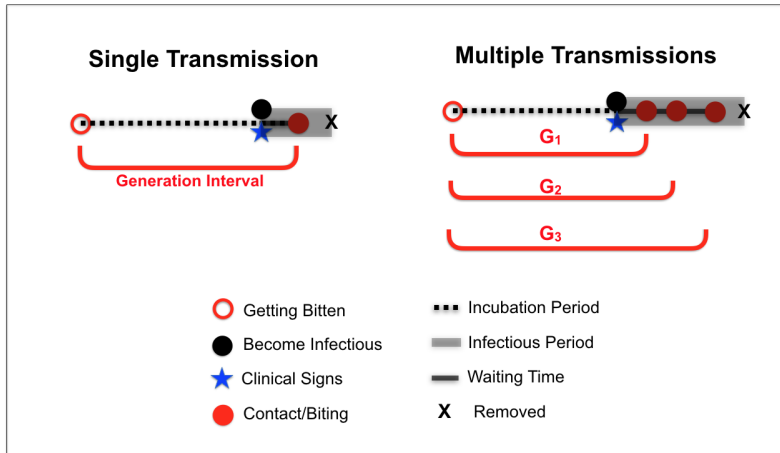


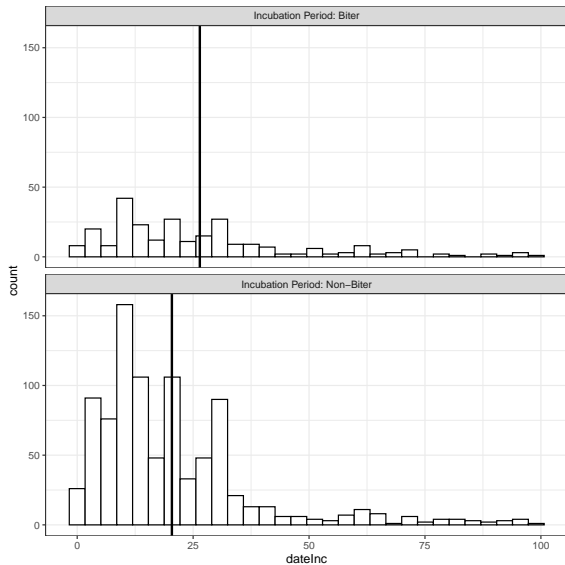
# Serial interval anomaly



What if individuals aren't homogeneous?

# Observed intervals



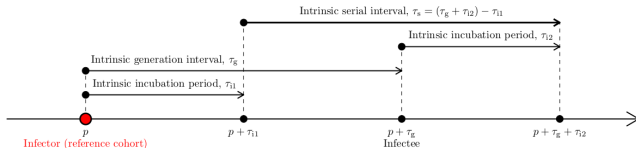


# The link paradox

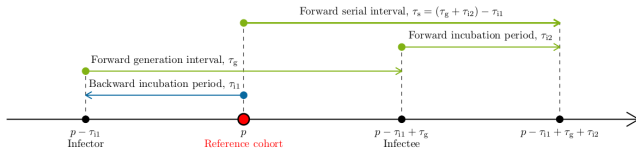
- ▶ Imagine a renewal process where symptoms in the infector cause symptoms in the infectee
  - ▶ Assume homogeneity
- ▶ This has to match the same  $r\mathcal{R}$  link as the true process
- ▶ But it also can't (because the serial interval is in general broader than the generation interval)

# The forward serial interval

A. Intrinsic serial interval

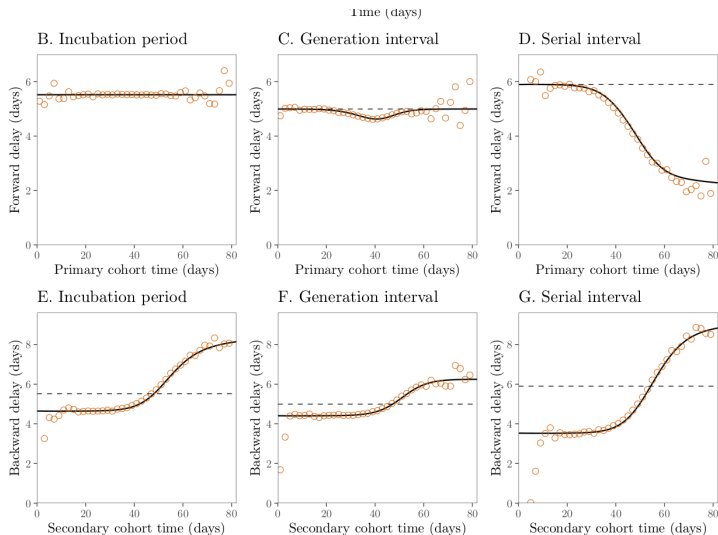


B. Forward serial interval



- Dynamical effects mean that the forward serial interval is shortened!

# Observed epidemiological intervals



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Real-time evaluation

# The speed paradigm

- ▶ Why are people scrambling to estimate  $\mathcal{R}$  and mostly ignoring  $r$ ?
  - ▶ History
  - ▶ Equilibrium and herd immunity
  - ▶ Modelers gotta model



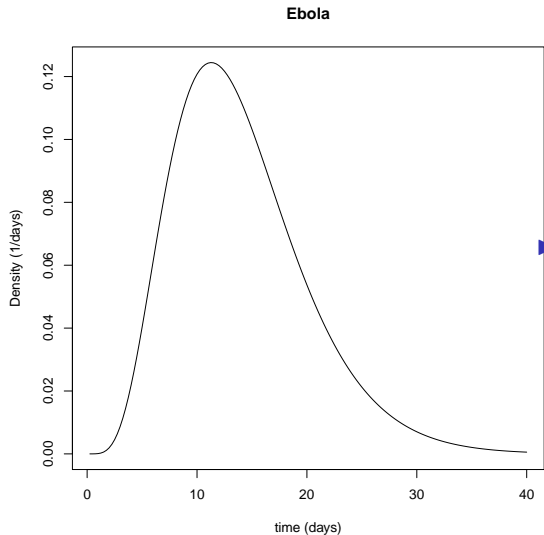
# The strength paradigm

- ▶  $\mathcal{R} > 1$  is a threshold
- ▶ If we can reduce transmission by a constant *factor* of  $\theta > \mathcal{R}$ , disease can be controlled
- ▶ In general, we can define  $\theta$  as a (harmonic) mean of the reduction factor over the course of an infection
  - ▶ weighted by the *intrinsic* generation interval
- ▶ Epidemic is controlled if  $\theta > \mathcal{R}$
- ▶ More direct information about long term (tells us about final size, equilibrium)

# The speed paradigm

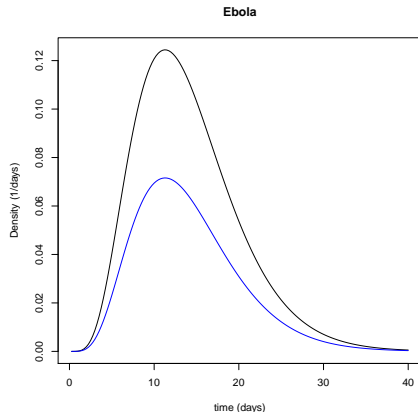
- ▶  $r > 0$  is a threshold
- ▶ If we can reduce transmission at a constant *hazard rate* of  $\phi > r$ , disease can be controlled
- ▶ In general, we can define  $\phi$  as a (very weird) mean of the reduction factor over the course of an infection
  - ▶ weighted by the *backward* generation interval
- ▶ Epidemic is controlled if  $\phi > r$
- ▶ More direct information about short term (tells us about, um, speed)

## *Epidemic strength (present)*



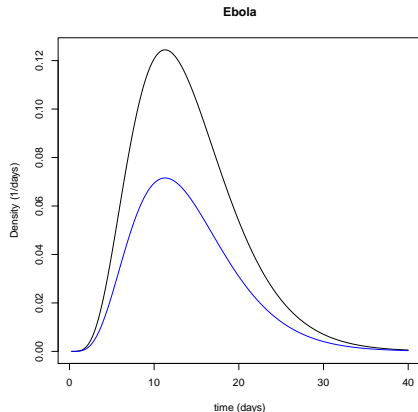
►  $\mathcal{R}$ , the epidemic strength, is the area under the curve.

# Strength of intervention



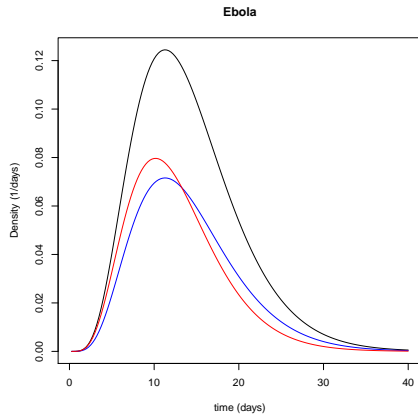
- ... by what factor do I need to reduce this curve to eliminate the epidemic?

# Strength-like interventions



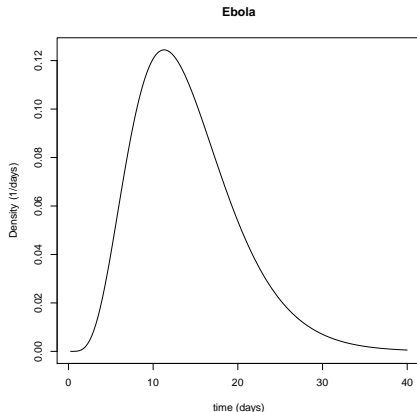
- ▶ idealized vaccination
- ▶ removes a fixed proportion of people

# Speed-like interventions



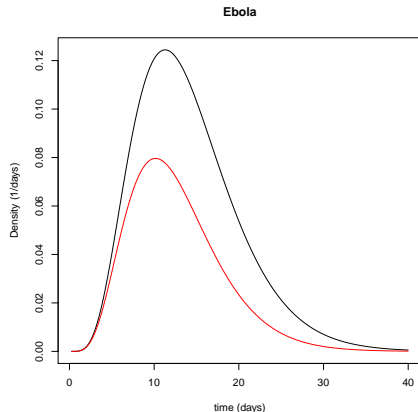
- ▶ idealized quarantine
- ▶ removes people at a fixed rate

# Epidemic speed



- $r$ , the epidemic speed, is the “discount” rate required to balance the tendency to grow

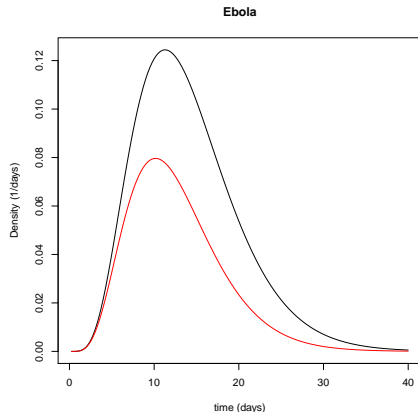
# Epidemic speed



- $k(\tau) = \exp(r\tau)b(\tau)$ ,  
where  $b(\tau)$  is the initial  
backward generation  
interval

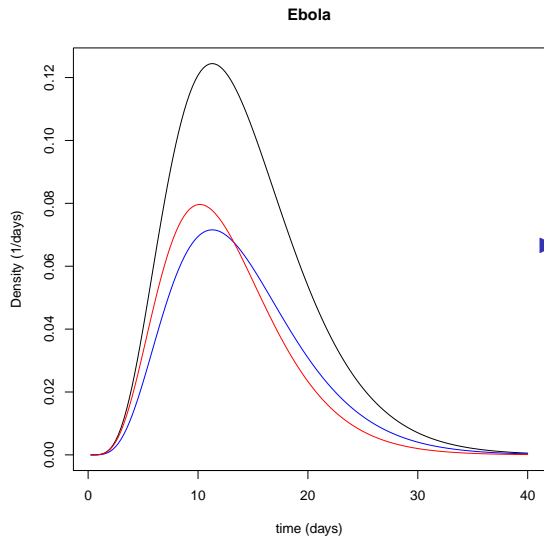


# Speed of intervention



- ...how *quickly* do I need to reduce this curve to eliminate the epidemic?

## *Different interventions (present)*



► Sometimes it's easier to estimate strength, sometimes speed

# Measuring the intervention



# Measuring the intervention

- ▶ We imagine an intervention that takes
- ▶ Assume the intervention takes
  - ▶  $k(\tau) \rightarrow \hat{k}(\tau)$
- ▶ Instantaneous strength of intervention is  $L(\tau) = k(\tau)/\hat{k}(\tau)$
- ▶ Instantaneous speed of intervention is  $h(\tau) = \frac{dL(\tau)}{L(\tau)d\tau}$

# The strength paradigm

- ▶  $k(\tau) = \mathcal{R}g(\tau)$ 
  - ▶  $g$  is the intrinsic generation interval
  - ▶  $\mathcal{R}$  is the strength of the epidemic
- ▶ If  $L(\tau) \equiv L$ , then  $\theta = L$  is the strength of the intervention
- ▶ In general,  $\theta$  is a (harmonic) mean of  $L$ 
  - ▶ weighted by  $g(\tau)$ , but not affected by  $\mathcal{R}$ .
- ▶ Epidemic is controlled if  $\theta > \mathcal{R}$

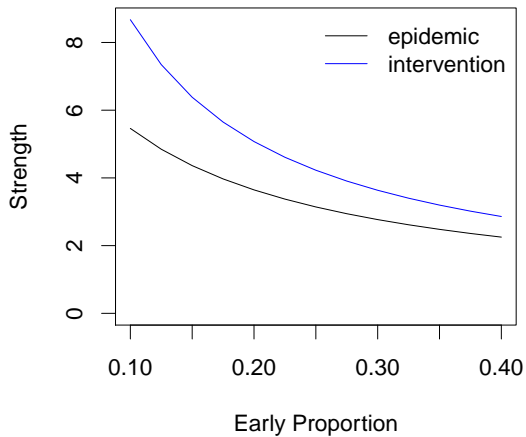
# The speed paradigm

- ▶  $k(\tau) = \exp(r\tau)b(\tau)$ ,
  - ▶  $r$  is the speed of the epidemic
  - ▶  $b$  is the initial backward generation interval
- ▶ If  $h(\tau) \equiv h$ , then  $\phi = h$  is the speed of the intervention
- ▶ In general,  $\phi$  is a (weird) mean of  $h$ 
  - ▶ weighted by  $b(\tau)$ , but not affected by  $r$ .
- ▶ Epidemic is controlled if  $\phi > r$

# HIV

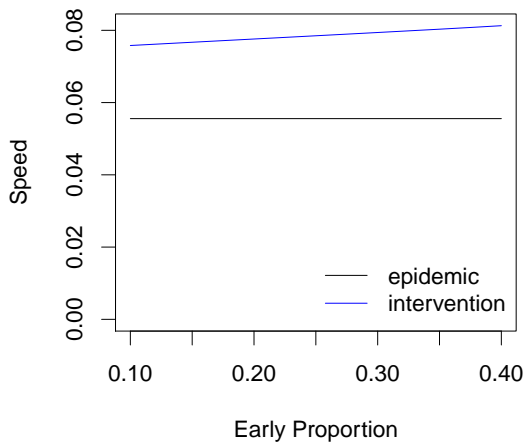
- ▶ The importance of transmission speed to HIV control is easier to understand using the speed paradigm
  - ▶ We know the speed of invasion
    - ▶  $\approx 0.7/\text{yr}$
    - ▶ Characteristic scale  $\approx 1.4\text{yr}$
  - ▶ And can hypothesize the speed of intervention
    - ▶ Or aim to go fast enough

# HIV test and treat





# HIV test and treat



# Coronavirus outbreak

- ▶ What do we think if the pathogen is actually quicker than we thought?
  - ▶ e.g., more pre-symptomatic transmission
- ▶ Initial speed is well known  $\implies$
- ▶ Estimate of invasion strength goes down
  - ▶ easier to control by universal changes like masking
- ▶ Does not change estimate of invasion speed
  - ▶ Puts more *weight* on what happens earlier in infection
  - ▶ Good news for event-based screening
  - ▶ Bad news for symptom-based screening

# Outline

Modeling disease spread

Linking strength and speed

Estimating transmission intervals

- Generations through time

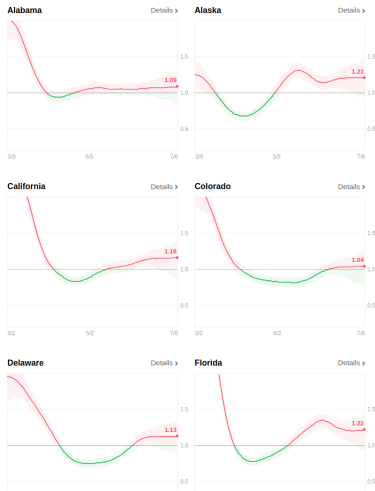
- Generations in space

- Serial intervals

The speed paradigm

Real-time evaluation

# How are conditions changing through time?



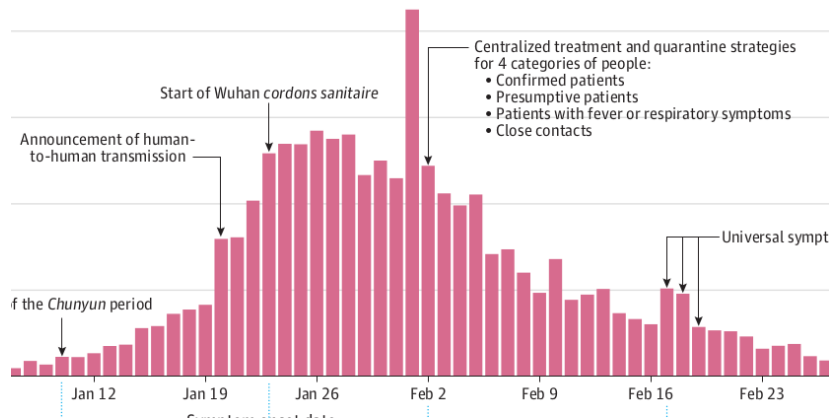
<https://coronavirus.jhu.edu> 2020  
Jul 08

<https://rt.live> 2020 Jul 08

# Using available data

- ▶ Time distributions are hard to measure
  - ▶ Infection date  $\implies$  Symptom onset date  $\implies$  Sample collection date  $\implies$  Test conducted  $\implies$  Test result recorded
- ▶ Deconvolution is hard

# Wuhan control measures



<https://jamanetwork.com/journals/jama/fullarticle/2764658>

# Time-varying reproductive numbers

- ▶ Instantaneous  $\mathcal{R}_i$  (Cori):

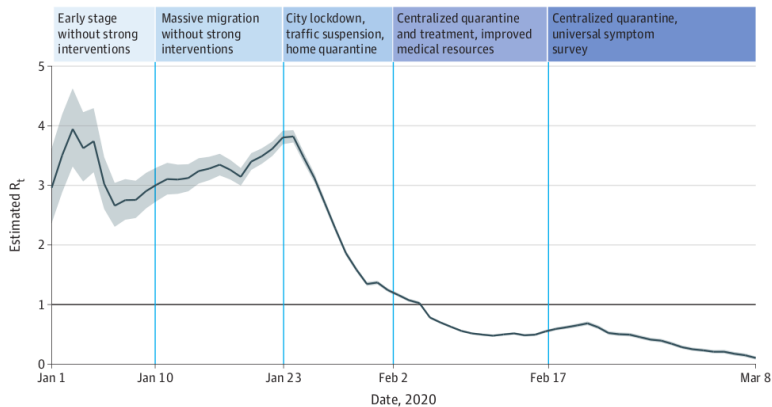
- ▶  $i(t) = \int \mathcal{R}_i(t) g(\tau) i(t - \tau) d\tau$

- ▶ Counterfactual: how many cases per case if conditions were frozen at time  $t$

- ▶ Case  $\mathcal{R}_c$  (Wallinga):

- ▶  $i(t) = \int \mathcal{R}_c(t = \tau) g(\tau) i(t - \tau) d\tau$

# Wuhan control measures



<https://jamanetwork.com/journals/jama/fullarticle/2764658>



# Shifts

- ▶ We could best evaluate current conditions by calculating  $\mathcal{R}_i$  using *incidence* data
  - ▶ Requires deconvolution
- ▶ If transmission is centered at “report” time, using  $\mathcal{R}_c$  with report data may be “second-best”

# Assumptions

- ▶ All current methods assume that (some version of) the generation interval does not change through time!
- ▶ This is a good match for 'strength-like' interventions (movement restrictions, masks for all)
- ▶ It's a bad match for 'speed-like' interventions (tracing, testing and isolation)

# New results

- ▶ Speed-like changes cannot be distinguished from strength-like changes using incidence data
  - ▶ They can give identical results
- ▶  $\mathcal{R}_i(t)$  based on incidence data gives a good measure of effectiveness of strength-like interventions
- ▶  $r(t)$  based on incidence data gives a good measure of effectiveness of speed-like interventions
- ▶ These insights do not solve the delay and deconvolution problems

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