

Measuring the strength and speed of epidemics

McMaster University Origins Institute Colloquium
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Outline

Introduction

- Speed of epidemics

- Strength of epidemics

Generation intervals through time

Estimating the effect of generation intervals

- Moment approximations

Strength and Speed of Epidemics

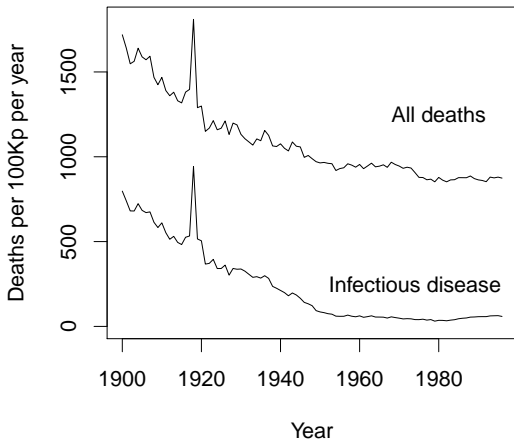
- HIV example

Infectious diseases

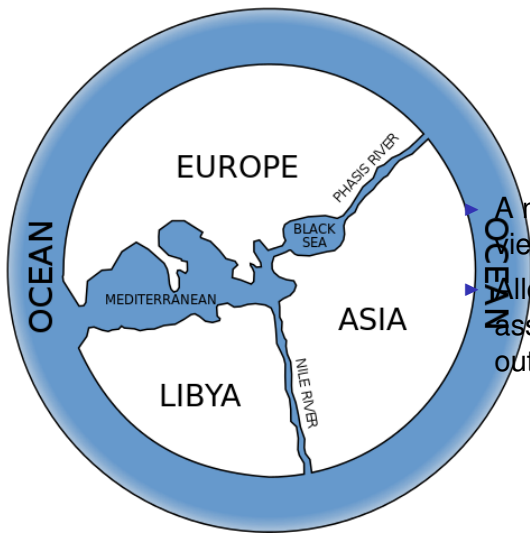




US annual mortality rate (CDC)



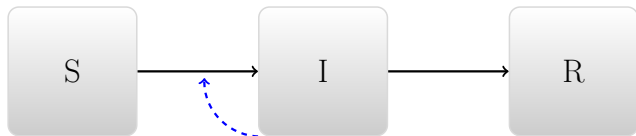
Models



A model is a simplified view of the world

Allows linking between assumptions and outcomes

Dynamic models

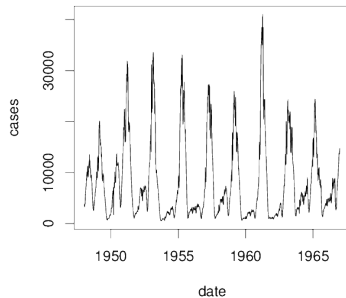


Small-scale events \Leftrightarrow Large-scale patterns and outcomes

Dynamic models

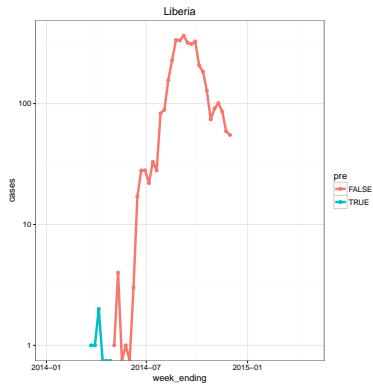


Measles reports from England and Wales

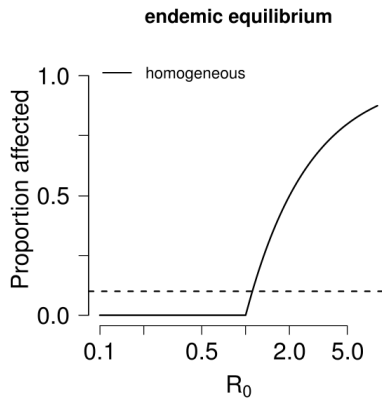


Dynamic modeling

Connects scales

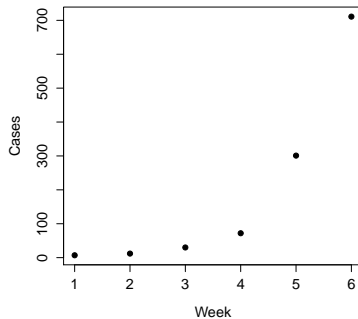


Yellow fever in Panama

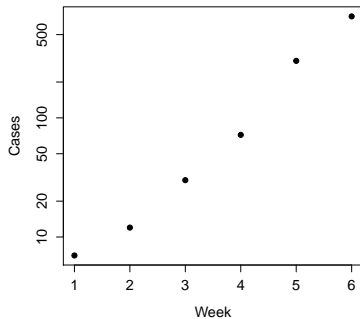
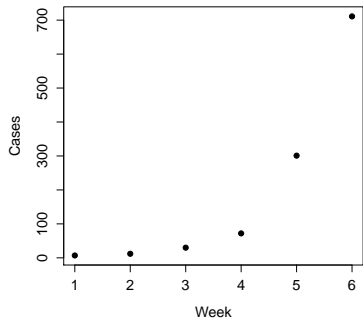


Speed of epidemics

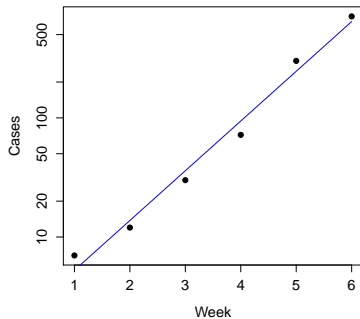
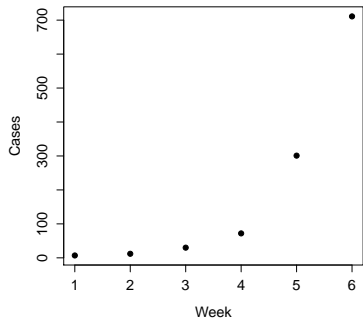
- ▶ Exponential growth:
 - ▶ Growth proportional to size



Exponential growth



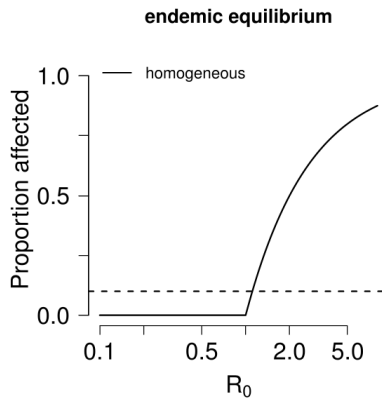
Exponential growth



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 $C = 1/r$
 - ▶ Ebola, $C \approx 1\text{month}$
 - ▶ HIV in SSA, $C \approx 18\text{month}$

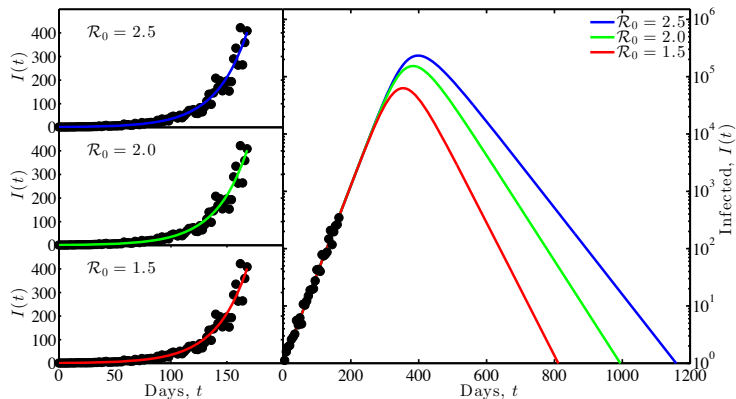
Strength of epidemics



Basic reproductive number

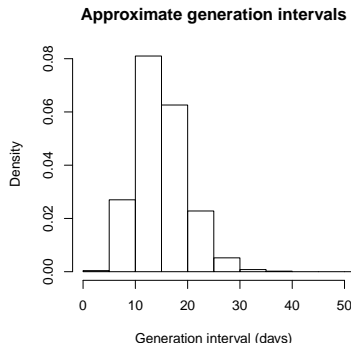
- ▶ We describe epidemic strength with big \mathcal{R}
- ▶ Number of potential new cases per case
- ▶ To eliminate disease, we must:
 - ▶ Reduce transmission by a factor of \mathcal{R} *or*
 - ▶ Reduce number of susceptible people by a factor of \mathcal{R} *or*
 - ...
- ▶ Examples:
 - ▶ Ebola, $\mathcal{R} \approx 2$
 - ▶ HIV in SSA, $\mathcal{R} \approx 5$

Linking little r and big \mathcal{R}

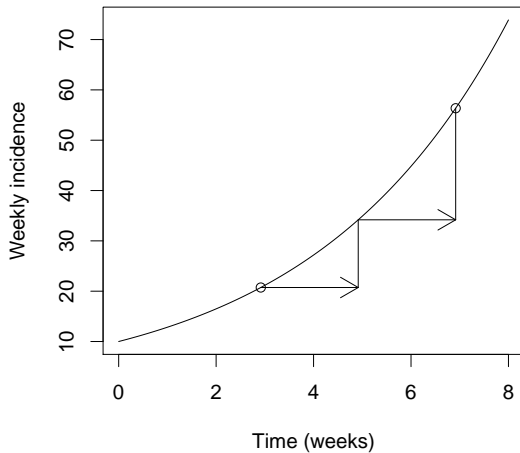


Generation intervals

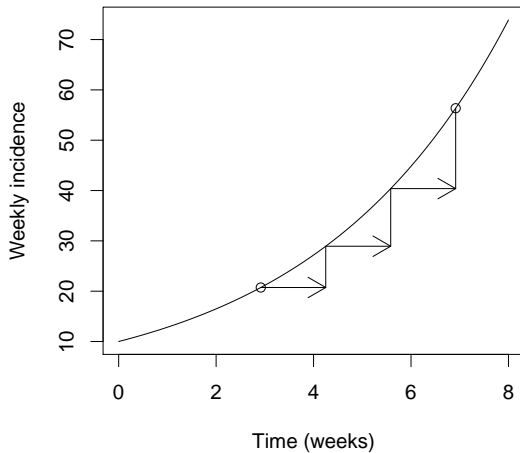
- ▶ The generation distribution measures generations of the disease
 - ▶ Interval between “index” infection and resulting infection
- ▶ What does G tell us about how dangerous the epidemic is?
 - ▶ It depends on what else we know!



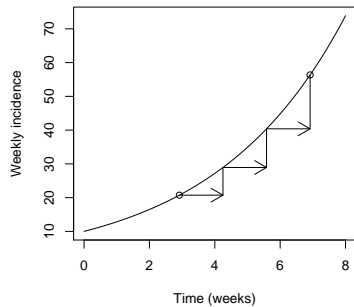
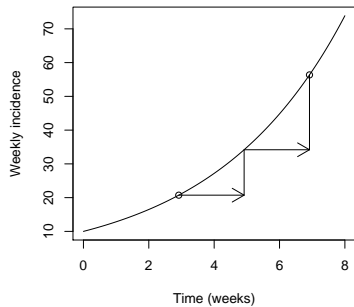
Generations and \mathcal{R}



Generations and \mathcal{R}



Generations and \mathcal{R}



Conditional effect of generation time

- ▶ *Given* the reproductive number \mathcal{R}
 - ▶ faster generation time G means faster spread time C
 - ▶ More danger
- ▶ *Given* the spread time C
 - ▶ faster generation time G means *smaller* \mathcal{R}
 - ▶ Less danger

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Strength and Speed of Epidemics

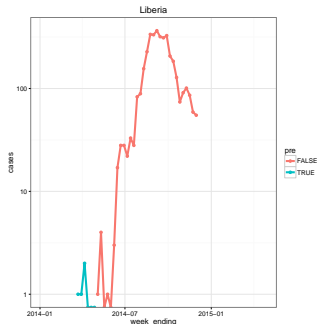
HIV example

Generation intervals through time

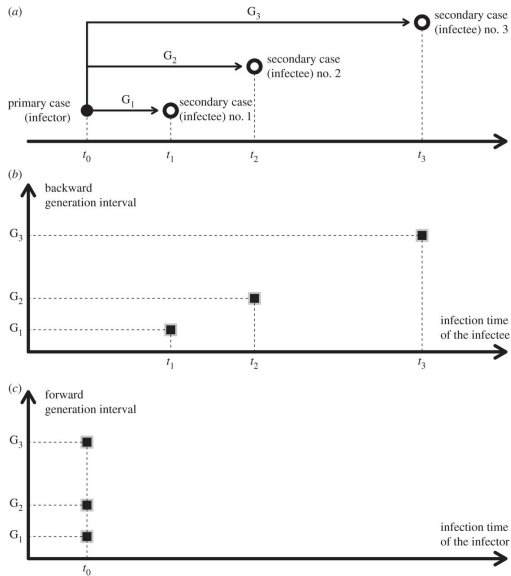
- ▶ Generation intervals can be estimated by:
 - ▶ Observing patients:
 - ▶ How long does it take to become infectious?
 - ▶ How long does it take to recover?
 - ▶ What is the time profile of infectiousness/activity?
 - ▶ Contact tracing
 - ▶ Who (probably) infected whom?
 - ▶ When did each become ill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

Growing epidemics

- ▶ Generation intervals look *faster* 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

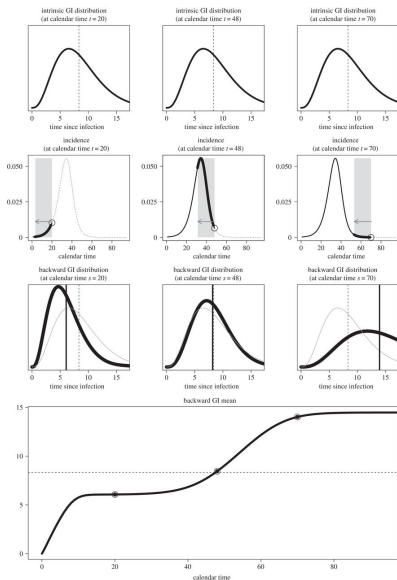


Forward and backward intervals

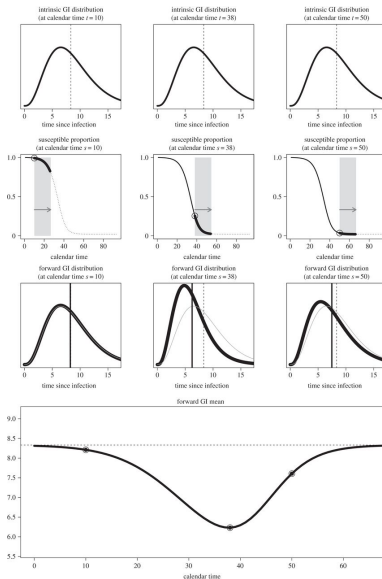


16 Champredon and Dushoff, 2015. DOI:10.1098/rspb.2015.2026

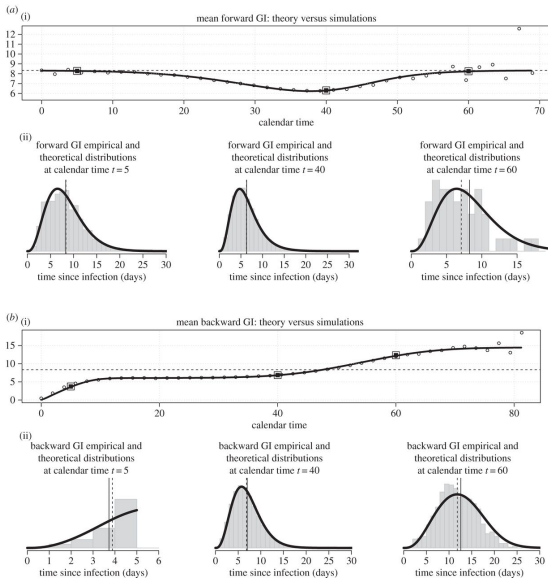
What changes backward intervals?



What changes forward intervals?



Comparison to simulations



Conclusion

- ▶ Backward intervals change if the number of infectious individuals is changing as you look back
- ▶ Forward intervals change if the number of *susceptible* individuals is changing as you look forward
- ▶ Lack of care in defining generation intervals can lead to bias
 - ▶ Results also tell us how to correct this bias

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HIV example

The “effective” generation time

- ▶ If the generation interval were absolutely fixed at a time interval of G , then



$$\mathcal{R} = \exp(G/C)$$

- ▶ *Define* the effective generation time so that this remains true:



$$\mathcal{R} = \exp(\hat{G}/C)$$

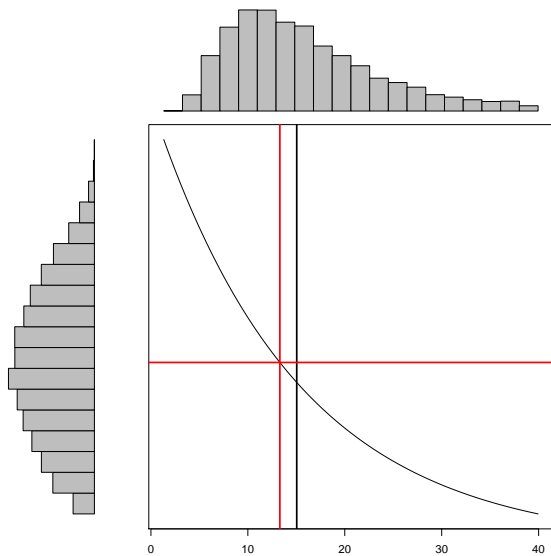
- ▶ We can show \hat{G} is a “filtered mean” of the distribution g :



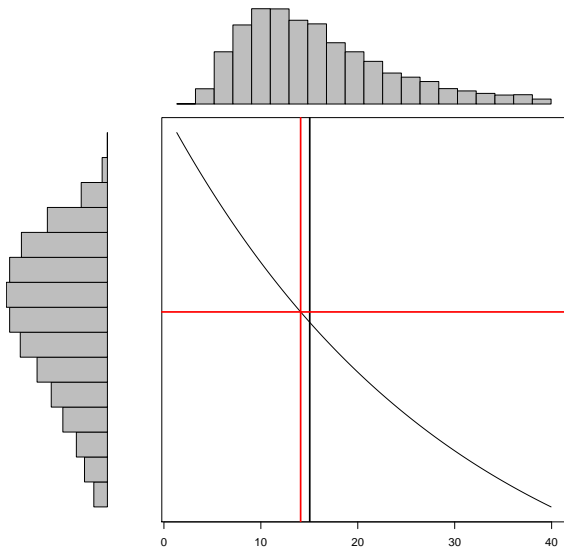
$$\exp(-\hat{G}/C) = \langle \exp(-\tau/C) \rangle_g.$$

,

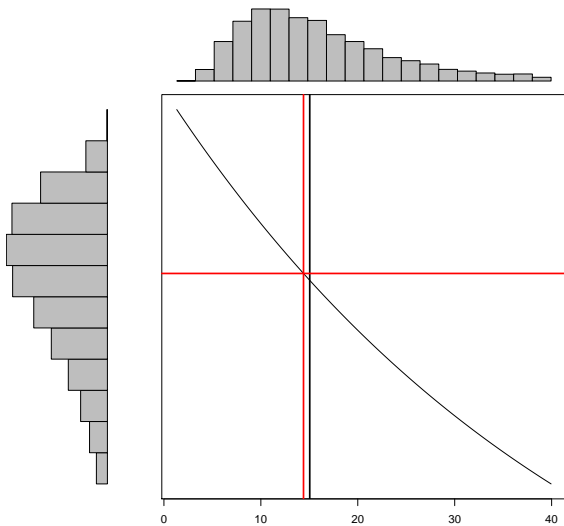
$$C = 15d$$



$$C = 30d$$



$$C = 45d$$

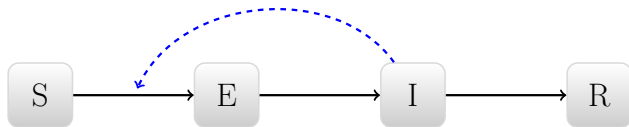


Example: Post-death transmission and safe burial

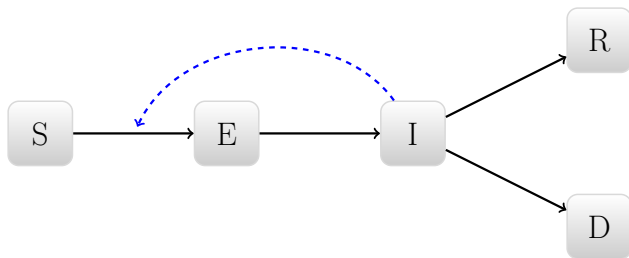
- ▶ How much Ebola spread occurs before vs. after death
- ▶ Highly context dependent
 - ▶ Funeral practices, disease knowledge
- ▶ *Weitz and Dushoff Scientific Reports 5:8751.*



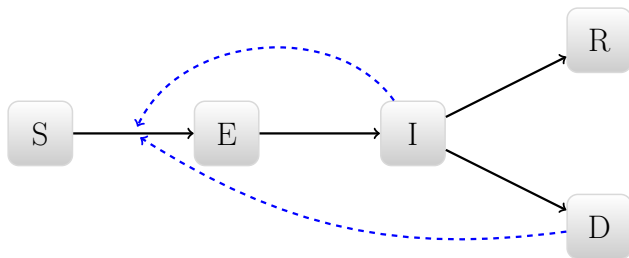
Standard disease model



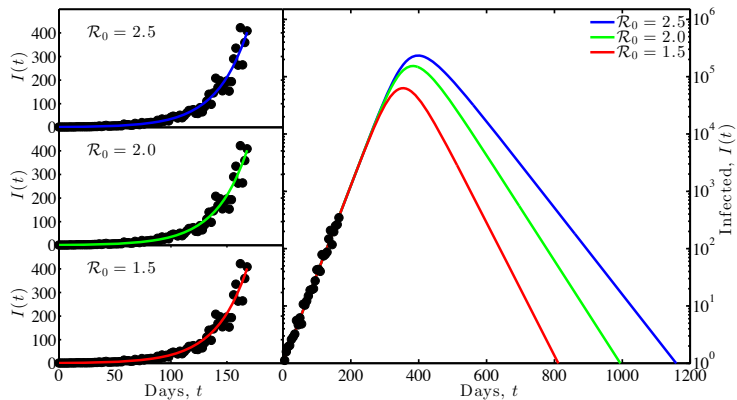
Disease model including post-death transmission



Disease model including post-death transmission



Scenarios



Conclusions

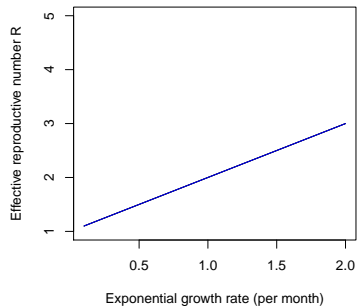
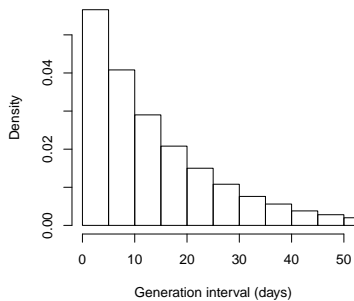
- ▶ Different parameters can produce indistinguishable early dynamics
- ▶ More after-death transmission implies
 - ▶ Higher \mathcal{R}_0
 - ▶ Larger epidemics
 - ▶ Larger importance of safe burials

An approximation

- ▶ We connect these quantities with a moment approximation
- ▶ Define $\kappa = \sigma_G^2 / \mu_G^2$ – the squared coefficient of variation of the generation distribution
- ▶ $\mathcal{R} \approx (1 + \kappa \bar{G} / C)^{1/\kappa}$
 - ▶ Equal when G has a gamma distribution
 - ▶ Simple and straightforward
 - ▶ When is it a useful approximation?

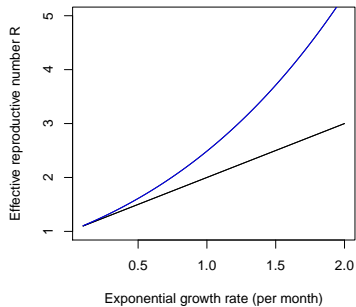
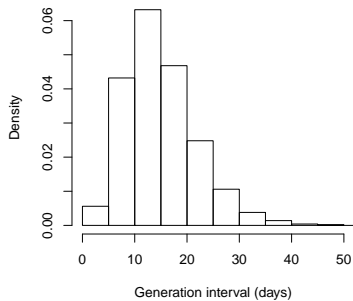
Moment approximation

Approximate generation intervals



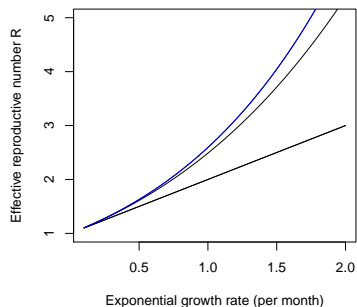
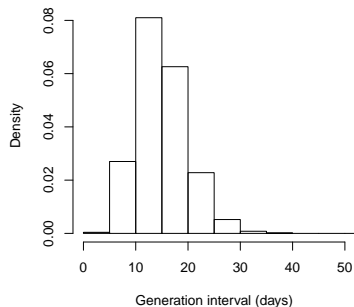
Moment approximation

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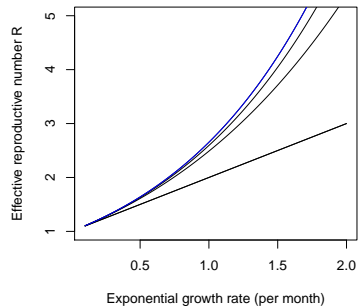
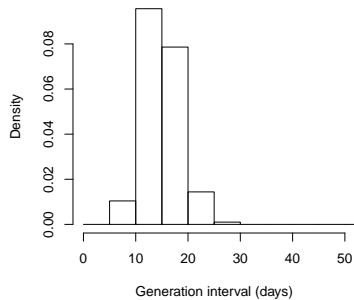
Moment approximation

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Moment approximation

Approximate generation intervals

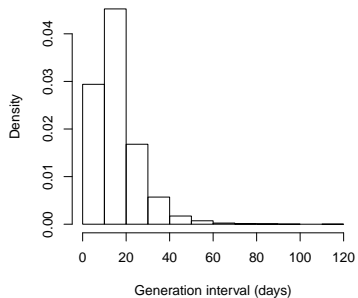


Fitting to Ebola

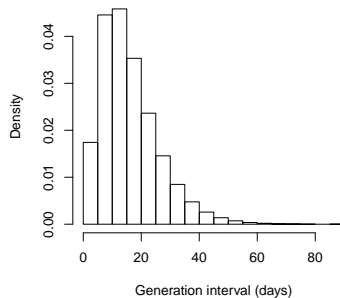
- ▶ Simulate generation intervals based on data and approach from WHO report
- ▶ Use both lognormals and gammas
 - ▶ WHO used gammas
 - ▶ Lognormals should be more challenging

Approximating the distribution

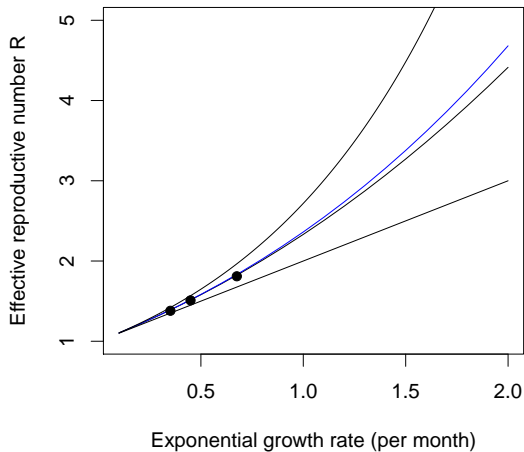
Lognormal SEIR



Single-gamma approximation



Approximating the curve



Summary

- ▶ Generation intervals are the missing link between r and \mathcal{R}
- ▶ We need better methods for estimating them, and propagating uncertainty to other parts of the model
- ▶ For many practical applications:
 - ▶ Knowing the mean generation interval is not enough
 - ▶ But knowing the mean and CV may be enough

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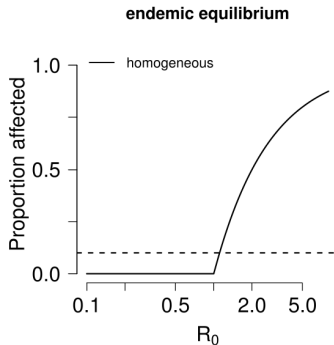
Moment approximations

Strength and Speed of Epidemics

HIV example

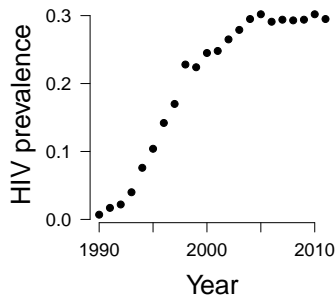
Strength: \mathcal{R} – the reproductive number

- ▶ Expected number of new cases per cases
- ▶ $\mathcal{R} = \beta DS/N$
 - ▶ Disease increases iff $\mathcal{R} > 1$



Speed: r – the growth rate

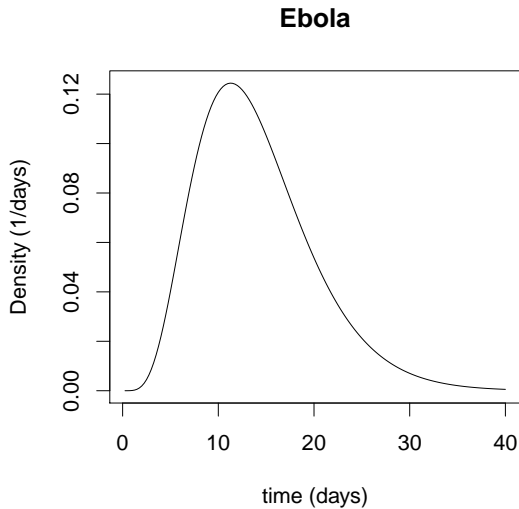
- ▶ $i(t) \approx i(0) \exp(rt)$
- ▶ $C = 1/r$
- ▶ $T_2 = \ln(2)/r$



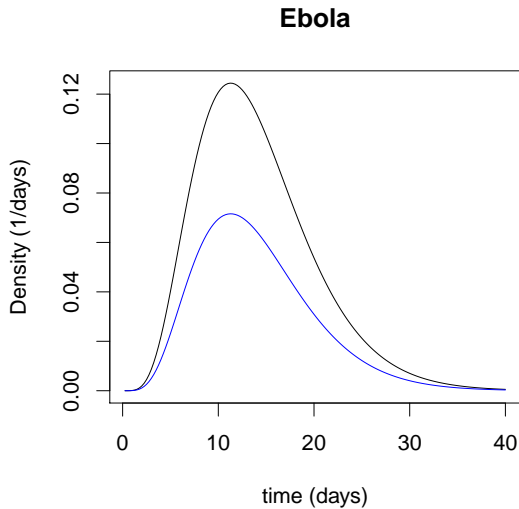
\mathcal{R} and the generation interval

- ▶ $i(t) = \int k(\tau) i(t - \tau) d\tau$
- ▶ $\mathcal{R} = \int k(\tau) d\tau$
- ▶ Define the intrinsic generation interval distribution:
 $k(\tau) = \mathcal{R} g(\tau)$

\mathcal{R} and the generation interval



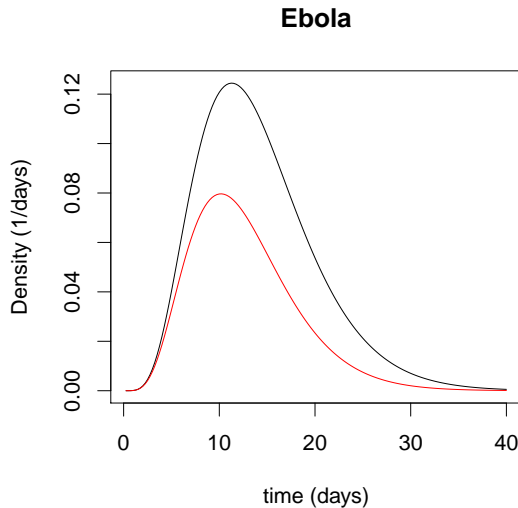
\mathcal{R} and the generation interval



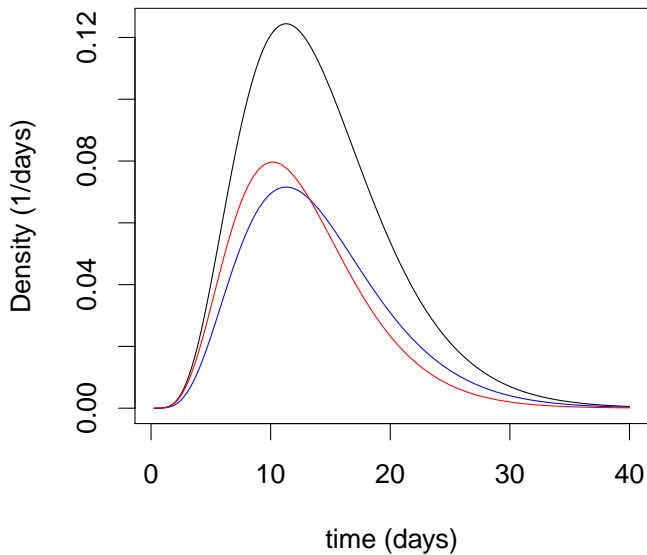
r and the (other) generation interval

- ▶ $i(t) = \int k(\tau) i(t - \tau) d\tau$
- ▶ if $i(t)$ grows like $\exp(rt)$, then
- ▶ $1 = \int k(\tau) \exp(-r\tau) d\tau$
- ▶ $b_0(\tau) = k(\tau) \exp(-r\tau)$ is the initial *backwards* generation interval

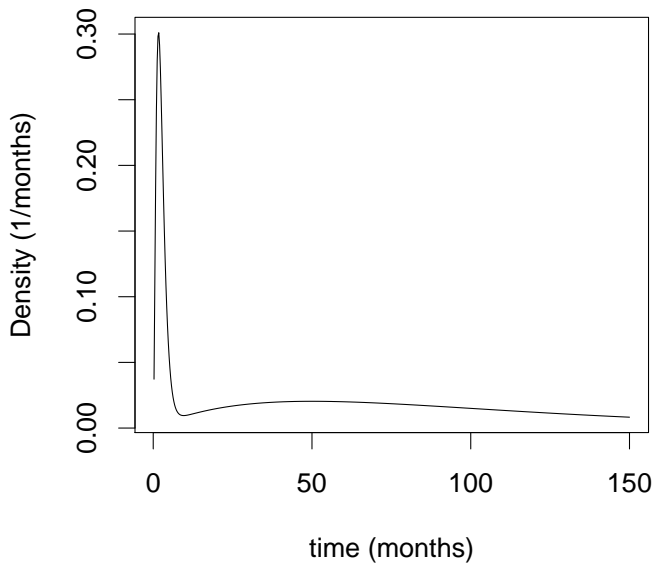
r and the (other) generation interval



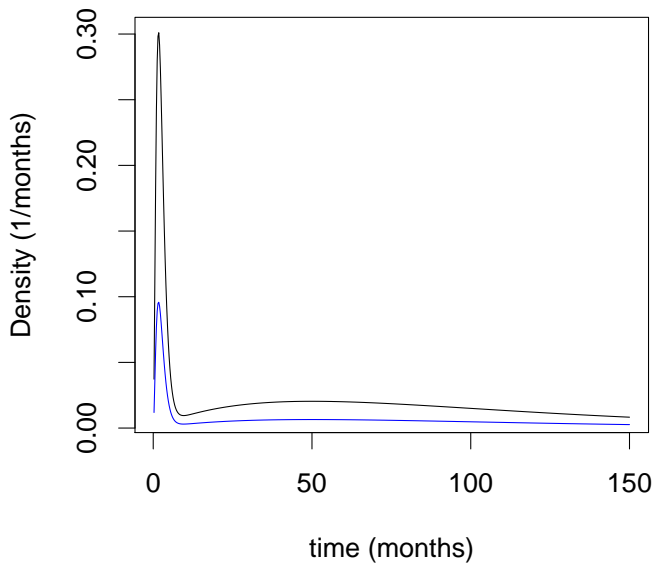
Ebola



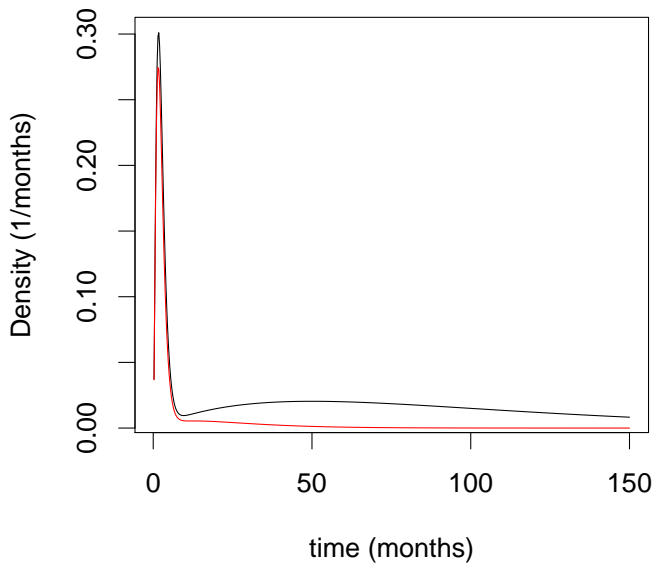
HIV



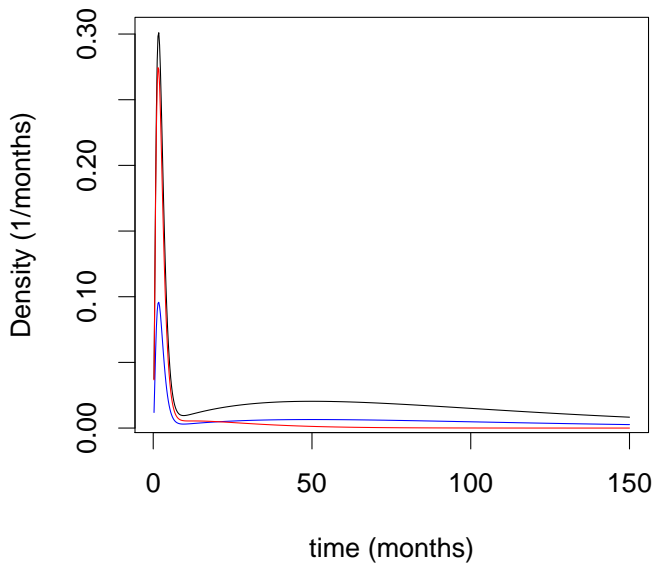
HIV



HIV



HIV



Strength of intervention

- ▶ Imagine we have an intervention that reduces transmission
 - ▶ $k(\tau) \rightarrow k(\tau)/L(\tau)$
 - ▶ Define *strength* $\theta = \mathcal{R}/\hat{\mathcal{R}}$ – the proportional amount by which the intervention reduces transmission.
- ▶ We then have:
 - ▶ $\theta = 1 / \langle 1/L(\tau) \rangle_{g(\tau)}$
 - ▶ θ is *the harmonic mean* of L , weighted by the generation distribution g .
- ▶ Outbreak can be controlled if $\theta > \mathcal{R}$

Speed of intervention

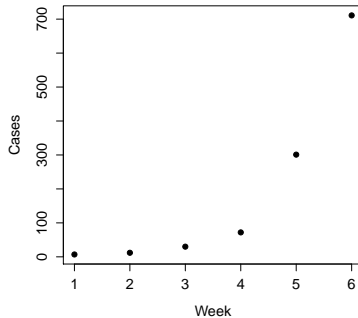
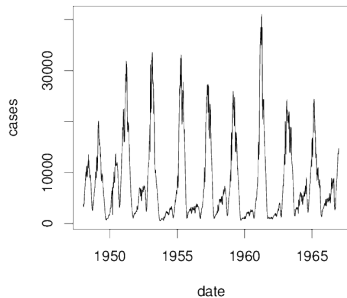
- ▶ Define the *speed* of an intervention be $\phi = r - \hat{r}$ – the amount by which the intervention slows down spread.
- ▶ $1 = \left\langle \frac{\exp(\phi\tau)}{L(\tau)} \right\rangle_{b(\tau)}$
- ▶ ϕ is *sort of a mean* of the *hazard* associated with L
 - ▶ Averaged over the initial *backwards* generation interval
- ▶ Outbreak can be controlled if $\phi > r$.

A new way of looking



Measuring the epidemic

Measles reports from England and Wales



Measuring the intervention

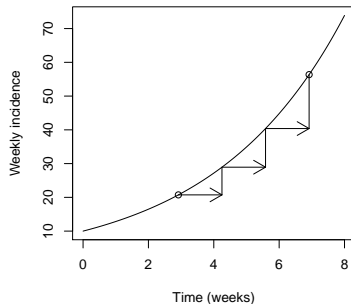
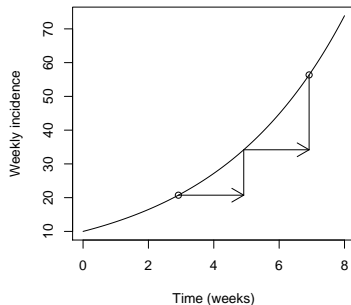


Can treatment stop the HIV epidemic?

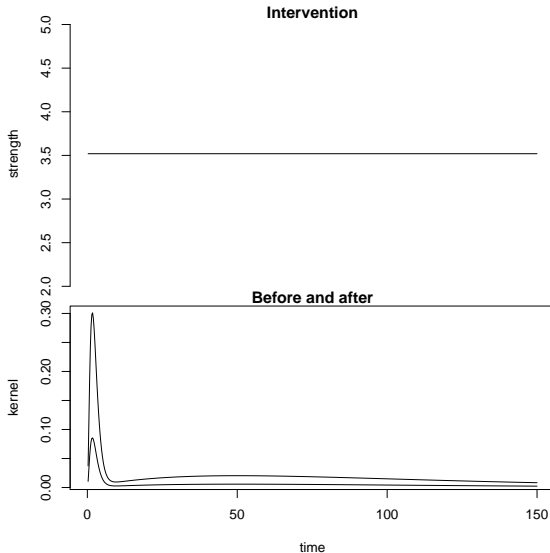


Are HIV generations fast or slow?

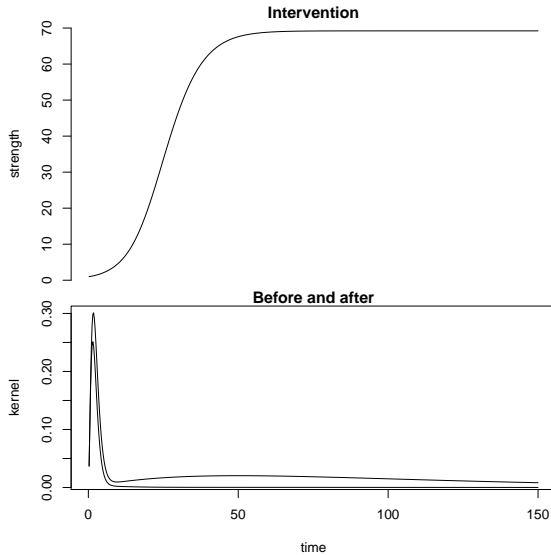
- ▶ Fast generations mean:
 - ▶ Testing and treating will help less
 - ▶ *but* lower epidemic strength



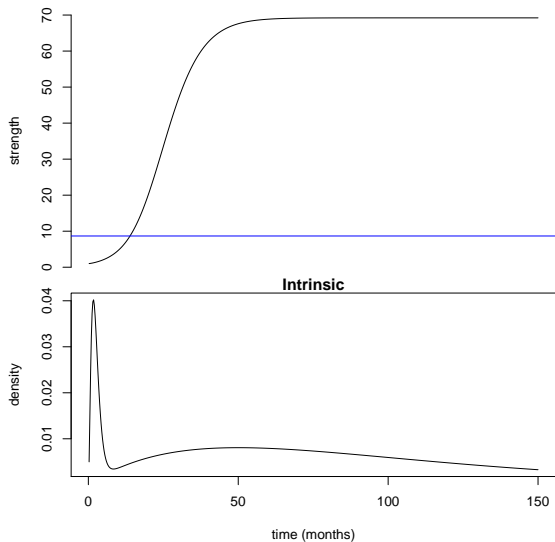
Condom intervention



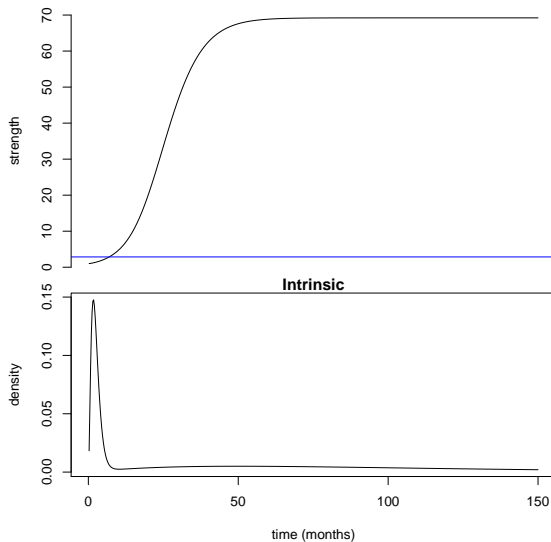
Find and treat



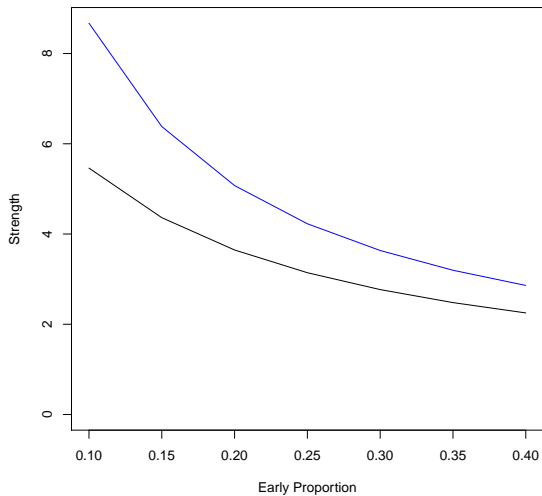
Low early transmission



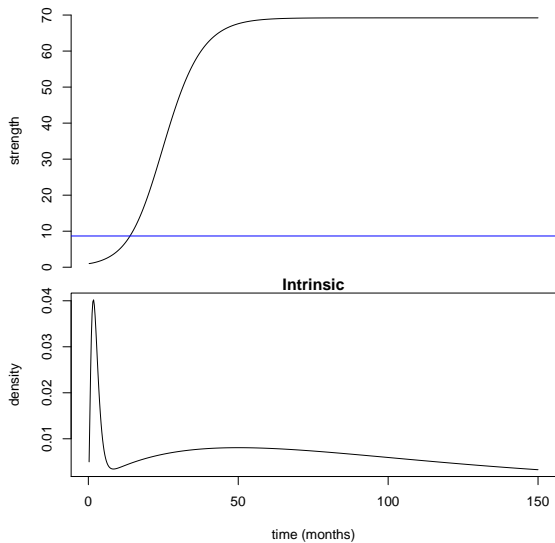
High early transmission



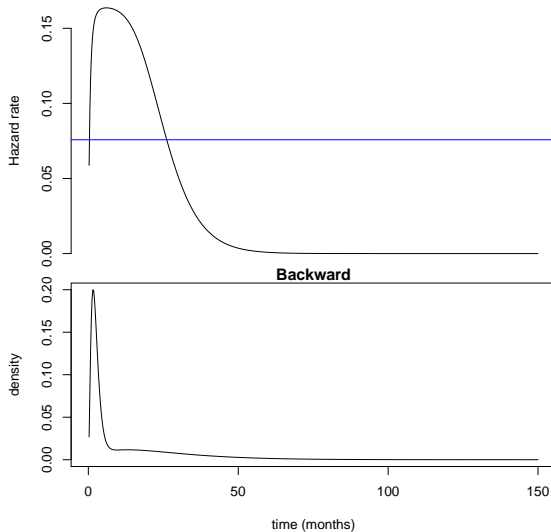
Range of estimates



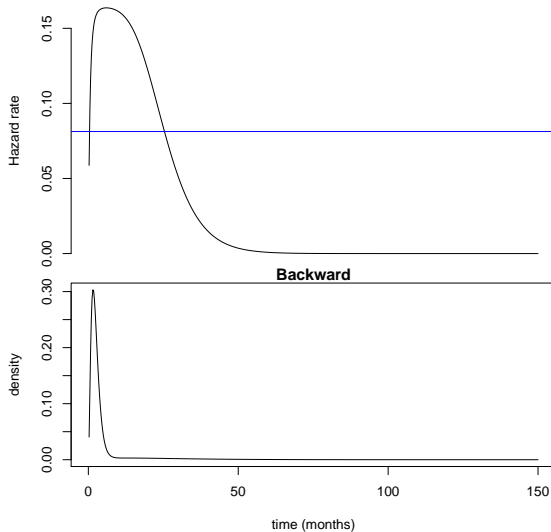
Find and treat



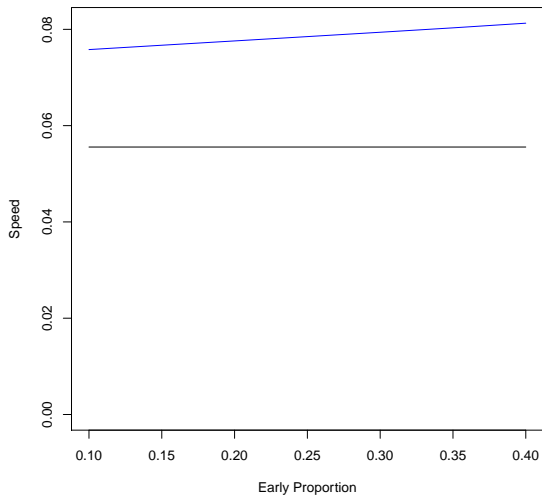
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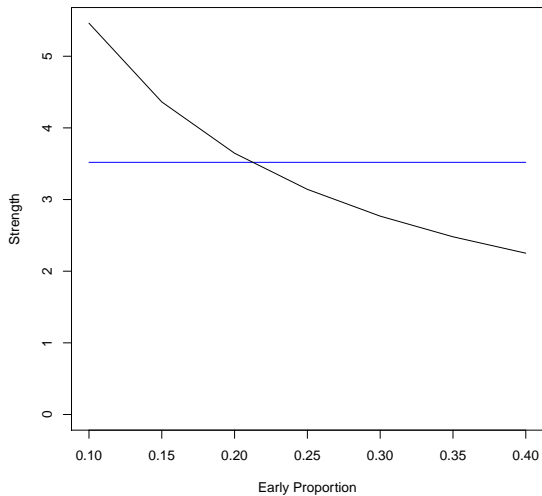
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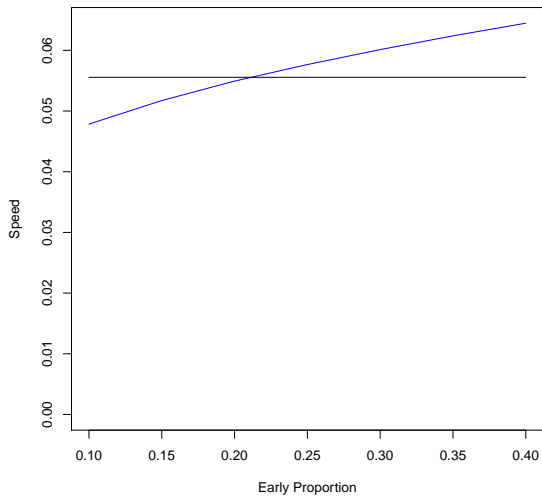
Range of estimates



Condom intervention



Condom intervention



Conclusion

- ▶ This perspective helps us understand why find and treat predictions are robust to assumptions about transmission
- ▶ Sometimes “strength” and sometimes “speed” can help us see epidemic control questions more clearly

Thanks

- ▶ Organizers
- ▶ Audience
- ▶ Collaborators
- ▶ Funders: NSERC, CIHR