Parametersing Markovian epidemic models using household level data

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Household models



homogeneous population of individuals

hetrogeneous population of households

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- Strong mixing within households.
- Weaker mixing between households.

Why do we like household models?

- Capture some realistic heterogeneity, but still simple to solve.
- Households are small, so must model dynamics stochastically.

- State space is small.
- Lots of data available.

Household data collection

Monitoring and tracking all a persons contacts is difficult.

Monitoring a household is much easier.

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If available, antivirals are given to whole households.

Challenge

Use all this data from within households to parametrise our models.

Within-household dynamics



generation time: the interval of time between successive infection events.

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Within-household dynamics



serial interval: the time between the onset of symptoms in an index case and that of a secondary.

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Observed events



time

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- Chain of symptomatic events.
- Estimating recovery is more difficult.

Serial interval data



- Most people just fit a parametric distribution to this and consider that a job well done.
- To learn something interesting from this data we need to fit a transmission model.

Stochastic SE(j)I(k)R model

Event	Transition	Rate
Infection	$(S, E_1) \rightarrow (S-1, E_1+1)$	$\beta \frac{S \sum_{1}^{k} I_m}{(N-1)}$
exposed progression, $(n=1,\ldots,j-1)$	$(E_n, E_{n+1}) \to (E_n - 1, E_{n+1} + 1)$	jσEn
Start shedding	$(\mathit{E_j},\mathit{I_1}) ightarrow (\mathit{E_j}-1,\mathit{I_1}+1)$	$j\sigma E_j$
Infection progression, $(m=1,\ldots,k-1)$	$(I_m, I_{m+1}) \rightarrow (I_m - 1, I_{m+1} + 1)$	$k\gamma I_m$
Recovery	$I_k ightarrow I_k - 1$	$k\gamma I_k$
Individual level:	$S E_1 E_2 I_1 I_2$ $ \longrightarrow \bigcirc^{-2\sigma E_1} \bigcirc^{-2\sigma E_2} \bigcirc^{-2\gamma I_1} \checkmark \bigcirc^{-2\sigma E_2} \bigcirc^{-2\gamma I_1} \checkmark \bigcirc^{-2\sigma E_2} \bigcirc^{-2\gamma I_1} \checkmark \bigcirc^{-2\sigma E_2} \bigcirc^{-2\sigma E_2} \bigcirc^{-2\gamma I_1} \checkmark \bigcirc^{-2\sigma E_2} \bigcirc^{-2\sigma E_$	R $2\gamma I_2 \rightarrow \bigcirc$
Within-household transmission:	$\beta \frac{S(I_1 + I_2)}{N - 1} \rightarrow 0$	

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Calculating the serial interval

Dynamics of model,

$$\frac{dp(t)}{dt} = p(t)Q \tag{1}$$

where Q is the stochastic transition matrix.

- Initial condition: $(I_1 = 1, S = N 1)$.
- Make the states which correspond to an serial interval event absorbing.
- Integrate forward the dynamics.

$$p(t) = p(0) \exp(Qt). \tag{2}$$

Calculating the serial interval

The cdf of the serial interval is then,

$$F(t) = \frac{1}{c} \sum_{s \in B} p_s(t), \qquad (3)$$

where c is the probability of infecting at least 1 person before recovering.

How we evaluate the dynamics is important. There are two methods we use:

- Expokit for calculating matrix exponentials.
- Lexicographic ordering, and forward substitution.

Basic results

The serial interval distribution depends on the household size.



Antiviral efficacy model

The impact of antivirals was limited in the 2009 influenza A(H1N1) pandemic.

We wanted to assess the impact of antivirals: were they not effective or was the delay too large?

There has already been a lot of modelling for this problem. What sets this apart?

Already have posteriors for β and serial interval data. Use Baysian MCMC to estiamte γ and σ

Pandemic Influenza model - parameters



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Model with explicit household size

Generate some test data, now stratified by household size.



Parameters: $\beta = 2$, $\gamma = 1/2$, $\sigma = 1/4$, j = k = 2.

Posterior distributions



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Complications

Symptoms and infectiousness don't coincide.

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- Asymptomatic individuals.
- External infections.
- Potentially wasteful.

Acknowledgements and Papers

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