

Christoph Zimmer

Influenza Prediction Challenge – Yale Team

Influenza forecasting meeting, August 2018

Overview

Data

- ILI Nearby (Delphi, CMU)

Computational model

- humidity based S I R S (Yang, Karspeck, Shaman PlosCompBio 2014)
- humidity data averaged over regions

Objective Function

- Linear noise approximation
- State updating mechanism

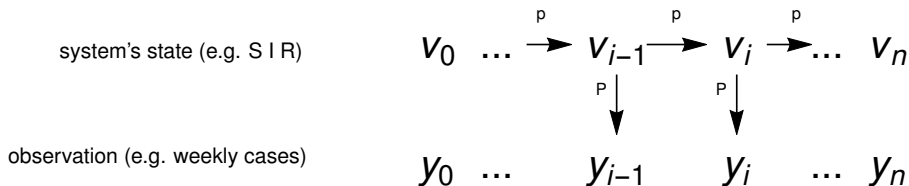
Optimization

- Filtering
- Re-sampling based on kernel density estimates

Prediction

Sampling from posterior + run simulation model (Gillespie in COPASI)

Deriving an objective function



- 1 Observation probability P known - Gaussian, Poisson, ...
- 2 No analytical solution for transition probability p in most models

$\Rightarrow$ Approximate $\nu_i | \hat{\nu}_{i-1} \sim \mathcal{N}(\mu_i, \Sigma_i)$

with μ_i - ODE solution on $[t_{i-1}, t_i]$

Σ_i - LNA solution on $[t_{i-1}, t_i]$ 

Zimmer 15, IET Systems Bio

- 3 State estimation

$$\hat{\nu}_i = \arg \max_{\nu_i} P(y_i | \nu_i) p(\nu_i | \hat{\nu}_{i-1})$$

Zimmer 15, Math Biosciences
Zimmer 17, PlosCompBio

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BOSCH



Gillespie algorithm

Assuming that the epidemic is at state $\nu(t)$ at time t :

- 1 Calculate the sum of rates: $\rho(\nu(t), \theta) = \sum_{r=1}^R \rho_r(\nu(t), \theta)$.

Gillespie algorithm

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$$\sum_{r=1}^{\tilde{r}-1} \frac{\rho_r(\nu(t), \theta)}{\rho(\nu(t), \theta)} < u_2 \leq \sum_{r=1}^{\tilde{r}} \frac{\rho_r(\nu(t), \theta)}{\rho(\nu(t), \theta)}$$

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- 4 Update epidemic state given the realized event $\tilde{r}$.

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- 5 Until a desired condition is satisfied, increment time $t \leftarrow t + \tau$ and move to Step 1.

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