

Risk assessment from small scale and early phase epidemics

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Background	Aim	Classical Swine Fever in East Anglia Norfolk in 2000
 Emerging and re-emerging pathogens usually lead to small scale epidemics Analysis of historical outbreaks informs control of future outbreaks Risk assessment is crucial to inform policy on potential new incursions 	 Infer historic outbreak characteristics from just observed cases (and small) Predict future evolution of ongoing outbreaks from its early phase Use data from small historic and ongoing outbreaks to select between models 	 Data N = 1703 farms with exact location or coordinates Times and location of 16 detected cases Inference and predictions Inference and predictions

exp

Modelling framework

► An individual location *i*, eg a farm, makes an infectious contact with a susceptible individual *j* at rate β_{ij} assumed to be

 $\beta_{ij}=\beta_0\boldsymbol{h}_{ij},$

 β_0 being the contact rate. β_{ij} is known as a spatial kernel transmission function and 4 forms widely used in the disease modelling literature are considered:

$$\circ \mathbf{K}_{1}: \mathbf{h}_{ij} = \exp \left\{ -\tau \mathbf{d}_{ij} \right\} \qquad \circ \mathbf{K}_{3}: \mathbf{h}_{ij} = \left(\mathbf{1} - \mathbf{K}_{2}: \mathbf{h}_{ij} = \left(\mathbf{1} + \left(\frac{\mathbf{d}_{ij}}{\mathbf{d}} \right)^{\tau} \right)^{-1} \qquad \circ \mathbf{K}_{4}: \mathbf{h}_{ij} = \mathbf{1} - \mathbf{K}_$$

Once infected the time to detection is assumed to follow a left-truncated gamma distribution:

$$R_i - I_i \sim \mathcal{TG}(\alpha, \gamma, c),$$

► The likelihood of observing the detections R_i , $i = 1, ..., n_R$, is

$$L = \prod_{i=1, i \neq v}^{n_i} \left(\sum_{j \in \mathcal{Y}_i} \beta_{ji} \right) \times \exp\left\{ -S \right\} \gamma^{\alpha n_R} \exp\left\{ -\gamma \sum_{i=1}^{n_R} (R_i - I_i) \right\} \prod_{i=1}^{n_R} \frac{(R_i - I_i)^{\alpha - 1}}{\Gamma(\alpha, \gamma c)},$$

where $S = \sum_{i=1}^{n_i} \sum_{i=1}^{N} \beta_{ij} (\min(R_i, I_j) - \min(I_i, I_j))$

Inference

Bayesian inference

The distribution of the model parameters and latent variables given the data is





Predicted risk maps under the 4 kernels

K4 with **95%** CI

Model selection

DIC and proportion of p-values less than 5% (Pr(p < 5%) for the LR under the 4 kernels

	DIC ₁	DIC ₂	Pr(<i>p</i> < 5%)
<i>K</i> ₁	429.301	156.682	27.78 %
<i>K</i> ₂	317.229	157.021	10.67%
K ₃	352.671	156.055	32.83%
<i>K</i> ₄	411.096	157.703	19.47 %

LR assessment correlates better with predicted risk

Inference during early phase of outbreak

 $\pi(\theta, \boldsymbol{l}|\boldsymbol{R}) \propto L(\boldsymbol{R}, \boldsymbol{l}; \theta) \pi(\theta),$

Metropolis-Hastings within Gibbs algorithm
 Non-centered parameterisation for computational efficiency

Parameters and latent variables updated simultaneously and helps reduce autocorrelation



Model assessment and selection

 \circ DIC = "goodness of fit" + "complexity"

Problems: non invariance to reparameterisation, lack of consistency, weak theoretical justification with multiple definitions in the case of latent variables -2 used

 Bayesian Latent residuals (LR): inferred from data, iid uniform r.v. if fitted model consistent with data generation process

LR constructed to test different components of model

Assess performance for historic outbreaks: simulated data

- * Coverage properties: true parameters are contained \approx **95%** in the CI
- Uncertainty of the estimates reduces as the epidemic size increases
- Evaluate the amount of data size needed for model selection
- * Increasing epidemic size increases the accuracy of identifying the correct model with the LR

 Predict future evolution of outbreak under various kernels
 Assess using ROC curve
 More observations imply better prediction











LR identify the correct kernel (K_2) and all kernels with similar prediction





Posterior distribution γ with true values $\alpha = 5, \beta_0 = 0.35, N = 201$ premises and n = 43 infected. The posterior is in blue, the prior in red and the true value in green

LR and DIC comparisons: proportion of simulated data sets where correct model is selected as function of outbreak size

Summary

Infer outbreak characteristics from small and ongoing outbreaks e.g. 16 CSF cases
 Novel model selection tools based on LR allow selection of models e.g. kernels
 LR approach leads to more reliable risk assessment

Reference

Acknowledgment

K Gamado, G Marion & T Porphyre. Data-Driven Risk Assessment from Small Scale Epidemics: Estimation and Model Choice for Spatio-Temporal Data with Application to a Classical Swine Fever Outbreak. Frontiers in Veterinary Science (2017) 4:16



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