Bayesian modelling with applications to sheep pox epidemic data

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Features of epidemic data

- Spatio-temporal nature.
- Environmental noise.
- Multicolinearity issues.
- Presence of excess zeros.

Motivating example

Sheep pox is a highly contagious viral infection of sheep that can have devastating consequences.

Major sheep pox epidemic in Evros Prefecture, northeastern Greece during 1994-98.

➤ Included 35,440 dead animals and 250 infected farms.

Bayesian regression modelling

We adopt the Bayesian paradigm for modelling the weekly frequencies of disease occurrence incorporating various factors such as spatial information, environmental covariates and autoregressive (O-U type) processes.

➤ We ameliorate the existing methodologies by improving accuracy of predictions through the incorporation of spatial information, implementing suitable zero-inflated distributions, dealing with correlated data and introducing an epidemic interpretation via a branching process approximation.

Let Y_{ij} be the number of occurrences for the ith year and the jth week (i=0,1,2,3,4; j=0,1,...,52). Poisson and ZIP models are special cases of:

$$\begin{split} Y_{ij} &\sim g(y_{ij} \mid \theta_{ij}; p_{ij}) \\ g(y_{ij} \mid \theta_{ij}; p_{ij}) &= p_{ij} I_{\{y_{ij}=0\}} + (1 - p_{ij}) f(y_{ij} \mid \theta_{ij}) \\ \theta_{ij} &= h(\mu_{ij}) = \log(\mu_{ij}) \\ \log(\mu_{ij}) &= \mathbf{X} \mathbf{O}^{*}_{\mathbf{\beta}} + b_{i} + U_{ij} + \theta_{\tau} * y_{i(j-1)} + K(\mathbf{O}, \mathbf{K}) \end{split}$$

where $\boldsymbol{\Theta} = \left(\boldsymbol{\Theta}_{\beta}, \theta_{\tau}, \boldsymbol{\Theta}_{\kappa}\right)^{t}$ comprises of fixed-effects parameters β , AR(1) parameter associated with number of cases in previous week (θ_{τ}) and parameters of transmission kernel functions, bi yearly random effects and U_{ij} an O-U process adjusting for serial correlation.

Epidemic control

We connect the Poisson component of our model to a suitable branching process.

> Using this representation we obtain the probability of epidemic extinction by solving $\exp(q\lambda) = q \exp(\lambda)$

> For ZIP model: $prob(\text{extinction}) = 1 \land (q(\lambda_{ij}) + p_{ij})$

➤ We decompose the average rate of infection to its endemic and epidemic components:

$$\lambda = \lambda_{endemic} \cdot \lambda_{epidemic} = \exp(\Theta_{endemic} + \Theta_{epidemic})$$

Results

Major findings:

Temperature levels had the strongest influence on disease spread
 Epidemic spread is also sensitive to distance between infected herds.

	temperature			
	min	average	max	distance
min	q=0.78	q=0	q=1	q=0.61
nedian	q=0.66	q=0.66	q=0.66	q=0.66
nax	q=0.41	q=1	q=0	q=0.66

Table 1: Estimated average extinction probabilities (q) for different covariate combinations

_	min	median	max
λendemic	0.17	2.84	121.6
λepidemic	1.27	1.005	3.19

Table 2: Endemic/epidemic decomposition of λ



Predicted vs observed counts based on the fit of the best (ZIP-type) model

Discussion

We have proposed a unified approach for effectively dealing with frequent problems of epidemic data.

Our modelling framework extends similar approaches (*Choi et al., 2012; Branscum et al., 2008*) in various ways:

➤ Incorporation of spatial information.

> Adopt g-prior-based approaches for coping with multicollinearity problems between covariates, especially those of environmental and/or meteorological data nature.

➤ Use of suitable distributions for modelling excess zeros datasets, particularly the zero-inflated Poisson (ZIP) distribution.

> Combine branching process theory with Bayesian regression models to identify epidemic potential.

Future directions

Model selection has been solely based on standard (deviancebased) predictive approaches. The temporal nature of this type of data suggests a prequential approach.

Explore continuous (DeWijs type) spatio-temporal models