

## Description

A zero-truncated Poisson model for data collected in three hierarchical levels (data, group, and population levels), with varying coefficients at the group level.

## Implementation

The file `zt.poisson.varying.coef.sim.3.R` simulates data according to the model statement presented below, and `zt.poisson.varying.coef.3.mcmc.R` contains the MCMC algorithm for model fitting.

## Derivation of zero-truncated Poisson distribution

The probability mass function of the (non-truncated) Poisson distribution is:

$$[z] = \frac{\lambda^z \exp(-\lambda)}{z!}. \quad (1)$$

It follows that the probability that  $z = 0$  is

$$[z | z = 0] = \frac{\lambda^0 \exp(-\lambda)}{0!} \quad (2)$$

$$= \exp(-\lambda), \quad (3)$$

and thus the probability that  $z > 0$  is  $1 - [z | z = 0] = 1 - \exp(-\lambda)$ . We arrive at the density function of the zero-truncated Poisson distribution by excluding the probability that  $z = 0$  from the standard Poisson distribution (Eq. 1). This is accomplished by dividing Eq. 1 by  $[z | z = 0]$ :

$$[z | z > 0] = \frac{\lambda^z \exp(-\lambda)}{(1 - \exp(-\lambda)) z!}. \quad (4)$$

We abbreviate the probability mass function for the zero-truncated Poisson distribution as  $ZTP(\lambda_i)$ .

## Model statement

Let  $z_{ij}$ , for  $i = 1, \dots, n_j$  and  $j = 1, \dots, J$ , denote observed, non-zero count data (i.e.,  $z_{ij}$  are integers greater than 0), where the index  $i$  denotes replicate observations within group  $j$ , and  $n_j$  is the number of observations in group  $j$ . Furthermore, let  $\mathbf{x}_{ij}$  be a vector of  $p$  covariates (including the intercept) associated with  $z_{ij}$  and  $\boldsymbol{\beta}_j$  be the corresponding vector of coefficients for group  $j$ .

$$\begin{aligned} z_{ij} | z_{ij} > 0 &\sim ZTP(\lambda_{ij}) \\ \log(\lambda_{ij}) &= \mathbf{x}_{ij}' \boldsymbol{\beta}_j \\ \boldsymbol{\beta}_j &\sim \mathcal{N}(\boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}) \\ \boldsymbol{\mu}_\beta &\sim \mathcal{N}(\mathbf{0}, \sigma_\beta^2 \mathbf{I}) \\ \boldsymbol{\Sigma}^{-1} &\sim \text{Wish}(\mathbf{S}_0^{-1}, \nu) \end{aligned}$$

## Full conditional distributions

*Regression coefficients ( $\boldsymbol{\beta}_j$ ):*

$$\begin{aligned} [\boldsymbol{\beta}_j | \cdot] &\propto \prod_{i=1}^{n_j} [z_{ij} | \mathbf{x}_{ij}' \boldsymbol{\beta}_j] [\boldsymbol{\beta}_j | \boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}] \\ &\propto \prod_{i=1}^{n_j} ZTP(z_{ij} | \mathbf{x}_{ij}' \boldsymbol{\beta}_j) \mathcal{N}(\boldsymbol{\beta}_j | \boldsymbol{\mu}_\beta, \boldsymbol{\Sigma}). \end{aligned}$$

The update for  $\beta_j$  proceeds using Metropolis-Hastings.

*Mean of regression coefficients ( $\mu_\beta$ ):*

$$\begin{aligned}
[\mu_\beta | \cdot] &\propto \prod_{j=1}^J [\beta_j | \mu_\beta, \Sigma] [\mu_\beta | \mathbf{0}, \sigma_\beta^2 \mathbf{I}] \\
&\propto \prod_{j=1}^J \mathcal{N}(\beta_j | \mu_\beta, \Sigma) \mathcal{N}(\mu_\beta | \mathbf{0}, \sigma_\beta^2 \mathbf{I}) \\
&\propto \exp \left\{ \sum_{j=1}^J \left( -\frac{1}{2} (\beta_j - \mu_\beta)' \Sigma^{-1} (\beta_j - \mu_\beta) \right) \right\} \\
&\quad \times \exp \left\{ -\frac{1}{2} (\mu_\beta - \mathbf{0})' (\sigma_\beta^2 \mathbf{I})^{-1} (\mu_\beta - \mathbf{0}) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} \left( -2 \left( \sum_{j=1}^J \beta_j' \Sigma^{-1} \right) \mu_\beta + \mu_\beta' (J \Sigma^{-1}) \mu_\beta \right) \right\} \\
&\quad \times \exp \left\{ -\frac{1}{2} (\mu_\beta' (\sigma_\beta^2 \mathbf{I})^{-1} \mu_\beta) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} \left( -2 \left( \sum_{j=1}^J \beta_j' \Sigma^{-1} \right) \mu_\beta + \mu_\beta' (J \Sigma^{-1} + (\sigma_\beta^2 \mathbf{I})^{-1}) \mu_\beta \right) \right\} \\
&= \mathcal{N}(\mathbf{A}^{-1} \mathbf{b}, \mathbf{A}^{-1}),
\end{aligned}$$

where  $\mathbf{A} = J \Sigma^{-1} + (\sigma_\beta^2 \mathbf{I})^{-1}$  and  $\mathbf{b}' = \beta' \Sigma^{-1}$ , where  $\beta$  is the vector sum  $\sum_{j=1}^J \beta_j$ .

*Variance-covariance of regression coefficients ( $\Sigma$ ):*

$$\begin{aligned}
[\Sigma | \cdot] &\propto \prod_{j=1}^J [\beta_j | \mu_\beta, \Sigma] [\Sigma | \mathbf{S}_0, \nu] \\
&\propto \prod_{j=1}^J \mathcal{N}(\beta_j | \mu_\beta, \Sigma) \text{Wish}(\Sigma | \mathbf{S}_0, \nu) \\
&\propto |\Sigma|^{-\frac{J}{2}} \exp \left\{ -\frac{1}{2} \sum_{j=1}^J (\beta_j - \mu_\beta)' \Sigma^{-1} (\beta_j - \mu_\beta) \right\} \\
&\quad \times |\mathbf{S}_0|^{-\frac{\nu}{2}} |\Sigma|^{-\frac{\nu-p-1}{2}} \exp \left\{ -\frac{1}{2} \text{tr}(\mathbf{S}_0 \Sigma^{-1}) \right\} \\
&\propto |\Sigma|^{-\frac{J+\nu-p-1}{2}} \exp \left\{ -\frac{1}{2} \left[ \sum_{j=1}^J \text{tr}((\beta_j - \mu_\beta)' \Sigma^{-1} (\beta_j - \mu_\beta)) + \text{tr}(\mathbf{S}_0 \Sigma^{-1}) \right] \right\} \\
&\propto |\Sigma|^{-\frac{J+\nu-p-1}{2}} \exp \left\{ -\frac{1}{2} \left[ \sum_{j=1}^J \text{tr}((\beta_j - \mu_\beta) (\beta_j - \mu_\beta)' \Sigma^{-1}) + \text{tr}(\mathbf{S}_0 \Sigma^{-1}) \right] \right\} \\
&\propto |\Sigma|^{-\frac{J+\nu-p-1}{2}} \exp \left\{ -\frac{1}{2} \left[ \text{tr} \left( \sum_{j=1}^J ((\beta_j - \mu_\beta) (\beta_j - \mu_\beta)') \Sigma^{-1} + \mathbf{S}_0 \Sigma^{-1} \right) \right] \right\}
\end{aligned}$$

$$\begin{aligned}
&\propto |\mathbf{\Sigma}|^{-\frac{J+\nu-p-1}{2}} \exp \left\{ -\frac{1}{2} \left[ \text{tr} \left( \sum_{j=1}^J \left( (\boldsymbol{\beta}_j - \boldsymbol{\mu}_\beta) (\boldsymbol{\beta}_j - \boldsymbol{\mu}_\beta)' \right) + \mathbf{S}_0 \right) \mathbf{\Sigma}^{-1} \right] \right\} \\
&= \text{Wish} \left( \left( \sum_{j=1}^J \left( (\boldsymbol{\beta}_j - \boldsymbol{\mu}_\beta) (\boldsymbol{\beta}_j - \boldsymbol{\mu}_\beta)' \right) + \mathbf{S}_0 \right)^{-1}, J + \nu \right).
\end{aligned}$$