

POISSON GENERALIZED LINEAR MIXED MODEL FOR ZERO-TRUNCATED COUNT DATA

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Description

A generalized linear mixed model with varying-coefficients for zero-truncated, grouped count data.

Implementation

The file `zt.poisson.varying.coef.sim.R` simulates data according to the model statement presented below, and `zt.poisson.varying.coef.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 (β_j):

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

The update for β_j proceeds using Metropolis-Hastings.

Mean of regression coefficients (μ_β):

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

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

Variance-covariance of regression coefficients (Σ):

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

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