

SEMIPARAMETRIC MIXED EFFECTS

PROBIT REGRESSION FOR BINARY DATA

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08 March 2016

Description

A semiparametric regression model with mixed effects for binary data using the probit link.

Implementation

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

Model statement

Let $y_j(t)$ denote longitudinal data observed at times $t \in \mathcal{T}$ in group j , for $j = 1, \dots, J$. Note that observations are binary; therefore $y_j(t) \in \{0, 1\}$. Let n_j denote the number of observations in group j . Furthermore, let $\mathbf{x}_j(t)$ be a vector of qX covariates (including the intercept) that are associated with $y_j(t)$, and $\boldsymbol{\beta}_j$ be the corresponding vector of group-level coefficients (i.e., they vary with j but share a common population-level distribution) for which inference is desired. Let $\mathbf{w}_j(t)$ be a vector of qW basis functions evaluated at time $t \in \mathcal{T}$ and $\boldsymbol{\alpha}_j$ be the vector of basis coefficients for group j . Note that the linear combination $\mathbf{w}_j(t) \boldsymbol{\alpha}_j$ models non-linear patterns or dependence non-parametrically.

$$\begin{aligned}
 y_j(t) &\sim \begin{cases} 0, & v_j(t) \leq 0 \\ 1, & v_j(t) > 0 \end{cases} \\
 v_j(t) &\sim \mathcal{N}(\mathbf{x}'_j(t) \boldsymbol{\beta}_j + \mathbf{w}_j(t) \boldsymbol{\alpha}_j, 1) \\
 \boldsymbol{\beta}_j &\sim \mathcal{N}(\boldsymbol{\mu}_\beta, \boldsymbol{\Lambda}) \\
 \boldsymbol{\mu}_\beta &\sim \mathcal{N}(\mathbf{0}, \sigma_\beta^2 \mathbf{I}) \\
 \boldsymbol{\alpha}_j &\sim \mathcal{N}(\mathbf{0}, \sigma_{\alpha_j}^2 \mathbf{I}) \\
 \boldsymbol{\Lambda}^{-1} &\sim \text{Wish}(\mathbf{S}_0^{-1}, \nu) \\
 \sigma_{\alpha_j}^2 &\sim \text{IG}(r, q)
 \end{aligned}$$

Models of this type are typically fit using a large number of basis vectors, more than necessary to approximate non-linear trends or dependence; therefore, regularization (e.g., a ridge penalty) is necessary. The parameter $\sigma_{\alpha_j}^2$ can be selected using cross-validation or some model selection criterion (e.g., DIC); alternatively, we model the variance of the basis coefficients ($\sigma_{\alpha_j}^2$) in order to shrink $\boldsymbol{\alpha}_j$ toward 0 where appropriate.

Full conditional distributions

Observation model auxiliary variable ($v_j(t)$):

$$\begin{aligned}
 [v_j(t) \mid \cdot] &\propto [y_j(t) \mid v_j(t)] [v_j(t) \mid \mathbf{x}'_j(t) \boldsymbol{\beta}_j + \mathbf{w}_j(t) \boldsymbol{\alpha}_j, 1] \\
 &\propto (1_{\{y_j(t)=0\}} 1_{\{v_j(t) \leq 0\}} + 1_{\{y_j(t)=1\}} 1_{\{v_j(t) > 0\}}) \times \mathcal{N}(v_j(t) \mid \mathbf{x}'_j(t) \boldsymbol{\beta}_j + \mathbf{w}_j(t) \boldsymbol{\alpha}_j, 1) \\
 &= \begin{cases} \mathcal{TN}(\mathbf{x}'_j(t) \boldsymbol{\beta}_j + \mathbf{w}_j(t) \boldsymbol{\alpha}_j, 1)_{-\infty}^0, & y_j(t) = 0 \\ \mathcal{TN}(\mathbf{x}'_j(t) \boldsymbol{\beta}_j + \mathbf{w}_j(t) \boldsymbol{\alpha}_j, 1)_0^{\infty}, & y_j(t) = 1 \end{cases}
 \end{aligned}$$

Regression coefficients (β_j):

$$\begin{aligned}
[\beta_j \mid \cdot] &\propto [\mathbf{v}_j \mid \mathbf{X}_j \beta_j + \mathbf{W}_j \alpha_j, \mathbf{1}] [\beta_j \mid \mu_\beta, \Lambda] \\
&\propto \mathcal{N}(\mathbf{v}_j \mid \mathbf{X}_j \beta_j + \mathbf{W}_j \alpha_j, \mathbf{1}) \mathcal{N}(\beta_j \mid \mu_\beta, \Lambda) \\
&\propto \exp \left\{ -\frac{1}{2} (\mathbf{v}_j - (\mathbf{X}_j \beta_j + \mathbf{W}_j \alpha_j))' (\mathbf{v}_j - (\mathbf{X}_j \beta_j + \mathbf{W}_j \alpha_j)) \right\} \\
&\quad \times \exp \left\{ -\frac{1}{2} (\beta_j - \mu_\beta)' \Lambda^{-1} (\beta_j - \mu_\beta) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} ((\mathbf{v}_j - \mathbf{W}_j \alpha_j) - \mathbf{X}_j \beta_j)' ((\mathbf{v}_j - \mathbf{W}_j \alpha_j) - \mathbf{X}_j \beta_j) \right\} \\
&\quad \times \exp \left\{ -\frac{1}{2} (\beta_j - \mu_\beta)' \Lambda^{-1} (\beta_j - \mu_\beta) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} (-2 (\mathbf{v}_j - \mathbf{W}_j \alpha_j)' \mathbf{X}_j \beta_j + \beta_j' \mathbf{X}_j' \mathbf{X}_j \beta_j) \right\} \\
&\quad \times \exp \left\{ -\frac{1}{2} (-2 (\mu_\beta' \Lambda^{-1}) \beta_j + \beta_j' \Lambda^{-1} \beta_j) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} (-2 ((\mathbf{v}_j - \mathbf{W}_j \alpha_j)' \mathbf{X}_j + \mu_\beta' \Lambda^{-1}) \beta_j + \beta_j' (\mathbf{X}_j' \mathbf{X}_j + \Lambda^{-1}) \beta_j) \right\} \\
&= \mathcal{N}(\mathbf{A}^{-1} \mathbf{b}, \mathbf{A}^{-1}),
\end{aligned}$$

where $\mathbf{A} = \mathbf{X}_j' \mathbf{X}_j + \Lambda^{-1}$, $\mathbf{b}' = (\mathbf{v}_j - \mathbf{W}_j \alpha_j)' \mathbf{X}_j + \mu_\beta' \Lambda^{-1}$, $\mathbf{v}_j' = \{v_j(t) : t \in \mathcal{T}\}$ (i.e., the vector collecting $v_j(t)$ for all times $t \in \mathcal{T}$), \mathbf{X}_j is an $n_j \times qX$ matrix collecting the vectors $\mathbf{x}_j(t)$ for all times $t \in \mathcal{T}$, and similarly \mathbf{W}_j is an $n_j \times qW$ basis expansion collecting the vectors $\mathbf{w}_j(t)$ for all times $t \in \mathcal{T}$.

Basis coefficients (α_j):

$$\begin{aligned}
[\alpha_j \mid \cdot] &\propto [\mathbf{v}_j \mid \mathbf{X}_j \beta_j + \mathbf{W}_j \alpha_j, \mathbf{1}] [\alpha_j \mid \mathbf{0}, \sigma_{\alpha_j}^2] \\
&\propto \mathcal{N}(\mathbf{v}_j \mid \mathbf{X}_j \beta_j + \mathbf{W}_j \alpha_j, \mathbf{1}) \mathcal{N}(\alpha_j \mid \mathbf{0}, \sigma_{\alpha_j}^2) \\
&\propto \exp \left\{ -\frac{1}{2} (\mathbf{v}_j - (\mathbf{X}_j \beta_j + \mathbf{W}_j \alpha_j))' (\mathbf{v}_j - (\mathbf{X}_j \beta_j + \mathbf{W}_j \alpha_j)) \right\} \\
&\quad \times \exp \left\{ -\frac{1}{2} (\alpha_j - \mathbf{0})' (\sigma_{\alpha_j}^2 \mathbf{I})^{-1} (\alpha_j - \mathbf{0}) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} ((\mathbf{v}_j - \mathbf{X}_j \beta_j) - \mathbf{W}_j \alpha_j)' ((\mathbf{v}_j - \mathbf{X}_j \beta_j) - \mathbf{W}_j \alpha_j) \right\} \\
&\quad \times \exp \left\{ -\frac{1}{2} (\alpha_j - \mathbf{0})' (\sigma_{\alpha_j}^2 \mathbf{I})^{-1} (\alpha_j - \mathbf{0}) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} (-2 (\mathbf{v}_j - \mathbf{X}_j \beta_j)' \mathbf{W}_j \alpha_j + \alpha_j' \mathbf{W}_j' \mathbf{W}_j \alpha_j) \right\} \\
&\quad \times \exp \left\{ -\frac{1}{2} (\alpha_j' (\sigma_{\alpha_j}^2 \mathbf{I})^{-1} \alpha_j) \right\} \\
&\propto \exp \left\{ -\frac{1}{2} (-2 ((\mathbf{v}_j - \mathbf{X}_j \beta_j)' \mathbf{W}_j) \alpha_j + \alpha_j' (\mathbf{W}_j' \mathbf{W}_j + (\sigma_{\alpha_j}^2 \mathbf{I})^{-1}) \alpha_j) \right\} \\
&= \mathcal{N}(\mathbf{A}^{-1} \mathbf{b}, \mathbf{A}^{-1}),
\end{aligned}$$

where $\mathbf{A} = \mathbf{W}_j' \mathbf{W}_j + (\sigma_{\alpha_j}^2 \mathbf{I})^{-1}$ and $\mathbf{b}' = (\mathbf{v}_j - \mathbf{X}_j \boldsymbol{\beta}_j)' \mathbf{W}_j$, $\mathbf{v}_j' = \{v_j(t) : t \in \mathcal{T}\}$, \mathbf{X}_j is an $n_j \times qX$ matrix collecting the vectors $\mathbf{x}_j(t)$ for all times $t \in \mathcal{T}$, and similarly \mathbf{W}_j is an $n_j \times qW$ basis expansion collecting the vectors $\mathbf{w}_j(t)$ for all times $t \in \mathcal{T}$.

Mean of regression coefficients ($\boldsymbol{\mu}_\beta$):

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

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

Variance-covariance of regression coefficients ($\boldsymbol{\Lambda}$):

$$\begin{aligned}
[\mathbf{A} \mid \cdot] &\propto \prod_{j=1}^J [\boldsymbol{\beta}_j \mid \boldsymbol{\mu}_\beta, \mathbf{A}] [\mathbf{A} \mid \mathbf{S}_0, \nu] \\
&\propto \prod_{j=1}^J \mathcal{N}(\boldsymbol{\beta}_j \mid \boldsymbol{\mu}_\beta, \mathbf{A}) \text{Wish}(\mathbf{A} \mid \mathbf{S}_0, \nu) \\
&\propto |\mathbf{A}|^{-\frac{J}{2}} \exp \left\{ -\frac{1}{2} \sum_{j=1}^J (\boldsymbol{\beta}_j - \boldsymbol{\mu}_\beta)' \mathbf{A}^{-1} (\boldsymbol{\beta}_j - \boldsymbol{\mu}_\beta) \right\} \\
&\quad \times |\mathbf{S}_0|^{-\frac{\nu}{2}} |\mathbf{A}|^{-\frac{\nu-qX-1}{2}} \exp \left\{ -\frac{1}{2} \text{tr}(\mathbf{S}_0 \mathbf{A}^{-1}) \right\} \\
&\propto |\mathbf{A}|^{-\frac{J+\nu-qX-1}{2}} \exp \left\{ -\frac{1}{2} \left[\sum_{j=1}^J \text{tr} \left((\boldsymbol{\beta}_j - \boldsymbol{\mu}_\beta)' \mathbf{A}^{-1} (\boldsymbol{\beta}_j - \boldsymbol{\mu}_\beta) \right) + \text{tr}(\mathbf{S}_0 \mathbf{A}^{-1}) \right] \right\} \\
&\propto |\mathbf{A}|^{-\frac{J+\nu-qX-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)' \mathbf{A}^{-1} \right) + \text{tr}(\mathbf{S}_0 \mathbf{A}^{-1}) \right] \right\} \\
&\propto |\mathbf{A}|^{-\frac{J+\nu-qX-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{A}^{-1} + \mathbf{S}_0 \mathbf{A}^{-1} \right) \right] \right\} \\
&\propto |\mathbf{A}|^{-\frac{J+\nu-qX-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{A}^{-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}$$

Variation in basis coefficients ($\sigma_{\alpha_j}^2$):

$$\begin{aligned}
[\sigma_{\alpha_j}^2 \mid \cdot] &\propto [\boldsymbol{\alpha}_j \mid \mathbf{0}, \sigma_{\alpha_j}^2] [\sigma_{\alpha_j}^2] \\
&\propto \mathcal{N}(\boldsymbol{\alpha}_j \mid \mathbf{0}, \sigma_{\alpha_j}^2 \mathbf{I}) \text{IG}(r, q) \\
&\propto |\sigma_{\alpha_j}^2 \mathbf{I}|^{-1/2} \exp \left\{ -\frac{1}{2} \left((\boldsymbol{\alpha}_j - \mathbf{0})' (\sigma_{\alpha_j}^2 \mathbf{I})^{-1} (\boldsymbol{\alpha}_j - \mathbf{0}) \right) \right\} \times \\
&\quad \left(\sigma_{\alpha_j}^2 \right)^{-(q+1)} \exp \left\{ -\frac{1}{r \sigma_{\alpha_j}^2} \right\} \\
&\propto \left(\sigma_{\alpha_j}^2 \right)^{-qW/2} \exp \left\{ -\frac{1}{2 \sigma_{\alpha_j}^2} \boldsymbol{\alpha}_j' \boldsymbol{\alpha}_j \right\} \\
&\quad \left(\sigma_{\alpha_j}^2 \right)^{-(q+1)} \exp \left\{ -\frac{1}{r \sigma_{\alpha_j}^2} \right\} \\
&\propto \left(\sigma_{\alpha_j}^2 \right)^{-(qW/2+q+1)} \exp \left\{ -\frac{1}{\sigma_{\alpha_j}^2} \left(\frac{\boldsymbol{\alpha}_j' \boldsymbol{\alpha}_j}{2} + \frac{1}{r} \right) \right\} \\
&= \text{IG} \left(\left(\frac{\boldsymbol{\alpha}_j' \boldsymbol{\alpha}_j}{2} + \frac{1}{r} \right)^{-1}, \frac{qW}{2} + q \right)
\end{aligned}$$

where qW is the number of columns in \mathbf{W} .