

## Model Specification

We assume that for each observation  $i$ , we observe  $y_i$  (possibly censored) and an indicator  $\Delta_i$  where:

$$\Delta_i = \begin{cases} 1, & \text{if } y_i \text{ is observed (uncensored);} \\ 0, & \text{if } y_i \text{ is censored.} \end{cases}$$

We work on the log-scale by defining a latent variable

$$\tilde{y}_i = \log(y_i) \quad (\text{or an adjusted value for censored observations}).$$

The regression model is

$$\tilde{y}_i = X_i\beta + r_{c(i)} + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2),$$

where:

- $X_i$  is the row vector of covariates for observation  $i$ .
- $\beta$  is the vector of fixed effects.
- $r_{c(i)}$  is the random effect associated with the cluster  $c(i)$  that observation  $i$  belongs to.
- $\sigma^2$  is the error variance.

The random effects for each cluster  $j = 1, \dots, I$  have a spatial structure through a weight matrix  $W$ . Let  $D_j = \sum_{k=1}^I W_{jk}$  be the degree (row sum) for cluster  $j$ . A spatial prior is imposed by further introducing:

- $\tau^2$ : spatial variance.
- $\rho$ : spatial correlation parameter satisfying  $\rho \in [\rho_{\text{lower}}, \rho_{\text{upper}}]$ .

## Gibbs Sampler Steps

### Step 1: Imputation of Latent Variables

For each observation  $i$ , if  $\Delta_i = 0$ ,  $\tilde{y}_i$  is missing (censored) and is imputed from a truncated normal distribution:

$$\tilde{y}_i \sim TN(a = \log(y_i), b = \infty; \mu_i, \sigma^2),$$

with

$$\mu_i = X_i\beta + r_{c(i)}.$$

For uncensored observations ( $\Delta_i = 1$ ), we set

$$\tilde{y}_i = \log(y_i).$$

## Step 2: Update of $\beta$ (Fixed Effects)

Define an adjusted outcome

$$y_i^* = \tilde{y}_i - r_{c(i)}.$$

Assuming a conjugate normal prior for  $\beta$ , that is,

$$\beta \sim N(0, V_\beta) \quad \text{with } V_\beta = \text{diag}(\beta)$$

the posterior for  $\beta$  is

$$\beta \mid \tilde{y}, r, \sigma^2 \sim N\left(\mu_\beta, V_\beta^{\text{post}}\right),$$

where

$$V_\beta^{\text{post}} = \left( \frac{X^T X}{\sigma^2} + V_\beta^{-1} \right)^{-1}, \quad \mu_\beta = V_\beta^{\text{post}} \left( \frac{X^T y^*}{\sigma^2} \right).$$

## Step 3: Update of Random Effects $r$ for Each Cluster

For each cluster  $j$ , let  $C_j$  be the set of observation indices belonging to cluster  $j$ , and let  $n_j = |C_j|$ . The full conditional for the random effect  $r_j$  is:

$$r_j \mid \cdot \sim N(m_j, v_j),$$

with

$$v_j = \left( \frac{n_j}{\sigma^2} + \frac{D_j}{\tau^2} \right)^{-1}, \quad m_j = v_j \left( \frac{1}{\sigma^2} \sum_{i \in C_j} (\tilde{y}_i - X_i \beta) + \frac{\rho}{\tau^2} \sum_{k=1}^I W_{jk} r_k \right).$$

## Step 4: Update of $\sigma^2$ (Error Variance)

The residual for each observation is given by

$$e_i = \tilde{y}_i - X_i \beta - r_{c(i)}.$$

An inverse-gamma prior is assumed for  $\sigma^2$ . The posterior distribution is

$$\sigma^2 \sim \text{Inv-Gamma} \left( a_\sigma + \frac{n}{2}, b_\sigma + \frac{1}{2} \sum_{i=1}^n e_i^2 \right).$$

## Step 5: Update of $\tau^2$ (Spatial Variance)

Define a quadratic form involving the random effects:

$$Q = \sum_{j=1}^I D_j r_j^2 - \rho \mathbf{r}^T W \mathbf{r}.$$

Then, with an inverse-gamma prior for  $\tau^2$ , the full conditional is

$$\tau^2 \sim \text{Inv-Gamma} \left( a_\tau + \frac{I}{2}, b_\tau + \frac{Q}{2} \right).$$

### Step 6: Update of $\rho$ (Spatial Correlation Parameter)

A Metropolis–Hastings step is used for  $\rho$ . A proposal  $\rho_{\text{prop}}$  is drawn from:

$$\rho_{\text{prop}} \sim N(\rho, \sigma_{\text{proposal}}^2),$$

with  $\sigma_{\text{proposal}} = 0.1$ . If  $\rho_{\text{prop}}$  is outside the allowable range  $[\rho_{\text{lower}}, \rho_{\text{upper}}]$ , then the proposal is rejected. Otherwise, compute the quadratic forms:

$$Q(\rho) = \sum_{j=1}^I D_j r_j^2 - \rho \mathbf{r}^T W \mathbf{r},$$

and

$$Q(\rho_{\text{prop}}) = \sum_{j=1}^I D_j r_j^2 - \rho_{\text{prop}} \mathbf{r}^T W \mathbf{r}.$$

The log acceptance ratio is then given by:

$$\log \alpha = -\frac{1}{2\tau^2} [Q(\rho_{\text{prop}}) - Q(\rho)].$$

Accept  $\rho_{\text{prop}}$  with probability  $\min(1, \exp(\log \alpha))$ , otherwise retain the current  $\rho$ .

## Summary

At each iteration, the sampler:

1. Imputes latent values  $\tilde{y}_i$  for censored observations.
2. Updates the fixed effects  $\beta$  via a conjugate normal posterior.
3. Updates the cluster-level random effects  $r_j$  based on the observed data and the spatial structure.
4. Updates  $\sigma^2$  and  $\tau^2$  using inverse-gamma full conditionals.
5. Updates  $\rho$  using a Metropolis–Hastings step.

Posterior samples for all these parameters are stored for later inference.