

$$y_i \sim N(\mu_i, \sigma^2)$$

← identity

$$\mu_i = \alpha + \beta_1 x_i + v_i$$

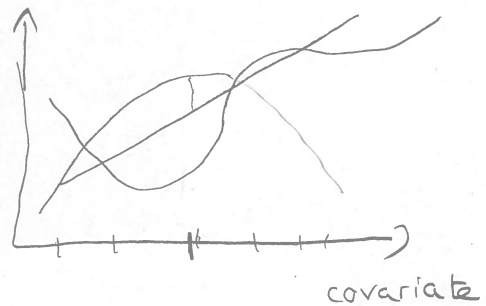
$$y_i | \eta_i \sim \text{Po}(\epsilon_i, \underline{\lambda_i})$$

$$\eta_i = \log(\lambda_i) = \alpha + \beta_1 x_i + v_i$$

$$y_i | \pi_i \sim \text{Bin}(n_i, \underline{\pi_i})$$

$$\text{logit}(\pi_i) = \alpha + \beta_1 x_i + v_i$$

$$\log\left(\frac{\pi_i}{1-\pi_i}\right)$$



Definition: GMRF

A random vector $x = (x_1, \dots, x_n)^T$ is called GMRF with respect to a labelled graph $G = (V, E)$ with mean vector μ and precision matrix (inverse covariance matrix) $Q > 0$, if its density has the form

$$\pi(x) = (2\pi)^{-n/2} |Q|^{1/2} \exp\left(-\frac{1}{2}(x-\mu)^T Q (x-\mu)\right)$$

and $Q_{ij} \neq 0 \Leftrightarrow \{i, j\} \in E$ for all $i \neq j$.

\Rightarrow any normal distribution with a symmetric positive definite covariance matrix is also a GMRF and vice versa.

$$\pi(x|\theta, y) = \frac{\pi(x, \theta|y)}{\pi(\theta|y)}$$

$$\pi(x|\theta) = \frac{\pi(x, \theta)}{\pi(\theta)}$$

$$\Rightarrow \pi(\theta|y) = \frac{\pi(x, \theta|y)}{\pi(x|\theta, y)} = \frac{\pi(x, \theta, y)}{\underbrace{\pi(y)}_{\text{unknown}} \pi(x|\theta, y)}$$

$$\propto \frac{\pi(x, \theta, y)}{\pi(x|\theta, y)} = \frac{\pi(\theta) \pi(x, y|\theta)}{\pi(x|\theta, y)}$$