Lecture 11 27/2 Week 9.1

Conditional Dependency and More INLA

Example (tokyo rainfall dependency graph)

$$\left.\begin{aligned} y_t \mid \tau_t &\overset{iid}{\sim} \mathrm{Bin}(n_t, \pi(\tau_t)) \\ \text{for } \pi(\tau_t) &= \frac{1}{1+e^{-\tau_t}} \end{aligned}\right\} \text{data model}$$

"expit" or "inverse logit" function

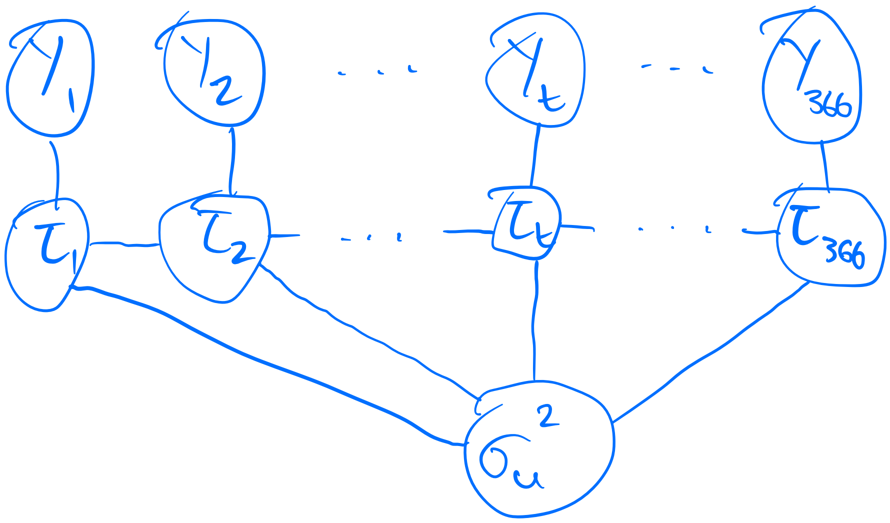
$$\left.\begin{aligned} \tau_t = \tau_{t-1} + u_t, \quad u_t \mid \sigma_u^2 \overset{iid}{\sim} N(0, \sigma_u^2), \\ t = 2, \dots, 366 \end{aligned}\right\} \text{latent model}$$

$$\left.\sigma_u^2 \sim \text{Inv-Gamma}(\alpha, \beta)\right\} \text{hyperprior}$$

Note: when drawing a conditional dependency graph, we first may need to reparameterize to explicitely state conditional dependencies (particularly for "=" statements).

$$\tau_t \mid \tau_{t-1}, \sigma_u^2 \sim N(\tau_{t-1}, \sigma_u^2), \quad t = 2, \dots, 366$$

Now for the conditional dependency graph:



This represents the model's conditional dependencies. For example, removing τ_1, we cannot reach Y_2 from Y_1. Main idea: $Y_1, \ldots, Y_{366}$ are conditionally independent given $\vec{\tau}$.

<u>Note</u>: This idea of paths after removing the conditioning variable representing conditional dependence does not apply when conditioning on the Y_i's. For more information look up "d-separation".