

Marginal likelihood for DAG-Gaussian

$$P(x_1, \dots, x_d | y) = \prod_{j=1}^d P(x_j | X_{A_j} y)$$

To define A_j , let $\gamma_{kj} = 1$ if x_k is a parent of x_j & $\gamma_{kj} = 0$ otherwise. Then

$$A_j = \{k; \gamma_{kj} = 1\}$$

Note $P(x_j | X_{A_j} y)$ is referred to as the marginal likelihood of x_j

Let $\beta_j = (\beta_0, \beta_{A_j})$ be the set of regression co-efficients, & let σ_j^2 be the variance of the error term e_j in

$$x_j = \beta_0 + X_{A_j} \beta_{A_j} + e_j; e_j \sim N(0, \sigma_j^2)$$

then the marginal likelihood

$$P(x_j | X_{A_j}) = \int_{\mathbb{R}^{|A_j|+1}} P(x_j | \beta_j, \sigma_j^2, X_{A_j}) P(\beta_j | \sigma_j^2) P(\sigma_j^2) d\beta_j d\sigma_j^2$$

where $|A_j|$ is the length of A_j

$$P(x_j | \beta_j, \sigma_j^2, X_{A_j}) = \frac{1}{(2\pi\sigma_j^2)^{n/2}} \exp\left\{-\frac{1}{2\sigma_j^2} (x_j - X_{A_j} \beta_j)' (x_j - X_{A_j} \beta_j)\right\}$$

Assume

$$\beta_j | \sigma_j^2 \sim N(0, g\sigma_j^2 D_j) \quad D_j \text{ is a } p_j \times p_j \text{ matrix}$$

$$\sigma_j^2 \sim IG(a, b)$$

$$\text{then } P(\beta_j | \sigma_j^2) = \frac{1}{(2\pi g\sigma_j^2)^{p_j/2}} |D_j|^{-1/2} \exp\left\{-\frac{1}{2} \beta_j' D_j^{-1} \beta_j / g\sigma_j^2\right\}$$

$$p_j = |A_j| + 1$$

$$\& P(\sigma_j^2) = \frac{b^a \sigma_j^{-(1+a)} e^{-b/\sigma_j^2}}{\Gamma(a)}$$

We will first integrate over β_j to get

$$P(x_j | X_{A_j}, \sigma_j^2) = \int_{\mathbb{R}^{|A_j|+1}} P(x_j | X_{A_j}, \sigma_j^2) P(\beta_j | \sigma_j^2) d\beta_j$$

$$= \int_{\mathbb{R}^p} \frac{1}{(2\pi\sigma_j^2)^{n/2}} \exp\left\{-\frac{1}{2\sigma_j^2} (x_j - X_{A_j} \beta_j)' (x_j - X_{A_j} \beta_j)\right\} \frac{|D_j|^{-1/2}}{(2\pi g\sigma_j^2)^{p_j/2}} \exp\left\{-\frac{1}{2} \beta_j' D_j^{-1} \beta_j / g\sigma_j^2\right\} d\beta_j$$

$$= \frac{|D_j|^{-1/2} g^{-p_j/2}}{(2\pi\sigma_j^2)^{n/2}} \exp\left\{-\frac{1}{2\sigma_j^2} x_j' x_j\right\} \times$$

$$\int \frac{1}{(2\pi\sigma_j^2)^{p_j/2}} \exp\left\{-\frac{1}{2\sigma_j^2} \left[\beta_j' X_{A_j}' X_{A_j} \beta_j + \beta_j' D_j^{-1} \beta_j - 2\beta_j' X_{A_j}' x_j \right]\right\} d\beta_j$$

Consider the integrand of the equation above & let

$$V_{\beta_j} = \left[\frac{X_{A_j}' X_{A_j} g + D_j^{-1}}{g} \right]^{-1} \& \text{let}$$

$$m_{\beta_j} = V_{\beta_j} X_{A_j}' x_j \text{ then}$$

$$\exp\left\{-\frac{1}{2\sigma_j^2} \left[\beta_j' \left[\frac{X_{A_j}' X_{A_j} g + D_j^{-1}}{g} \right] \beta_j - 2\beta_j' X_{A_j}' x_j \right]\right\}$$

$$= \exp\left\{-\frac{1}{2\sigma_j^2} \left[\beta_j' V_{\beta_j}^{-1} \beta_j - 2\beta_j' V_{\beta_j}^{-1} m_{\beta_j} \right]\right\}$$

which is Gaussian in β_j with variance

$$\sigma_j^2 V_{\beta_j} \& \text{mean } V_{\beta_j} X_{A_j}' x_j$$

What is missing is a term $\frac{m_{\beta_j}' V_{\beta_j}^{-1} m_{\beta_j}}{\sigma_j^2}$

which we can add & subtract so that

$$\exp\left\{-\frac{1}{2\sigma_j^2} \left[\beta_j' \left[\frac{X_{A_j}' X_{A_j} g + D_j^{-1}}{g} \right] \beta_j - 2\beta_j' X_{A_j}' x_j \right]\right\} =$$

$$\exp\left\{-\frac{1}{2} \left[\frac{\beta_j' V_{\beta_j}^{-1} \beta_j}{\sigma_j^2} - \frac{2\beta_j' V_{\beta_j}^{-1} m_{\beta_j}}{\sigma_j^2} + \frac{m_{\beta_j}' V_{\beta_j}^{-1} m_{\beta_j}}{\sigma_j^2} \right]\right\}$$

& hence the integral

$$\int_{\mathbb{R}^{p_j}} \frac{1}{(2\pi\sigma_j^2)^{p_j/2}} \exp\left\{-\frac{1}{2\sigma_j^2} \left[\frac{\beta_j' (X_{A_j}' X_{A_j} g + D_j^{-1}) \beta_j - 2\beta_j' X_{A_j}' x_j \right]\right\} d\beta_j$$

$$= |V_{\beta_j}|^{1/2} \exp\left\{-\frac{1}{2\sigma_j^2} \frac{m_{\beta_j}' V_{\beta_j}^{-1} m_{\beta_j}}{g}\right\} \times$$

$$\int_{\mathbb{R}^{p_j}} \frac{1}{(2\pi\sigma_j^2)^{p_j/2}} |V_{\beta_j}|^{1/2} \exp\left\{-\frac{1}{2\sigma_j^2} (\beta_j - m_{\beta_j})' V_{\beta_j}^{-1} (\beta_j - m_{\beta_j})\right\} d\beta_j$$

$$= |V_{\beta_j}|^{1/2} \exp\left\{-\frac{1}{2\sigma_j^2} (m_{\beta_j}' V_{\beta_j}^{-1} m_{\beta_j})\right\}$$

$$\therefore P(x_j | X_{A_j}, \sigma_j^2) = \frac{|D_j|^{-1/2} g^{-p_j/2}}{(2\pi\sigma_j^2)^{n/2}} \exp\left\{-\frac{1}{2\sigma_j^2} (x_j' H_j x_j)\right\}$$

$$H_j = I - X_{A_j} V_{\beta_j} X_{A_j}'$$

with

$$V_{\beta_j} = \left(\frac{X_{A_j}' X_{A_j} g + D_j^{-1}}{g} \right)^{-1}$$

$$= g(g X_{A_j}' X_{A_j} + D_j^{-1})^{-1}$$

Integrating over σ_j^2

$$P(x_j | X_{A_j}) = \int_0^\infty P(x_j | X_{A_j}, \sigma_j^2) P(\sigma_j^2) d\sigma_j^2$$

$$= \frac{|D_j|^{-1/2} g^{-p_j/2}}{(2\pi)^{n/2}} \int_0^\infty \sigma_j^{-(1+a)} \exp\left\{-\frac{1}{2\sigma_j^2} x_j' H_j x_j\right\} \times \frac{\sigma_j^{2(-1+a)} b^a e^{-b/\sigma_j^2}}{\Gamma(a)} d\sigma_j^2$$

$$= \frac{|D_j|^{-1/2} g^{-p_j/2} b^a}{(2\pi)^{n/2} \Gamma(a)} \int_0^\infty \sigma_j^{2-(1+a+p_j/2)} \exp\left\{-\frac{x_j' H_j x_j + b}{2\sigma_j^2}\right\} d\sigma_j^2$$

$$= \frac{|D_j|^{-1/2} g^{-p_j/2} b^a \Gamma(a^*)}{(2\pi)^{n/2} \Gamma(a) b^{a^*}} \int_0^\infty \frac{\sigma_j^{2-(1+a^*)} b^{a^*} \exp\left\{-\frac{b^*}{\sigma_j^2}\right\}}{\Gamma(a^*)} d\sigma_j^2$$

$$= \frac{|D_j|^{-1/2} g^{-p_j/2} b^a \Gamma(a^*)}{(2\pi)^{n/2} \Gamma(a) b^{a^*}} \quad \text{where } a^* = a + \frac{p_j}{2} \& b^* = \frac{x_j' H_j x_j + b}{2}$$

So that for each $j=1, \dots, d$

$$P(x_j | X_{A_j}) \propto |D_j|^{-1/2} g^{-p_j/2} \Gamma(a^*) b_j^{a^*-a_j}$$

where

$$b_j^* = \frac{x_j' H_j x_j + b}{2} \&$$

$$H_j = I - X_{A_j} V_{\beta_j} X_{A_j}'$$

$$V_{\beta_j} = g(g X_{A_j}' X_{A_j} + D_j^{-1})^{-1}$$

$$a_j^* = \frac{p_j}{2} + a \quad p_j = |A_j| + 1$$

$|D_j|^{-1/2}$ is the determinant of a $p_j \times p_j$ covariance matrix