

# Parameter estimation of Hierarchical Model

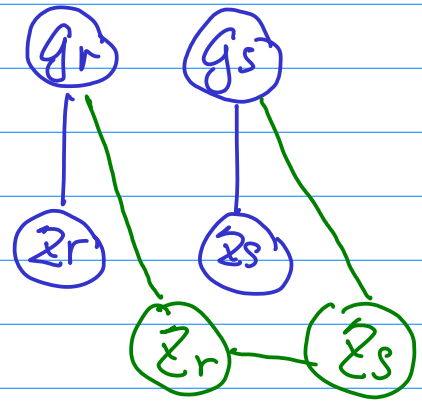
$$\theta = \text{argmax } E[-\log P(G, Z)]$$

$$P(G, Z) = P(G) \cdot P(Z|G)$$

$$= P(G) \cdot \prod_j P(Z^j|G)$$

$$= \frac{1}{Z_G} \exp\left\{-\beta_g \sum_{(r,s)} [g_r \neq g_s]\right\}$$

$$\cdot \prod_j \frac{1}{Z_z} \exp\left\{-\alpha \sum_s [g_s \neq z_s^j] - \beta_z \sum_{(r,s)} [z_r^j \neq z_s^j]\right\}$$



(Using Pseudo-likelihood approximation)

$$= \prod_{s \in G} P(g_s|\cdot) \cdot \prod_{s \in Z^j} P(g_s|\cdot)$$

$$= \prod_{s \in G} \frac{1}{Z_g} \exp\left\{-\beta_g \sum_{r \in N_s} [g_r \neq g_s] - \alpha \sum_{j \in J} [g_s \neq z_s^j]\right\} \quad \text{group nodes}$$

$$\cdot \prod_{s \in Z^j} \frac{1}{Z_z} \exp\left\{-\alpha [g_s \neq z_s^j] - \beta_z \sum_{r \in N_s} [z_r^j \neq z_s^j]\right\} \quad \text{subject nodes}$$

$$Z_g = \sum_k \exp\left\{-\beta_g \sum_{r \in N_s} [g_r \neq k] - \alpha \sum_j [z_s^j \neq k]\right\}$$

$$Z_z = \sum_k \exp\left\{-\alpha [g_s \neq k] - \beta_z \sum_{r \in N_s} [z_r^j \neq k]\right\}$$

$$\text{Let } a = -\sum_j [g_s \neq z_s^j], \quad b = -\sum_{r \in N_s} [g_r \neq g_s]$$

$$a_1 = -[g_s \neq z_s^j], \quad b_1 = -\sum_{r \in N_s} [z_r^j \neq z_s^j]$$

$$-\log p(G, \mathbf{z}) = \sum_{s \in G} (-a\alpha - b\beta_g + \log \sum_k e^{a\alpha + b\beta_g}) \\ + \sum_{s \in \mathbf{z}^i} (-a_1\alpha - b_1\beta_z + \log \sum_k e^{a_1\alpha + b_1\beta_z}) = \sum_{s \in G} q_1 + \sum_{s \in \mathbf{z}^i} q_2$$

$$q_1 = -a\alpha - b\beta_g + \log \sum_k e^{a\alpha + b\beta_g}$$

$$q_2 = -a_1\alpha - b_1\beta_z + \log \sum_k e^{a_1\alpha + b_1\beta_z}$$

$$E[-\log p(G, \mathbf{z})] \approx \frac{1}{M} \sum_m (-\log p(G^m, \mathbf{z}^m))$$

$$= \frac{1}{M} \sum_{m, s \in G} \underbrace{q_1}_{q_1(\alpha, \beta_g)} + \frac{1}{M} \sum_{m, s \in \mathbf{z}^i} \underbrace{q_2}_{q_2(\alpha, \beta_z)}$$

$$\frac{\partial q_1}{\partial \beta_g} = -b + \frac{\sum_k e^{a\alpha + b\beta_g} \cdot b}{\sum_k e^{a\alpha + b\beta_g}}$$

$$\frac{\partial^2 q_1}{\partial \beta_g^2} = \frac{(\sum_k e^{a\alpha + b\beta_g} \cdot b^2)(\sum_k e^{a\alpha + b\beta_g}) - (\sum_k e^{a\alpha + b\beta_g} \cdot b)^2}{(\sum_k e^{a\alpha + b\beta_g})^2}$$

$$M_0 = \sum_k e^{a\alpha + b\beta_g}, \quad M_1 = \sum_k e^{a\alpha + b\beta_g} \cdot b, \quad M_2 = \sum_k e^{a\alpha + b\beta_g} \cdot b^2$$

$$\frac{\partial q_1}{\partial \beta_g} = -b + \frac{M_1}{M_0}, \quad \frac{\partial^2 q_1}{\partial \beta_g^2} = \frac{M_2 \cdot M_0 - M_1^2}{M_0^2}$$

$$\frac{\partial q_1}{\partial \alpha} = -a + \frac{\sum_k e^{a\alpha + b\beta_g} \cdot a}{\sum_k e^{a\alpha + b\beta_g}} =$$

$$\frac{\partial^2 q_1}{\partial \alpha^2} = \frac{(\sum_k e^{a\alpha + b\beta_g} \cdot a^2)(\sum_k e^{a\alpha + b\beta_g}) - (\sum_k e^{a\alpha + b\beta_g} \cdot a)^2}{(\sum_k e^{a\alpha + b\beta_g})^2}$$

$$M_0 = \sum_K e^{a\alpha + b\beta}, \quad M_1 = \sum_K e^{a\alpha + b\beta} \cdot a, \quad M_2 = \sum_K e^{a\alpha + b\beta} \cdot a^2$$

$$\frac{\partial \mathcal{Q}_1}{\partial \alpha} = -a + \frac{M_1}{M_0}, \quad \frac{\partial^2 \mathcal{Q}_1}{\partial \alpha^2} = \frac{M_2 \cdot M_0 - M_1^2}{M_0^2}$$

$$\frac{\partial \mathcal{Q}_2}{\partial \alpha} = -a_1 + \frac{M_1}{M_0}, \quad \frac{\partial^2 \mathcal{Q}_2}{\partial \alpha^2} = \frac{M_2 \cdot M_0 - M_1^2}{M_0^2}$$

↪ Replacing  $\begin{cases} a \text{ with } a_1 \\ b \text{ with } b_1 \end{cases}$  in  $M_0, M_1, M_2$

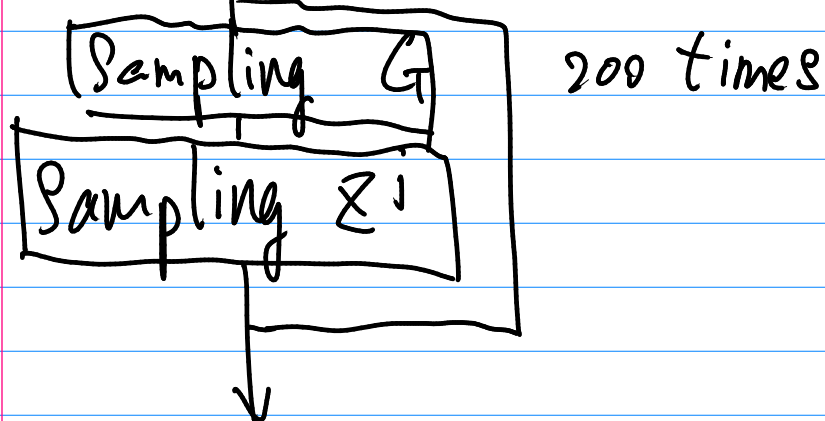
$$\frac{\partial \mathcal{Q}_2}{\partial \beta_2} = -b + \frac{M_1}{M_0}, \quad \frac{\partial^2 \mathcal{Q}_2}{\partial \beta_2^2} = \frac{M_2 M_0 - M_1^2}{M_0^2}$$

$$\downarrow$$

$$M_0 = \sum_K e^{a_1 \alpha + b_1 \beta_2}, \quad M_1 = \sum_K e^{a_1 \alpha + b_1 \beta_2} \cdot b_1, \quad M_2 = \sum_K e^{a_1 \alpha + b_1 \beta_2} \cdot b_1^2$$

genest:

input:  $\alpha$ ,  $\beta_1$ ,  $\beta_2$



Sample  $G$  only

estimate  $\beta_g$

Compute  $-\log P(G, z)$

Define hidden variable  $Y = (G, Z)$

$$\theta^* = \operatorname{argmax}_{\theta} \log P(Y; \theta)$$

EM: E step, given  $\theta^{\text{old}}$

$$Q = E_{P(Y|X, \theta^{\text{old}})} [\log P(X, Y | \theta)]$$

M step:  $\theta^{\text{new}} = \operatorname{argmax}_{\theta} Q(\theta, \theta^{\text{old}})$

Monte-Carlo EM:

$$\text{E step: } \tilde{Q}(\theta, \theta^{\text{old}}) = \frac{1}{m} \sum_m \log P(X, Y^m | \theta)$$

$Y^m$  is sample of  $P(Y|X, \theta^{\text{old}})$

for a single sample  $Y^m$ ,

$$\log P(X, Y) = \log P(Y) + \log P(X|Y)$$

$$E = -\log P(X, Y) = -\log P(Y) - \log P(X|Y)$$

$$E(X, Y) = E(Y) + E(X|Y)$$

$$E(Y) = E(G, Z)$$

$$E(G, Z) = -\log p(G, Z)$$

$$p(G, Z) \approx \prod_{s \in G} p(g_s | \cdot) \cdot \prod_{s \in Z^j} p(z_s | \cdot)$$

$$= \prod_{s \in G} \frac{1}{Z_g} \exp \left\{ -\beta_g \sum_{r \in N_s} [g_r \neq g_s] - \alpha \sum_{j \in J} [g_s \neq z_s^j] \right\} \quad \text{grp}$$

$$\cdot \prod_{s \in Z^j} \frac{1}{Z_z} \exp \left\{ -\alpha [z_s \neq g_s] - \beta_z \sum_{r \in N_s} [z_s^j \neq z_r^j] \right\} \quad \text{pub}$$

$$Z_g = \sum_k \exp \left\{ -\beta_g \sum_{r \in N_s} [g_r \neq k] - \alpha \sum_{j \in J} [z_s^j \neq k] \right\}$$

$$Z_z = \sum_k \exp \left\{ -\alpha [g_s \neq k] - \beta_z \sum_{r \in N_s} [z_r^j \neq k] \right\}$$

$$\text{Let } a_1 = -\sum_{j \in J} [g_s \neq z_s^j] \quad b_1 = -[g_s \neq g_r]$$

$$a_2 = -[z_s \neq g_s], \quad b_2 = -\sum_{r \in N_s} [z_s^j \neq z_r^j]$$

$$E(Y) = E(G, Z) = -\log p(G, Z)$$

$$= \sum_{s \in G} \left( -a_1 \alpha - b_1 \beta_g + \log \sum_k e^{a_1 \alpha + b_1 \beta_g} \right)$$

$$+ \sum_{s \in Z^j} \left( -a_2 \alpha - b_2 \beta_z + \log \sum_k e^{a_2 \alpha + b_2 \beta_z} \right)$$