

• Basic model set:

$$D = \{(x_i, y_i)\}_{i=1}^n \quad \text{with} \quad x_i \in \mathbb{R}^n$$

$$\beta_m \sim N(0, \sigma_\beta^2) \tau_{0\beta} + \delta_0(\beta_m)(1 - \tau_{0\beta}) \quad m=0, 1, \dots, M$$

$$y_i \sim N(\beta_0 + \sum_{m=1}^M \beta_m x_{im}, \sigma_e^2) \quad , i=1, \dots, n$$

$$\tau_{0\beta} \sim \text{Beta}(a, b) \quad , a > 0, b > 0$$

$$\sigma_e^2 \sim \text{Inverse Gamma}(q_1, q_2)$$

$\theta = (\sigma_\beta^2, a, b, \beta_0)$ are hyperparameters optimized using gradient descent

Now we reparametrize β_m as

$$\beta_m = \delta_m \tilde{\beta}_m$$

where $\tilde{\beta}_m \sim N(0, \sigma_\beta^2)$

$$\delta_m \sim \tau_{0\beta}^{\delta_m} (1 - \tau_{0\beta})^{1 - \delta_m}$$

$$\Rightarrow f(\tilde{\beta}_m, \delta) \sim N(\tilde{\beta}_m | 0, \sigma_\beta^2) \tau_{0\beta}^{\delta_m} (1 - \tau_{0\beta})^{1 - \delta_m}$$

achieving the same likelihood with $\beta_m = \tilde{\beta}_m \delta$

We want to approximate $p(\beta, \tau_{0\beta}, \sigma_e^2 | X, y) = p(\tilde{\beta}, \delta, \tau_{0\beta}, \sigma_e^2 | X, y)$

We select the following approximation:

$$q(\tilde{\beta}, \delta, \tau_{0\beta}, \sigma_e^2) = \prod_{i=1}^M N(\tilde{\beta}_m | \mu_m, \sigma_{\beta_m}^2) \tau_{0m}^{\delta_m} (1 - \tau_{0m})^{(1 - \delta_m)} \times$$

$$\text{Beta}(\tau_{0\beta} | c, d) \times \text{IG}(q_3, q_4)$$

The variational parameters are $\phi = (\mu_m, \pi_m, \sigma_{\beta_m}^2, c, d, q_3, q_4)$
 By introducing δ , we get a smooth variational approximation function once integrating out δ .

Evidence lower bound:

$$ELBO = \mathbb{E}_{\substack{\tilde{\beta}, \delta \sim q_{\phi} \\ \pi_{\beta}, \sigma_e}} \left[\ln \frac{P_{\theta}(\tilde{\beta}, \delta, \pi_{\beta}, \sigma_e | y | X)}{q_{\phi}(\tilde{\beta}, \delta, \pi_{\beta}, \sigma_e)} \right]$$

$$= \mathbb{E}_{\substack{\tilde{\beta}, \delta \sim q_{\phi} \\ \pi_{\beta}, \sigma_e}} \left[\ln P_{\theta}(\tilde{\beta}, \delta, \pi_{\beta}, \sigma_e | y | X) - \ln q_{\phi}(\tilde{\beta}, \delta, \pi_{\beta}, \sigma_e) \right]$$

$$= \mathbb{E}_{\substack{\tilde{\beta}, \delta \sim q_{\phi} \\ \pi_{\beta}, \sigma_e}} \left\{ \ln \left[P_{\theta}(y | \tilde{\beta}, \delta, X) P_{\theta}(\tilde{\beta}, \delta) \right] \right\} \\ - \mathbb{E}_{\substack{\tilde{\beta}, \delta \sim q_{\phi} \\ \pi_{\beta}, \sigma_e}} \left[\ln q_{\phi}(\tilde{\beta}, \delta, \pi_{\beta}, \sigma_e) \right]$$

$$= \mathbb{E}_{\substack{\tilde{\beta}, \delta \sim q_{\phi} \\ \pi_{\beta}, \sigma_e}} \left\{ \underbrace{\log P_{\theta}(y | \tilde{\beta}, \delta, X)}_{\text{data likelihood}} + \underbrace{\log P_{\theta}(\tilde{\beta}, \delta)}_{\text{prior}} \right\} \\ - \underbrace{\mathbb{E}_{\substack{\tilde{\beta}, \delta \sim q_{\phi} \\ \pi_{\beta}, \sigma_e}} \left[\log q_{\phi}(\tilde{\beta}, \delta, \pi_{\beta}, \sigma_e) \right]}_{\text{entropy}}$$

① Data likelihood

$$P_{\theta}(y|\tilde{\beta}, \delta, x) = \prod_{i=1}^n \frac{1}{\sigma_e \sqrt{2\pi}} \exp \left\{ -\frac{(y_i - \sum_{m=1}^M x_{im}(\tilde{\beta}_m \delta_m) - \beta_0)^2}{2\sigma_e^2} \right\}$$

$$\begin{aligned} \log P_{\theta}(y|\tilde{\beta}, \delta, x) &= \sum_{i=1}^n \left[-\log(\sigma_e \sqrt{2\pi}) - \frac{(y_i - \sum_{m=1}^M x_{im}(\tilde{\beta}_m \delta_m) - \beta_0)^2}{2\sigma_e^2} \right] \\ &= -\frac{n}{2} \log(\sigma_e^2 2\pi) - \frac{1}{2\sigma_e^2} \sum_{i=1}^n (y_i - \sum_{m=1}^M x_{im}(\tilde{\beta}_m \delta_m) - \beta_0)^2 \end{aligned}$$

We can take the expectation for σ_e^2 by independence of the guide

$$\mathbb{E}_{q_{\theta}}[\log P_{\theta}(y|\tilde{\beta}, \delta, \pi_{\beta}, \sigma_e)]$$

$$= -\frac{n}{2} [\ln(q_4) - \psi(q_3) + \ln(2\pi)] + \frac{1}{2} \frac{q_3}{q_4} \sum_{i=1}^n (y_i - \sum_{m=1}^M x_{im}(\tilde{\beta}_m \delta_m) - \beta_0)^2$$

Need to use numerical approximation to expectation of $\tilde{\beta}, \pi_{\beta}, \delta$
there is no π_{β} since it is dependent on δ .

(2) Prior

$$P_{\theta}(\tilde{\beta}, \delta, \pi_p) = \left[\prod_{m=1}^M \pi_p^{\delta_m} (1-\pi_p)^{1-\delta_m} \frac{1}{\sigma_p \sqrt{2\pi}} \exp\left(-\frac{\tilde{\beta}_m^2}{2\sigma_p^2}\right) \right] \frac{\pi_p^{a-1} (1-\pi_p)^{b-1}}{B(a,b)} \\ \times \frac{q_1}{\Gamma(q_1)} \left(\frac{1}{\sigma_e^2}\right)^{q_1+1} \exp\left(-\frac{q_2}{\sigma_e^2}\right)$$

$$\log P_{\theta}(\tilde{\beta}, \delta, \pi_p) = \sum_{m=1}^M \left[\delta_m \log(\pi_p) + (1-\delta_m) \log(1-\pi_p) - \log(\sigma_p \sqrt{2\pi}) - \frac{\tilde{\beta}_m^2}{2\sigma_p^2} \right] + (a-1) \log \pi_p + (b-1) \log(1-\pi_p) \\ - (\log(\Gamma(a)) + \log(\Gamma(b)) - \log(\Gamma(a+b))) \\ + q_1 \log(q_1) - \log(\Gamma(q_1)) - (q_1+1) \log(\sigma_e^2) - \frac{q_2}{\sigma_e^2}$$

$$= \log(\pi_p) \sum_{m=1}^M \delta_m + \log(1-\pi_p) \sum_{m=1}^M (1-\delta_m) - M \log(\sigma_p \sqrt{2\pi}) \\ - \frac{\sum_{m=1}^M \tilde{\beta}_m^2}{2\sigma_p^2} + (a-1) \log \pi_p + (b-1) \log(1-\pi_p) \\ - \log(\Gamma(a)) - \log(\Gamma(b)) + \log(\Gamma(a+b)) \\ + q_1 \log(q_1) - \log(\Gamma(q_1)) - (q_1+1) \log(\sigma_e^2) - \frac{q_2}{\sigma_e^2}$$

$$E_{\pi_p \sim p}(\log \pi_p) = \psi(c) - \psi(c+d)$$

$$E_{\pi_p \sim p}(\log(1-\pi_p)) = \psi(d) - \psi(c+d)$$

$$E_{\sigma_e^2 \sim p}(\log(\sigma_e^2)) = \ln(q_4) - \psi(q_3)$$

$$E_{\sigma_e^2 \sim p}(\sigma_e^2)^{-1} = \frac{q_3}{q_4}$$

$$\Rightarrow E \left[\log P_{\theta}(\tilde{\beta}, \delta, \pi_p) \right]$$

$$\begin{aligned}
 & \mathbb{E}_{\tilde{\beta}, \delta, \pi_{\beta} \sim q_{\phi}} [\log(1 - \pi_{\beta})] \\
 &= \mathbb{E}(\log \pi_{\beta}) \sum_{m=1}^M \pi_m + \mathbb{E}[\log(1 - \pi_{\beta})] \sum_{m=1}^M (1 - \pi_m) - M \log(\sigma_{\beta} \sqrt{\pi_{\beta}}) \\
 &\quad - \frac{\sum_{m=1}^M (\sigma_{\beta m}^2 + \mu_m^2)}{2\sigma_{\beta}^2} + (a-1) \mathbb{E}(\log \pi_{\beta}) + \\
 &\quad (b-1) \mathbb{E}(\log(1 - \pi_{\beta})) - \log(\Gamma(a)) - \log(\Gamma(b)) + \log(\Gamma(a+b)) \\
 &\quad + q_1 \log(q_2) - \log(\Gamma(q_1)) - (q_1+1) \mathbb{E}(\log(\sigma_{\beta}^2)) - q_2 \mathbb{E}(\sigma_{\beta}^2)
 \end{aligned}$$

ψ is the digamma function, Γ is the gamma function.
 No need to do numerical integration
 include all the variational parameters

③ The negative entropy term

We separate into three parts: $\tilde{\beta}, \delta$; π_{β} ; σ_{β}^2

① For $\tilde{\beta}, \delta$

$$q_{\phi}(\tilde{\beta}, \delta) = \prod_{m=1}^M \frac{1}{\sigma_{\beta m} \sqrt{2\pi}} \exp\left(-\frac{(\tilde{\beta}_m - \mu_m)^2}{2\sigma_{\beta m}^2}\right) \pi_m^{\delta_m} (1 - \pi_m)^{1 - \delta_m}$$

$$\log q_{\phi}(\tilde{\beta}, \delta) = \sum_{m=1}^M \left[-\log(\sigma_{\beta m} \sqrt{2\pi}) - \frac{(\tilde{\beta}_m - \mu_m)^2}{2\sigma_{\beta m}^2} + \delta_m \log(\pi_m) + (1 - \delta_m) \log(1 - \pi_m) \right]$$

$$\mathbb{E}[\log q_{\phi}(\tilde{\beta}, \delta)]$$

$$\stackrel{\tilde{\beta}, \delta \sim q_{\phi}}{=} \sum_{m=1}^M \mathbb{E}_{\tilde{\beta}, \delta} [\log q_{\phi}(\tilde{\beta}_m, \delta_m)] \quad \text{by independent variables entropy}$$

$$\begin{aligned}
&= \sum_{m=1}^M \mathbb{E}_{\tilde{\beta}_m} \left[\log \tau_m (1-\tau_m) N(\tilde{\beta}_m | \mu_m, \sigma_{\beta_m}) \right] \\
&= \sum_{m=1}^M \left[\mathbb{E}_{\tilde{\beta}} [\tau_m \log \tau_m N(\tilde{\beta}_m | \mu_m, \sigma_{\beta_m})] \right. \\
&\quad \left. + \mathbb{E}_{\tilde{\beta}} [(1-\tau_m) \log (1-\tau_m) N(\tilde{\beta}_m | \mu_m, \sigma_{\beta_m})] \right] \\
&= \sum_{m=1}^M \left[\tau_m (\log \tau_m + \mathbb{E}_{\tilde{\beta}} [N(\tilde{\beta}_m | \mu_m, \sigma_{\beta_m})]) \right. \\
&\quad \left. + (1-\tau_m) (\log (1-\tau_m) + \mathbb{E}_{\tilde{\beta}} [N(\tilde{\beta}_m | \mu_m, \sigma_{\beta_m})]) \right] \\
&= \sum_{m=1}^M \left[\tau_m (\log \tau_m - H(N(\tilde{\beta}_m | \mu_m, \sigma_{\beta_m}))) \right. \\
&\quad \left. + (1-\tau_m) (\log (1-\tau_m) - H(N(\tilde{\beta}_m | \mu_m, \sigma_{\beta_m}))) \right] \\
&= \sum_{m=1}^M \left[\tau_m (\log \tau_m - 0.5 \log (2\pi e \sigma_{\beta_m}^2)) \right. \\
&\quad \left. + (1-\tau_m) (\log (1-\tau_m) - 0.5 \log (2\pi e \sigma_{\beta_m}^2)) \right] \\
&= \sum_{m=1}^M \left[\tau_m \log \tau_m - 0.5 \tau_m \log (2\pi e \sigma_{\beta_m}^2) + \right. \\
&\quad \left. (1-\tau_m) \log (1-\tau_m) - 0.5 (1-\tau_m) \log (2\pi e \sigma_{\beta_m}^2) \right]
\end{aligned}$$

(b) For π_β

$$\mathbb{E}_{\pi_\beta} [-\log q_\phi(\pi_\beta)] = \ln \left(\frac{\Gamma(c)\Gamma(d)}{\Gamma(c+d)} \right)$$

$$- (c-1)\psi(c) - (d-1)\psi(d) + (c+d-2)\psi(c+d)$$

(c) For σ_e^2

$$\mathbb{E}_{\sigma_e^2 \sim q_\phi} [-\log q_\phi(\sigma_e^2)]$$

$$= q_3 + \ln(q_4) + \ln(\Gamma(q_3)) - (q_3+1)\psi(q_3)$$