0725

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$$Y - \bar{y}1_n = b^*(X)\gamma + Z^*\beta + \epsilon$$
$$\tilde{Y} = b^*(X)\gamma + Z^*\beta + \epsilon$$
$$\tilde{Y} = W\Theta + \epsilon$$

Where

$$\Theta = \{\gamma', \beta'\}' = \{\theta_{11}, \dots, \theta_{Gm_G}\}'W = \{b^*(X), Z^*\} = \{W_{11}, \dots W_{Gm_G}\}\epsilon \sim N(0, \sigma^2)$$

0.1 Prior

$$\begin{split} Y|W,\Theta &\sim N(W\Theta,\sigma^2I) \\ \theta_{gj}|\pi_g,\sigma^2,v_{gj}^2 &\sim^{ind} \pi_g I(\theta_{gj}=0) + (1-\pi_g)N(0,\sigma^2v_{gj}^2), \quad g=1\ldots,G \quad ,j=1,\ldots,m_g \\ v_{gj}^2|\lambda^2 &\sim^{iid} Exp(\lambda^2/2) \\ \lambda^2 &\sim Gamma(a_{\lambda^2},b_{\lambda^2}) \\ \pi_g &\sim^{ind} Beta(a_{\pi_g},b_{\pi_g}) \\ \sigma^2 &\sim Inverse-Gamma(a,b), \quad a=0, \ b=1 \end{split}$$

0.2 Posterior

$$\begin{split} p(\Theta, V, \lambda^2, \pi, \sigma^2 | \tilde{Y}) &\propto p(\tilde{Y} | \Theta, \sigma^2) \prod_{g=1}^G \prod_{j=1}^{m_g} p(\theta_{gj} | \pi_g, \sigma^2, v_{gj}^2) \\ &\prod_{g=1}^G \prod_{j=1}^{m_g} p(v_{gj}^2 | \lambda^2) \prod_{g=1}^G p(\pi_g) p(\lambda^2) p(\sigma^2) \\ &\propto (\sigma^2)^{-n/2} \prod_{g=1}^G \prod_{j=1}^{m_g} exp\left(-\frac{\theta_{gj}^2}{2\sigma^2} W_{gj}' W_{gj} + \frac{\theta_{gj}}{\sigma^2} W_{gj}' (\tilde{Y} - W_{-gj} \Theta_{-gj})\right) \\ &\prod_{g=1}^G \prod_{j=1}^{m_g} \left[\pi_g I(\theta_{gj} = 0) + (1 - \pi_g) (\sigma^2 v_{gj}^2)^{-1/2} exp\left(-\frac{1}{2\sigma^2 v_{gj}^2} \theta_{gj}^2\right) \right] \\ &\prod_{g=1}^G \prod_{j=1}^{m_g} v_{gj}^2 \frac{\lambda^2}{2} exp\left(-\frac{\lambda^2}{2} v_{gj}^2\right) \\ &\prod_{g=1}^G (\pi_g)^{a_{\pi_g} - 1} (1 - \pi_g)^{b_{\pi_g} - 1} \\ &(\lambda^2)^{a_{\lambda^2} - 1} exp(-b_{\lambda^2} \lambda^2) \\ &(\sigma^2)^{-1} exp\left(\frac{1}{\sigma^2}\right) \end{split}$$

0.3 MFVB

$$\begin{split} p(\Theta, V, \lambda^2, \pi, \sigma^2 | \tilde{Y}) &\approx q(\Theta, V, \lambda^2, \pi, \sigma^2) \\ &= \prod_{g=1}^G \prod_{j=1}^{m_g} q_1(\theta_{gj}) \prod_{g=1}^G \prod_{j=1}^{m_g} q_2(v_{gj}) \prod_{g=1}^G q_3(\pi_g) q_4(\lambda^2) q_5(\sigma^2) \end{split}$$

0.3.1 Variational Distribution of Θ

$$\begin{split} q^*(\theta_{gj}) \propto & E_{-\theta_{gj}} \left[p(\Theta, V, \lambda^2, \pi, \sigma^2 | \tilde{Y}) \right] \\ \propto & l_{gj} I(\theta_{gj} = 0) + (1 - l_{gj}) N(\mu_{gj}, \Sigma_{gj}) \end{split}$$

where

$$\Sigma_{gj} = \left\langle \sigma^2 \right\rangle \left\langle \frac{1}{W_{gj}'W_{gj} + \frac{1}{v_{gj}^2}} \right\rangle \mu_{gj} = \left\langle \frac{1}{\sigma^2} \right\rangle \Sigma_{gj} (\tilde{Y} - W_{-gj} \left\langle \Theta - gj \right\rangle)' W_{gj} l_{gj} = \left\langle \frac{\pi_g}{\pi_g + (1 - \pi_g)(1 + v_{gj}W_{gj}'W_{gj})^{-1/2} exp^{-1/2} exp^{-1/$$

and

$$E[\theta_{gj}] = (1 - l_{gj})\mu_{gj}E[\theta_{gj}^2] = (1 - l_{gj})(\Sigma_{gj} + \mu_{gj})E[I(\theta_{gj}) = 0] = l_{gj}$$

0.3.2 Variational Distribution of π_g

$$\begin{split} q^*(\pi_g) \propto & E_{-pi_g} \left[p(\Theta, V, \lambda^2, \pi, \sigma^2 | \tilde{Y}) \right] \\ \sim & Beta(a_{\pi_g} + \sum_{j=1}^{m_g} < I(\theta_{gj}) = 0 >), b_{\pi_g} + m_g - \sum_{j=1}^{m_g} < I(\theta_{gj}) = 0 >)) \end{split}$$

0.3.3 Variational Distribution of σ^2

$$\begin{split} q^*(\sigma^2) \propto & E_{-\sigma^2} \left[p(\Theta, V, \lambda^2, \pi, \sigma^2 | \tilde{Y}) \right] \\ \sim & IG \left(\frac{n + \sum_{g=1}^G m_g - \sum_{g=1}^G \sum_{j=1}^{m_g} < I(\theta_{gj} = 0) > -1}{2}, \frac{<\|(\tilde{Y} - W\Theta\|_2^2 > + < \Theta >' D^{-1} < \Theta >)}{2} \right) \end{split}$$

where

$$D = diag(\langle v_{11}^2 \rangle, \dots, \langle v_{Gm_G}^2 \rangle)$$

0.3.4 Variational Distribution of λ^2

$$\begin{split} q^*(\lambda^2) \propto & E_{-\lambda^2} \left[p(\Theta, V, \lambda^2, \pi, \sigma^2 | \tilde{Y}) \right] \\ \sim & Gamma \left(\sum_{g=1}^G m_g + a_{\lambda^2}, \frac{\sum_{g=1}^G \sum_{j=1}^{m_g} v_{gj}^2}{2} + b_{\lambda^2} \right) \end{split}$$

0.3.5 Variational Distribution of $(v_{gj}^2)^{-1}$

$$\begin{split} q^*((v_{gj}^2)^{-1}) \propto & E_{-v_{gj}^2} \left[p(\Theta, V, \lambda^2, \pi, \sigma^2 | \tilde{Y}) \right] \\ \sim & < I(\theta_{gj} = 0) > Inverse - Gamma(1, \lambda^2/2) \\ & + < I(\theta_{gj} \neq 0) > Inverse - Gaussian(<\theta_{gj}^{-1} > < \sqrt{\lambda^2} > < \sqrt{\sigma^2} >, < \lambda^2 >) \end{split}$$

1 Simulation when G=1