

Multivariable Two-sample MR with tissue indicator

Without considering LD, the causal relationship is:

$$\begin{aligned}\hat{\gamma}_j \mid \gamma_j, \hat{\mathbf{S}}_{\gamma_j} &\sim \mathcal{N}(\gamma_j, \hat{\mathbf{S}}_{\gamma_j}) \\ \hat{\mathbf{\Gamma}} \mid \mathbf{\Gamma}, \hat{\mathbf{S}}_{\mathbf{\Gamma}} &\sim \mathcal{N}(\mathbf{\Gamma}, \hat{\mathbf{S}}_{\mathbf{\Gamma}})\end{aligned}\tag{1}$$

The causal relationship is:

$$\Gamma_i = \alpha_i + \delta_1 \beta_1 \gamma_{i1} + \cdots + \delta_K \beta_K \gamma_{iK}\tag{2}$$

Assume that

$$\gamma_{ij} \sim \mathcal{N}(0, \sigma_\gamma^2), \delta_j \sim \text{Bernoulli}(\pi_j)\tag{3}$$

The latent variable: γ, α, δ and the parameter set $\Theta \stackrel{\text{def}}{=} \{\sigma_\alpha^2, \sigma_\gamma^2, \beta, \pi\}$. The complete-data likelihood of model is

$$\begin{aligned}&\log \Pr(\hat{\mathbf{\Gamma}}, \hat{\gamma}_1, \dots, \hat{\gamma}_K, \alpha \mid \hat{\mathbf{S}}_{\gamma_1}, \dots, \hat{\mathbf{S}}_{\gamma_K}, \hat{\mathbf{S}}_{\mathbf{\Gamma}}; \Theta) \\&= \log \mathcal{N}(\hat{\mathbf{\Gamma}} \mid \alpha + \sum \delta_j \beta_j \gamma_j, \hat{\mathbf{S}}_{\mathbf{\Gamma}}) \left(\prod_{j=1}^K \mathcal{N}(\hat{\gamma}_j \mid \gamma_j, \hat{\mathbf{S}}_{\gamma_j}) \right) \mathcal{N}(\alpha \mid \mathbf{0}, \sigma_\alpha^2 \mathbf{I}_p) \prod_{j=1}^K \mathcal{N}(\gamma_j \mid 0, \sigma_\gamma^2 \mathbf{I}_p) \prod_{j=1}^K \mathbf{B}(1, \pi_j) \\&= -\frac{p}{2} \log(2\pi) - \frac{p}{2} \log |\hat{\mathbf{S}}_{\mathbf{\Gamma}}| - \frac{1}{2} \left(\hat{\mathbf{\Gamma}} - \alpha - \sum_{j=1}^K \delta_j \beta_j \gamma_j \right)^\top \hat{\mathbf{S}}_{\mathbf{\Gamma}}^{-1} \left(\hat{\mathbf{\Gamma}} - \alpha - \sum_{j=1}^K \delta_j \beta_j \gamma_j \right) \\&\quad + \sum_{j=1}^K \left[-\frac{p}{2} \log(2\pi) - \frac{p}{2} \log |\hat{\mathbf{S}}_{\gamma_j}| - \frac{1}{2} (\hat{\gamma}_j - \gamma_j)^\top \hat{\mathbf{S}}_{\gamma_j}^{-1} (\hat{\gamma}_j - \gamma_j) \right] \\&\quad - \frac{p}{2} \log(2\pi) - \frac{p}{2} \log \sigma_\alpha^2 - \frac{1}{2\sigma_\alpha^2} \sum_{i=1}^p \alpha_i^2 \\&\quad + \sum_{j=1}^K \left[-\frac{p}{2} \log(2\pi) - \frac{p}{2} \log \sigma_\gamma^2 - \frac{1}{2\sigma_\gamma^2} \sum_{i=1}^p \gamma_{ij}^2 \right] \\&\quad + \sum_{j=1}^K [\delta_j \log \pi_j + (1 - \delta_j) \log(1 - \pi_j)] \\&= \sum_{j=1}^K \left(\delta_j \beta_j \hat{\mathbf{\Gamma}}^\top \hat{\mathbf{S}}_{\mathbf{\Gamma}}^{-1} - \delta_j \beta_j \alpha^\top \hat{\mathbf{S}}_{\mathbf{\Gamma}}^{-1} - \delta_j \beta_j \sum_{t \neq j}^K \delta_t \beta_t \gamma_t^\top \hat{\mathbf{S}}_{\mathbf{\Gamma}}^{-1} + \hat{\gamma}_j^\top \hat{\mathbf{S}}_{\gamma_j}^{-1} \right) \gamma_j - \sum_{j=1}^K \frac{1}{2} \gamma_j^\top \left(\delta_j^2 \beta_j^2 \hat{\mathbf{S}}_{\mathbf{\Gamma}}^{-1} + \hat{\mathbf{S}}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \gamma_j \\&\quad + \hat{\mathbf{\Gamma}}^\top \hat{\mathbf{S}}_{\mathbf{\Gamma}}^{-1} \alpha - \frac{1}{2} \alpha^\top \left(\hat{\mathbf{S}}_{\mathbf{\Gamma}}^{-1} + \sigma_\alpha^{-2} \mathbf{I} \right) \alpha \\&\quad - \frac{pK}{2} \log \sigma_\gamma^2 - \frac{p}{2} \log \sigma_\alpha^2 + \sum_{j=1}^K [\delta_j \log \pi_j + (1 - \delta_j) \log(1 - \pi_j)] + \text{const.}\end{aligned}\tag{4}$$

We use mean field theory to approximate the posterior $q(\gamma, \alpha) = \prod_{i=1}^p q(\alpha_i) \prod_{i=1}^p \prod_{j=1}^K q(\gamma_{ij} \mid \delta_j) \prod_{j=1}^K q(\delta_j)$. The posterior distribution of $\gamma_{ij} \sim \mathcal{N}(\mu_{ij}, \sigma_{ij}^2)$ when $\delta_j = 1$, where

$$\begin{aligned}-\frac{1}{2\sigma_{ij}^2} &= -\frac{\beta_j^2}{2} \frac{1}{\hat{\mathbf{S}}_{\mathbf{\Gamma}_i}^2} - \frac{1}{2\hat{\mathbf{S}}_{\gamma_i}^2} - \frac{1}{2\sigma_\gamma^2} \\ \frac{\mu_{ij}}{\sigma_{ij}^2} &= \beta_j \frac{\hat{\mathbf{\Gamma}}_i}{\hat{\mathbf{S}}_{\mathbf{\Gamma}_i}^2} - \frac{\beta_j}{\hat{\mathbf{S}}_{\mathbf{\Gamma}_i}} \cdot \frac{\langle \alpha_i \rangle}{\hat{\mathbf{S}}_{\mathbf{\Gamma}_i}} + \frac{\hat{\gamma}_i}{\hat{\mathbf{S}}_{\gamma_i}^2} - \frac{\beta_j \sum_{t \neq j}^K \beta_t \langle \delta_t \gamma_{it} \rangle}{\hat{\mathbf{S}}_{\mathbf{\Gamma}_i}^2}\end{aligned}\tag{5}$$

when $\delta_j = 0$, we have $\gamma_{ij} \sim \mathcal{N}(\mu_{ij}^*, \sigma_{ij}^{2*})$, where

$$\begin{aligned}-\frac{1}{2\sigma_{ij}^{2*}} &= -\frac{1}{2\hat{\mathbf{S}}_{\gamma_i}^2} - \frac{1}{2\sigma_\gamma^2} \\ \frac{\mu_{ij}^*}{\sigma_{ij}^{2*}} &= \frac{\hat{\gamma}_{ij}}{\hat{\mathbf{S}}_{\gamma_i}^2}\end{aligned}$$

The posterior distribution of $\alpha_i \sim \mathcal{N}(\tilde{\mu}_i, \tilde{\sigma}_i^2)$, where

$$\begin{aligned} -\frac{1}{2\tilde{\sigma}_i^2} &= -\frac{1}{2\hat{\Sigma}_{\Gamma_i}^2} - \frac{1}{2\sigma_\alpha^2}, \\ \frac{\tilde{\mu}_i}{\tilde{\sigma}_i^2} &= \frac{\hat{\Gamma}_i}{\hat{\Sigma}_{\Gamma_i}^2} - \frac{\sum_{j=1}^K \beta_j \langle \delta_j \gamma_{ij} \rangle}{\hat{\Sigma}_{\Gamma_i}^2}, \end{aligned} \quad (6)$$

where $\langle \gamma_k \rangle \stackrel{\text{def}}{=} E_q(\gamma_k)$. Similarly, $\alpha \sim \mathcal{N}(\alpha | \mu_\alpha, \Sigma_\alpha)$, where $\mu_\alpha = (\tilde{\mu}_1, \dots, \tilde{\mu}_p)^\top$ and $\Sigma_\alpha = \text{diag}(\{\tilde{\sigma}_1^2, \dots, \tilde{\sigma}_p^2\})$.

We know that δ_j is a binary random variable, so we can let $\omega_j = q(\delta_j = 1)$, then the optimal variational distribution will be given by,

$$q(\gamma_{ij}, \alpha_i, \delta_j) = [\omega_j \mathcal{N}(\gamma_{ij} | \mu_{ij}, \sigma_{ij}^2)]^{\delta_j} [(1 - \omega_j) \mathcal{N}(\gamma_{ij} | \mu_{ij}^*, \sigma_{ij}^{2*})]^{1-\delta_j} \mathcal{N}(\alpha_i | \tilde{\mu}_i, \tilde{\sigma}_i^2)$$

In the M-step, we obtain the new updates for all the parameters θ by setting the derivative of

$$E_q \left\{ \log \Pr \left(\hat{\Gamma}, \hat{\gamma}_1, \dots, \hat{\gamma}_K, \alpha | \hat{\Sigma}_{\gamma_1}, \dots, \hat{\Sigma}_{\gamma_K}, \hat{\Sigma}_\Gamma; \Theta \right) \right\}$$

to zeros.

We have

$$\begin{aligned} & \mathbb{E}_q \left[\gamma_j^\top \left(\delta_j^2 \beta_j^2 \hat{\Sigma}_\Gamma^{-1} + \hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \gamma_j \right] \\ &= \mathbb{E}_q \left[\gamma_j^\top \left(\delta_j^2 \beta_j^2 \hat{\Sigma}_\Gamma^{-1} + \hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \gamma_j | \delta_j = 0 \right] \mathbb{P}(\delta_j = 0) + \mathbb{E}_q \left[\gamma_j^\top \left(\delta_j^2 \beta_j^2 \hat{\Sigma}_\Gamma^{-1} + \hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \gamma_j | \delta_j = 1 \right] \mathbb{P}(\delta_j = 1) \\ &= (1 - \omega_j) \left\{ \mu_j^{*\top} \left(\hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \mu_j^* + \text{Tr} \left(\left(\hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \Sigma_{\gamma_j}^* \right) \right\} \\ &+ \omega_j \left\{ \mu_j^\top \left(\beta_j^2 \hat{\Sigma}_\Gamma^{-1} + \hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \mu_j + \text{Tr} \left(\left(\beta_j^2 \hat{\Sigma}_\Gamma^{-1} + \hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \Sigma_{\gamma_j} \right) \right\} \end{aligned}$$

and

$$\begin{aligned} & \mathbb{E}_q \left[\left(\delta_j \beta_j \hat{\Gamma}^\top \hat{\Sigma}_\Gamma^{-1} - \delta_j \beta_j \alpha^\top \hat{\Sigma}_\Gamma^{-1} - \delta_j \beta_j \sum_{t \neq j}^K \delta_t \beta_t \gamma_t^\top \hat{\Sigma}_\Gamma^{-1} + \hat{\gamma}_j^\top \hat{\Sigma}_{\gamma_j}^{-1} \right) \gamma_j \right] \\ &= \left(\omega_j \beta_j \hat{\Gamma}^\top \hat{\Sigma}_\Gamma^{-1} - \omega_j \beta_j \mu_\alpha^\top \hat{\Sigma}_\Gamma^{-1} - \omega_j \beta_j \sum_{t \neq j}^K \omega_t \beta_t \mu_t^\top \hat{\Sigma}_\Gamma^{-1} + \hat{\gamma}_j^\top \hat{\Sigma}_{\gamma_j}^{-1} \right) \mu_j \end{aligned}$$

and

$$\mathbb{E}_q \left[\hat{\Gamma}^\top \hat{\Sigma}_\Gamma^{-1} \alpha - \frac{1}{2} \alpha^\top \left(\hat{\Sigma}_\Gamma^{-1} + \sigma_\alpha^{-2} \mathbf{I} \right) \alpha \right] = \hat{\Gamma}^\top \hat{\Sigma}_\Gamma^{-1} \mu_\alpha - \left\{ \mu_\alpha^\top \left(\hat{\Sigma}_\Gamma^{-1} + \sigma_\alpha^{-2} \mathbf{I} \right) \mu_\alpha + \text{Tr} \left(\left(\hat{\Sigma}_\Gamma^{-1} + \sigma_\alpha^{-2} \mathbf{I} \right) \Sigma_\alpha \right) \right\}$$

and

$$\mathbb{E} [\delta_j \log \pi_j + (1 - \delta_j) \log (1 - \pi_j)] = \omega_j \log \pi_j + (1 - \omega_j) \log (1 - \pi_j)$$

We can evaluate the ELBO $\mathcal{L}(\Theta)$:

$$\mathcal{L}(\Theta) = E_q \left\{ \log \Pr \left(\hat{\Gamma}, \hat{\gamma}_1, \dots, \hat{\gamma}_K, \alpha, \gamma_1, \dots, \gamma_K, \delta | \hat{\Sigma}_{\gamma_1}, \dots, \hat{\Sigma}_{\gamma_K}, \hat{\Sigma}_\Gamma; \Theta \right) \right\} - \mathbb{E}_q \log q(\alpha, \gamma_1, \dots, \gamma_K, \delta)$$

Thus, we have

$$\begin{aligned} & E_q \left\{ \log \Pr \left(\hat{\Gamma}, \hat{\gamma}_1, \dots, \hat{\gamma}_K, \alpha, \gamma_1, \dots, \gamma_K, \delta | \hat{\Sigma}_{\gamma_1}, \dots, \hat{\Sigma}_{\gamma_K}, \hat{\Sigma}_\Gamma; \Theta \right) \right\} \\ &= \sum_{j=1}^K \left(\omega_j \beta_j \hat{\Gamma}^\top \hat{\Sigma}_\Gamma^{-1} - \omega_j \beta_j \mu_\alpha^\top \hat{\Sigma}_\Gamma^{-1} - \omega_j \beta_j \sum_{t \neq j}^K \omega_t \beta_t \mu_t^\top \hat{\Sigma}_\Gamma^{-1} + \hat{\gamma}_j^\top \hat{\Sigma}_{\gamma_j}^{-1} \right) \mu_j \\ &\quad - \frac{1}{2} \sum_{j=1}^K (1 - \omega_j) \left\{ \mu_j^{*\top} \left(\hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \mu_j^* + \text{Tr} \left(\left(\hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \Sigma_{\gamma_j}^* \right) \right\} \\ &\quad - \frac{1}{2} \sum_{j=1}^K \omega_j \left\{ \mu_j^\top \left(\beta_j^2 \hat{\Sigma}_\Gamma^{-1} + \hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \mu_j + \text{Tr} \left(\left(\beta_j^2 \hat{\Sigma}_\Gamma^{-1} + \hat{\Sigma}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I} \right) \Sigma_{\gamma_j} \right) \right\} \\ &\quad + \hat{\Gamma}^\top \hat{\Sigma}_\Gamma^{-1} \mu_\alpha - \left\{ \mu_\alpha^\top \left(\hat{\Sigma}_\Gamma^{-1} + \sigma_\alpha^{-2} \mathbf{I} \right) \mu_\alpha + \text{Tr} \left(\left(\hat{\Sigma}_\Gamma^{-1} + \sigma_\alpha^{-2} \mathbf{I} \right) \Sigma_\alpha \right) \right\} \\ &\quad - \frac{pK}{2} \log \sigma_\gamma^2 - \frac{p}{2} \log \sigma_\alpha^2 + \sum_{j=1}^K [\omega_j \log \pi_j + (1 - \omega_j) \log (1 - \pi_j)] + \text{const.} \end{aligned}$$

Since

$$q(\gamma_{ij}, \alpha_i, \delta_j) = [\omega_j \mathcal{N}(\gamma_{ij} | \mu_{ij}, \sigma_{ij}^2)]^{\delta_j} [(1 - \omega_j) \mathcal{N}(\gamma_{ij} | \mu_{ij}^*, \sigma_{ij}^{2*})]^{1 - \delta_j} \mathcal{N}(\alpha_i | \tilde{\mu}_i, \tilde{\sigma}_i^2)$$

The second term is

$$-\mathbb{E}_q \log q(\boldsymbol{\alpha}, \boldsymbol{\gamma}_1, \dots, \boldsymbol{\gamma}_K, \boldsymbol{\delta}) = \sum_{j=1}^K \frac{1}{2} \omega_j \log \det(\boldsymbol{\Sigma}_{\gamma_j}) + \frac{1}{2} (1 - \omega_j) \log \det(\boldsymbol{\Sigma}_{\gamma_j}^*) - \omega_j \log \omega_j - (1 - \omega_j) \log (1 - \omega_j)$$

Maximizing \mathcal{L} w.r.t. ω_j is equivalent to set the following equation to zero

$$\begin{aligned} & \left(\beta_j \hat{\boldsymbol{\Gamma}}^\top \hat{\mathbf{S}}_\Gamma^{-1} - \beta_j \boldsymbol{\mu}_\alpha^\top \hat{\mathbf{S}}_\Gamma^{-1} - \beta_j \sum_{t \neq j}^K \omega_t \beta_t \boldsymbol{\mu}_t^\top \hat{\mathbf{S}}_\Gamma^{-1} \right) \boldsymbol{\mu}_j \\ & + \frac{1}{2} \left\{ \boldsymbol{\mu}_j^{*\top} (\hat{\mathbf{S}}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I}) \boldsymbol{\mu}_j^* + \text{Tr} \left((\hat{\mathbf{S}}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I}) \boldsymbol{\Sigma}_{\gamma_j}^* \right) \right\} \\ & - \frac{1}{2} \left\{ \boldsymbol{\mu}_j^\top (\beta_j^2 \hat{\mathbf{S}}_\Gamma^{-1} + \hat{\mathbf{S}}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I}) \boldsymbol{\mu}_j + \text{Tr} \left((\beta_j^2 \hat{\mathbf{S}}_\Gamma^{-1} + \hat{\mathbf{S}}_{\gamma_j}^{-1} + \sigma_\gamma^{-2} \mathbf{I}) \boldsymbol{\Sigma}_{\gamma_j} \right) \right\} \\ & + \log \frac{\pi_j}{1 - \pi_j} \\ & + \frac{1}{2} \log \det(\boldsymbol{\Sigma}_{\gamma_j}) - \frac{1}{2} \log \det(\boldsymbol{\Sigma}_{\gamma_j}^*) - \log \frac{\omega_j}{1 - \omega_j} \end{aligned}$$

which is

$$\boldsymbol{\mu}_j^\top (\boldsymbol{\Sigma}_{\gamma_j}^{-1} \boldsymbol{\mu}_j - \hat{\mathbf{S}}_{\gamma_j}^{-1} \hat{\boldsymbol{\gamma}}_j) + \frac{1}{2} \left\{ \boldsymbol{\mu}_j^{*\top} \boldsymbol{\Sigma}_{\gamma_j}^{*-1} \boldsymbol{\mu}_j^* \right\} - \frac{1}{2} \left\{ \boldsymbol{\mu}_j^\top \boldsymbol{\Sigma}_{\gamma_j}^{-1} \boldsymbol{\mu}_j \right\} + \log \frac{\pi_j}{1 - \pi_j} + \frac{1}{2} \log \det(\boldsymbol{\Sigma}_{\gamma_j}) - \frac{1}{2} \log \det(\boldsymbol{\Sigma}_{\gamma_j}^*) - \log \frac{\omega_j}{1 - \omega_j} = 0$$

So we obtain

$$\omega_j = \frac{1}{1 + \exp(-\mathbf{b}_j)}$$

where

$$\mathbf{b}_j = \frac{1}{2} \boldsymbol{\mu}_j^\top \boldsymbol{\Sigma}_{\gamma_j}^{-1} \boldsymbol{\mu}_j + \frac{1}{2} \boldsymbol{\mu}_j^{*\top} \boldsymbol{\Sigma}_{\gamma_j}^{*-1} \boldsymbol{\mu}_j^* - \hat{\boldsymbol{\gamma}}_j^\top \hat{\mathbf{S}}_{\gamma_j}^{-1} \boldsymbol{\mu}_j + \log \frac{\pi_j}{1 - \pi_j} + \frac{1}{2} \log \frac{\det(\boldsymbol{\Sigma}_{\gamma_j})}{\det(\boldsymbol{\Sigma}_{\gamma_j}^*)}$$

M-step. We derive the updating equations for parameters $\beta_j, \pi_j, \sigma_\gamma^2, \sigma_\alpha^2$. We first derive the updating equation for β_j . The terms in $\partial \mathcal{L}(\Theta) / \partial \beta_j$ involving β_j are

$$\left(\omega_j \hat{\boldsymbol{\Gamma}}^\top \hat{\mathbf{S}}_\Gamma^{-1} - \omega_j \boldsymbol{\mu}_\alpha^\top \hat{\mathbf{S}}_\Gamma^{-1} - \omega_j \sum_{t \neq j}^K \omega_t \beta_t \boldsymbol{\mu}_t^\top \hat{\mathbf{S}}_\Gamma^{-1} \right) \boldsymbol{\mu}_j - \beta_j \omega_j \left\{ \boldsymbol{\mu}_j^\top (\hat{\mathbf{S}}_\Gamma^{-1}) \boldsymbol{\mu}_j + \text{Tr} \left((\hat{\mathbf{S}}_\Gamma^{-1}) \boldsymbol{\Sigma}_{\gamma_j} \right) \right\} = 0$$

Finally, we have

$$\beta_j = \frac{(\hat{\boldsymbol{\Gamma}}^\top \hat{\mathbf{S}}_\Gamma^{-1} - \boldsymbol{\mu}_\alpha^\top \hat{\mathbf{S}}_\Gamma^{-1} - \sum_{t \neq j}^K \omega_t \beta_t \boldsymbol{\mu}_t^\top \hat{\mathbf{S}}_\Gamma^{-1}) \boldsymbol{\mu}_j}{\boldsymbol{\mu}_j^\top \hat{\mathbf{S}}_\Gamma^{-1} \boldsymbol{\mu}_j + \text{Tr}(\hat{\mathbf{S}}_\Gamma^{-1} \boldsymbol{\Sigma}_{\gamma_j})}$$

By setting $\partial \mathcal{L}(\Theta) / \partial \sigma_\alpha^2 = 0$, we have

$$\frac{1}{2} \sigma_\alpha^{-4} \{ \boldsymbol{\mu}_\alpha^\top \boldsymbol{\mu}_\alpha + \text{Tr}(\boldsymbol{\Sigma}_\alpha) \} - \frac{p}{2} \sigma_\alpha^{-2} = 0$$

So we have

$$\sigma_\alpha^2 = \frac{\boldsymbol{\mu}_\alpha^\top \boldsymbol{\mu}_\alpha + \text{Tr}(\boldsymbol{\Sigma}_\alpha)}{p}$$

By setting $\partial \mathcal{L}(\Theta) / \partial \sigma_\gamma^2 = 0$, we have

$$\sum_{j=1}^K \left\{ \frac{\sigma_\gamma^{-4}}{2} (1 - \omega_j) \left\{ \boldsymbol{\mu}_j^{*\top} \boldsymbol{\mu}_j^* + \text{Tr}(\boldsymbol{\Sigma}_{\gamma_j}^*) \right\} + \frac{\sigma_\gamma^{-4}}{2} \omega_j \left\{ \boldsymbol{\mu}_j^\top \boldsymbol{\mu}_j + \text{Tr}(\boldsymbol{\Sigma}_{\gamma_j}) \right\} \right\} - \frac{pK}{2} \sigma_\gamma^{-2} = 0$$

So we have

$$\sigma_\gamma^2 = \frac{\sum_{j=1}^K \left\{ (1 - \omega_j) \left\{ \boldsymbol{\mu}_j^{*\top} \boldsymbol{\mu}_j^* + \text{Tr}(\boldsymbol{\Sigma}_{\gamma_j}^*) \right\} + \omega_j \left\{ \boldsymbol{\mu}_j^\top \boldsymbol{\mu}_j + \text{Tr}(\boldsymbol{\Sigma}_{\gamma_j}) \right\} \right\}}{pK}$$

By setting $\partial \mathcal{L}(\Theta) / \partial \sigma_\gamma^2 = 0$, we have

$$\pi_j = \omega_j$$