

Appendix

Appendix: The procedure of parameter estimation

Denote $\theta^* = (\beta^T, \alpha, \omega, u^T, \sigma_0^2)$, and $a(x) = a(x; \beta^T, \alpha, \omega | V_F, V_B)$ since $a(x)$ is a functional vector of β^T, α, ω for given V_F and V_B . The log-likelihood function of θ^* with observations Y_{ij} at replication j of dose-level x_i ($j=1,2,\dots, k_i; i=1,2,\dots, n$) for given all of V_F and V_B is

$$l(\theta^* | x, y; V_F, V_B) = -\frac{N}{2} \log(2\pi\sigma_0^2) - \frac{1}{2\pi\sigma_0^2} \sum_{i=1}^n \sum_{j=1}^{k_i} \left(y_{ij} - 100u^T a(x_i; \beta^T, \alpha, \omega | V_F, V_B) \right)^2 \quad (\text{A1})$$

where $N = k_1 + \dots + k_n$. Then, the maximum likelihood estimates (MLEs) of u and σ_0^2 are given by

$$u = \left(\sum_{i=1}^n k_i a^T(x_i) a(x_i) \right)^{-1} \sum_{i=1}^n \sum_{j=1}^{k_i} (100 - y_{ij}) a(x_i) \quad (\text{A2})$$

$$\sigma_0^2 = \frac{1}{N} \sum_{i=1}^n \sum_{j=1}^{k_i} \left(y_{ij} - 100 - u^T a(x_i) \right)^2$$

and the MLEs of β^T, α, ω are determined by

$$\min_{\beta^T, \alpha, \omega} \sum_{i=1}^n \sum_{j=1}^{k_i} \left(y_{ij} - 100 - u^T a(x_i; \beta^T, \alpha, \omega | V_F, V_B) \right)^2 \quad (\text{A3})$$

The iteration algorithm of parameter estimation:

Step 1. For given $\mu_1^{(t)}$ and $\sigma_0^{2(t)}$ we take iid samples $\{V_{F_i}^{(t)}, V_{B_i}^{(t)}; i=1,2,\dots\}$ from the normal distribution $N(\mu_1^{(t)}, \sigma_0^{2(t)})$, an ECM algorithm is employed to get the MLEs of parameters $\theta^{(t)} = (\beta^{T(t)}, \alpha^{(t)}, \omega^{(t)}, u^{T(t)}, \sigma_0^{2(t)})$, based on (A2) and (A3).

Step 2. Using equation (3), we have that for given dose-level x_i

$$\begin{aligned} EY(x_i) &= \frac{1}{k_i} \sum_{j=1}^{k_i} y_{ij} = 100 + u^{T(t)} E \left(a(x_i; \beta^{T(t)}, \alpha^{(t)}, \omega^{(t)} | V_F, V_B) \right) \\ &= 100 + u^{T(t)} a(x_i; \beta^{T(t)}, \alpha^{(t)}, \omega^{(t)} | E(V_F) = E(V_B) = \psi) \end{aligned} \quad (\text{A4})$$

for $i=1, 2, \dots, n$. Solve equation (A4) with respect to ψ . Denote the solutions by $\psi_1, \psi_2, \dots, \psi_n$, we obtain the estimates of μ_1 and σ_1^2 as

$$\mu_1^{(t+1)} = \frac{1}{n} \sum_{i=1}^n \psi_i \text{ and } \sigma_1^{2(t+1)} = \frac{1}{n-1} \sum_{i=1}^n \left(\psi_i - \mu_1^{(t+1)} \right)^2$$

The algorithm is iterated until $\|\theta^{(t+1)} - \theta^{(t)}\|$ is sufficiently small. Assume that the algorithm converged at the $(t+1)$ th iteration, then the MLE $\hat{\theta} = \theta^{(t+1)}$.