

Online Supplementary Material for
**On the Determination of Varying Group Sizes for Pooling
 Procedure**

1 Calculation of the Fisher information matrix $I_{\beta,k}$

The log likelihood function is defined by $l = \log L$, where the likelihood function

$$L = \prod_{i=1}^m \left[S_e - r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)) \right]^{z_i} \left[1 - S_e + r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)) \right]^{1-z_i}.$$

We obtain the first and second derivative of l , which are

$$\frac{\partial l}{\partial \beta} = \sum_{i=1}^m \left[z_i \frac{r \sum_{l=1}^{k_i} g'(X_{il}^T \beta) X_{il} \prod_{j \neq l} (1 - g(X_{ij}^T \beta))}{S_e - r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta))} - (1 - z_i) \frac{r \sum_{l=1}^{k_i} g'(X_{il}^T \beta) X_{il} \prod_{j \neq l} (1 - g(X_{ij}^T \beta))}{1 - S_e + r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta))} \right],$$

and

$$\begin{aligned} \frac{\partial^2 l}{\partial \beta \partial \beta^T} &= \sum_{i=1}^m \left(\frac{z_i}{S_e - r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta))} - \frac{1 - z_i}{1 - S_e + r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta))} \right) \frac{\partial A_i(\beta, \mathbf{k})}{\partial \beta} \\ &\quad - \sum_{i=1}^m \left(\frac{z_i}{(S_e - r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)))^2} + \frac{1 - z_i}{(1 - S_e + r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)))^2} \right) A_i(\beta, \mathbf{k}) A_i^T(\beta, \mathbf{k}), \end{aligned}$$

where $A_i(\beta, \mathbf{k}) = r \sum_{l=1}^{k_i} g'(X_{il}^T \beta) X_{il} \prod_{j \neq l} (1 - g(X_{ij}^T \beta))$. Then the Fisher information matrix of the maximum likelihood estimator $\hat{\beta}$ is

$$\begin{aligned} I(\beta, \mathbf{k}) &= \sum_{i=1}^m \frac{A_i(\beta, \mathbf{k}) A_i^T(\beta, \mathbf{k})}{(S_e - r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)))(1 - S_e + r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)))} \\ &= \sum_{i=1}^m \frac{(r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)))^2}{(S_e - r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)))(1 - S_e + r \prod_{j=1}^{k_i} (1 - g(X_{ij}^T \beta)))} \\ &\quad \cdot \sum_{l=1}^{k_i} \frac{g'(X_{il}^T \beta)}{1 - g(X_{il}^T \beta)} X_{il} \sum_{l=1}^{k_i} \frac{g'(X_{il}^T \beta)}{1 - g(X_{il}^T \beta)} X_{il}^T. \end{aligned}$$

Let $H_i(k_i, \beta) = -\frac{1}{k_i} \sum_{j=1}^{k_i} \log(1 - g(X_{ij}^T \beta))$, $G_i(k_i, \beta) = \frac{\partial}{\partial \beta} H_i(k_i, \beta)$,

$$C_i(\beta, k_i) = (S_e - r \exp^{-k_i H_i(k_i, \beta)})(1 - S_e + r \exp^{-k_i H_i(k_i, \beta)}) r^{-2} k_i^{-2} \exp^{2k_i H_i(k_i, \beta)}.$$

Then we have

$$I(\beta, \mathbf{k}) = \sum_{i=1}^m \frac{G_i(k_i, \beta) G_i^T(k_i, \beta)}{C_i(\beta, k_i)}.$$

□

2 Proof of Step 2

After determining the i^{th} group size, we would like to choose the group size for the $i+1$ group. Let $W_{i+1}^s(k, \beta) = \frac{1}{k} \sum_{j=n_i+1}^{n_i+k} -\ln(1 - g(Z_j^{sT} \beta))$, then we have $\prod_{j=n_i+1}^{n_i+k} (1 - g(Z_j^{sT} \beta)) = e^{-kW_{i+1}(k, \beta)}$ and

$$\begin{aligned} C_{i+1}(\beta, k) &= \frac{(S_e - r \prod_{j=n_i+1}^{n_i+k} (1 - g(Z_j^{sT} \beta))) (1 - S_e + r \prod_{j=n_i+1}^{n_i+k} (1 - g(Z_j^{sT} \beta)))}{k^2 r^2 (\prod_{j=n_i+1}^{n_i+k} (1 - g(Z_j^{sT} \beta)))^2} \\ &= \frac{[S_e - r e^{-kW_{i+1}(k, \beta)}] [(1 - S_e) + r e^{-kW_{i+1}(k, \beta)}]}{k^2 r^2 e^{-2kW_{i+1}(k, \beta)}} = \frac{[S_e e^{kW_{i+1}(k, \beta)} - r] [(1 - S_e) e^{kW_{i+1}(k, \beta)} + r]}{k^2 r^2} \\ &= k^{-2} r^{-2} \left[S_e (1 - S_e) (e^{k \cdot 2W_{i+1}(k, \beta)} - 1) + r (2S_e - 1) (e^{k \cdot W_{i+1}(k, \beta)} - 1) + S_p (1 - S_p) \right]. \end{aligned}$$

Denote $f(k, \delta) = k^{-2} r^{-2} [S_e (1 - S_e) (e^{k \cdot 2\delta} - 1) + r (2S_e - 1) (e^{k \cdot \delta} - 1) + S_p (1 - S_p)]$.

The function $f(k, \delta)$ is a convex function of k . The proof is as follows.

$$\begin{aligned} f(k, \delta) &= k^{-2} r^{-2} \left[S_e (1 - S_e) (e^{k \cdot 2\delta} - 1) + r (2S_e - 1) (e^{k \cdot \delta} - 1) + S_p (1 - S_p) \right] \\ &= \frac{S_e (1 - S_e)}{r^2} \sum_{j=1}^{+\infty} \frac{k^{j-2} (2\delta)^j}{j!} + \frac{2S_e - 1}{r} \sum_{j=1}^{+\infty} \frac{k^{j-2} \delta^j}{j!} + \frac{S_p (1 - S_p)}{k^2 r^2}. \end{aligned}$$

Then the second derivative of the function $f(k, \delta)$ relative to k is

$$\begin{aligned} \frac{\partial^2}{\partial k^2} f(k, \delta) &= \frac{S_e (1 - S_e)}{r^2} \sum_{j=1}^{+\infty} \frac{(j-2)(j-3) k^{j-4} (2\delta)^j}{j!} \\ &\quad + \frac{2S_e - 1}{r} \sum_{j=1}^{+\infty} \frac{(j-2)(j-3) k^{j-4} \delta^j}{j!} + 3! \frac{S_p (1 - S_p)}{k^4 r^2}. \end{aligned}$$

Therefore, $\frac{\partial^2}{\partial k^2} f(k, \delta)$ is positive and thus the function $f(k, \delta)$ is a convex function of k .

Let ϕ_0 be the solution of the following equation $2S_e(1 - S_e)(\phi - 1)e^{2\phi} + r(2S_e - 1)(\phi - 2)e^\phi + 2r^2 = 0$. Then we obtain $k_{opt}(\delta) = \operatorname{argmin}_k f(k, \delta) = \phi_0/\delta$ for fixed δ . Then, we obtain that $f(k_1, \delta) \geq f(k_2, \delta)$ for $k_1 \leq k_2 \leq k_{opt}(\delta)$. Since $k_{opt}(\delta) = \phi_0/\delta$, then $k_{opt}(\delta_1) \geq k_{opt}(\delta_2)$ for $\delta_1 \leq \delta_2$.

As described of the pooling strategy, $W_{i+1}^s(k, \beta) = \frac{1}{k} \sum_{j=n_i+1}^{n_i+k} -\ln(1 - g(Z_j^{sT} \beta))$ with decreasing order series $g(Z_j^{sT} \beta), j = 1, 2, \dots, N$. Thus, we have $W_{i+1}^s(k, \beta) \geq W_{i+1}^s(k_{\max}, \beta)$ and $k_{opt}(W_{i+1}^s(k, \beta)) \leq k_{opt}(W_{i+1}^s(k_{\max}, \beta))$ for $k \leq k_{\max}$.

Let $W_{i+1}(\beta) = H_{i+1}^s(1, \beta)$ for simplicity and $k_{opt}^* = k_{opt}(W_{i+1}^s(\beta))$, $\delta_1 = W_{i+1}(k, \beta)$ and $\delta_2 = W_{i+1}(k_{\max}, \beta)$, then $f(k, \delta_1) \geq f(k_{\max}, \delta_1)$ for $k \leq k_{\max} \leq k_{opt}^*$. Since $f(k, \delta_1) \geq f(k, \delta_2)$ for $\delta_1 \geq \delta_2$, we obtain that $f(k, \delta_1) \geq f(k_{\max}, \delta_1) \geq f(k_{\max}, \delta_2)$. Since $C_{i+1}(\beta, k) = f(k, H_{i+1}(k, \beta))$, we have that

$$C_{i+1}(\beta, k) \geq f(k_{\max}, \delta_1) \geq C_{i+1}(\beta, k_{\max}), \text{ for } k \leq k_{\max} \leq k_{opt}^*.$$

In this situation, we obtain that $k_{i+1} = \operatorname{argmin}_{k \in \mathcal{K}} C_{i+1}(\beta, k) = k_{\max}$.

□