



## LAMPIRAN 1

Menunjukkan  $\theta$  memaksimumkan  $L(\theta) \leftrightarrow \theta$  memaksimumkan  $\ln L(\theta)$

Keterangan:  $\theta = (\theta_1, \theta_2, \dots, \theta_p)$ .

Bukti:

( $\rightarrow$ ) Adit:  $\theta$  memaksimumkan  $L(\theta) \rightarrow \theta$  memaksimumkan  $\ln L(\theta)$

Oleh karena  $\theta$  memaksimumkan  $L(\theta)$ , maka:

- $\frac{\partial L(\theta)}{\partial \theta_1} = 0,$
- $\frac{\partial L(\theta)}{\partial \theta_2} = 0,$
- $\vdots$
- $\frac{\partial L(\theta)}{\partial \theta_p} = 0,$
- $\frac{\partial^2 L(\theta)}{\partial \theta_i^2} < 0, i = 1, 2, \dots, p,$
- $D = \frac{\partial^2 L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 > 0, i = 1, 2, \dots, p, j = 1, 2, \dots, p, i \neq j.$

Akan ditunjukkan bahwa  $\theta$  juga memaksimumkan  $\ln L(\theta)$ , yaitu:

- $\frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_1} = 0,$

$$\frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_1} = \frac{1}{L(\boldsymbol{\theta})} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_1} = \frac{1}{L(\boldsymbol{\theta})} \cdot 0 = 0$$

$$\therefore \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_1} = 0,$$

- $\frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_2} = 0$

$$\frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_2} = \frac{1}{L(\boldsymbol{\theta})} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_2} = \frac{1}{L(\boldsymbol{\theta})} \cdot 0 = 0$$

$$\therefore \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_2} = 0,$$

⋮

- $\frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_p} = 0$

$$\frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_p} = \frac{1}{L(\boldsymbol{\theta})} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_p} = \frac{1}{L(\boldsymbol{\theta})} \cdot 0 = 0$$

$$\therefore \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_p} = 0,$$

- $\frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} < 0, \quad i = 1, 2, \dots, p,$

$$\begin{aligned}
\frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} &= \frac{\partial}{\partial \theta_i} \left( \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_i} \right) = \frac{\partial}{\partial \theta_i} \left( \frac{1}{L(\boldsymbol{\theta})} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \right) \\
&= \frac{\partial}{\partial \theta_i} \left( \frac{1}{L(\boldsymbol{\theta})} \right) \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} + \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{1}{L(\boldsymbol{\theta})} \\
&= \frac{\partial}{\partial \theta_i} \left( \frac{1}{L(\boldsymbol{\theta})} \right) \cdot 0 + \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{1}{L(\boldsymbol{\theta})} \\
&= \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{1}{L(\boldsymbol{\theta})} < 0 \cdot \frac{1}{L(\boldsymbol{\theta})} = 0
\end{aligned}$$

$$\therefore \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} < 0, \quad i = 1, 2, \dots, p,$$

$$\bullet D = \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_j^2} - \left( \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right)^2 > 0, \quad i = 1, 2, \dots, p, j = 1, 2, \dots, p, i \neq j$$

$$\begin{aligned}
\frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} &= \frac{\partial}{\partial \theta_i} \left( \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_i} \right) = \frac{\partial}{\partial \theta_i} \left( \frac{\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i}}{L(\boldsymbol{\theta})} \right), \quad i = 1, 2, \dots, p \\
&= \frac{\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot L(\boldsymbol{\theta}) - \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i}}{L^2(\boldsymbol{\theta})}
\end{aligned}$$

$$\begin{aligned}
\frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_j^2} &= \frac{\partial}{\partial \theta_j} \left( \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_j} \right) = \frac{\partial}{\partial \theta_j} \left( \frac{\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j}}{L(\boldsymbol{\theta})} \right), \quad j = 1, 2, \dots, p \\
&= \frac{\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_j^2} \cdot L(\boldsymbol{\theta}) - \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j}}{L^2(\boldsymbol{\theta})}
\end{aligned}$$

$$\frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} = \frac{\partial}{\partial \theta_i} \left( \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_j} \right) = \frac{\partial}{\partial \theta_i} \left( \frac{\frac{\partial L(\boldsymbol{\theta})}{L(\boldsymbol{\theta})}}{\partial \theta_j} \right), i = 1, 2, \dots, p, j = 1, 2, \dots, p$$

$$= \frac{\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \cdot L(\boldsymbol{\theta}) - \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j}}{L^2(\boldsymbol{\theta})}.$$

$$D = \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_j^2} - \left( \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right)^2$$

$$= \left( \frac{\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot L(\boldsymbol{\theta}) - \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i}}{L^2(\boldsymbol{\theta})} \cdot \frac{\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_j^2} \cdot L(\boldsymbol{\theta}) - \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j}}{L^2(\boldsymbol{\theta})} \right)$$

$$- \left( \frac{\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \cdot L(\boldsymbol{\theta}) - \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i}}{L^2(\boldsymbol{\theta})} \right)^2, i = 1, 2, \dots, p, j = 1, 2, \dots, p$$

$$= \frac{1}{L^4(\boldsymbol{\theta})} \left[ \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_j^2} \cdot L^2(\boldsymbol{\theta}) + \left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \right)^2 \right.$$

$$\left. - \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \right)^2 \cdot L(\boldsymbol{\theta}) - \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_j^2} \cdot \left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \right)^2 \cdot L(\boldsymbol{\theta}) \right]$$

$$- \frac{1}{L^4(\boldsymbol{\theta})} \left[ \left( \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right)^2 \cdot L^2(\boldsymbol{\theta}) + \left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \right)^2 \right.$$

$$\left. - 2 \left( \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \cdot L(\boldsymbol{\theta}) \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \right) \right]$$

$$\begin{aligned}
&= \frac{L^2(\theta)}{L^4(\theta)} \left[ \frac{\partial^2 L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 \right] \\
&\quad + \frac{L(\theta)}{L^4(\theta)} \left[ 2 \cdot \frac{\partial^2 L(\theta)}{\partial \theta_i \partial \theta_j} \cdot \frac{\partial L(\theta)}{\partial \theta_i} \cdot \frac{\partial L(\theta)}{\partial \theta_j} - \frac{\partial^2 L(\theta)}{\partial \theta_i^2} \cdot \left( \frac{\partial L(\theta)}{\partial \theta_j} \right)^2 \right. \\
&\quad \left. - \frac{\partial^2 L(\theta)}{\partial \theta_j^2} \cdot \left( \frac{\partial L(\theta)}{\partial \theta_i} \right)^2 \right] \\
&= \frac{1}{L^2(\theta)} \left[ \frac{\partial^2 L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 \right] \\
&\quad + \frac{1}{L^3(\theta)} \left[ 2 \cdot \frac{\partial^2 L(\theta)}{\partial \theta_i \partial \theta_j} \cdot 0 \cdot 0 - \frac{\partial^2 L(\theta)}{\partial \theta_i^2} \cdot (0)^2 - \frac{\partial^2 L(\theta)}{\partial \theta_j^2} \cdot (0)^2 \right] \\
&= \frac{1}{L^2(\theta)} \left[ \frac{\partial^2 L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 \right] > \frac{1}{L^2(\theta)} \cdot 0 = 0 \\
\therefore D &= \frac{\partial^2 \ln L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 \ln L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 > 0, \quad i = 1, 2, \dots, p, \quad j = 1, 2, \dots, p, \quad i \neq j.
\end{aligned}$$

Dengan perkataan lain terbukti bahwa  $\theta$  juga memaksimumkan  $\ln L(\theta)$ .

( $\leftarrow$ ) Adit:  $\theta$  memaksimumkan  $\ln L(\theta) \rightarrow \theta$  memaksimumkan  $L(\theta)$

Oleh karena  $\theta$  memaksimumkan  $\ln L(\theta)$ , maka

- $\frac{\partial \ln L(\theta)}{\partial \theta_1} = 0,$
- $\frac{\partial \ln L(\theta)}{\partial \theta_2} = 0,$
- $\vdots$

- $\frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_n} = 0,$
- $\frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} < 0, i = 1, 2, \dots, p,$
- $D = \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_j^2} - \left( \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right)^2 > 0, i = 1, 2, \dots, p, j = 1, 2, \dots, p, i \neq j.$

Akan ditunjukkan bahwa  $\boldsymbol{\theta}$  juga memaksimumkan  $L(\boldsymbol{\theta})$ , yaitu:

- $\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_1} = 0,$
- $\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_1} = L(\boldsymbol{\theta}) \cdot \frac{1}{L(\boldsymbol{\theta})} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_1} = L(\boldsymbol{\theta}) \cdot \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_1} = L(\boldsymbol{\theta}) \cdot 0 = 0$
- $\therefore \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_1} = 0,$
- $\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_2} = 0,$
- $\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_2} = L(\boldsymbol{\theta}) \cdot \frac{1}{L(\boldsymbol{\theta})} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_2} = L(\boldsymbol{\theta}) \cdot \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_2} = L(\boldsymbol{\theta}) \cdot 0 = 0$
- $\therefore \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_2} = 0,$
- $\vdots$

- $\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_p} = 0,$

$$\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_p} = L(\boldsymbol{\theta}) \cdot \frac{1}{L(\boldsymbol{\theta})} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_p} = L(\boldsymbol{\theta}) \cdot \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_p} = L(\boldsymbol{\theta}) \cdot 0 = 0$$

$$\therefore \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_p} = 0,$$

- $\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} < 0, i = 1, 2, \dots, p,$

$$\begin{aligned} \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} &= \frac{\partial \left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \right)}{\partial \theta_i} \\ &= \frac{\partial \left( L(\boldsymbol{\theta}) \cdot \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_i} \right)}{\partial \theta_i} \\ &= \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial \ln L(\boldsymbol{\theta})}{\partial \theta_i} + L(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} \\ &= \frac{1}{L(\boldsymbol{\theta})} \cdot \left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \right)^2 + L(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} \\ &= \frac{1}{L(\boldsymbol{\theta})} \cdot \left[ \left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \right)^2 + L^2(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} \right] \\ &= \frac{1}{L(\boldsymbol{\theta})} \cdot \left[ (0)^2 + L^2(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} \right] \\ &= L(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2} < L(\boldsymbol{\theta}) \cdot 0 = 0 \end{aligned}$$

$$\therefore \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} < 0, i = 1, 2, \dots, p,$$



$$\bullet D = \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_j^2} - \left( \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right)^2 > 0, \quad i = 1, 2, \dots, p, j = 1, 2, \dots, p, i \neq j$$

$$\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} = \frac{\left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \right)^2 + L^2(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2}}{L(\boldsymbol{\theta})}, \quad i = 1, 2, \dots, p$$

$$\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_j^2} = \frac{\left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \right)^2 + L^2(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_j^2}}{L(\boldsymbol{\theta})}, \quad j = 1, 2, \dots, p$$

$$\frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} = \frac{\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} + L^2(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j}}{L(\boldsymbol{\theta})}, \quad i = 1, 2, \dots, p, j = 1, 2, \dots, p$$

$$\begin{aligned} D &= \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i^2} \cdot \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_j^2} - \left( \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j} \right)^2 \\ &= \left( \frac{\left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \right)^2 + L^2(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i^2}}{L(\boldsymbol{\theta})} \right) \cdot \left( \frac{\left( \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} \right)^2 + L^2(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_j^2}}{L(\boldsymbol{\theta})} \right) \\ &\quad - \left( \frac{\frac{\partial L(\boldsymbol{\theta})}{\partial \theta_i} \cdot \frac{\partial L(\boldsymbol{\theta})}{\partial \theta_j} + L^2(\boldsymbol{\theta}) \cdot \frac{\partial^2 \ln L(\boldsymbol{\theta})}{\partial \theta_i \partial \theta_j}}{L(\boldsymbol{\theta})} \right)^2, \quad i = 1, 2, \dots, p, j = 1, 2, \dots, p, i \neq j \end{aligned}$$

$$\begin{aligned}
&= \frac{1}{L^2(\theta)} \cdot \left[ \left( \frac{\partial L(\theta)}{\partial \theta_i} \cdot \frac{\partial L(\theta)}{\partial \theta_j} \right)^2 + L^4(\theta) \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_j^2} + \right. \\
&\quad \left. + L^2(\theta) \cdot \left( \frac{\partial L(\theta)}{\partial \theta_i} \right)^2 \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_j^2} + L^2(\theta) \cdot \left( \frac{\partial L(\theta)}{\partial \theta_j} \right)^2 \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_i^2} \right] \\
&\quad - \frac{1}{L^2(\theta)} \cdot \left[ \left( \frac{\partial L(\theta)}{\partial \theta_i} \cdot \frac{\partial L(\theta)}{\partial \theta_j} \right)^2 + L^4(\theta) \cdot \left( \frac{\partial^2 \ln L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 + 2 \cdot L^2(\theta) \cdot \frac{\partial L(\theta)}{\partial \theta_i} \cdot \frac{\partial L(\theta)}{\partial \theta_j} \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_i \partial \theta_j} \right] \\
&= \frac{L^4(\theta)}{L^2(\theta)} \cdot \left[ \frac{\partial^2 \ln L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 \ln L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 \right] \\
&\quad + \frac{L^2(\theta)}{L^2(\theta)} \cdot \left[ \left( \frac{\partial L(\theta)}{\partial \theta_i} \right)^2 \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_j^2} + \left( \frac{\partial L(\theta)}{\partial \theta_j} \right)^2 \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_i^2} - 2 \cdot \frac{\partial L(\theta)}{\partial \theta_i} \cdot \frac{\partial L(\theta)}{\partial \theta_j} \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_i \partial \theta_j} \right] \\
&= L^2(\theta) \cdot \left[ \frac{\partial^2 \ln L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 \ln L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 \right] \\
&\quad + 1 \cdot \left[ (0)^2 \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_j^2} + (0)^2 \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_i^2} - 2 \cdot 0 \cdot 0 \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_i \partial \theta_j} \right] \\
&= L^2(\theta) \cdot \left[ \frac{\partial^2 \ln L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 \ln L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 \ln L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 \right] > L^2(\theta) \cdot 0 = 0 \\
\therefore D &= \frac{\partial^2 L(\theta)}{\partial \theta_i^2} \cdot \frac{\partial^2 L(\theta)}{\partial \theta_j^2} - \left( \frac{\partial^2 L(\theta)}{\partial \theta_i \partial \theta_j} \right)^2 > 0, \quad i = 1, 2, \dots, p, \quad j = 1, 2, \dots, p, \quad i \neq j
\end{aligned}$$

Dengan perkataan lain, terbukti bahwa  $\theta$  juga memaksimumkan  $L(\theta)$ .

Terbukti bahwa  $\theta$  memaksimumkan  $L(\theta) \leftrightarrow \theta$  memaksimumkan  $\ln L(\theta)$ ,

$$\theta = (\theta_1, \theta_2, \dots, \theta_p).$$

## LAMPIRAN 2

Mencari matriks  $\mathbf{T}$ , dimana  $\mathbf{T} \mathbf{T}' = \Sigma_{\delta}$ , dengan dekomposisi Cholesky.

Misalkan  $\mathbf{T} = \begin{pmatrix} t_{00} & 0 & \cdots & 0 \\ t_{10} & t_{11} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ t_{R0} & t_{R1} & \cdots & t_{RR} \end{pmatrix}$

- $t_{00} = \sigma_{\delta_1}$
- $t_{10} = \frac{\sigma_{\delta_1 \delta_0}}{t_{00}} = \frac{\sigma_{\delta_1 \delta_0}}{\sigma_{\delta_0}}$
- $\vdots$
- $t_{R0} = \frac{\sigma_{\delta_R \delta_0}}{t_{00}} = \frac{\sigma_{\delta_R \delta_0}}{\sigma_{\delta_0}}$
- $t_{11} = \sqrt{\sigma_{\delta_1}^2 - (t_{10}^2)} = \sqrt{\sigma_{\delta_1}^2 - \frac{\sigma_{\delta_1 \delta_0}^2}{\sigma_{\delta_0}^2}} = \sqrt{\frac{\sigma_{\delta_1}^2 \sigma_{\delta_0}^2 - \sigma_{\delta_1 \delta_0}^2}{\sigma_{\delta_0}^2}}$
- $\vdots$
- $t_{RR} = \sqrt{\sigma_{\delta_R}^2 - (t_{R0}^2 + t_{R1}^2 + \cdots + t_{R,R-1}^2)} = \sqrt{\frac{(\sigma_{\delta_1}^2)(\sigma_{\delta_0}^2) - (\sigma_{\delta_R \delta_0}^2 + \sigma_{\delta_R \delta_1}^2 + \cdots + \sigma_{\delta_R \delta_{R-1}}^2)}{\sigma_{\delta_0}^2}}$
- $\vdots$
- $t_{R1} = \frac{\sigma_{\delta_0 \delta_1} - (t_{R0} t_{10})}{t_{11}} = \frac{\sigma_{\delta_0 \delta_1} - \left( \frac{\sigma_{\delta_R \delta_1} \sigma_{\delta_2 \delta_0}}{\sigma_{\delta_0}^2} \right)}{\sqrt{\frac{(\sigma_{\delta_1}^2)(\sigma_{\delta_0}^2) - \sigma_{\delta_1 \delta_0}^2}{\sigma_{\delta_0}^2}}}$
- $t_{12} = 0, \dots, t_{1r} = 0$

$$t_{12} = 0, \dots, t_{1R} = 0$$

$$\vdots$$

$$t_{R-1,R} = 0$$

Sehingga diperoleh matriks T sebagai berikut:

$$\mathbf{T} = \begin{pmatrix} \sigma_{\delta_0} & 0 & \dots & 0 \\ \frac{\sigma_{\delta_1\delta_0}}{\sigma_{\delta_0}} & \sqrt{\frac{\sigma_{\delta_1}^2\sigma_{\delta_0}^2 - \sigma_{\delta_1\delta_0}^2}{\sigma_{\delta_0}^2}} & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ \frac{\sigma_{\delta_R\delta_0}}{\sigma_{\delta_0}} & \sigma_{\delta_R\delta_1} - \left( \frac{\sigma_{\delta_R\delta_0}\sigma_{\delta_1\delta_0}}{\sigma_{\delta_0}^2} \right) & \dots & \sqrt{\frac{(\sigma_{\delta_1}^2)(\sigma_{\delta_0}^2) - (\sigma_{\delta_R\delta_0}^2 + \sigma_{\delta_R\delta_1}^2 + \dots + \sigma_{\delta_R\delta_{R-1}}^2)}{\sigma_{\delta_0}^2}} \\ \vdots & \sqrt{\frac{(\sigma_{\delta_1}^2)(\sigma_{\delta_0}^2) - \sigma_{\delta_1\delta_0}^2}{\sigma_{\delta_0}^2}} & \dots & \vdots \end{pmatrix}$$

dan

$$\mathbf{T}\mathbf{T}' = \begin{pmatrix} \sigma_{\delta_0} & 0 & \dots & 0 \\ \frac{\sigma_{\delta_1\delta_0}}{\sigma_{\delta_0}} & \sqrt{\frac{\sigma_{\delta_1}^2\sigma_{\delta_0}^2 - \sigma_{\delta_1\delta_0}^2}{\sigma_{\delta_0}^2}} & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ \frac{\sigma_{\delta_R\delta_0}}{\sigma_{\delta_0}} & \sigma_{\delta_R\delta_1} - \left( \frac{\sigma_{\delta_R\delta_0}\sigma_{\delta_1\delta_0}}{\sigma_{\delta_0}^2} \right) & \dots & \sqrt{\frac{(\sigma_{\delta_1}^2)(\sigma_{\delta_0}^2) - (\sigma_{\delta_R\delta_0}^2 + \sigma_{\delta_R\delta_1}^2 + \dots + \sigma_{\delta_R\delta_{R-1}}^2)}{\sigma_{\delta_0}^2}} \\ \vdots & \sqrt{\frac{(\sigma_{\delta_1}^2)(\sigma_{\delta_0}^2) - \sigma_{\delta_1\delta_0}^2}{\sigma_{\delta_0}^2}} & \dots & \vdots \end{pmatrix} \begin{pmatrix} \sigma_{\delta_0} & \frac{\sigma_{\delta_1\delta_0}}{\sigma_{\delta_0}} & \dots & \frac{\sigma_{\delta_R\delta_0}}{\sigma_{\delta_0}} \\ 0 & \sqrt{\frac{\sigma_{\delta_1}^2\sigma_{\delta_0}^2 - \sigma_{\delta_1\delta_0}^2}{\sigma_{\delta_0}^2}} & \dots & \frac{\sigma_{\delta_R\delta_0}}{\sigma_{\delta_0}} - \left( \frac{\sigma_{\delta_R\delta_0}\sigma_{\delta_1\delta_0}}{\sigma_{\delta_0}^2} \right) \\ \vdots & \vdots & \dots & \vdots \\ 0 & \dots & \dots & \sqrt{\frac{(\sigma_{\delta_1}^2)(\sigma_{\delta_0}^2) - (\sigma_{\delta_R\delta_0}^2 + \sigma_{\delta_R\delta_1}^2 + \dots + \sigma_{\delta_R\delta_{R-1}}^2)}{\sigma_{\delta_0}^2}} \end{pmatrix}$$

$$= \begin{pmatrix} \sigma_{\delta_0}^2 & \sigma_{\delta_1\delta_0} & \dots & \sigma_{\delta_R\delta_0} \\ \sigma_{\delta_1\delta_0} & \sigma_{\delta_1}^2 & \dots & \sigma_{\delta_R\delta_1} \\ \vdots & \vdots & \dots & \vdots \\ \sigma_{\delta_R\delta_0} & \sigma_{\delta_R\delta_1} & \dots & \sigma_{\delta_R}^2 \end{pmatrix}$$

Karena  $\sigma_{\delta_i\delta_j} = \sigma_{\delta_j\delta_i}$ ,  $i, j = 0, 1, \dots, R$ , maka matriks di atas dapat juga ditulis

sebagai:

$$\mathbf{TT}' = \begin{pmatrix} \sigma_{\delta_0}^2 & \sigma_{\delta_1\delta_0} & \cdots & \sigma_{\delta_R\delta_0} \\ \sigma_{\delta_1\delta_0} & \sigma_{\delta_1}^2 & \cdots & \sigma_{\delta_R\delta_1} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{\delta_R\delta_0} & \sigma_{\delta_R\delta_1} & \cdots & \sigma_{\delta_R}^2 \end{pmatrix} = \begin{pmatrix} \sigma_{\delta_0}^2 & \sigma_{\delta_0\delta_1} & \cdots & \sigma_{\delta_0\delta_R} \\ \sigma_{\delta_1\delta_0} & \sigma_{\delta_1}^2 & \cdots & \sigma_{\delta_1\delta_R} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{\delta_R\delta_0} & \sigma_{\delta_R\delta_1} & \cdots & \sigma_{\delta_R}^2 \end{pmatrix} = \boldsymbol{\Sigma}_{\delta}$$



### LAMPIRAN 3

Membuktikan variabel  $\boldsymbol{\theta}$ ,  $\boldsymbol{\theta} = \mathbf{T}^{-1}(\boldsymbol{\beta} - \boldsymbol{\mu})$  berdistribusi  $N_{R+1}(\mathbf{0}, \mathbf{I})$  Jika diketahui  $\boldsymbol{\beta}$  berdistribusi  $N_{R+1}(\boldsymbol{\mu}, \boldsymbol{\Sigma}_{\delta})$

Misalkan  $\boldsymbol{\beta} = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_R \end{pmatrix}$  adalah suatu variabel random dari distribusi *multivariate*

normal dengan

Mean:  $\boldsymbol{\mu} = \begin{pmatrix} \mu_0 \\ \mu_1 \\ \vdots \\ \mu_R \end{pmatrix}$  dan covariansi matrix :  $\boldsymbol{\Sigma}_{\delta} = \begin{pmatrix} \sigma_{\delta_0}^2 & \sigma_{\delta_0\delta_1} & \cdots & \sigma_{\delta_0\delta_R} \\ \sigma_{\delta_1\delta_0} & \sigma_{\delta_1}^2 & \cdots & \sigma_{\delta_1\delta_R} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{\delta_R\delta_0} & \sigma_{\delta_R\delta_1} & \cdots & \sigma_{\delta_R}^2 \end{pmatrix}$

Perhatikan transformasi:

$\boldsymbol{\theta} = \mathbf{T}^{-1}(\boldsymbol{\beta} - \boldsymbol{\mu})$ , dimana  $\mathbf{T}\mathbf{T}' = \boldsymbol{\Sigma}_{\delta}$  adalah dekomposisi *Cholesky* dari  $\boldsymbol{\Sigma}_{\delta}$ .

Akan dibuktikan bahwa variabel  $\boldsymbol{\theta}$  berdistribusi *multivariate* normal standar  $N_{R+1}(\mathbf{0}, \mathbf{I})$ .

#### **Bukti:**

Diketahui bahwa :  $E(\boldsymbol{\beta}) = \boldsymbol{\mu}$ , dan

$$\text{cov}(\boldsymbol{\beta}) = E[(\boldsymbol{\beta} - \boldsymbol{\mu})(\boldsymbol{\beta} - \boldsymbol{\mu})'] = \boldsymbol{\Sigma}_{\delta}$$

Maka,

$$\begin{aligned}
 E(\boldsymbol{\theta}) &= E(\mathbf{T}^{-1}(\boldsymbol{\beta} - \boldsymbol{\mu})) \\
 &= \mathbf{T}^{-1}E(\boldsymbol{\beta} - \boldsymbol{\mu}) \\
 &= \mathbf{0}; \quad \text{karena } E(\boldsymbol{\beta}) = \boldsymbol{\mu}
 \end{aligned}$$

dan,

$$\begin{aligned}
 \text{cov}(\boldsymbol{\theta}) &= E(\boldsymbol{\theta}\boldsymbol{\theta}') - [E(\boldsymbol{\theta})]^2 \\
 &= E(\boldsymbol{\theta}\boldsymbol{\theta}'); \quad \text{karena } E(\boldsymbol{\theta}) = \mathbf{0} \\
 &= E\left(\mathbf{T}^{-1}(\boldsymbol{\beta} - \boldsymbol{\mu})(\mathbf{T}^{-1}(\boldsymbol{\beta} - \boldsymbol{\mu}))'\right) \\
 &= \mathbf{T}^{-1}E\left((\boldsymbol{\beta} - \boldsymbol{\mu})(\boldsymbol{\beta} - \boldsymbol{\mu})'(\mathbf{T}^{-1})'\right) \\
 &= \mathbf{T}^{-1}E\left((\boldsymbol{\beta} - \boldsymbol{\mu})(\boldsymbol{\beta} - \boldsymbol{\mu})'\right)(\mathbf{T}^{-1})' \\
 &= \mathbf{T}^{-1}\boldsymbol{\Sigma}_{\boldsymbol{\beta}}(\mathbf{T}^{-1})' \\
 &= \mathbf{T}^{-1}(\mathbf{T}\mathbf{T}')(\mathbf{T}^{-1})' \\
 &= (\mathbf{T}^{-1}\mathbf{T})(\mathbf{T}^{-1}\mathbf{T}') \\
 &= \mathbf{I}
 \end{aligned}$$

Terbukti bahwa variabel  $\boldsymbol{\theta}$  berdistribusi *multivariate* normal standar dengan mean  $\mathbf{0}$  dan matriks kovariansi  $\mathbf{I}$  (matriks identitas), dinotasikan  $N_{R+1}(\mathbf{0}, \mathbf{I})$ .

## LAMPIRAN 4

### Metode Newton Raphson

Misalkan  $\Theta$  adalah vektor dari parameter-parameter yang tidak diketahui, yaitu :

$$\Theta = (\mu_0, \dots, \mu_R \quad \alpha_1, \dots, \alpha_p \quad \gamma_2, \dots, \gamma_{C-1} \quad t_{00}, \dots, t_{RR})' \quad (1)$$

Misalkan pula,  $l(\Theta)$  adalah fungsi *marginal log-likelihood* dari vektor  $\Theta$ ,

$U(\Theta)$  adalah vektor turunan parsial pertama dari  $l(\Theta)$ , yaitu

$$U(\Theta) = \begin{bmatrix} U_{\mu_0}(\Theta) \\ \vdots \\ U_{\mu_R}(\Theta) \\ U_{\alpha_1}(\Theta) \\ \vdots \\ U_{\alpha_p}(\Theta) \\ U_{\gamma_2}(\Theta) \\ \vdots \\ U_{\gamma_{C-1}}(\Theta) \\ U_{t_{00}}(\Theta) \\ \vdots \\ U_{t_{RR}}(\Theta) \end{bmatrix} = \begin{bmatrix} \frac{\partial l(\Theta)}{\partial \mu_0} \\ \vdots \\ \frac{\partial l(\Theta)}{\partial \mu_R} \\ \frac{\partial l(\Theta)}{\partial \alpha_1} \\ \vdots \\ \frac{\partial l(\Theta)}{\partial \alpha_p} \\ \frac{\partial l(\Theta)}{\partial \gamma_2} \\ \vdots \\ \frac{\partial l(\Theta)}{\partial \gamma_{C-1}} \\ \frac{\partial l(\Theta)}{\partial t_{00}} \\ \vdots \\ \frac{\partial l(\Theta)}{\partial t_{RR}} \end{bmatrix}$$



$H(\Theta)$  adalah matriks turunan parsial kedua dari  $I(\Theta)$ , yaitu:

$$H(\Theta) = \frac{\partial U(\Theta)}{\partial \Theta'}$$

$$= \begin{bmatrix} \frac{\partial U(\Theta)}{\partial \mu_0} & \dots & \frac{\partial U(\Theta)}{\partial \mu_R} & \frac{\partial U(\Theta)}{\partial \alpha_1} & \dots & \frac{\partial U(\Theta)}{\partial \alpha_p} & \frac{\partial U(\Theta)}{\partial \gamma_2} & \dots & \frac{\partial U(\Theta)}{\partial \gamma_{C-1}} & \frac{\partial U(\Theta)}{\partial t_{00}} & \dots & \frac{\partial U(\Theta)}{\partial t_{RR}} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\partial^2 I(\Theta)}{\partial \mu_0^2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \mu_0} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \mu_0} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \mu_0} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \mu_0} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \mu_0} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \mu_0} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \mu_0} \\ \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \mu_R} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R^2} & \frac{\partial^2 I(\Theta)}{\partial \alpha_R \partial \mu_R} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \mu_R} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \mu_R} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \mu_R} & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \mu_R} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \mu_R} \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \alpha_1} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \alpha_1} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1^2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \alpha_1} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \alpha_1} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \alpha_1} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \alpha_1} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \alpha_1} \\ \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \alpha_p} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \alpha_p} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \alpha_p} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p^2} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \alpha_p} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \alpha_p} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \alpha_p} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \alpha_p} \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \gamma_2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \gamma_2} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \gamma_2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \gamma_2} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2^2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \gamma_2} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \gamma_2} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \gamma_2} \\ \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \gamma_{C-1}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \gamma_{C-1}} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \gamma_{C-1}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \gamma_{C-1}} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \gamma_{C-1}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1}^2} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \gamma_{C-1}} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \gamma_{C-1}} \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial t_{11}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial t_{00}} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial t_{00}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial t_{00}} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial t_{00}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial t_{00}} & \frac{\partial^2 I(\Theta)}{\partial t_{00}^2} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial t_{11}} \\ \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial t_{RR}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_{RR} \partial t_{RR}} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial t_{RR}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial t_{RR}} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial t_{RR}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial t_{RR}} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial t_{RR}} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR}^2} \end{bmatrix}$$

Dengan menggunakan metode *Newton Raphson*, akan dicari taksiran dari  $\Theta$  yang merupakan penyelesaian dari  $U(\Theta) = \mathbf{0}$ . Jika diberi taksiran awal dari  $\Theta$ , yaitu  $\hat{\Theta}^{(0)}$ , maka dapat diperoleh pendekatan deret Taylor orde pertama dari vektor  $U(\Theta)$  di sekitar  $\Theta = \hat{\Theta}^{(0)}$ , yaitu:

$$U(\Theta) \approx U(\hat{\Theta}^{(0)}) + \left. \frac{\partial U(\Theta)}{\partial \mu_0} \right|_{\Theta=\hat{\Theta}^{(0)}} (\mu_0 - \hat{\mu}_0^{(0)}) + \dots + \left. \frac{\partial U(\Theta)}{\partial \mu_R} \right|_{\Theta=\hat{\Theta}^{(0)}} (\mu_r - \hat{\mu}_r^{(0)}) + \left. \frac{\partial U(\Theta)}{\partial \alpha_1} \right|_{\Theta=\hat{\Theta}^{(0)}} (\alpha_1 - \hat{\alpha}_1^{(0)}) + \dots + \left. \frac{\partial U(\Theta)}{\partial \alpha_p} \right|_{\Theta=\hat{\Theta}^{(0)}} (\alpha_p - \hat{\alpha}_p^{(0)})$$

$$+ \left. \frac{\partial U(\Theta)}{\partial \gamma_2} \right|_{\Theta=\hat{\Theta}^{(0)}} (\gamma_2 - \hat{\gamma}_2^{(0)}) + \dots + \left. \frac{\partial U(\Theta)}{\partial \gamma_{C-1}} \right|_{\Theta=\hat{\Theta}^{(0)}} (\gamma_{C-1} - \hat{\gamma}_{C-1}^{(0)}) + \left. \frac{\partial U(\Theta)}{\partial t_{00}} \right|_{\Theta=\hat{\Theta}^{(0)}} (t_{00} - \hat{t}_{00}^{(0)}) + \dots + \left. \frac{\partial U(\Theta)}{\partial t_{RR}} \right|_{\Theta=\hat{\Theta}^{(0)}} (t_{RR} - \hat{t}_{RR}^{(0)})$$

$$\approx U(\hat{\Theta}^{(0)}) + \left[ \begin{array}{cccccccc} \frac{\partial U(\Theta)}{\partial \mu_0} & \dots & \frac{\partial U(\Theta)}{\partial \mu_R} & \frac{\partial U(\Theta)}{\partial \alpha_1} & \dots & \frac{\partial U(\Theta)}{\partial \alpha_p} & \frac{\partial U(\Theta)}{\partial \gamma_2} & \dots & \frac{\partial U(\Theta)}{\partial \gamma_{C-1}} & \frac{\partial U(\Theta)}{\partial t_{00}} & \dots & \frac{\partial U(\Theta)}{\partial t_{RR}} \end{array} \right]_{\Theta=\hat{\Theta}^{(0)}} \left[ \begin{array}{c} (\mu_0 - \hat{\mu}_0^{(0)}) \\ \vdots \\ (\mu_r - \hat{\mu}_r^{(0)}) \\ (\alpha_1 - \hat{\alpha}_1^{(0)}) \\ \vdots \\ (\alpha_p - \hat{\alpha}_p^{(0)}) \\ (\gamma_2 - \hat{\gamma}_2^{(0)}) \\ \vdots \\ (\gamma_{C-1} - \hat{\gamma}_{C-1}^{(0)}) \\ (t_{00} - \hat{t}_{00}^{(0)}) \\ \vdots \\ (t_{RR} - \hat{t}_{RR}^{(0)}) \end{array} \right]$$

$$\approx U(\hat{\Theta}^{(0)}) + \left[ \begin{array}{cccccccc} \frac{\partial^2 I(\Theta)}{\partial \mu_0^2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \mu_0} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \mu_0} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \mu_0} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \mu_0} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \mu_0} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \mu_0} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \mu_0} \\ \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \mu_R} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R^2} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \mu_R} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \mu_R} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \mu_R} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \mu_R} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \mu_R} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \mu_R} \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \alpha_1} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \alpha_1} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1^2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \alpha_1} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \alpha_1} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \alpha_1} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \alpha_1} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \alpha_1} \\ \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \alpha_p} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \alpha_p} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \alpha_p} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p^2} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \alpha_p} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \alpha_p} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \alpha_p} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \alpha_p} \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \gamma_2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \gamma_2} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \gamma_2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \gamma_2} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2^2} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial \gamma_2} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \gamma_2} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \gamma_2} \\ \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial \gamma_{C-1}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial \gamma_{C-1}} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial \gamma_{C-1}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \gamma_{C-1}} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial \gamma_{C-1}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1}^2} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial \gamma_{C-1}} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial \gamma_{C-1}} \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial t_{11}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_R \partial t_{00}} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial t_{00}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial t_{00}} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial t_{00}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial t_{00}} & \frac{\partial^2 I(\Theta)}{\partial t_{00}^2} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR} \partial t_{11}} \\ \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots & \vdots & & \vdots \\ \frac{\partial^2 I(\Theta)}{\partial \mu_0 \partial t_{RR}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \mu_{RR} \partial t_{RR}} & \frac{\partial^2 I(\Theta)}{\partial \alpha_1 \partial t_{RR}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial t_{RR}} & \frac{\partial^2 I(\Theta)}{\partial \gamma_2 \partial t_{RR}} & \dots & \frac{\partial^2 I(\Theta)}{\partial \gamma_{C-1} \partial t_{RR}} & \frac{\partial^2 I(\Theta)}{\partial t_{00} \partial t_{RR}} & \dots & \frac{\partial^2 I(\Theta)}{\partial t_{RR}^2} \end{array} \right]_{\Theta=\hat{\Theta}^{(0)}} (\Theta - \hat{\Theta}^{(0)})$$

$$\approx U(\hat{\Theta}^{(0)}) + H(\hat{\Theta}^{(0)}) (\Theta - \hat{\Theta}^{(0)})$$

dengan,

$U(\hat{\Theta}^{(0)})$  adalah vektor turunan parsial pertama dari  $l(\Theta)$  dihitung pada  $\Theta = \hat{\Theta}^{(0)}$ .

$H(\hat{\Theta}^{(0)})$  adalah matriks turunan parsial kedua dari  $l(\Theta)$  dihitung pada  $\Theta = \hat{\Theta}^{(0)}$ .

Karena ingin dicari penyelesaian dari  $U(\Theta) = \mathbf{0}$ , maka dapat ditulis:

$$\begin{aligned}\mathbf{0} &= U(\Theta) \approx U(\hat{\Theta}^{(0)}) + H(\hat{\Theta}^{(0)})(\Theta - \hat{\Theta}^{(0)}) \\ H(\hat{\Theta}^{(0)})(\Theta - \hat{\Theta}^{(0)}) &= -U(\hat{\Theta}^{(0)})\end{aligned}$$

Jika matriks  $H(\hat{\Theta}^{(0)})$  nonsingular maka,

$$\begin{aligned}\left[ H(\hat{\Theta}^{(0)}) \right]^{-1} H(\hat{\Theta}^{(0)})(\Theta - \hat{\Theta}^{(0)}) &= -\left[ H(\hat{\Theta}^{(0)}) \right]^{-1} U(\hat{\Theta}^{(0)}) \\ (\Theta - \hat{\Theta}^{(0)}) &= -\left[ H(\hat{\Theta}^{(0)}) \right]^{-1} U(\hat{\Theta}^{(0)}) \\ \Theta &= \hat{\Theta}^{(0)} - \left[ H(\hat{\Theta}^{(0)}) \right]^{-1} U(\hat{\Theta}^{(0)})\end{aligned}$$

Nilai  $\Theta$  kemudian menjadi taksiran baru yang kemudian dinotasikan dengan  $\hat{\Theta}^{(1)}$ , yaitu:

$$\hat{\Theta}^{(1)} = \hat{\Theta}^{(0)} - \left[ H(\hat{\Theta}^{(0)}) \right]^{-1} U(\hat{\Theta}^{(0)})$$

Jika  $\hat{\Theta}^{(1)} \approx \hat{\Theta}^{(0)}$  (misalkan  $\|\hat{\Theta}^{(1)} - \hat{\Theta}^{(0)}\| < 10^{-4}$ ), maka hentikan proses iterasi dan

kemudian ambil  $\hat{\Theta}^{(1)}$  sebagai taksiran dari  $\Theta$ . Sebaliknya, lanjutkan iterasi. Jika

diberikan taksiran  $\hat{\Theta}^{(1)}$ , maka dapat diperoleh pendekatan deret Taylor orde

pertama dari vektor  $U(\Theta)$  sekitar  $\Theta = \hat{\Theta}^{(1)}$ , yaitu:

$$U(\Theta) \approx U(\hat{\Theta}^{(1)}) + H(\hat{\Theta}^{(1)})(\Theta - \hat{\Theta}^{(1)})$$

dengan:

$U(\hat{\Theta}^{(1)})$  adalah vektor turunan parsial pertama dari  $l(\Theta)$  dihitung pada  $\Theta = \hat{\Theta}^{(1)}$ .

$H(\hat{\Theta}^{(1)})$  adalah matriks turunan parsial kedua dari  $l(\Theta)$  dihitung pada  $\Theta = \hat{\Theta}^{(1)}$ .

Dengan menyelesaikan ,

$$\mathbf{0} = U(\Theta) \approx U(\hat{\Theta}^{(1)}) + H(\hat{\Theta}^{(1)})(\Theta - \hat{\Theta}^{(1)})$$

diperoleh

$$H(\hat{\Theta}^{(1)})(\Theta - \hat{\Theta}^{(1)}) = -U(\hat{\Theta}^{(1)})$$

Jika matriks  $H(\hat{\Theta}^{(1)})$  nonsingular, maka:

$$\begin{aligned} [H(\hat{\Theta}^{(1)})]^{-1} H(\hat{\Theta}^{(1)})(\Theta - \hat{\Theta}^{(1)}) &= -[H(\hat{\Theta}^{(1)})]^{-1} U(\hat{\Theta}^{(1)}) \\ (\Theta - \hat{\Theta}^{(1)}) &= -[H(\hat{\Theta}^{(1)})]^{-1} U(\hat{\Theta}^{(1)}) \\ \Theta &= \hat{\Theta}^{(1)} - [H(\hat{\Theta}^{(1)})]^{-1} U(\hat{\Theta}^{(1)}) \end{aligned}$$

Nilai  $\Theta$  kemudian menjadi taksiran baru yang kemudian dinotasikan dengan

$\hat{\Theta}^{(2)}$ , yaitu:

$$\hat{\Theta}^{(2)} = \hat{\Theta}^{(1)} - [H(\hat{\Theta}^{(1)})]^{-1} U(\hat{\Theta}^{(1)})$$

Dengan mengulang langkah yang sama dapat diperoleh taksiran  $\hat{\Theta}^{(3)}$ ,  $\hat{\Theta}^{(4)}$ , dan seterusnya.

Secara umum, dapat ditentukan taksiran dari  $\Theta$  pada iterasi ke  $m+1$ , yaitu  $\hat{\Theta}^{(m+1)}$ , secara iteratif menggunakan algoritma:

$$\hat{\Theta}^{(m+1)} = \hat{\Theta}^{(m)} - [H(\hat{\Theta}^{(m)})]^{-1} U(\hat{\Theta}^{(m)}), \quad m = 0, 1, \dots$$

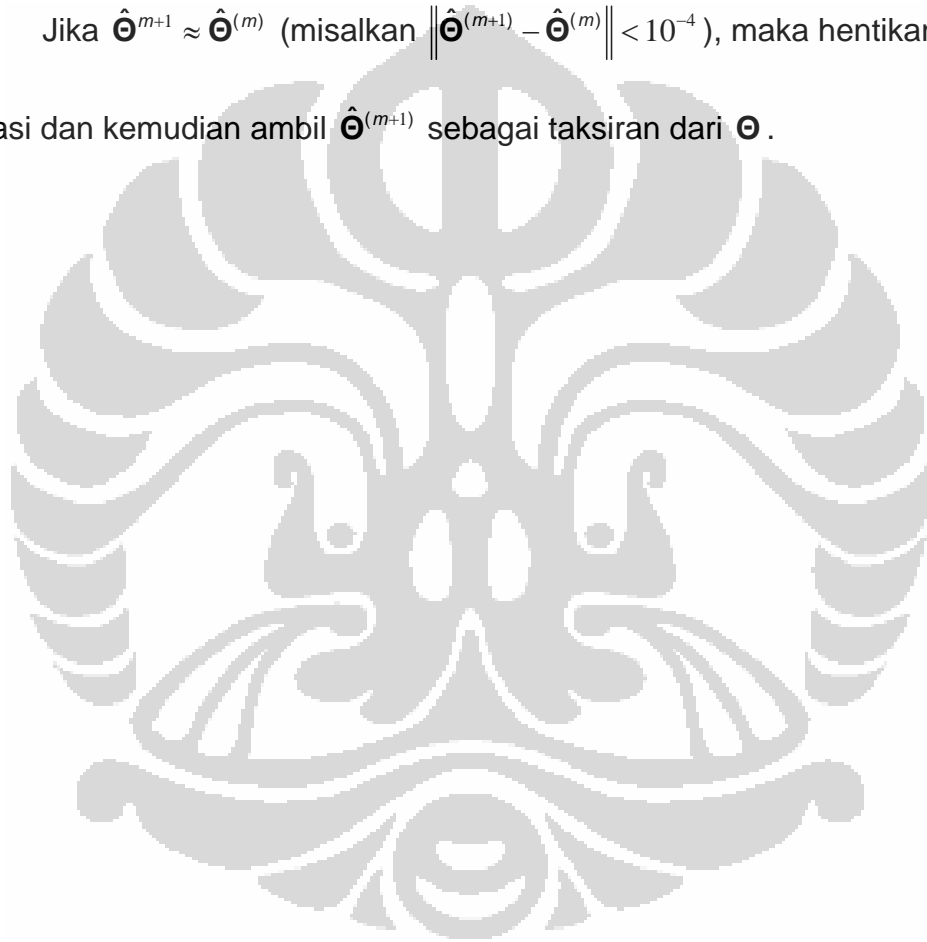
Dengan:

$U(\hat{\Theta}^{(m)})$  adalah vektor turunan parsial pertama dari  $l(\Theta)$  dihitung pada  $\Theta = \hat{\Theta}^{(m)}$ .

$H(\hat{\Theta}^{(m)})$  adalah matriks turunan parsial kedua dari  $l(\Theta)$  dihitung pada  $\Theta = \hat{\Theta}^{(m)}$ .

Jika  $\hat{\Theta}^{m+1} \approx \hat{\Theta}^{(m)}$  (misalkan  $\|\hat{\Theta}^{(m+1)} - \hat{\Theta}^{(m)}\| < 10^{-4}$ ), maka hentikan proses

iterasi dan kemudian ambil  $\hat{\Theta}^{(m+1)}$  sebagai taksiran dari  $\Theta$ .



## LAMPIRAN 5

Menunjukkan 
$$E\left[H(\hat{\Theta}^{(m)})\right] = -\sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left(\frac{\partial h(\mathbf{Y}_i)}{\partial \hat{\Theta}^{(m)}}\right) \cdot \left(\frac{\partial h(\mathbf{Y}_i)}{\partial \hat{\Theta}^{(m)}}\right)'$$

Untuk tujuan tersebut mula-mula dimisalkan terdapat N observasi yang saling bebas, dan  $\mathbf{Y}_i$  merupakan vektor dari variabel respon ordinal untuk sembarang observasi ke- $i$ ,  $i = 1, 2, \dots, N$ .

$h(\mathbf{Y}_i)$  merupakan pdf. marginal dari  $\mathbf{Y}_i$  dalam populasi, dari persamaan (3.2.1.40) pada bab 3, diketahui:

$$h(\mathbf{Y}_i) = \int_{\Theta} \ell(\mathbf{Y}_i | \theta, \alpha) g(\theta) d\theta$$

Fungsi marginal likelihood dari N unit level-2 adalah:

$$L(\Theta) = \prod_{i=1}^N h(\mathbf{Y}_i)$$

Misalkan  $l(\Theta)$  adalah fungsi *log likelihood* dari vektor  $\Theta$ ,

$$l(\Theta) = \log L = \sum_{i=1}^N \log h(\mathbf{Y}_i)$$

$U(\Theta)$  adalah vektor turunan parsial pertama dari  $l(\Theta)$  seperti yang diberikan pada lampiran 4.

$H(\Theta)$  adalah matriks turunan parsial kedua dari  $l(\Theta)$  seperti yang diberikan pada lampiran 4.

Ekspektasi dari matriks  $H(\Theta)$  dinyatakan dengan,



- Ekspektasi turunan parsial kedua dari  $l(\Theta)$  terhadap nilai tertentu

$\mu_{r'}$  dan  $\mu_{r''}$ ,  $r', r'' = 0, 1, \dots, R$  adalah

$$\begin{aligned}
 E \left[ \frac{\partial^2 l(\Theta)}{\partial \mu_{r'} \partial \mu_{r''}} \right] &= E \left[ \frac{\partial^2 \left( \sum_{i=1}^N \log h(\mathbf{Y}_i) \right)}{\partial \mu_{r'} \partial \mu_{r''}} \right] = E \left[ \sum_{i=1}^N \left( \frac{\partial^2 \log h(\mathbf{Y}_i)}{\partial \mu_{r'} \partial \mu_{r''}} \right) \right] \\
 &= \sum_{i=1}^N E \left[ \frac{\partial^2 \log h(\mathbf{Y}_i)}{\partial \mu_{r'} \partial \mu_{r''}} \right] = \sum_{i=1}^N E \left[ \frac{\partial}{\partial \mu_{r'}} \left( \frac{\partial \log h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right] \\
 &= \sum_{i=1}^N E \left[ \frac{\partial}{\partial \mu_{r'}} \left( \frac{1}{h(\mathbf{Y}_i)} \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right] \\
 &= \sum_{i=1}^N E \left[ \left( \frac{\partial}{\partial \mu_{r'}} \cdot \frac{1}{h(\mathbf{Y}_i)} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right] \\
 &= \sum_{i=1}^N E \left[ -\frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) + \frac{1}{h(\mathbf{Y}_i)} \frac{\partial^2 h(\mathbf{Y}_i)}{\partial \mu_{r'} \partial \mu_{r''}} \right] \\
 &= \sum_{i=1}^N \left[ E \left( -\frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right) + E \left( \frac{1}{h(\mathbf{Y}_i)} \frac{\partial^2 h(\mathbf{Y}_i)}{\partial \mu_{r'} \partial \mu_{r''}} \right) \right] \\
 &= \sum_{i=1}^N \left\{ -E \left( \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right) + \left[ \sum_{\mathbf{Y}_i} \left( \frac{1}{h(\mathbf{Y}_i)} \frac{\partial^2 h(\mathbf{Y}_i)}{\partial \mu_{r'} \partial \mu_{r''}} \right) \cdot h(\mathbf{Y}_i) \right] \right\} \\
 &= \sum_{i=1}^N \left\{ -E \left( \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right) + \left[ \sum_{\mathbf{Y}_i} \left( \frac{\partial^2 h(\mathbf{Y}_i)}{\partial \mu_{r'} \partial \mu_{r''}} \right) \right] \right\} \\
 &= \sum_{i=1}^N \left\{ -E \left( \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right) + \left[ \frac{\partial^2}{\partial \mu_{r'} \partial \mu_{r''}} \cdot \sum_{\mathbf{Y}_i} h(\mathbf{Y}_i) \right] \right\} \\
 &= \sum_{i=1}^N \left\{ -E \left( \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right) + \underbrace{\left[ \frac{\partial^2}{\partial \mu_{r'} \partial \mu_{r''}} \cdot 1 \right]}_0 \right\} \\
 &= \sum_{i=1}^N \left[ -E \left( \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right) \right] \\
 &= E \left[ -\sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r''}} \right) \right]
 \end{aligned}$$



Dengan mengikuti prosedur yang sama seperti pada persamaan (1), maka diperoleh:

- Ekspektasi turunan parsial kedua dari  $I(\Theta)$  terhadap nilai tertentu

$\alpha_p$  dan  $\alpha_{p'}$ ,  $p, p' = 1, \dots, P$  adalah

$$E \left[ \frac{\partial^2 I(\Theta)}{\partial \alpha_p \partial \alpha_{p'}} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \alpha_p} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \alpha_{p'}} \right) \right] \quad (2)$$

- Ekspektasi turunan parsial kedua dari  $I(\Theta)$  terhadap nilai tertentu

$\gamma_{c'}$  dan  $\gamma_{c''}$ ,  $c', c'' = 2, \dots, C-2$  adalah

$$E \left[ \frac{\partial^2 I(\Theta)}{\partial \gamma_{c'} \partial \gamma_{c''}} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \gamma_{c'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \gamma_{c''}} \right) \right] \quad (3)$$

- Ekspektasi turunan parsial kedua dari  $I(\Theta)$  terhadap nilai tertentu

$t_{rh}$  dan  $t_{r'h'}$ ,  $0 \leq r \leq h \leq R$ ;  $0 \leq r' \leq h' \leq R$  adalah

$$E \left[ \frac{\partial^2 I(\Theta)}{\partial t_{rh} \partial t_{r'h'}} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial t_{rh}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial t_{r'h'}} \right) \right] \quad (4)$$

- Ekspektasi turunan parsial kedua dari  $I(\Theta)$  terhadap nilai tertentu

$\mu_r$  dan  $\alpha_p$ ,  $r = 0, 1, \dots, R$ ;  $p = 1, \dots, P$  adalah

$$E \left[ \frac{\partial^2 I(\Theta)}{\partial \mu_r \partial \alpha_p} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_r} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \alpha_p} \right) \right] \quad (5)$$

(1)

- Ekspektasi turunan parsial kedua dari  $l(\Theta)$  terhadap nilai tertentu

$\mu_r$  dan  $\gamma_{c'}$ ,  $r = 0, 1, \dots, R$ ;  $c' = 2, \dots, C-1$  adalah

$$E \left[ \frac{\partial^2 l(\Theta)}{\partial \mu_r \partial \gamma_{c'}} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_r} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \gamma_{c'}} \right) \right] \quad (6)$$

- Ekspektasi turunan parsial kedua dari  $l(\Theta)$  terhadap nilai tertentu

$\mu_{r'}$  dan  $t_{rh}$ ,  $r' = 0, 1, \dots, R$ ;  $0 \leq r \leq h \leq R$  adalah

$$E \left[ \frac{\partial^2 l(\Theta)}{\partial \mu_{r'} \partial t_{rh}} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \mu_{r'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial t_{rh}} \right) \right] \quad (7)$$

- Ekspektasi turunan parsial kedua dari  $l(\Theta)$  terhadap nilai tertentu

$\alpha_p$  dan  $\gamma_{c'}$ ,  $p = 1, \dots, P$ ;  $c' = 2, \dots, C-1$  adalah

$$E \left[ \frac{\partial^2 l(\Theta)}{\partial \alpha_p \partial \gamma_{c'}} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \alpha_p} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \gamma_{c'}} \right) \right] \quad (8)$$

- Ekspektasi turunan parsial kedua dari  $l(\Theta)$  terhadap nilai tertentu

$\alpha_p$  dan  $t_{rh}$ ,  $p = 1, \dots, P$ ;  $0 \leq r \leq h \leq R$  adalah

$$E \left[ \frac{\partial^2 l(\Theta)}{\partial \alpha_p \partial t_{rh}} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \alpha_p} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial t_{rh}} \right) \right] \quad (9)$$

- Ekspektasi turunan parsial kedua dari  $l(\Theta)$  terhadap nilai tertentu

$\gamma_{c'}$  dan  $t_{rh}$ ,  $c' = 2, \dots, C-1$ ;  $0 \leq r \leq h \leq R$  adalah

$$E \left[ \frac{\partial^2 l(\Theta)}{\partial \gamma_{c'} \partial t_{rh}} \right] = E \left[ - \sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left( \frac{\partial h(\mathbf{Y}_i)}{\partial \gamma_{c'}} \right) \left( \frac{\partial h(\mathbf{Y}_i)}{\partial t_{rh}} \right) \right] \quad (10)$$

dengan,

$$\bullet \quad \frac{\partial(h(\mathbf{Y}_i))}{\partial \gamma_{c'}} = \int_{\theta} \left( \sum_{k=1}^{n_i} \sum_{c=1}^C d_{ikc} \left( \frac{\phi(\gamma_c - z_{ik}) \delta_{cc'} - \phi(\gamma_{c-1} - z_{ik}) \delta_{c-1, c'}}{\Phi(\gamma_c - z_{ik}) - \Phi(\gamma_{c-1} - z_{ik})} \right) \right) \ell(\mathbf{Y}_i | \theta, \alpha) g(\theta) d\theta$$

,  $c' = 2, \dots, C-1$

$$\bullet \quad \frac{\partial(h(\mathbf{Y}_i))}{\partial \mu_{r'}} = \int_{\theta} \left( \sum_{k=1}^{n_i} \sum_{c=1}^C d_{ikc} \left( \frac{\phi(\gamma_{c-1} - z_{ik}) - \phi(\gamma_c - z_{ik})}{\Phi(\gamma_c - z_{ik}) - \Phi(\gamma_{c-1} - z_{ik})} \right) x_{r'ik} \right) \ell(\mathbf{Y}_i | \theta, \alpha) g(\theta) d\theta$$

,  $r' = 0, 1, \dots, R$

$$\bullet \quad \frac{\partial(h(\mathbf{Y}_i))}{\partial \alpha_{p'}} = \int_{\theta} \left( \sum_{k=1}^{n_i} \sum_{c=1}^C d_{ikc} \left( \frac{\phi(\gamma_{c-1} - z_{ik}) - \phi(\gamma_c - z_{ik})}{\Phi(\gamma_c - z_{ik}) - \Phi(\gamma_{c-1} - z_{ik})} \right) w_{p'ik} \right) \ell(\mathbf{Y}_i | \theta, \alpha) g(\theta) d\theta$$

,  $p' = 1, \dots, P$

$$\bullet \quad \frac{\partial(h(\mathbf{Y}_i))}{\partial t_{rh}} = \int_{\theta} \left( \sum_{k=1}^{n_i} \sum_{c=1}^C d_{ikc} \left( \frac{\phi(\gamma_{c-1} - z_{ik}) - \phi(\gamma_c - z_{ik})}{\Phi(\gamma_c - z_{ik}) - \Phi(\gamma_{c-1} - z_{ik})} \right) \theta_h x_{rik} \right) \ell(\mathbf{Y}_i | \theta, \alpha) g(\theta) d\theta$$

$0 \leq r \leq h \leq R$

Sehingga, dari persamaan (1), (2), ..., (10) di atas diperoleh:



Jadi, ekspektasi dari taksiran matriks turunan parsial kedua dari  $l(\Theta)$  pada iterasi ke- $m$ ,  $m = 0, 1, 2, \dots$  yaitu:

$$E\left[H(\hat{\Theta}^{(m)})\right] = E\left[-\sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left(\frac{\partial h(\mathbf{Y}_i)}{\partial \hat{\Theta}^{(m)}}\right) \cdot \left(\frac{\partial h(\mathbf{Y}_i)}{\partial \hat{\Theta}^{(m)}}\right)'\right] \quad (11)$$

Karena  $h(\mathbf{Y}_i)$  merupakan fungsi dari

$\Theta = [\mu_0, \dots, \mu_R \quad \alpha_1, \dots, \alpha_P \quad \gamma_2, \dots, \gamma_{C-1} \quad t_{00}, \dots, t_{RR}]'$  yang nilainya diketahui, maka

$\left[-\sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left(\frac{\partial h(\mathbf{Y}_i)}{\partial \hat{\Theta}^{(m)}}\right) \cdot \left(\frac{\partial h(\mathbf{Y}_i)}{\partial \hat{\Theta}^{(m)}}\right)'\right]$  merupakan suatu konstanta, sehingga

persamaan (11) dapat ditulis:

$$E\left[H(\hat{\Theta}^{(m)})\right] = -\sum_{i=1}^N \frac{1}{h(\mathbf{Y}_i)^2} \cdot \left(\frac{\partial h(\mathbf{Y}_i)}{\partial \hat{\Theta}^{(m)}}\right) \cdot \left(\frac{\partial h(\mathbf{Y}_i)}{\partial \hat{\Theta}^{(m)}}\right)'$$

∴ Terbukti

## LAMPIRAN 6

## Data untuk Contoh 4.1

No	Class ID	Post-THKS	Pre-THKS	CC	TV	CC*TV
1	403101	3	2	1	0	0
2	403101	4	4	1	0	0
3	403101	3	4	1	0	0
4	403101	4	3	1	0	0
5	403101	4	3	1	0	0
6	403101	3	4	1	0	0
7	403101	2	2	1	0	0
8	403101	4	4	1	0	0
9	403101	5	5	1	0	0
10	403101	4	3	1	0	0
11	403101	3	3	1	0	0
12	403101	4	3	1	0	0
13	403101	3	1	1	0	0
14	403101	4	2	1	0	0
15	403101	2	2	1	0	0
16	403101	4	1	1	0	0
17	403101	4	4	1	0	0
18	403101	3	3	1	0	0
19	403101	3	0	1	0	0
20	403101	4	3	1	0	0
21	403102	2	0	1	0	0
22	403102	5	1	1	0	0
23	403102	3	5	1	0	0
24	404101	3	1	1	1	1
25	404101	4	2	1	1	1
26	404101	2	4	1	1	1
27	404101	3	3	1	1	1
28	404101	2	1	1	1	1
29	404101	1	1	1	1	1
30	404101	3	2	1	1	1
31	404101	5	0	1	1	1
32	404101	2	1	1	1	1
33	404101	3	2	1	1	1
34	404101	4	2	1	1	1
35	404102	3	1	1	1	1
36	404102	1	1	1	1	1
37	404102	0	0	1	1	1

38	404102	4	4	1	1	1
39	404102	5	1	1	1	1
40	404102	3	2	1	1	1
41	404102	3	1	1	1	1
42	404102	4	2	1	1	1
43	404102	2	2	1	1	1
44	404103	3	2	1	1	1
45	404103	2	1	1	1	1
46	404103	2	2	1	1	1
47	404103	3	1	1	1	1
48	404103	3	1	1	1	1
49	193101	2	1	0	0	0
50	193101	2	3	0	0	0
51	193101	3	0	0	0	0
52	193101	2	3	0	0	0
53	193101	1	1	0	0	0
54	193101	2	2	0	0	0
55	193101	4	3	0	0	0
56	193101	2	3	0	0	0
57	193101	3	3	0	0	0
58	193101	3	1	0	0	0
59	193101	1	5	0	0	0
60	193101	2	1	0	0	0
61	193101	1	3	0	0	0
62	193101	2	2	0	0	0
63	193101	1	0	0	0	0
64	193101	4	3	0	0	0
65	193101	3	4	0	0	0
66	193101	5	2	0	0	0
67	193101	4	2	0	0	0
68	193101	1	3	0	0	0
69	193101	3	2	0	0	0
70	193101	3	3	0	0	0
71	193101	2	1	0	0	0
72	193101	4	2	0	0	0
73	193101	3	0	0	0	0
74	193101	2	3	0	0	0
75	194101	1	3	0	0	0
76	194101	2	1	0	0	0
77	194101	3	2	0	0	0
78	194101	3	2	0	0	0
79	194101	1	0	0	0	0
80	194101	3	0	0	0	0
81	194101	2	4	0	0	0
82	194101	2	2	0	0	0
83	194101	3	1	0	0	0

## LAMPIRAN 7

### Output MIXOR 2.0 for Windows untuk Contoh 4.1

MIXOR - The program for mixed-effects ordinal regression analysis  
(version 2)

TVSFP study - Post-Test Tobacco & Health Knowledge ORDINAL  
Students nested within CLASSROOMS - 1 random effect

Response function: normal  
Random-effects distribution: normal

Covariate(s) and random-effect(s) mean subtracted from thresholds  
==> positive coefficient = positive association between regressor  
and ordinal outcome

Numbers of observations

-----  
Level 1 observations = 1600  
Level 2 observations = 135

The number of Level 1 observations per Level 2 unit are:

20	3	11	9	5	26	11	10	15	12	12	10	21	10	17	19	2	4	21
16	15	13	2	14	13	1	12	18	21	17	16	15	16	21	21	27	17	3
2	15	7	24	22	15	19	7	12	8	6	11	7	7	8	3	5	8	3
8	9	8	2	11	9	21	13	12	12	14	9	6	11	10	12	11	6	6
14	10	14	2	3	2	4	3	6	10	14	11	6	22	4	7	22	18	23
19	14	5	14	28	15	15	11	12	11	11	15	17	24	20	15	6	8	14
5	11	9	17	14	11	17	15	6	7	14	10	14	18	4	9	7	12	15
11	10																	

Descriptive statistics for all variables

Variable	Minimum	Maximum	Mean	Stand. Dev.
THKScore	1.00000	4.00000	2.58688	1.11612



Intrcpt	1.00000	1.00000	1.00000	0.00000
PreTHKS	0.00000	6.00000	2.06938	1.26018
CC	0.00000	1.00000	0.47688	0.49962
TV	0.00000	1.00000	0.49938	0.50016
CC*TV	0.00000	1.00000	0.23938	0.42684

Categories of the response variable THKScore

Category	Frequency	Proportion
1.00	355.00	0.22188
2.00	398.00	0.24875
3.00	400.00	0.25000
4.00	447.00	0.27938

Starting values

mean	1.206
covariates	-0.212 -0.451 -0.140 0.201
var. terms	0.316
thresholds	0.711 1.376

==> The number of level 2 observations with non-varying responses  
= 6 ( 4.44 percent )

\* Final Results - Maximum Marginal Likelihood Estimates \*

Total Iterations	=	15
Quad Pts per Dim	=	10
Log Likelihood	=	-2117.717
Deviance (-2logL)	=	4235.433
Ridge	=	0.000

Variable	Estimate	Stand. Error	Z	p-value
Intrcpt	0.06220	0.09132	0.68114	0.49578 (2)
PreTHKS	0.24247	0.02351	10.31253	0.00000 (2)
CC	0.50945	0.11225	4.53860	0.00001 (2)
TV	0.12363	0.10032	1.23232	0.21783 (2)
CC*TV	-0.19378	0.15013	-1.29074	0.19679 (2)

Random effect variance term (standard deviation)				
Intrcpt	0.26163	0.04504	5.80822	0.00000 (1)
Thresholds (for identification: threshold 1 = 0)				
2	0.76063	0.03584	21.22279	0.00000 (1)
3	1.48749	0.04403	33.78686	0.00000 (1)

note: (1) = 1-tailed p-value

(2) = 2-tailed p-value

Calculation of the intraclass correlation

-----  
 residual variance = 1 (assumed)

cluster variance =  $(0.262 * 0.262) = 0.068$

intraclass correlation =  $0.068 / (0.068 + 1.000) = 0.064$

## LAMPIRAN 8

## Data untuk Contoh 4.2

No.	Patient ID	Ordinal IMPS79 Score	Drug	Time		Drug*Time
				Week	Sqrt Week	
1	1103	4	1	0	0	0
2	1103	2	1	1	1	1
3	1103	-9	1	2	1,4142	1,4142
4	1103	2	1	3	1,7321	1,7321
5	1103	-9	1	4	2	2
6	1103	-9	1	5	2,2361	2,2361
7	1103	2	1	6	2,4495	2,4495
8	1104	4	1	0	0	0
9	1104	2	1	1	1	1
10	1104	-9	1	2	1,4142	1,4142
11	1104	1	1	3	1,7321	1,7321
12	1104	-9	1	4	2	2
13	1104	-9	1	5	2,2361	2,2361
14	1104	2	1	6	2,4495	2,4495
15	1105	2	1	0	0	0
16	1105	2	1	1	1	1
17	1105	-9	1	2	1,4142	1,4142
18	1105	1	1	3	1,7321	1,7321
19	1105	-9	1	4	2	2
20	1105	-9	1	5	2,2361	2,2361
21	1105	-9	1	6	2,4495	2,4495
22	1106	2	1	0	0	0
23	1106	1	1	1	1	1
24	1106	-9	1	2	1,4142	1,4142
25	1106	1	1	3	1,7321	1,7321
26	1106	-9	1	4	2	2
27	1106	-9	1	5	2,2361	2,2361
28	1106	1	1	6	2,4495	2,4495
29	1107	3	0	0	0	0
30	1107	3	0	1	1	0
31	1107	-9	0	2	1,4142	0
32	1107	3	0	3	1,7321	0
33	1107	-9	0	4	2	0
34	1107	-9	0	5	2,2361	0
35	1107	4	0	6	2,4495	0
36	1108	4	1	0	0	0
37	1108	4	1	1	1	1

38	1108	-9	1	2	1,4142	1,4142
39	1108	2	1	3	1,7321	1,7321
40	1108	-9	1	4	2	2
41	1108	-9	1	5	2,2361	2,2361
42	1108	3	1	6	2,4495	2,4495
43	1109	2	1	0	0	0
44	1109	1	1	1	1	1
45	1109	-9	1	2	1,4142	1,4142
46	1109	1	1	3	1,7321	1,7321
47	1109	-9	1	4	2	2
48	1109	-9	1	5	2,2361	2,2361
49	1109	2	1	6	2,4495	2,4495
50	1110	2	1	0	0	0
51	1110	3	1	1	1	1
52	1110	-9	1	2	1,4142	1,4142
53	1110	2	1	3	1,7321	1,7321
54	1110	-9	1	4	2	2
55	1110	-9	1	5	2,2361	2,2361
56	1110	2	1	6	2,4495	2,4495
57	1111	4	1	0	0	0
58	1111	4	1	1	1	1
59	1111	-9	1	2	1,4142	1,4142
60	1111	4	1	3	1,7321	1,7321
61	1111	-9	1	4	2	2
62	1111	-9	1	5	2,2361	2,2361
63	1111	2	1	6	2,4495	2,4495
64	1112	3	0	0	0	0
65	1112	-9	0	1	1	0
66	1112	-9	0	2	1,4142	0
67	1112	2	0	3	1,7321	0
68	1112	-9	0	4	2	0
69	1112	-9	0	5	2,2361	0
70	1112	2	0	6	2,4495	0
71	1113	2	1	0	0	0
72	1113	2	1	1	1	1
73	1113	-9	1	2	1,4142	1,4142
74	1113	3	1	3	1,7321	1,7321
75	1113	-9	1	4	2	2
76	1113	-9	1	5	2,2361	2,2361
77	1113	2	1	6	2,4495	2,4495
78	1114	4	1	0	0	0
79	1114	4	1	1	1	1
80	1114	-9	1	2	1,4142	1,4142
81	1114	4	1	3	1,7321	1,7321
82	1114	-9	1	4	2	2
83	1114	-9	1	5	2,2361	2,2361

## LAMPIRAN 9

### Output MIXOR 2.0 for Windows untuk Contoh 4.2

MIXOR - The program for mixed-effects ordinal regression analysis  
(version 2)

NIMH Schiz Data - two grps - seven timepoints  
IMPS79 (ordinal) across SQRT Week - two random effects

Response function: normal  
Random-effects distribution: normal

Covariate(s) and random-effect(s) mean subtracted from thresholds  
==> positive coefficient = positive association between regressor  
and ordinal outcome

Numbers of observations

-----  
Level 1 observations = 1603  
Level 2 observations = 437

The number of level 1 observations per level 2 unit are:

4	4	3	4	4	4	4	4	4	3	4	4	4	2	3	4	3	4	3
4	4	4	3	3	2	4	4	4	4	4	3	4	4	4	4	4	4	4
4	4	2	3	4	3	4	4	4	3	4	4	2	2	4	5	4	2	4
4	3	4	4	3	2	3	4	4	4	4	4	4	2	4	4	4	5	4
4	2	2	4	2	4	4	3	3	4	4	4	4	4	4	4	4	3	3
4	2	3	4	4	4	2	5	3	4	4	2	4	4	4	2	4	4	4
4	4	4	4	4	4	5	2	4	3	4	4	2	2	4	4	4	4	4
2	4	4	4	4	4	4	4	4	4	4	4	4	4	2	4	4	2	4
4	4	3	4	2	4	4	3	2	3	4	4	3	3	4	3	4	4	4
4	4	4	4	4	4	4	4	4	4	4	4	2	3	3	5	4	3	4
3	2	4	4	4	4	4	3	3	4	4	4	4	4	4	4	4	4	4
4	4	4	4	4	3	4	4	4	4	4	4	4	2	3	4	4	4	2
4	4	4	3	4	4	4	4	4	4	4	4	4	3	4	4	3	4	2
4	4	4	4	2	4	4	4	2	4	4	4	3	3	4	3	4	2	4
4	4	3	3	4	4	4	4	3	3	4	3	4	4	4	4	4	3	4
4	4	4	4	3	3	4	2	4	4	4	4	4	4	4	4	3	4	4

3	3	4	2	4	3	3	3	4	4	4	4	4	4	4	3	2	3	4
4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
4	4	4	4	4	2	4	4	4	4	4	4	4	4	4	4	4	4	4
4	4	2	4	4	4	4	3	4	4	4	4	3	4	4	4	4	4	4
3	3	3	4	4	4	4	4	2	3	4	2	4	2	2	4	4	3	4
4	4	2	4	4	4	4	3	4	4	4	4	4	4	4	4	4	4	4
4	4	4	4	4	4	4	3	4	4	4	4	2	4	4	4	4	4	4

Descriptive statistics for all variables

Variable	Minimum	Maximum	Mean	Stand. Dev.
Imps790	1.00000	4.00000	2.79601	1.02840
Intercpt	1.00000	1.00000	1.00000	0.00000
SqrtWeek	0.00000	2.44950	1.22041	0.89651
TxDrug	0.00000	1.00000	0.76419	0.42464
Tx*SWeek	0.00000	2.44950	0.94424	0.94541

Categories of the response variable Imps790

Category	Frequency	Proportion
1.00	190.00	0.11853
2.00	474.00	0.29570
3.00	412.00	0.25702
4.00	527.00	0.32876

Crosstabulation of variable SqrtWeek by the response variable Imps790

SqrtWeek	Imps790				Total
	1.00	2.00	3.00	4.00	
0.00	1.0 (0.00)	54.0 (0.12)	122.0 (0.28)	257.0 (0.59)	434.0
1.00	23.0 (0.05)	135.0 (0.32)	124.0 (0.29)	144.0 (0.34)	426.0

1.41	3.0	4.0	2.0	5.0	14.0
	(0.21)	(0.29)	(0.14)	(0.36)	
1.73	54.0	132.0	113.0	75.0	374.0
	(0.14)	(0.35)	(0.30)	(0.20)	
2.00	5.0	3.0	2.0	1.0	11.0
	(0.45)	(0.27)	(0.18)	(0.09)	
2.24	3.0	4.0	0.0	2.0	9.0
	(0.33)	(0.44)	(0.00)	(0.22)	
2.45	101.0	142.0	49.0	43.0	335.0
	(0.30)	(0.42)	(0.15)	(0.13)	
Total	190.0	474.0	412.0	527.0	1603.0

## Starting values

```
-----
mean      0.835  0.264
covariates 0.028  0.345
var. terms 1.000  0.000  0.500
thresholds 1.037  1.700
```

```
==> The number of level 2 observations with non-varying responses
=      79 ( 18.08 percent )
```

## \* Final Results - Maximum Marginal Likelihood Estimates \*

```
-----
Total Iterations = 21
Quad Pts per Dim = 10
Log Likelihood = -1663.352
Deviance (-2logL) = 3326.704
Ridge = 0.000
```

Variable	Estimate	Stand. Error	Z	p-value
-----	-----	-----	-----	-----
Intercpt	4.10997	0.25191	16.31505	0.00000 (2)
SqrtWeek	-0.50548	0.13048	-3.87407	0.00011 (2)
TxDrug	0.03823	0.22470	0.17013	0.86491 (2)
Tx*SWeek	-0.95018	0.14885	-6.38358	0.00000 (2)

Random effect variance & covariance terms (Cholesky of var-covariance matrix)

Intercpt	1.48627	0.14130	10.51880	0.00000 (1)
covariance	-0.31473	0.08992	-3.49999	0.00047 (2)
SqrtWeek	0.73025	0.06950	10.50782	0.00000 (1)

Thresholds (for identification: threshold 1 = 0)

2	2.18411	0.10992	19.86965	0.00000 (1)
3	3.65352	0.14423	25.33155	0.00000 (1)

note: (1) = 1-tailed p-value

(2) = 2-tailed p-value

Calculation of the random effects variance-covariance matrix

-----

Intercpt variance =  $(1.486 * 1.486) = 2.209$

covariance =  $(1.486 * -.315) = -.468$

SqrtWeek variance =  $(-.315 * -.315) + (0.730 * 0.730) = 0.632$

Covariance expressed as a correlation =  $-.396$