

1) a)  $y_{ij} | a_i \stackrel{\text{iid}}{\sim} N(\mu + a_i + \beta_j, \sigma^2)$ ,  $a_i \stackrel{\text{iid}}{\sim} N(0, \sigma_a^2)$

$$y | a \in \mathbb{R}^{m \times n}, \quad y | a = \begin{bmatrix} y_{11} & y_{12} & \dots & y_{1n} \\ y_{21} & y_{22} & \dots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \dots & y_{mn} \end{bmatrix} = \begin{bmatrix} \mu + a_1 + \beta_1 + \varepsilon_{11} & \mu + a_1 + \beta_2 + \varepsilon_{12} & \dots & \mu + a_1 + \beta_n + \varepsilon_{1n} \\ \mu + a_2 + \beta_1 + \varepsilon_{21} & \mu + a_2 + \beta_2 + \varepsilon_{22} & \dots & \mu + a_2 + \beta_n + \varepsilon_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mu + a_m + \beta_1 + \varepsilon_{m1} & \mu + a_m + \beta_2 + \varepsilon_{m2} & \dots & \mu + a_m + \beta_n + \varepsilon_{mn} \end{bmatrix}$$

Marginal Mean

$$\begin{aligned} \Rightarrow E(y_{ij}) &= E[E(y_{ij} | a_i)] \text{ , using the double expectation theorem} \\ &= E[\mu + a_i + \beta_j] \text{ , using the assumption } a_i \sim N(0, \sigma_a^2) \\ &= \mu + \beta_j \end{aligned}$$

Marginal Variance

$$\begin{aligned} \Rightarrow \text{Var}(y_{ij}) &= E[\text{Var}(y_{ij} | a_i)] + \text{Var}[E(y_{ij} | a_i)] \text{ , using the double expectation theorem} \\ &= E[\sigma^2] + \text{Var}(\mu + a_i + \beta_j) \\ &= \sigma^2 + \sigma_a^2 \end{aligned}$$

$$\therefore E(y) = [\mu + \beta_1 \quad \mu + \beta_2 \quad \dots \quad \mu + \beta_n]$$

$$\text{Var}(y) = (\sigma^2 + \sigma_a^2) I_n$$

b) Marginal Mean

$$\begin{aligned} \Rightarrow E(y_{ij}) &= E[E(y_{ij} | a_i, b_j)] \text{ , using the double expectation theorem} \\ &= E[\mu + a_i + b_j] \text{ , using } a_i \stackrel{\text{iid}}{\sim} N(0, \sigma_a^2), b_j \stackrel{\text{iid}}{\sim} N(0, \sigma_b^2) \\ &= \mu \end{aligned}$$

Marginal Variance

$$\begin{aligned} \Rightarrow \text{Var}(y_{ij}) &= E[\text{Var}(y_{ij} | a_i, b_j)] + \text{Var}[E(y_{ij} | a_i, b_j)] \text{ , using the double expectation theorem} \\ &= E[\sigma^2] + \text{Var}(\mu + a_i + b_j) \\ &= \sigma^2 + \sigma_a^2 + \sigma_b^2 \end{aligned}$$

c) Marginal Mean

$$\begin{aligned}\Rightarrow E(Y_{ij}) &= E[E(Y_{ij} | a_i, b_j, g_{ij})], \text{ using the double expectation theorem} \\ &= E[\mu + a_i + b_j + g_{ij}], \text{ using } a_i \stackrel{\text{IID}}{\sim} N(0, \sigma_a^2), b_j \stackrel{\text{IID}}{\sim} N(0, \sigma_b^2), g_{ij} \stackrel{\text{IID}}{\sim} N(0, \sigma_g^2) \\ &= \mu\end{aligned}$$

Marginal Variance

$$\begin{aligned}\Rightarrow \text{Var}(Y_{ij}) &= E[\text{Var}(Y_{ij} | a_i, b_j, g_{ij})] + \text{Var}[E(Y_{ij} | a_i, b_j, g_{ij})], \text{ using the double expectation theorem} \\ &= E[\sigma^2] + \text{Var}(\mu + a_i + b_j + g_{ij}) \\ &= \sigma^2 + \sigma_a^2 + \sigma_b^2 + \sigma_g^2\end{aligned}$$

2) a) 
$$\begin{aligned}\text{Var}(Y_{ij}) &= \text{Var}(\beta_{0i} + \beta_{1i} t_{ij} + \varepsilon_{ij}) \\ &= \text{Var}(\beta_{0i}) + \text{Var}(\beta_{1i} t_{ij}) + \text{Var}(\varepsilon_{ij}) + 2 \cdot \text{Cov}(\beta_{0i}, \beta_{1i} t_{ij}) \\ &= D_{11} + t_{ij}^2 D_{22} + \sigma^2 + 2 t_{ij} D_{12}\end{aligned}$$

$$\begin{aligned}\text{Cov}(Y_{ij}, Y_{ik}) &= \text{Cov}(\beta_{0i} + \beta_{1i} t_{ij} + \varepsilon_{ij}, \beta_{0i} + \beta_{1i} t_{ik} + \varepsilon_{ik}) \\ &= \text{Var}(\beta_{0i}) + \text{Cov}(\beta_{0i}, \beta_{1i} t_{ik}) + \text{Cov}(\beta_{1i} t_{ij}, \beta_{0i}) + \text{Cov}(\beta_{1i} t_{ij}, \beta_{1i} t_{ik}) \\ &= D_{11} + t_{ik} D_{12} + t_{ij} D_{12} + t_{ij} t_{ik} D_{22}\end{aligned}$$

b) 
$$\begin{aligned}\text{Cov}(Y_{ij}, Y_{ik}) &= D_{11} + t_{ik} D_{12} + t_{ij} D_{12} + t_{ij} t_{ik} D_{22}, \text{ let } D_{12} = 0 \\ &= D_{11} + t_{ij} t_{ik} D_{22}\end{aligned}$$

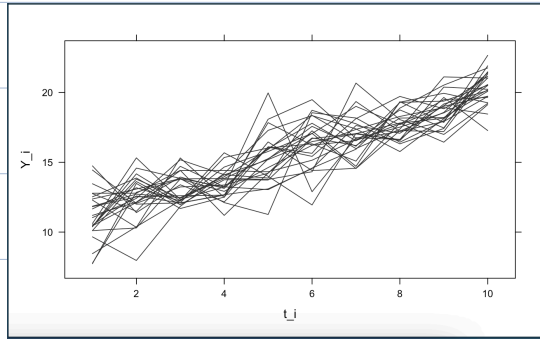
$\therefore Y_{ij}$  and  $Y_{ik}$  are correlated since within-subject variation still exists.

c) 
$$\begin{aligned}\text{Var}(Y_{ij}) &= \text{Cov}(\beta_{0i} + \beta_{1i} t_{ij} + \varepsilon_{ij}, \beta_{0i} + \beta_{1i} t_{ij} + \varepsilon_{ij}) \\ &= \text{Var}(\beta_{0i}) + t_{ij}^2 \text{Var}(\beta_{1i}) + 2 \text{Cov}(\beta_{0i}, \beta_{1i} t_{ij}) + \text{Var}(\varepsilon_{ij}) \\ &= D_{11} + t_{ij}^2 D_{22} + \sigma_1^2 + \sigma_2^2\end{aligned}$$

$$\begin{aligned}\text{Cov}(Y_{ij}, Y_{ik}) &= \text{Cov}(\beta_{0i} + \beta_{1i} t_{ij} + \varepsilon_{ij}, \beta_{0i} + \beta_{1i} t_{ik} + \varepsilon_{ik}) \\ &= \text{Var}(\beta_{0i}) + \text{Cov}(\beta_{1i} t_{ij}, \beta_{1i} t_{ik}) + (t_{ij} + t_{ik}) \text{Cov}(\beta_{0i}, \beta_{1i}) + \text{Cov}(\varepsilon_{ij}, \varepsilon_{ik}) \\ &= D_{11} + t_{ij} t_{ik} D_{22} + (t_{ij} + t_{ik}) D_{12} + \rho^{|j-k|} \sigma_1^2\end{aligned}$$

3) default conditions: (i)  $n_i = 10$ ,  $t_{ij} = j$ ,  $E(Y_{ij}|X_i) = \beta_0 + \beta_1 t_{ij}$ ,  $m = 25$  subjects,  $\beta = [10 \ 1]$

a)  $\sigma = 1$ ,  $\tau = 1$

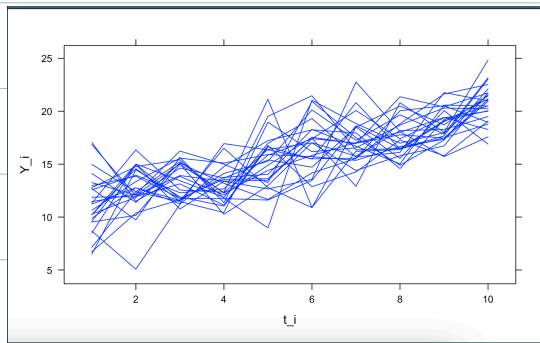


$$\Rightarrow \text{COV}(Y_{ij}, Y_{ik}) = \text{COV}(b_{0,i}, b_{0,i}) + \text{COV}(\varepsilon_{ij}, \varepsilon_{ik})$$

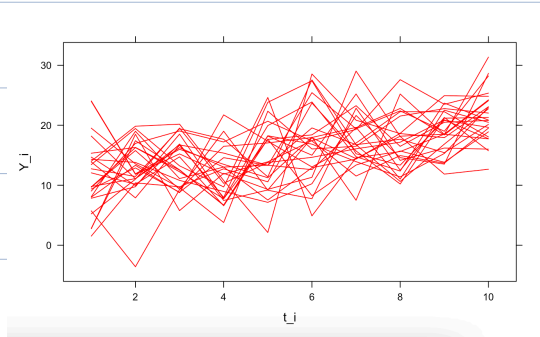
$$= \begin{cases} \tau^2 & , \forall i \neq k \\ \sigma^2 + \tau^2 & , \forall i = k \end{cases}$$


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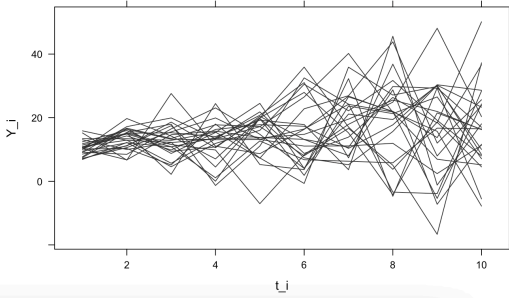
$\sigma = 1$ ,  $\tau = 2$



$\sigma = 1$ ,  $\tau = 5$



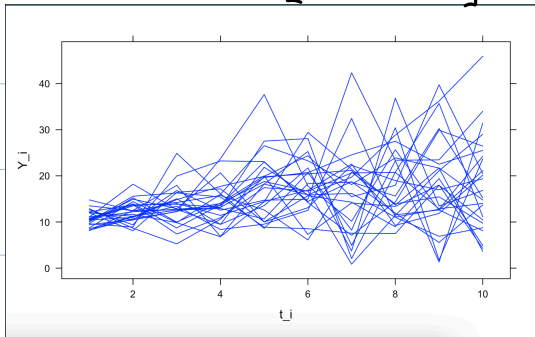
b)  $\sigma = 1$  ,  $D = \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$



$$\begin{aligned} \text{COV}(Y_{ij}, Y_{ik}) &= \text{COV}(\beta_0 + \beta_1 t_{ij} + b_{0,i} + b_{1,i} t_{ij} + \varepsilon_{ij}, \beta_0 + \beta_1 t_{ik} + b_{0,i} + b_{1,i} t_{ik} + \varepsilon_{ik}) \\ &= \text{Var}(\beta_0) + \text{COV}(b_{1,i} t_{ij}, b_{1,i} t_{ik}) + \text{COV}(b_{0,i}, b_{1,i} t_{ij}) + \text{COV}(b_{0,i}, b_{1,i} t_{ik}) + \text{COV}(\varepsilon_{ij}, \varepsilon_{ik}) \\ &= \begin{cases} D_{11} + t_{ij} t_{ik} D_{22} + (t_{ij} + t_{ik}) D_{12}, & \forall j \neq k \\ D_{11} + t_{ij}^2 D_{22} + 2 t_{ij} D_{12} + \sigma^2, & \forall j = k \end{cases} \end{aligned}$$

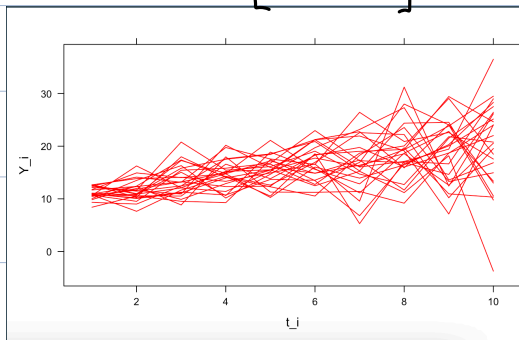
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$\sigma = 1$  ,  $D = \begin{bmatrix} 2 & -0.2 \\ -0.2 & 2 \end{bmatrix}$

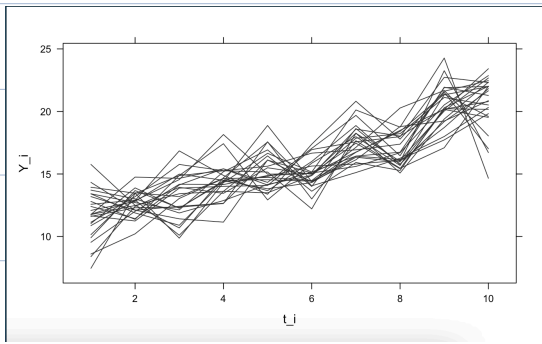


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$\sigma = 1$  ,  $D = \begin{bmatrix} 0.5 & 0 \\ 0 & 0.4 \end{bmatrix}$



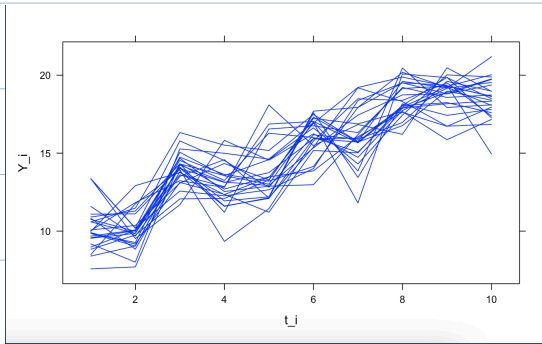
c)  $\sigma = 1, \tau = 2$



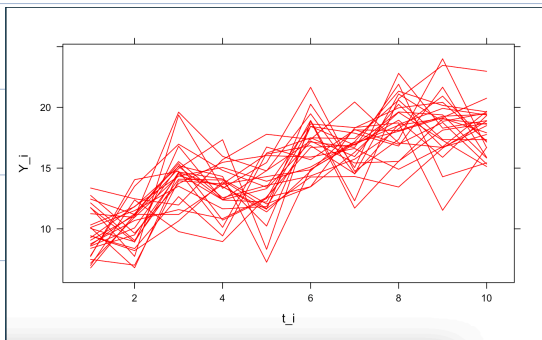
$$\begin{aligned} \text{COV}(Y_{ij}, Y_{ik}) &= \text{COV}(\beta_0 + \beta_1 t_{ij} + W_i(t_{ij}) + \varepsilon_{ij}, \beta_0 + \beta_1 t_{ik} + W_i(t_{ik}) + \varepsilon_{ik}) \\ &= \text{COV}(W_i(t_{ij}), W_i(t_{ik})) + \text{COV}(\varepsilon_{ij}, \varepsilon_{ik}) = \begin{cases} \tau^2 \rho^{|j-k|} & , \forall j \neq k \\ \tau^2 + \sigma^2 & , \forall j = k \end{cases} \end{aligned}$$


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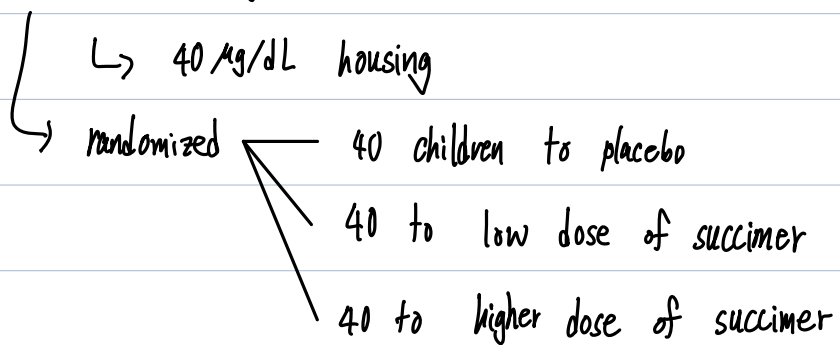
$\sigma = 1, \tau = 2$



$\sigma = 2, \tau = 2$



4) 120 children : greater than or equal to 15  $\mu\text{g}/\text{dL}$



a) R로 풀어서 답인적음

b) (i) lead level과 상관없는 error가 포함되어 있다 → 결국 근데 에러가 일괄적으로 포함이 되었고,

에러가 lead level과 독립적이라는 말 아닐까

(ii) 0, 2, 4, 6, 8 주마다 각 어린이들에게서 lead level 검사를 해왔는데, 이 검사간격 텀이 길어서 within-subject

variation이 반영되지 못했다. linear mixed model - serial correlation

(iii) 모든 treatment group에 관해서 within-child variation이 동일한가

(iv) 그냥 모든 어린이들에 대해서 동일한 모델을 사용할 수 있느냐 인가

c)

d)