

# Problem 1

$$\begin{aligned}\text{Var}(Y_{ij}) &= \text{Var}(\mu + b_i + e_{ij}) \\ &= \text{Var}(b_i) + \text{Var}(e_{ij}) \quad (b_i \perp e_{ij}) \\ &= \sigma_b^2 + \sigma_e^2\end{aligned}$$

$$\begin{aligned}\text{Cov}(Y_{ij}, Y_{ik}) &= E(Y_{ij} - EY_{ij})(Y_{ik} - EY_{ik}) \\ &= E(Y_{ij} - \mu)(Y_{ik} - \mu) \\ &= E(b_i + e_{ij})(b_i + e_{ik}) \\ &= E(b_i^2 + b_i e_{ik} + b_i e_{ij} + e_{ij} e_{ik}) \\ &= E b_i^2 + E b_i E e_{ik} + E b_i E e_{ij} + E e_{ij} E e_{ik} \quad (e_{ij} \perp e_{ik}, b_i \perp e_{i\cdot}) \\ &= E b_i^2 \\ &= \text{Var}(b_i) + (E b_i)^2 \\ &= \sigma_b^2\end{aligned}$$

$$\begin{aligned}\text{Corr}(Y_{ij}, Y_{ik}) &= \frac{\text{Cov}(Y_{ij}, Y_{ik})}{\sqrt{\text{Var}(Y_{ij}) \cdot \text{Var}(Y_{ik})}} \\ &= \frac{\sigma_b^2}{\sigma_b^2 + \sigma_e^2}\end{aligned}$$

Both the variance and correlation is constant across visits, so this corresponds to compound symmetry pattern.

## Problem 2 Question 2

Note: Answers to Questions 1 & 3 of Problem 2 are attached after this.

$$Y_{ij} = \beta_0 + a_i + b_0 * I_{(sex_i=0)} + b_1 * I_{(sex_i=1)} + \beta_1 * age_{ij} + e_{ij}$$

$$\begin{aligned} E(Y_{ij}) &= E(\beta_0 + a_i + b_0 I_{(sex_i=0)} + b_1 I_{(sex_i=1)} + \beta_1 \cdot age_{ij} + e_{ij}) \\ &= \beta_0 + \beta_1 \cdot age_{ij} \end{aligned}$$

$$\text{var}(Y_{ij}) = \text{var}(a_i + b_k + e_{ij}) = \text{var}(a_i) + \text{var}(b_k) + \text{var}(e_{ij}) = \sigma_a^2 + \sigma_b^2 + \sigma_e^2$$

Variance-covariance matrices :

① Within-subject covariance :

$$\begin{aligned} \text{cov}(Y_{ij}, Y_{ik}) &= E[(Y_{ij} - E Y_{ij})(Y_{ik} - E Y_{ik})] \\ &= E[(a_i + b_k + e_{ij})(a_i + b_k + e_{ik})] \\ &= E[a_i^2 + b_k^2 + e_{ij}e_{ik}] \\ &= \sigma_a^2 + \sigma_b^2 \quad (\text{since } e_{ij} \perp e_{ik}) \end{aligned}$$

② Between-subject covariance :

(i) if the subjects are of the same gender :

$$\begin{aligned} \text{cov}(Y_{mj}, Y_{nk}) &= E[(Y_{mj} - E_{mj})(Y_{nk} - E_{nk})] \\ &= E[(a_m + b_l + e_{mj})(a_n + b_l + e_{nk})] \quad (l=0,1) \\ &= E[b_l^2] \\ &= \sigma_b^2 \end{aligned}$$

(ii) if the subjects are of different genders :

$$\begin{aligned} \text{cov}(Y_{mj}, Y_{nk}) &= E[(Y_{mj} - E_{mj})(Y_{nk} - E_{nk})] \\ &= E[(a_m + b_1 + e_{mj})(a_n + b_0 + e_{nk})] \\ &= 0 \quad (\text{since } b_1 \perp b_0) \end{aligned}$$

Based on the above calculation, We construct matrices A and B:

$$A = \begin{bmatrix} \sigma_a^2 + \sigma_b^2 + \sigma_e^2 & \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 \\ \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 + \sigma_e^2 & \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 \\ \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 + \sigma_e^2 & \sigma_a^2 + \sigma_b^2 \\ \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 & \sigma_a^2 + \sigma_b^2 + \sigma_e^2 \end{bmatrix}_{4 \times 4}, \quad B = \begin{bmatrix} \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 \\ \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 \\ \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 \\ \sigma_b^2 & \sigma_b^2 & \sigma_b^2 & \sigma_b^2 \end{bmatrix}_{4 \times 4},$$

where  $A_{4 \times 4}$  is the covariance within a subject, and B is the covariance between measurements from 2 subjects of the same gender.

Therefore, we get

$$C_{\text{boy}} = \begin{bmatrix} A & B & \dots & B \\ B & A & \dots & B \\ \vdots & \vdots & \ddots & \vdots \\ B & B & B & A \end{bmatrix}_{16 \times 16}, \quad D_{\text{girl}} = \begin{bmatrix} A & B & \dots & B \\ B & A & \dots & B \\ \vdots & \vdots & \ddots & \vdots \\ B & B & B & A \end{bmatrix}_{11 \times 11},$$

and finally

$$\text{Var}(\underline{Y}) = \begin{bmatrix} C_{\text{boy}} & 0 \\ 0 & D_{\text{girl}} \end{bmatrix}_{108 \times 108} \quad [108 = (16+11) \times 4]$$

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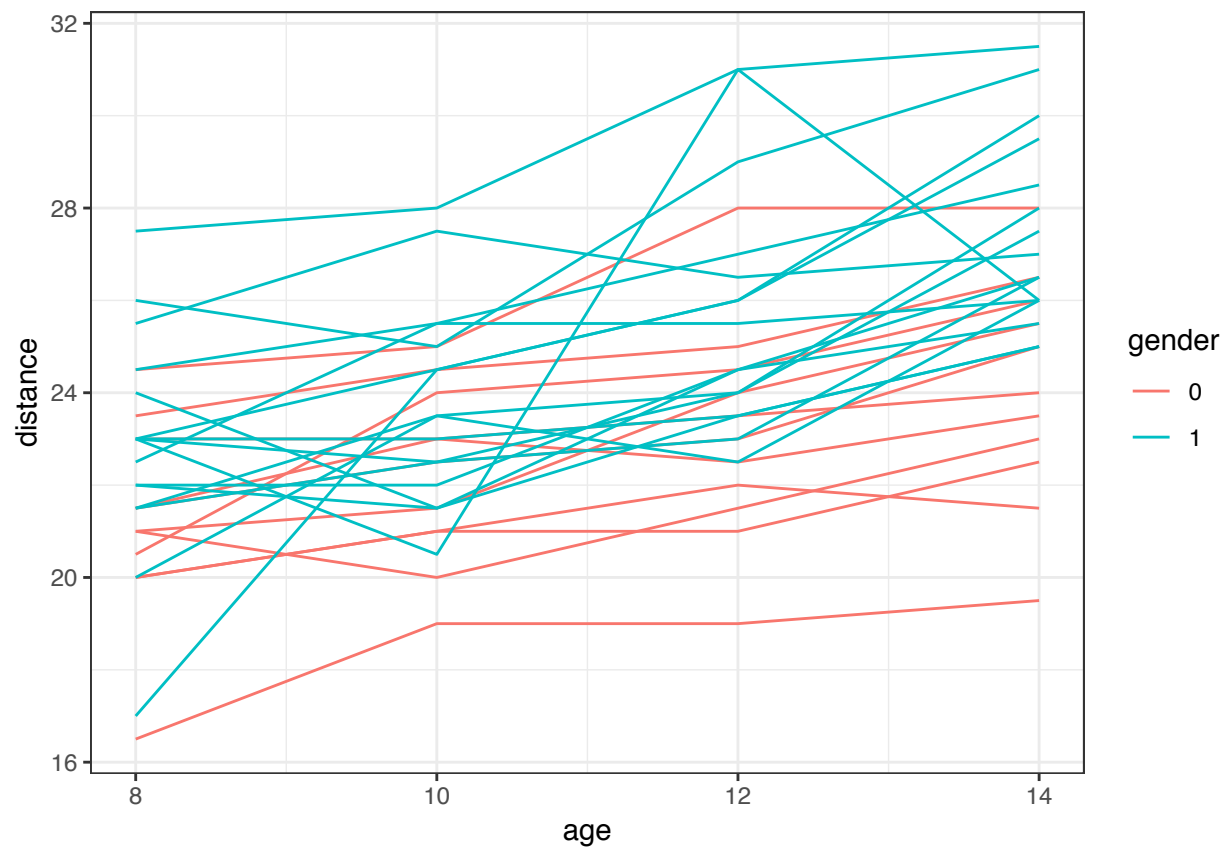
3/31/2019

## Problem 2

### 2.1 Spaghetti Plot

```
# Import data
dental <-
  read.table('HW6-dental.txt', header = TRUE) %>%
  as.tibble() %>% janitor::clean_names() %>%
  mutate(gender = as.factor(gender))

# Spaghetti plot
dental %>%
  ggplot(aes(x = age, y = distance, group = child, color = gender)) +
  geom_line() +
  theme_bw()
```



### 2.2 Marginal Form

Answer to this question is hand-written above.

## 2.3 Comparing models with different covariance patterns

For the following 3 models, we assume equal variance across measurements at different ages.

```
# Compound Symmetry covariance
compsym = gls(distance ~ gender + age,
              data = dental,
              correlation = corCompSymm(form = ~1 | child),
              method="REML")

# Exponential covariance
expo = gls(distance ~ gender + age,
            data = dental,
            correlation = corExp(form = ~1 | child),
            method = 'REML')

# Autoregressive covariance
auto1 = gls(distance ~ gender + age,
             data = dental,
             correlation = corAR1(form = ~1 | child),
             method = 'REML')

# Compare coefficient parameter estimates
bind_rows(
  compsym$coefficients,
  expo$coefficients,
  auto1$coefficients,
) %>%
  mutate(CovType = c('CompSym', 'Exp', 'Auto')) %>%
  select(CovType, everything()) %>%
  knitr::kable()
```

CovType	(Intercept)	gender1	age
CompSym	15.38569	2.321023	0.6601852
Exp	15.45999	2.418714	0.6529597
Auto	15.45999	2.418714	0.6529597

The coefficient parameter estimates are similar across the 3 covariance patterns.

```
# Compare covariance estimates
# Compound Symmetry
compsym$sigma^2 * corMatrix(compsym$modelStruct$corStruct)[[1]]

##           [,1]      [,2]      [,3]      [,4]
## [1,] 5.316240 3.266784 3.266784 3.266784
## [2,] 3.266784 5.316240 3.266784 3.266784
## [3,] 3.266784 3.266784 5.316240 3.266784
## [4,] 3.266784 3.266784 3.266784 5.316240

# Exponential covariance
expo$sigma^2 * corMatrix(expo$modelStruct$corStruct)[[1]]

##           [,1]      [,2]      [,3]      [,4]
## [1,] 5.296881 3.315144 2.074839 1.298574
## [2,] 3.315144 5.296881 3.315144 2.074839
## [3,] 2.074839 3.315144 5.296881 3.315144
## [4,] 1.298574 2.074839 3.315144 5.296881
```

```
# Autoregressive covariance
auto1$sigma^2 * corMatrix(auto1$modelStruct$corStruct)[[1]]

##           [,1]      [,2]      [,3]      [,4]
## [1,] 5.296881 3.315144 2.074840 1.298574
## [2,] 3.315144 5.296881 3.315144 2.074840
## [3,] 2.074840 3.315144 5.296881 3.315144
## [4,] 1.298574 2.074840 3.315144 5.296881
```

The covariance estimates are similar across the 3 covariance patterns.