24. R Code for Repeated Measures

- These slides illustrate a few example R commands for fitting general linear models to repeated measures data.
- We focus on the experiment designed to compare the effectiveness of three strength training programs.
- We will fit models that allows for a distinct mean for each of the $3 \times 7 = 21$ combinations of training program and time.

- We assume independence between subjects.

- The models differ in the choice for $\boldsymbol{W}$, which is the variance-covariance structure assumed for the 7 observations from each subject.

```
#Read the data

d=read.delim(
  "http://dnett.github.io/S510/RepeatedMeasures.txt")

#Create Factors

d$Program = factor(d$Program)
d$Subj = factor(d$Subj)
d$Timef = factor(d$Time)

#Load the nlme package

library(nlme)
```

Compound Symmetry Structure for $\boldsymbol{W}$

$$
\begin{bmatrix}
\sigma_e^2+\sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 \\
\sigma_s^2 & \sigma_e^2+\sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 \\
\sigma_s^2 & \sigma_s^2 & \sigma_e^2+\sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 \\
\sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_e^2+\sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 \\
\sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_e^2+\sigma_s^2 & \sigma_s^2 & \sigma_s^2 \\
\sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_e^2+\sigma_s^2 & \sigma_s^2 \\
\sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_s^2 & \sigma_e^2+\sigma_s^2
\end{bmatrix}
$$

```
o.lme = lme(Strength ~ Program * Timef, data = d,
                        random = ~ 1 | Subj)
```

```
> summary(o.lme)
Linear mixed-effects model fit by REML
 Data: d
      AIC      BIC    logLik
  1466.82 1557.323 -710.4101



Random effects:
 Formula: ~1 | Subj
        (Intercept) Residual
StdDev:    3.098924 1.094017

.
.
.
```

```
> #  Examine the estimated variance-covariance
> #  matrix for the subvector of responses
> #  from a single subject.
>
> getVarCov(o.lme, individuals = 1, type = "marginal")
Subj 1
Marginal variance covariance matrix
        1       2       3       4       5       6       7
1 10.8000  9.6033  9.6033  9.6033  9.6033  9.6033  9.6033
2  9.6033 10.8000  9.6033  9.6033  9.6033  9.6033  9.6033
3  9.6033  9.6033 10.8000  9.6033  9.6033  9.6033  9.6033
4  9.6033  9.6033  9.6033 10.8000  9.6033  9.6033  9.6033
5  9.6033  9.6033  9.6033  9.6033 10.8000  9.6033  9.6033
6  9.6033  9.6033  9.6033  9.6033  9.6033 10.8000  9.6033
7  9.6033  9.6033  9.6033  9.6033  9.6033  9.6033 10.8000
```

Alternative Parameterizaton for Compound Symmetry

$$\sigma^2 \begin{bmatrix} 1 & \rho & \rho & \rho & \rho & \rho & \rho \\ \rho & 1 & \rho & \rho & \rho & \rho & \rho \\ \rho & \rho & 1 & \rho & \rho & \rho & \rho \\ \rho & \rho & \rho & 1 & \rho & \rho & \rho \\ \rho & \rho & \rho & \rho & 1 & \rho & \rho \\ \rho & \rho & \rho & \rho & \rho & 1 & \rho \\ \rho & \rho & \rho & \rho & \rho & \rho & 1 \end{bmatrix}$$

```
o.cs = gls(Strength ~ Program * Timef, data = d,
       correlation = corCompSymm(form = ~ 1 | Subj))
```

```
> summary(o.cs)
Generalized least squares fit by REML
  Model: Strength ~ Program * Timef
  Data: d
      AIC      BIC    logLik
  1466.82 1557.323 -710.4101

Correlation Structure: Compound symmetry
 Formula: ~1 | Subj
 Parameter estimate(s):
      Rho
0.8891805
.
.
.
Residual standard error: 3.286366
Degrees of freedom: 399 total; 378 residual
```

```
> getVarCov(o.cs)
Marginal variance covariance matrix
        [,1]    [,2]    [,3]    [,4]    [,5]    [,6]    [,7]
[1,] 10.8000  9.6033  9.6033  9.6033  9.6033  9.6033  9.6033
[2,]  9.6033 10.8000  9.6033  9.6033  9.6033  9.6033  9.6033
[3,]  9.6033  9.6033 10.8000  9.6033  9.6033  9.6033  9.6033
[4,]  9.6033  9.6033  9.6033 10.8000  9.6033  9.6033  9.6033
[5,]  9.6033  9.6033  9.6033  9.6033 10.8000  9.6033  9.6033
[6,]  9.6033  9.6033  9.6033  9.6033  9.6033 10.8000  9.6033
[7,]  9.6033  9.6033  9.6033  9.6033  9.6033  9.6033 10.8000
```

AR(1) Structure for $\boldsymbol{W}$

$$\sigma^2 \begin{bmatrix} 1 & \phi & \phi^2 & \phi^3 & \phi^4 & \phi^5 & \phi^6 \\ \phi & 1 & \phi & \phi^2 & \phi^3 & \phi^4 & \phi^5 \\ \phi^2 & \phi & 1 & \phi & \phi^2 & \phi^3 & \phi^4 \\ \phi^3 & \phi^2 & \phi & 1 & \phi & \phi^2 & \phi^3 \\ \phi^4 & \phi^3 & \phi^2 & \phi & 1 & \phi & \phi^2 \\ \phi^5 & \phi^4 & \phi^3 & \phi^2 & \phi & 1 & \phi \\ \phi^6 & \phi^5 & \phi^4 & \phi^3 & \phi^2 & \phi & 1 \end{bmatrix}$$

```
o.ar1 = gls(Strength ~ Program * Timef, data = d,
        correlation = corAR1(form = ~ 1 | Subj))
```

```
> summary(o.ar1)
Generalized least squares fit by REML
  Model: Strength ~ Program * Timef
  Data: d
       AIC      BIC    logLik
  1312.804 1403.306 -633.4018

Correlation Structure: AR(1)
 Formula: ~1 | Subj
 Parameter estimate(s):
      Phi
0.9517769
.
.
.
Residual standard error: 3.280242
Degrees of freedom: 399 total; 378 residual
```

```
> getVarCov(o.ar1, individual = 3)
Marginal variance covariance matrix
        [,1]    [,2]    [,3]    [,4]    [,5]    [,6]    [,7]
[1,] 10.7600 10.2410  9.7473  9.2772  8.8298  8.4040  7.9988
[2,] 10.2410 10.7600 10.2410  9.7473  9.2772  8.8298  8.4040
[3,]  9.7473 10.2410 10.7600 10.2410  9.7473  9.2772  8.8298
[4,]  9.2772  9.7473 10.2410 10.7600 10.2410  9.7473  9.2772
[5,]  8.8298  9.2772  9.7473 10.2410 10.7600 10.2410  9.7473
[6,]  8.4040  8.8298  9.2772  9.7473 10.2410 10.7600 10.2410
[7,]  7.9988  8.4040  8.8298  9.2772  9.7473 10.2410 10.7600
```

General Positive Definite Structure for $\boldsymbol{W}$

With δ_1 set equal to 1 for identifiablility purposes, a general 7×7 positive definite variance-covariance matrix is parameterized by R as follows:

$$\sigma^2 \text{ diag}(\delta_1, ..., \delta_7) \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \rho_{14} & \rho_{15} & \rho_{16} & \rho_{17} \\ \rho_{12} & 1 & \rho_{23} & \rho_{24} & \rho_{25} & \rho_{26} & \rho_{27} \\ \rho_{13} & \rho_{23} & 1 & \rho_{34} & \rho_{35} & \rho_{36} & \rho_{37} \\ \rho_{14} & \rho_{24} & \rho_{34} & 1 & \rho_{45} & \rho_{46} & \rho_{47} \\ \rho_{15} & \rho_{25} & \rho_{35} & \rho_{45} & 1 & \rho_{56} & \rho_{57} \\ \rho_{16} & \rho_{26} & \rho_{36} & \rho_{46} & \rho_{56} & 1 & \rho_{67} \\ \rho_{17} & \rho_{27} & \rho_{37} & \rho_{47} & \rho_{57} & \rho_{67} & 1 \end{bmatrix} \text{ diag}(\delta_1, ..., \delta_7)$$

The 7×7 case doesn't fit on one slide, but here is the 5×5 case.

$$\begin{bmatrix} \sigma^2\delta_1^2 & \sigma^2\rho_{12}\delta_1\delta_2 & \sigma^2\rho_{13}\delta_1\delta_3 & \sigma^2\rho_{14}\delta_1\delta_4 & \sigma^2\rho_{15}\delta_1\delta_5 \\ \sigma^2\rho_{12}\delta_1\delta_2 & \sigma^2\delta_2^2 & \sigma^2\rho_{23}\delta_2\delta_3 & \sigma^2\rho_{24}\delta_2\delta_4 & \sigma^2\rho_{25}\delta_2\delta_5 \\ \sigma^2\rho_{13}\delta_1\delta_3 & \sigma^2\rho_{23}\delta_2\delta_3 & \sigma^2\delta_3^2 & \sigma^2\rho_{34}\delta_3\delta_4 & \sigma^2\rho_{35}\delta_3\delta_5 \\ \sigma^2\rho_{14}\delta_1\delta_4 & \sigma^2\rho_{24}\delta_2\delta_4 & \sigma^2\rho_{34}\delta_3\delta_4 & \sigma^2\delta_4^2 & \sigma^2\rho_{45}\delta_4\delta_5 \\ \sigma^2\rho_{15}\delta_1\delta_5 & \sigma^2\rho_{25}\delta_2\delta_5 & \sigma^2\rho_{35}\delta_3\delta_5 & \sigma^2\rho_{45}\delta_4\delta_5 & \sigma^2\delta_5^2 \end{bmatrix}$$

```
o.un = gls(Strength ~ Program * Timef, data = d,
        correlation = corSymm(form = ~ 1 | Subj),
        weight = varIdent(form = ~ 1 | Timef))
```

```
> summary(o.un)
Generalized least squares fit by REML
  Model: Strength ~ Program * Timef
  Data: d
       AIC      BIC    logLik
  1332.896 1525.706 -617.4479
```

```
Correlation Structure: General
 Formula: ~1 | Subj
 Parameter estimate(s):
 Correlation:
  1     2     3     4     5     6
2 0.960
3 0.925 0.940
4 0.872 0.877 0.956
5 0.842 0.860 0.937 0.960
6 0.809 0.827 0.898 0.909 0.951
7 0.797 0.792 0.876 0.887 0.917 0.953
```

```
Variance function:
 Structure: Different standard deviations per stratum
 Formula: ~1 | Timef
 Parameter estimates:
    2     4     6     8    10    12    14
1.000 1.039 1.104 1.071 1.174 1.157 1.203
.
.
.
Residual standard error: 2.963129
Degrees of freedom: 399 total; 378 residual
```

```
> getVarCov(o.un, individual = 3)
Marginal variance covariance matrix
       [,1]   [,2]    [,3]    [,4]    [,5]    [,6]    [,7]
[1,] 8.7801 8.7571  8.9656  8.1984  8.6781  8.2203  8.4169
[2,] 8.7571 9.4730  9.4631  8.5686  9.2012  8.7307  8.6875
[3,] 8.9656 9.4631 10.7080  9.9266 10.6660 10.0700 10.2140
[4,] 8.1984 8.5686  9.9266 10.0770 10.6000  9.8987 10.0430
[5,] 8.6781 9.2012 10.6660 10.6000 12.0950 11.3440 11.3640
[6,] 8.2203 8.7307 10.0700  9.8987 11.3440 11.7560 11.6500
[7,] 8.4169 8.6875 10.2140 10.0430 11.3640 11.6500 12.7100
```

- To understand the reason for an identifiability constraint, notice that an arbitrary positive definite 7×7 covariance matrix depends on only

$$7+6+5+4+3+2+1 = \frac{7(7+1)}{2} = 28$$

parameters. However, we have $\sigma^2,\ 6+5+4+3+2+1 = 21\ \rho$ parameters, and $\delta_1, \ldots, \delta_7$.

- That's 29 parameters for a symmetric positive definite matrix that depends on at most 28 parameters.

- Thus, R chooses to set δ_1 to 1.
- Without such a constraint, it is easy to use different values of the parameters to define the same matrix. For example,

$$\begin{bmatrix} 3 & -1 \\ -1 & 7 \end{bmatrix} = 3 \begin{bmatrix} 1 & -\frac{1}{3} \\ -\frac{1}{3} & \frac{7}{3} \end{bmatrix} = 1 \begin{bmatrix} 3 & -1 \\ -1 & 7 \end{bmatrix}$$

σ^2	3	1
δ_1	1	$\sqrt{3}$
δ_2	$\sqrt{\frac{7}{3}}$	$\sqrt{7}$
ρ_{12}	$\frac{-1}{3\sqrt{\frac{7}{3}}}$	$\frac{-1}{\sqrt{21}}$

```
> #  Compare the fit of various covariance
> #  structures.
>
> anova(o.cs, o.un)
     Model df    AIC    BIC logLik   Test L.Ratio p-value
o.cs     1 23 1466.8 1557.3 -710.4
o.un     2 49 1332.9 1525.7 -617.4 1 vs 2  185.92  <.0001
```

```
> anova(o.ar1, o.un)
      Model df    AIC    BIC logLik   Test L.Ratio p-value
o.ar1     1 23 1312.8 1403.3 -633.4
o.un      2 49 1332.9 1525.7 -617.4 1 vs 2  31.908  0.1962
```

AIC and BIC for Repeated Measures in R

- $AIC = -2\ell(\hat{\boldsymbol{\theta}}) + 2k$

- $BIC = -2\ell(\hat{\boldsymbol{\theta}}) + k \ln(n)$

- $k =$ number of mean parameters (rank of $\boldsymbol{X}$)
  $+$ number of variance parameters

- For REML,

$$n = \text{total number of observations} - \text{rank}(\boldsymbol{X})$$

- For ML,

$$n = \text{total number of observations}$$

More about Repeated Measures in R

If you are interested in learning about how to fit other variance-covariance structures in R, the following help commands may be useful.

```
?corClasses
```

```
?varClasses
```

To see functions for accessing `lme` and `gls` results, use

```
methods(class = 'lme')
```

```
methods(class = 'gls')
```

Fitting More Complex Models in R

See `RepeatedMeasures.R` for several other examples, including

- treating time as a continuous variable and assuming a mean function that is quadratic in time for each program
- assuming random subject-specific coefficients when the mean function is quadratic in time for each program

Example Code for Random Subject-Specific Coefficients

```
lme(Strength ~ Program + Time + Program*Time + I(Time^2),
               random = ~ Time + I(Time^2) | Subj,
               correlation = corAR1(form = ~ 1 | Subj),
               data = d)
```

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{Zu} + \boldsymbol{e}$$

$$\boldsymbol{u} \sim N(\boldsymbol{0}, \boldsymbol{G})$$

$$\boldsymbol{e} \sim N(\boldsymbol{0}, \boldsymbol{R})$$