# Advanced mixed-models workshop: Session 3

Dale Barr

University of Glasgow

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# Coding categorical predictors

- *simple* vs *main* effects in factorial designs

$$
\begin{array}{cccc}
 & B_1 & B_2 & \\
 & & & \\
A_1 & \bar{Y}_{11} & \bar{Y}_{12} & \bar{Y}_{1.} \\
A_2 & \bar{Y}_{21} & \bar{Y}_{22} & \bar{Y}_{2.} \\
 & & & \\
 & \bar{Y}_{.1} & \bar{Y}_{.2} &
\end{array}
$$

| | |
|---|---|
| test of simple effect of $B$ at $A_1$ | $H_0 : \bar{Y}_{11} = \bar{Y}_{12}$ |
| test of main effect of $B$ | $H_0 : \bar{Y}_{.1} = \bar{Y}_{.2}$ |

# Coding schemes for categorical predictors

If you have a single IV, the choice of coding scheme doesn't really matter.
In factorial designs, coding schemes impact:

1. the intercept
2. all except the highest-order effects and interactions
3. random effects (see `http://talklab.psy.gla.ac.uk/simgen/rsonly.html`).

# Main coding schemes to use with experimental data

| Scheme | *A* | V |
|---|---|---|
| Dummy* | A1 | 0 |
| | A2 | 1 |
| Sum | A1 | -1 |
| | A3 | 1 |
| Deviation | A1 | -.5 |
| | A2 | .5 |

* aka treatment / contrast

| Scheme | *A* | V1 | V2 |
|---|---|---|---|
| Dummy* | A1 | 0 | 0 |
| | A2 | 1 | 0 |
| | A3 | 0 | 1 |
| Sum | A1 | -1 | -1 |
| | A2 | 1 | 0 |
| | A3 | 0 | 1 |
| Deviation | A1 | $-1/3$ | $-1/3$ |
| | A2 | $2/3$ | $-1/3$ |
| | A3 | $-1/3$ | $2/3$ |

NB: deviation codes = centered contrast codes

# Simple and main effects

In a design with three two-level factors $A$, $B$, and $C$:

- If all factors are deviation or sum coded, all main effects and interactions have their "canonical" ANOVA interpretation.
- If $A$ is dummy coded, then the coefficient of $BC$ corresponds to the $BC$ interaction at the level where $A = 0$; $B$ is the simple effect of $B$ where $A = 0$; etc.
- If $B$ and $C$ are dummy coded, then $A$ is the effect of $A$ where $B = 0$ and $C = 0$.

Best practice for ANOVA-style interpretation: deviation coding; use dummy coding in follow-up tests.

# Interacting categorical-by-continuous variables

If $A$ is a continuous variable (e.g., age) and $B$ is a categorical design factor, then:

- The $B$ coefficient is the effect of $B$ where $A$ is zero
- This is a problem when $A = 0$ lies outside of the observed data (e.g., "age" where the observed age range is 20–50 years old)
- Usually best to center continuous predictors when they interact, unless zero is meaningful

# Learning proper names

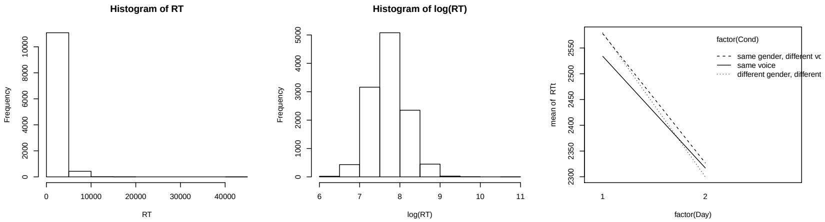
- 20 participants learned proper names for pictures of 96 target people
- each name heard consistently in one of four voices during training (2M, 2F)
- two test phases on two consecutive days (*Day*: 1 or 2)
- on each day, pictures/names presented in one of three conditions (*Cond*):
  - same voice
  - different voice, same gender
  - different voice, different gender
- we measured RT and accuracy

# Read in the data

```
fan <- readRDS("FAN.rds")

head(fan)

# have a look at the design
xtabs(~Day + Cond + SessionID + ItemID, fan)
xtabs(~Day + Cond + SessionID, fan)
xtabs(~Day + Cond + ItemID, fan)
```

# Define predictors

```
par(mfrow = c(1, 3))
with(fan, hist(RT))
with(fan, hist(log(RT)))

cutoff <- with(fan, quantile(RT, .975))
fan$RTt <- with(fan, ifelse(RT > cutoff, cutoff, RT))

with(fan,
     interaction.plot(factor(Day), factor(Cond), RTt))
```



# Define predictors

```r
fan$T <- with(fan, Day - mean(Day))

fan$V1 <- with(fan,
               (Cond == "same voice") - mean(Cond == "same voice"))

fan$V2 <- with(fan,
               (Cond == "same gender, different voice") -
                   mean(Cond == "same gender, different voice"))
```

# Fit models

```r
library("lme4")

## doesn't converge
mod <- lmer(RTt ~ T * (V1 + V2) +
                (T * (V1 + V2) | SessionID) +
                (T * (V1 + V2) | ItemID) +
                (1 | SessionID:ItemID),
            fan, REML = FALSE)
```

# Sources of nonconvergence

- Misspecification of random effects
  - *unidentifiable* parameters in the model
- Using old/unstable version of `lme4` (<1.1-7)
- Using suboptimal optimizer for `glmer`
  - use argument `glmerControl(optimizer='bobyqa')`
- Uncentered predictors
- Too few subjects/items
- Distributional assumptions unsatisfied
- Null effects

# What to do?

- Make sure effects are identifiable
- Increase iterations
  - `control=lmerControl(maxfit = 20000)` (or `glmerControl()`)
- Check distributional assumptions
- Start removing random effects
  - constrain covariances to zero ("diagonal" model)

# Increase iterations

```r
## increase iterations from 10000 (default) to 20000
mod_ii <- lmer(RTt ~ T * (V1 + V2) +
                (T * (V1 + V2) | SessionID) +
                (T * (V1 + V2) | ItemID) +
                (1 | SessionID:ItemID),
               fan, REML = FALSE,
               control = lmerControl(maxfun = 20000))
```

# Constrain covariances to zero

- "diagonal model"

```
## fit a "diagonal" model
## (constraint covariances to zero)
mod_diag <- lmer(RTt ~ T * (V1 + V2) +
                   (T * (V1 + V2) || SessionID) +
                   (T * (V1 + V2) || ItemID) +
                   (1 | SessionID:ItemID),
            fan, REML = FALSE)
```

# View results

```
Linear mixed model fit by maximum likelihood  ['lmerMod']
Formula: RTt ~ T * (V1 + V2) + ((1 | SessionID) + (0 + T | SessionID) +
    (0 + V1 | SessionID) + (0 + V2 | SessionID) + (0 + T:V1 |
    SessionID) + (0 + T:V2 | SessionID)) + ((1 | ItemID) + (0 +
    T | ItemID) + (0 + V1 | ItemID) + (0 + V2 | ItemID) + (0 +
    T:V1 | ItemID) + (0 + T:V2 | ItemID)) + (1 | SessionID:ItemID)
   Data: fan

     AIC      BIC   logLik deviance df.resid
187510.1 187657.1 -93735.0 187470.1    11500

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.8900 -0.6175 -0.1114  0.4791  4.4215

Random effects:
 Groups           Name        Variance Std.Dev.
 SessionID.ItemID (Intercept) 110838   332.92
 ItemID           T:V2             0     0.00
 ItemID.1         T:V1             0     0.00
 ItemID.2         V2           13313   115.38
 ItemID.3         V1           21559   146.83
 ItemID.4         T                0     0.00
 ItemID.5         (Intercept)  47686   218.37
```

# Clean up the model

```
mod_diag2 <- lmer(RTt ~ T * (V1 + V2) +
                    (1 | SessionID) +
                    (0 + T | SessionID) +
                    (0 + T:V1 | SessionID) +
                    (1 | ItemID) +
                    (0 + V1 | ItemID) +
                    (0 + V2 | ItemID) +
                    (1 | SessionID:ItemID),
           fan, REML = FALSE)
```

# Likelihood ratio tests

```
## test 2x3 interaction
mod_diag2_no_ix <- update(mod_diag2, . ~ . - T:V1 - T:V2)

## test main effect of voice
mod_diag2_no_voice <- update(mod_diag2, . ~ . - V1 - V2)

## test main effect of day
mod_diag2_no_day <- update(mod_diag2, . ~ . -T)

anova(mod_diag2, mod_diag2_no_ix)
anova(mod_diag2, mod_diag2_no_voice)
anova(mod_diag2, mod_diag2_no_day)
```

```
                Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
mod_diag2_no_ix 12 187497 187585 -93736   187473
mod_diag2       14 187498 187601 -93735   187470 2.8551      2     0.2399

                   Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
mod_diag2_no_voice 12 187495 187583 -93736   187471
mod_diag2          14 187498 187601 -93735   187470 1.0804      2     0.5826

                 Df    AIC    BIC logLik deviance  Chisq Chi Df Pr(>Chisq)
mod_diag2_no_day 13 187511 187607 -93743   187485
mod_diag2        14 187498 187601 -93735   187470 15.176      1  9.792e-05 ***
```