

Advanced mixed-models workshop: Session 3

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Bremen March 2015

Coding categorical predictors

- *simple vs main* effects in factorial designs

	B_1	B_2	
A_1	\bar{Y}_{11}	\bar{Y}_{12}	$\bar{Y}_{1.}$
A_2	\bar{Y}_{21}	\bar{Y}_{22}	$\bar{Y}_{2.}$
	$\bar{Y}_{.1}$	$\bar{Y}_{.2}$	

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)

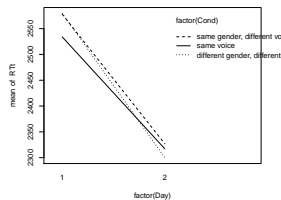
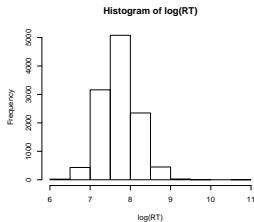
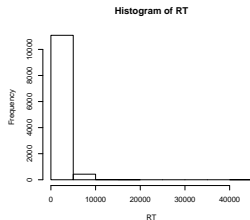
# have a look at the design
xtabs(~Day + Cond + SessionID + ItemID, fan)
xtabs(~Day + Cond + SessionID, fan)
xtabs(~Day + Cond + ItemID, fan)
```


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

```
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

```
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

```
## 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 ***