

Advanced mixed-models workshop: Session 2

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Determining Maximal Random Effects

Barr, Levy, Scheepers, & Tily (2013); Barr (2013)

- Random intercept is needed whenever there are multiple observations per unit
- Any within-unit factor gets a random slope, *unless there is only one observation per level per unit*
- Between-unit factors do not get a random slope
- For each interaction, include a slope for the highest order combination of within-subject factors subsumed by the interaction
- For time-series data, include random slopes for time predictors if you have more than one time series per unit

Keysar, Barr, Balin, & Brauner (2000)

Task and Design

Keysar, B., Barr, D. J., Balin, J. A., & Brauner, J. S. (2000). Taking perspective in conversation: The role of mutual knowledge in comprehension. *Psychological Science*, 11, 32–38.

- When interpreting expressions e.g. *the small candle*, do listeners experience interference?

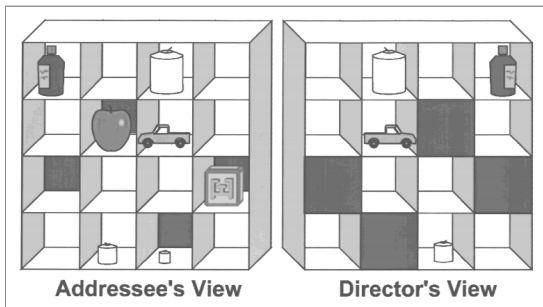


Fig. 1. The 16 slots with a typical set of objects. The addressee's and director's views are distinct because of the occluded slots. The critical instruction (referring to "the small candle") picks out a different candle from the director's perspective (shared candle) than from the addressee's perspective (occluded candle).

Keysar, Barr, Balin, & Brauner (2000)

Description of the Dataset

- 20 subjects, 12 items for each subject (N=240)
- one factor: condition (competitor vs. noncompetitor)
- data recorded using a 60 Hz eyetracker
- DV: latency to fixate the target object, measured from onset of the critical word

Field	Description
SubjID	Subject identifier (N=20)
cond	Condition (E=competitor, C=noncompetitor)
crit	Moment of onset of critical word (frames)
targfix	Moment the hand touched the target (frames)
object	Name of the experimental item

Keysar, Barr, Balin, & Brauner (2000)

Analysis Tasks

- 1 load the data from `KeysarEtAl2000.rds` into dataframe `dat`
- 2 calculate `tfix`, the latency for touching the target in milliseconds, store this in the dataframe `dat`
- 3 make histogram of `tfix`
- 4 create “truncated” versions of `tfix`, `tfixTrunc`, truncating values higher than the 97.5th percentile
- 5 calculate means in each condition

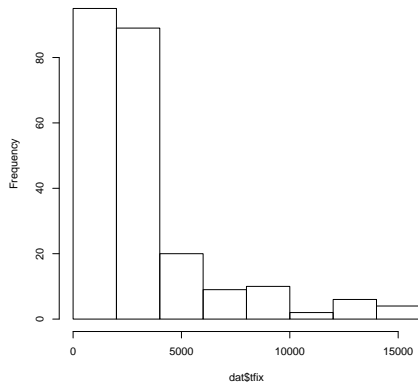
Linear mixed-model analysis

- ➊ Now do the analysis using model comparison in a linear mixed effects model, with maximal random effects
 - ▶ tip: use deviation coding for condition
- ➋ Derive p -values using:
 - ▶ Wald z statistic ("t-as-z")
 - ▶ Likelihood ratio tests
- ➌ Would you say that subjects or items introduce more overall variation in grand mean target latencies?
- ➍ Do subjects or items vary more in terms of the effect of condition (competitor)?
- ➎ Look at the BLUPS.
 - ▶ Which items show the effect most strongly?
 - ▶ Which subjects?
 - ▶ Do all subjects show the effect?
 - ▶ Do all items show the effect?

Load and preprocess

```
dat <- readRDS("kbbb.rds")  
# calculate latencies  
dat$tfix <- 1000*((dat$targfix - dat$crit) / 60)  
  
hist(dat$tfix)
```

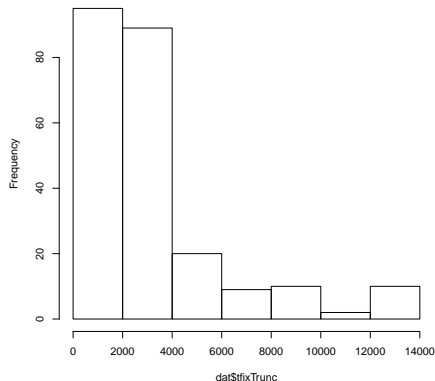
Histogram of dat\$tfix



Clean up the latency data

```
# truncate outliers at 97.5th percentile of distribution  
cutoff.tfix <- quantile(dat$tfix, probs=.975, na.rm=TRUE)  
dat$tfixTrunc <- ifelse(dat$tfix > cutoff.tfix, cutoff.tfix, dat$tfix)  
  
hist(dat$tfixTrunc)
```

Histogram of dat\$tfixTrunc



Descriptive stats

```
# aggregate  
aggregate(tfixTrunc ~ cond, dat, mean)
```

```
cond tfixTrunc  
1    C  2589.641  
2    E  4036.625
```

Run t-test (aggregating first by subject)

```
# re-create data: t-test
dat.subj <- aggregate(tfixTrunc ~ SubjID + cond, dat, mean)
dat.subj <- dat.subj[order(dat.subj$SubjID, dat.subj$cond), ]

dat.t <- t.test(subset(dat.subj, cond=="C")$tfixTrunc,
                subset(dat.subj, cond=="E")$tfixTrunc, paired=TRUE)
print(dat.t)
```

Paired t-test

```
data: subset(dat.subj, cond == "C")$tfixTrunc and subset(dat.subj, cond == "E")$tfixTrunc
t = -4.3608, df = 19, p-value = 0.0003364
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -2129.4142 -748.2524
sample estimates:
mean of the differences
 -1438.833
```

Run linear mixed model

```
# linear mixed model
# create deviation-coded predictor
dat$D <- dat$cond == "E"
dat$C2 <- dat$D - mean(dat$D)

library("lme4")
mod1 <- lmer(tfixTrunc ~ C2 +
             (1 + C2 | SubjID) +
             (1 + C2 | object),
             data=dat,
             subset = complete.cases(dat),
             REML=FALSE)
```

Loading required package: Matrix

Loading required package: Rcpp

View results

```
Linear mixed model fit by maximum likelihood ['lmerMod']
Formula: tfixTrunc ~ C2 + (1 + C2 | SubjID) + (1 + C2 | object)
Data: dat
Subset: complete.cases(dat)
```

AIC	BIC	logLik	deviance	df.resid
4421.9	4453.0	-2201.9	4403.9	226

Random effects:

Groups	Name	Variance	Std.Dev.	Corr
SubjID	(Intercept)	417282	645.97	
	C2	758341	870.83	1.00
object	(Intercept)	616982	785.48	
	C2	6765	82.25	1.00
Residual		7236631	2690.10	

Number of obs: 235, groups: SubjID, 20; object, 12

Fixed effects:

	Estimate	Std. Error	t value
(Intercept)	3306.4	321.1	10.296
C2	1439.6	402.2	3.579

Wald z statistics

a.k.a. "t-as-z" method

```
paramest <- fixef(mod1)
stderrs <- sqrt(diag(vcov(mod1)))
tstats <- paramest / stderrs
pvals <- 2 * (1 - pnorm(abs(tstats)))

data.frame(b = paramest, se = stderrs, t = tstats, p = pvals)
```

	b	se	t	p
(Intercept)	3306.446	321.1306	10.296267	0.0000000000
C2	1439.572	402.2187	3.579078	0.0003448088

Likelihood ratio tests

```
mod2 <- update(mod1, . ~ . -C2)

anova(mod1, mod2)

chi2 <- deviance(mod2) - deviance(mod1)
pchi <- pchisq(chi2, 1, lower.tail = FALSE)

c(chisq = chi2, p = pchi)
```

Data: dat

Subset: complete.cases(dat)

Models:

mod2: tfixTrunc ~ (1 + C2 | SubjID) + (1 + C2 | object)

mod1: tfixTrunc ~ C2 + (1 + C2 | SubjID) + (1 + C2 | object)

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
mod2	8	4430.4	4458.1	-2207.2	4414.4				
mod1	9	4421.9	4453.0	-2201.9	4403.9	10.539	1		0.001169 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

	chisq	p
	10.538911764	0.001168872

```
blups <- ranef(mod1)
blups$SubjID$C2 + fixef(mod1)[2] # every subject shows effect
blups$Object$C2 + fixef(mod1)[2] # every item shows effect
```

```
[1] 1480.1108  781.4079  650.9276 1738.6800 1221.5055 2844.7430 1442.4837
[8] 1182.7265 2373.9572 1758.3663 1279.2353 1600.2375  773.5742  689.4678
[15] 1279.2739 1720.9333 2675.1397 1351.8773 1152.1319  794.6589
```

```
[1] 1404.950 1377.372 1375.472 1403.316 1504.187 1478.570 1486.604 1397.842
[9] 1417.357 1551.797 1347.852 1529.544
```

Additional stats

```
library("pbkrtest")

mod_kr <- KRmodcomp(mod1, mod2)

summary(mod_kr)
```

F-test with Kenward-Roger approximation; computing time: 1.14 sec.

large : tfixTrunc ~ C2 + (1 + C2 | SubjID) + (1 + C2 | object)

small : tfixTrunc ~ (1 + C2 | SubjID) + (1 + C2 | object)

	stat	ndf	ddf	F.scaling	p.value
Ftest	12.4550	1.0000	8.9771	1	0.006448 **
FtestU	12.4550	1.0000	8.9771		0.006448 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Parametric bootstrap

```
mod_pb <- PBmodcomp(mod1, mod2)

summary(mod_pb)
```

```
There were 50 or more warnings (use warnings() to see the first 50)
Parametric bootstrap test; time: 156.28 sec; samples: 1000 extremes: 0;
Requested samples: 1000 Used samples: 996 Extremes: 0
large : tfixTrunc ~ C2 + (1 + C2 | SubjID) + (1 + C2 | object)
small : tfixTrunc ~ (1 + C2 | SubjID) + (1 + C2 | object)
```

	stat	df	ddf	p.value
PBtest	10.539			0.0010030 **
Gamma	10.539			0.0005716 ***
Bartlett	11.161	1.000		0.0008356 ***
F	10.539	1.000	-33.912	
LRT	10.539	1.000		0.0011689 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Warning message:

In pf(Fobs, df1 = ndf, df2 = ddf) : NaNs produced