



LINEAR MIXED-EFFECTS MODELING WITH CROSSED RANDOM FACTORS

STATISTICAL MODELS

PSYCHOLOGY, UNIVERSITY OF GLASGOW

OVERVIEW

- generalizing to subjects and stimuli
 - dealing with "crossed" random factors
- random effects in complex designs
- non-convergence and model validation

GENERALIZING TO SUBJECTS AND STIMULI

LANGUAGE-AS-FIXED-EFFECT FALLACY

- Psycholinguistic experiments sample language materials as well as subjects
- Language stimuli should be treated as a random, not fixed factor
- Clark's suggestion: F' , min- F'
- Modern solution: Linear-mixed effects with crossed random factors of subjects and stimuli

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). [Mixed-effects modeling with crossed random effects for subjects and items](#). *Journal of Memory and Language*, 59, 390-412.

Clark, H. H. (1973). [The language-as-fixed-effect fallacy: A critique of language statistics in psychological research](#). *Journal of Verbal Learning and Verbal Behavior*, 12, 335-359.

CROSSED RANDOM FACTORS

```
inner_join(subj, lists, "list_id")
```

	subj_id	list_id	stim_id	condition
1	1	1	A	treatment
2	1	1	B	treatment
3	1	1	C	control
4	1	1	D	control
5	2	2	A	control
6	2	2	B	control
7	2	2	C	treatment
8	2	2	D	treatment
9	3	1	A	treatment
10	3	1	B	treatment
11	3	1	C	control
12	3	1	D	control
13	4	2	A	control
14	4	2	B	control
15	4	2	C	treatment
16	4	2	D	treatment

GENERALIZING OVER ENCOUNTERS

The target of inference in much of psychology and related fields has been misidentified as a population of *subjects* or *stimuli*, when the actual target of inference is a population of events: **encounters**

- readers encountering particular types of words
- male participants judging attractiveness of female faces, or vice versa
- gamers encountering particular types of violent games
- audience members encountering particular types of dance movements
- insomniacs (versus controls) encountering emotional expressions
- birds hearing particular types of birdsongs

SPECIFYING RANDOM EFFECTS

GENERAL PROCEDURE FOR FACTORIAL DESIGNS

for each random factor (subjects/stimuli):

1. identify within-unit factors
2. check highest-order combination of within-subject factors
 - *NO pseudoreplications*: no random slopes
 - *YES pseudoreplications*: all interactions/main effects get slopes

between-unit factors (or interactions involving them) never get random slopes

Barr, D. J. (2013). [Random effects structure for testing interactions in linear mixed-effects models](#). *Frontiers in Psychology*, 4, 328.

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). [Random effects structure for confirmatory hypothesis testing: Keep it maximal](#). *Journal of Memory and Language*, 68, 255-278.

DETERMINING THE DESIGN FROM DATA

three way design, subjects only random factor

```
# A tibble: 128 x 5
  subj_id A      B      C      DV
  <int> <chr> <chr> <chr> <dbl>
1       5 A1    B1    C2    4.80
2       5 A1    B2    C1    7.40
3       1 A2    B1    C2    0.444
4       6 A2    B1    C2    3.97
5       4 A1    B1    C2    2.90
6       4 A1    B2    C1   -0.0699
7       3 A1    B2    C2    2.75
8       1 A2    B2    C2    2.86
9       3 A1    B2    C2    0.452
10      8 A1    B1    C1   -0.694
# ... with 118 more rows
```

```
count(dat1, subj_id, A, B, C)
```

```
# A tibble: 32 x 5
  subj_id A      B      C      n
  <int> <chr> <chr> <chr> <int>
1       1 A2    B1    C1     4
2       1 A2    B1    C2     4
3       1 A2    B2    C1     4
4       1 A2    B2    C2     4
5       2 A2    B1    C1     4
6       2 A2    B1    C2     4
7       2 A2    B2    C1     4
8       2 A2    B2    C2     4
9       3 A1    B1    C1     4
10      3 A1    B1    C2     4
# ... with 22 more rows
```

A is between, *BC* within, 4 obs / cell

$DV \sim A * B * C + (B * C \mid \text{subj_id})$

EXAMPLE WITH CROSSED RANDOM FACTORS

$DV \sim A * B * C + (? | \text{subj_id}) + (? | \text{item_id})$

```
dat2
```

```
# A tibble: 128 x 6
```

	subj_id	item_id	A	B	C	DV
	<int>	<int>	<chr>	<chr>	<chr>	<dbl>
1	7	13	A1	B2	C2	1.41
2	3	6	A1	B1	C2	3.62
3	3	1	A2	B2	C2	2.79
4	2	4	A1	B2	C1	-1.41
5	4	10	A2	B1	C1	0.971
6	7	5	A2	B2	C2	8.12
7	7	16	A2	B1	C1	7.66
8	6	3	A2	B1	C1	3.00
9	7	10	A1	B1	C2	0.644
10	6	9	A2	B2	C2	10.7

```
# ... with 118 more rows
```

BY-SUBJECT RANDOM EFFECTS

```
dat2 %>%  
  count(subj_id, A, B, C)  
  
# A tibble: 64 x 5  
  subj_id A      B      C      n  
    <int> <chr> <chr> <chr> <int>  
1         1 A1    B1    C1      2  
2         1 A1    B1    C2      2  
3         1 A1    B2    C1      2  
4         1 A1    B2    C2      2  
5         1 A2    B1    C1      2  
6         1 A2    B1    C2      2  
7         1 A2    B2    C1      2  
8         1 A2    B2    C2      2  
9         2 A1    B1    C1      2  
10        2 A1    B1    C2      2  
# ... with 54 more rows
```

```
DV ~ A * B * C + (A * B * C | subj_id) + (? | item_id)
```

BY-STIMULUS RANDOM EFFECTS

```
dat2 %>%
```

```
  count(item_id, A, B, C)
```

```
# A tibble: 128 x 5
```

	item_id	A	B	C	n
	<int>	<chr>	<chr>	<chr>	<int>
1	1	A1	B1	C1	1
2	1	A1	B1	C2	1
3	1	A1	B2	C1	1
4	1	A1	B2	C2	1
5	1	A2	B1	C1	1
6	1	A2	B1	C2	1
7	1	A2	B2	C1	1
8	1	A2	B2	C2	1
9	2	A1	B1	C1	1
10	2	A1	B1	C2	1

```
# ... with 118 more rows
```

```
DV ~ A * B * C + (A * B * C | subj_id) + (1 | item_id)
```

NON-CONVERGENCE AND MODEL VALIDATION

NON-CONVERGENCE

When you get a convergence warning you should in the first instance:

- double-check the model specification
- make sure all predictors are scaled and centred

then re-fit the model. If it still does not converge, seek to reduce the random effects structure, but **proceed with caution**.

You can also try different optimizers (see ?lme4::convergence)

"model is singular" is NOT a convergence warning

REDUCING RANDOM EFFECTS STRUCTURE

Reducing random effects can help convergence, but the worst thing you can do is remove the slope for a theory-critical predictor.

1. Remove random correlations and re-fit
 - Use $(A * B || \text{subject})$
2. Worst case scenario: effectwise testing, e.g.:
 - test A using $(A | \text{subject}) + (A | \text{stimulus})$
 - test B using $(B | \text{subject}) + (B | \text{stimulus})$
 - test AB using $(A:B | \text{subject}) + (A:B | \text{stimulus})$

CHECKING ASSUMPTIONS

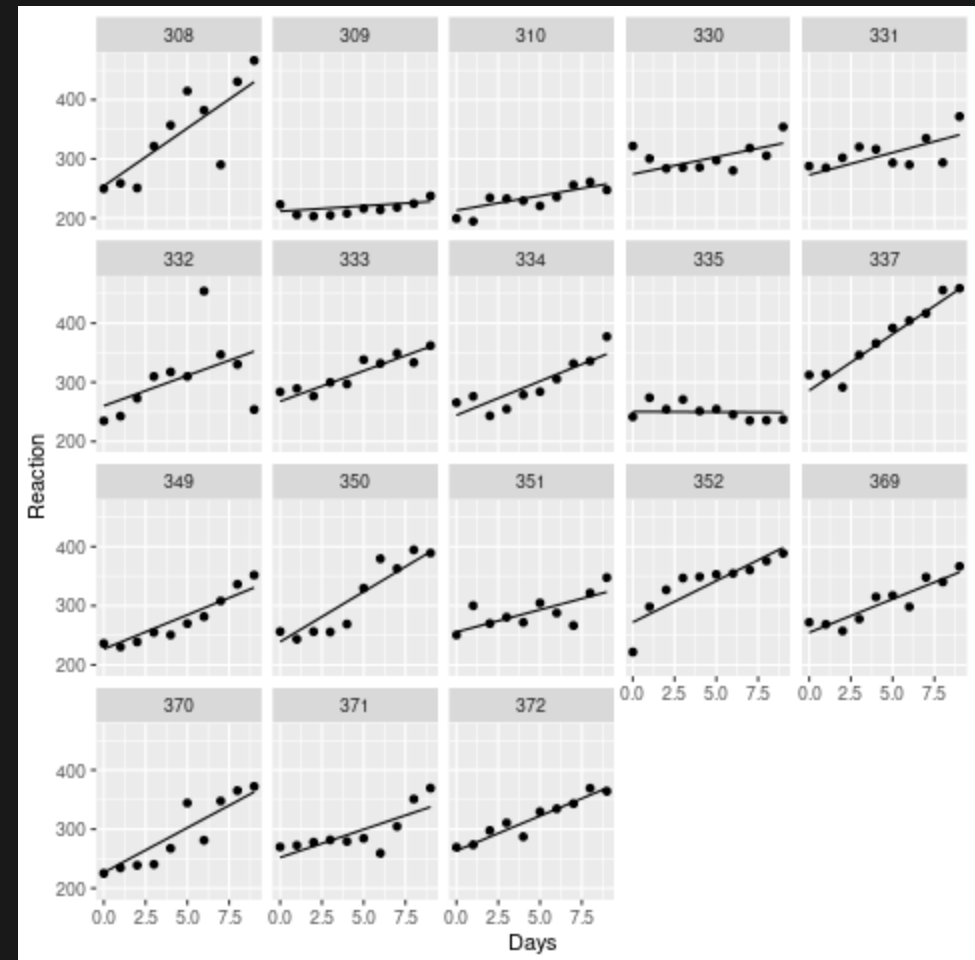
- linearity
- homogeneity of variance
- normality of residuals
 - outliers
 - multimodality
 - other weirdness (skew, etc)

LINEARITY

- fitted (line) v. observed (points)

```
mod <- lmer(Reaction ~ Days +  
            (Days | Subject),  
            sleepstudy, REML = FALSE)
```

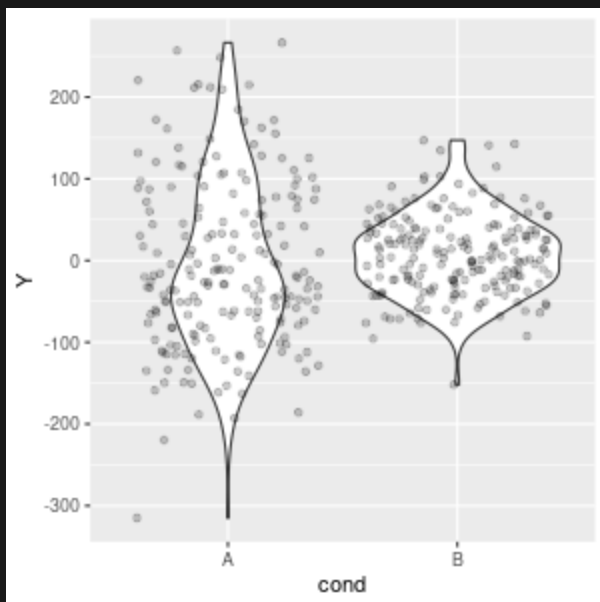
```
## fitted values:  
##   fitted(mod)  
## residuals:  
##   residuals(mod)
```



HOMOGENEITY OF VARIANCE

```
n_obs <- 200L
dat3 <- tibble(cond = rep(c("A", "B"),
                          each = n_obs)
               , Y = c(rnorm(n_obs, 0, 100),
                      rnorm(n_obs, 0, 50))

ggplot(dat3, aes(cond, Y)) +
  geom_violin() +
  geom_jitter(alpha = .2)
```



```
n_pts <- 10L
n_obs <- 50
dat4 <- tibble(
  x = seq_len(n_pts),
  y = map(x, # purrr::map()
          ~ rnorm(n_obs, 5 * .x, 10 * .
                  )
  ) %>% unnest() # tidyr::unnest()

ggplot(dat4, aes(x, y)) +
  geom_point(alpha = .2) +
  geom_smooth(method = "lm")
```

NORMALITY OF RESIDUALS

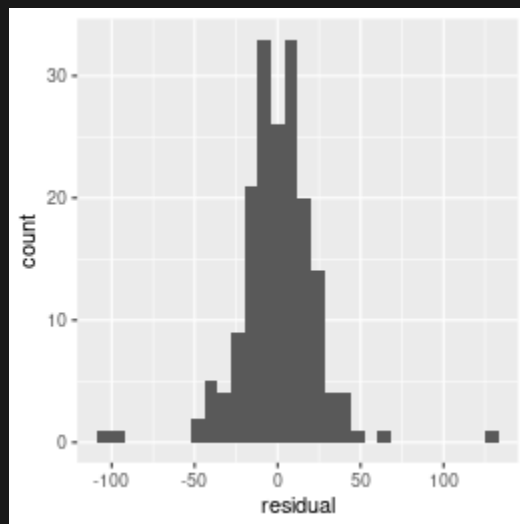
- don't visualize the raw DV to check for normality!

https://dalejbarr.shinyapps.io/raw_vs_resids/

VISUAL CHECKS

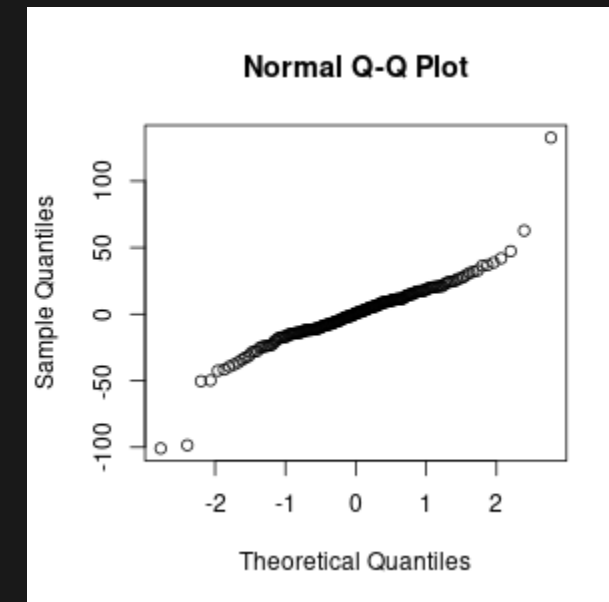
- histogram

```
## resids from the model fit to sleepst  
my_resids <- residuals(mod)  
  
## it is a vector, must put into a tibble  
## for ggplot  
rtbl <- tibble(residual = my_resids)  
  
ggplot(rtbl, aes(residual)) +  
  geom_histogram()
```



- Q-Q plot (quantile-quantile)

```
## sadly there is no qqplot for ggplot  
## so we use base::qqnorm()  
qqnorm(my_resids)
```



Vanhove, J. (2018). *Checking the assumptions of your statistical model without getting paranoid*. Preprint at <https://psyarxiv.com/zvawb/>.

