

Course outline

- Session 1. Simple Regression; Individual Difference; Intro to Linear mixed-effect models (LMMs)
- Session 2. LMMs (lmer); Generalised LMMs (glmer)
- Session 3. Practical
- Session 4. Ggeneralised LMMs continued; Model assumptions and diagnostics
- Session 5. Practical

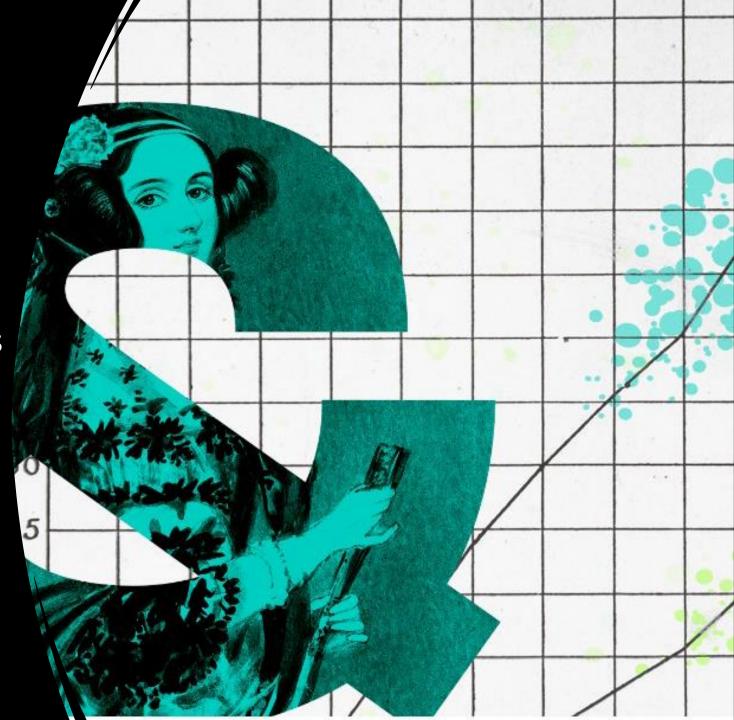


Session 2 Roadmap (today)

Characteristics and objectives of LMMs

Random Effects

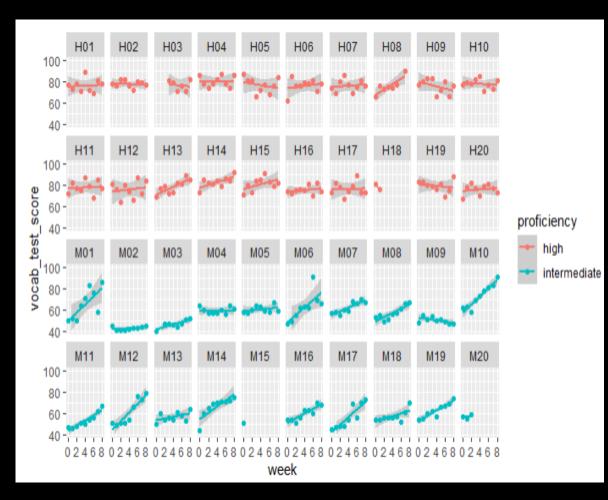
Model Comparison

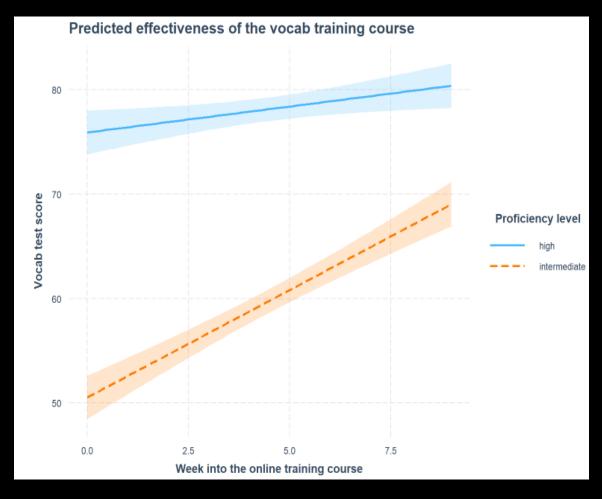




Linear Mixed Effects Models (LMMs) -Imer()

Recall problems with simple regression

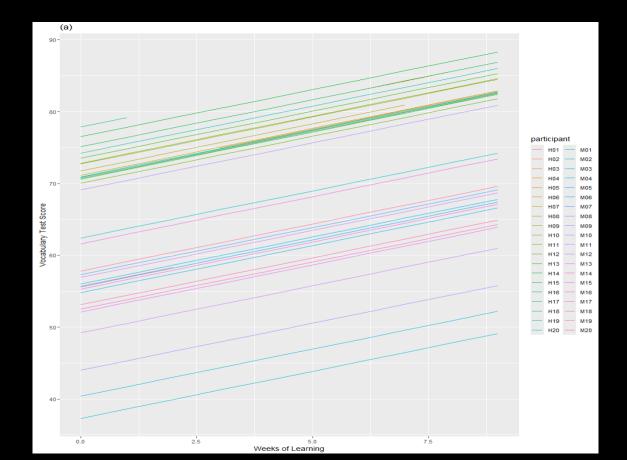


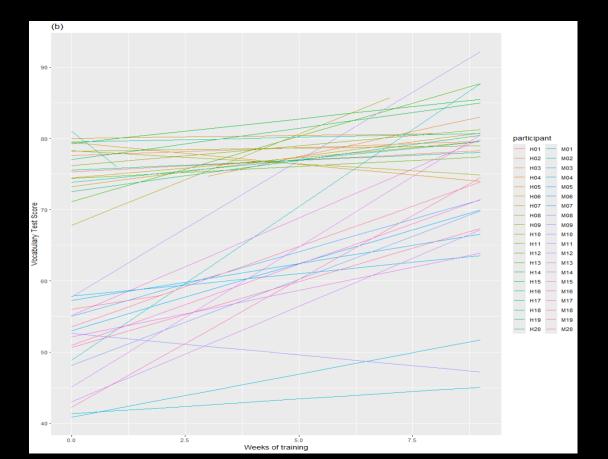


Recall simple regression

• Treating participant as a predictor

```
m3a <- lm(vocab_test_score ~ week + participant,
data = vocabdata)
```





Structure of LMMS: Random effects

The structure of a simple regression

```
m2bv2 <- lm vocab_test_score ~ week * proficiency, data = vocabdata)
```

• The structure of linear mixed-effect models

```
mixedm1 <- Imer (vocab_test_score ~ week * proficiency + (1 | participant), data = vocabdata)

mixedm2 <- Imer (vocab_test_score ~ week*proficiency + (1 + week | participant), data = vocabdata)

Fixed effects

Random effects
```

Characteristics of LMMs

- Repeated-measures Factorial Design
 - a person or item being observed multiple times

- Measurements from a participant or an item are correlated
 - Thus cannot use simple regression due to violation of assumptions
 - more on this next week

- Random variability
 - More than one source
 - Across different groups of observations
 - Variance resulting from taking a random sample of observations

Objectives of LMMs

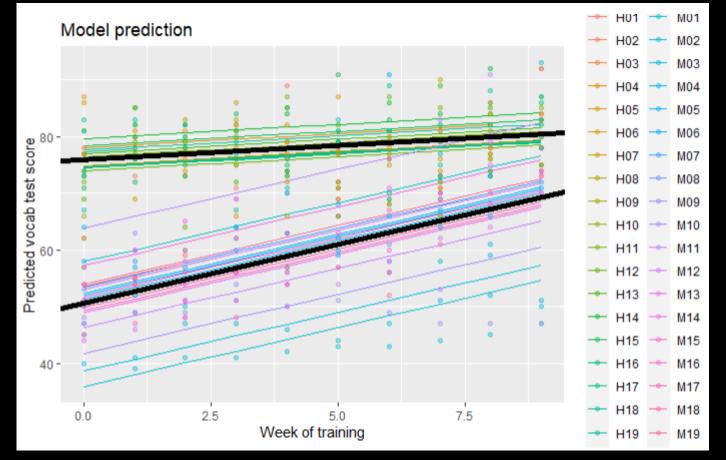
- Description
 - What occurs to subjects over time? etc.

- Inference
 - Is a treatment effective? Does substantial change occur over time?
- Prediction
 - What is the trend?



Random Intercepts

Structure of LMMS: Random Intercepts



Random intercept

Grouping

Structure of LMMS: Random Intercepts

```
(3) mixedm2 <- Imer(vocab test score ~ week * proficiency + (1 | participant), data = vocabdata)</p>
Linear mixed model fit by REML. t-tests use Satterthwaite's method [lmerModLmerTest
Formula: vocab_test_score ~ week * proficiency + (1 | participant)
   Data: vocabdata
REML criterion at convergence: 2438.8
Scaled residuals:
            10 Median
-3.3014 -0.5552 0.0434 0.6075 4.4641
Random effects:
 Groups
            Name
                        Variance Std.Dev.
 participant (Intercept) 25.47
 Residual
                        35.45
                                5.954
Number of obs: 369, groups: participant, 40
Fixed effects:
                            Estimate Std. Error
(Intercept)
                            75.9310
                             0.5023
week
                            -25.3754
                                               65.0011 -12.896 < 2e-16
proficiencyintermediate
week:proficiencyintermediate 1.5755
                                        0.2185 334.4965
                                                        7.210 3.76e-12 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
Correlation of Fixed Effects:
           (Intr) week prfcnc
           -0.486
week
prfcncyntrm -0.708 0.344
```

wk:prfcncyn 0.346 -0.713 -0.477

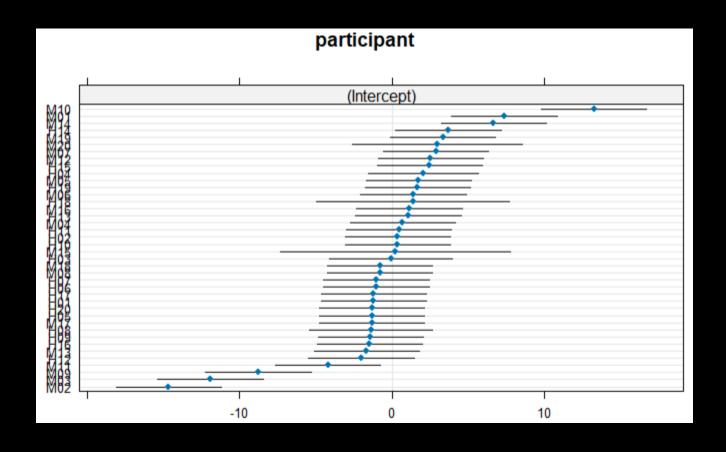
Random intercept Grouping

What happens to the overall quality of the model???

No direct output of R² or other simple goodness-of-fit metrics (though these can be easily calculated using handy packages, e.g., broom.mixed; sjPlot)

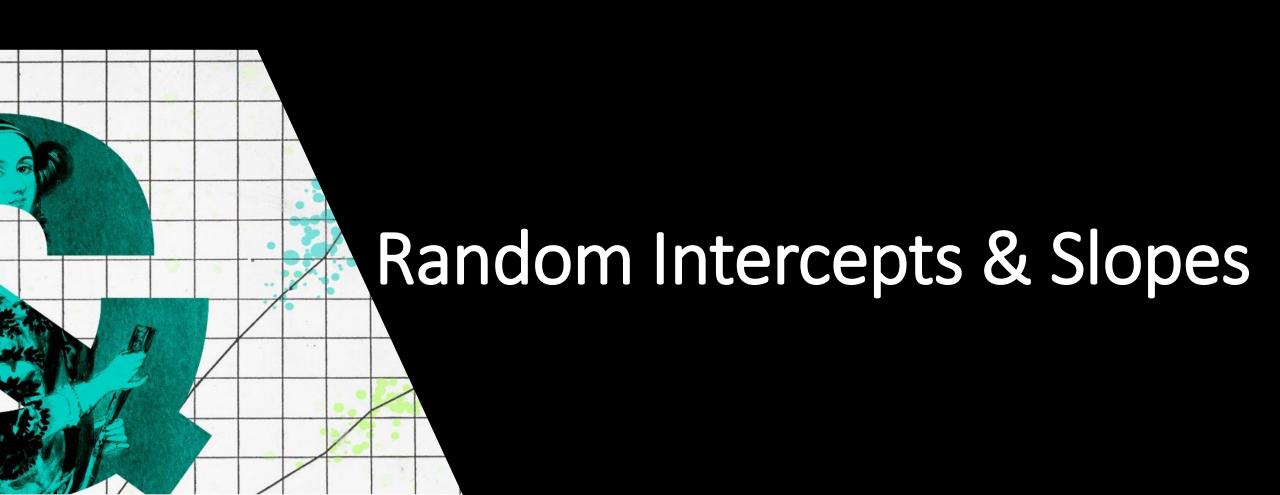
Structure of LMMS: Random Intercepts

(3) mixedm2 <- Imer(vocab_test_score ~ week * proficiency + (1) [participant), data = vocabdata)



Random intercept

grouping



Structure of LMMS: Random Slops as well

(2) mixedm1 <- Imer(vocab_test_score ~ week * proficiency + (1 + week | participant), data = vocabdata) Model prediction Grouping Predicted vocab test score Random Random M07 M08 H09 M09 M10

7.5

0.0

2.5

Week of training

M14

H19

intercept

slope

Structure of LMMS: Random Slops as well

```
(2) mixedm1 <- Imer(vocab test score ~ week * proficiency + (1 + week | participant), data = vocabdata)
Linear mixed model fit by REML. t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: vocab_test_score ~ week * proficiency + (1 + week | participant)
   Data: vocabdata
REML criterion at convergence: 2398.8
Scaled residuals:
            10 Median
-3.5994 -0.5566 0.0445 0.6019 4.9182
Random effects:
                       Variance Std.Dev. Corr
 Groups
            Name
 participant (Intercept) 10.0871 3.1760
                        0.6937 0.8329
                                         0.11
                       29.5112 5.4324
 Residual
Number of obs: 369, groups: participant, 40
Fixed effects:
                           Estimate Std. Error
                                                    df t value Pr(>|t|)
(Intercept)
                            75.8547
                                        1.0317
                                               38.5521 73.526 < 2e-16 ***
                             0.5255
                                        0.2392
week
                                               36.0100
proficiencyintermediate
                           -25.3129
                                        1.4532
                                               38.2004 -17.419 < 2e-16 ***
week:proficiencyintermediate 1.5555
                                        0.3395 35.1552
                                                       4.582 5.59e-05 ***
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
           (Intr) week
                        prfcnc
           -0.306
week
```

prfcncyntrm -0.710 0.217

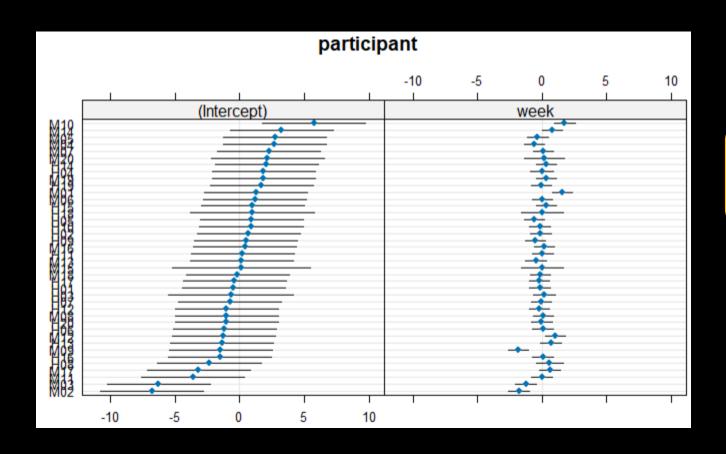
wk:prfcncyn 0.216 -0.705 -0.296

Grouping

Random intercept Random

Structure of LMMS: Random Slops as well

(2) mixedm1 <- Imer(vocab_test_score ~ week * proficiency + (1 + week) participant), data = vocabdata)



Grouping

Random intercept

Random slope

Structure of LMMS: Summary

```
• Imer (y \sim X<sub>1</sub> * X<sub>2</sub> + 
 (1 + X<sub>1</sub> * X<sub>2</sub> | Grouping<sub>1</sub>) + 
 (1 + X<sub>1</sub> | Grouping<sub>2</sub>), 
 data = datafilename)
```



You can have more than one source of individual differences (e.g., group by student, by class, by teacher etc)



Deal with common issues: Convergence

```
Warning message:
In checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
    Model failed to converge with max|grad| = 0.0206805 (tol = 0.002, component 1)
```

Solutions:

- Adjust stopping (convergence) tolerances for the nonlinear optimizer, using the optCtrl() argument to ImerControl.
- Center and scale continuous predictor variables (e.g., vocabdata<-scale(vocabdata\$week, center=TRUE, scale=FALSE)



Deal with common issues: Boundary singular fit

boundary (singular) fit: see ?isSingular

Solutions:

- Remove the most complex part of the random effects structure (i.e. random slopes)
- Maybe acceptable to remove a specific random effect term when its variance estimates are very low



Model Selection

Model Comparison & Selection

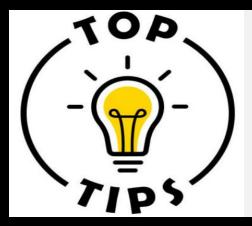
Which model should you choose?

- Hint: remember the anova() function we used last time?
 - anova(simpler model, complex model)

Model Comparison & Selection

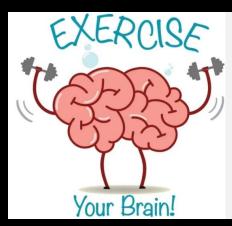
Which model should you choose?

- Barr, Levy, Scheepers, & Tily, (2013): keep it maximal
- Matuschek, Kliegl, Vasishth, Baayen & Bates (2017): make it parsimonious to balance Type1 error and power



Different approaches been promoted by different researchers; either is fine as long as you explain your rationale.

Exercise (rest of today + Friday)



Can you fit a model with a different structure of random effects to analyse this dataset?

- Hint: consider including some or all of the following:
 - random intercept?
 - random slope of one predictor?
 - random slopes of both predictors?
 - random slope of the interaction between the two predictors?

Friday: Applications: Self-reflection & Discussion



BYOD

In what ways can linear mixedeffects models help you address the research questions of your own project ?

Further reading

Paper

Brown, VA. (2021). An Introduction to Linear Mixed-Effects Modeling in R. *Advances in Methods and Practices in Psychological Science*. 4(1). doi:10.1177/2515245920960351

Advances in Methods and Practices in Psychological Science

Openaccess © Textographic

An Introduction to Linear Mixed-Effects Modeling in R

Violet A. Brown © View all authors and affiliations

All Articles | https://doi.org/10.1177/2515245920960351

E-Book

https://vasishth.github.io/Freq CogSci/

Shravan Vasishth, Daniel Schad, Audrey Bürki, Reinhold Kliegl

Linear Mixed Models in Linguistics and Psychology: A Comprehensive Introduction

THANK YOU

