

Inference with mixed effects models

Data: flipped classrooms?

Data set has 375 rows (one per student), and the following variables:

- + professor: which professor taught the class (1 -- 15)
- + style: which teaching style the professor used (no flip, some flip, fully flipped)
- + score: the student's score on the final exam

Inference with linear models

$$Score_i = \beta_0 + \beta_1 \text{SomeFlipped}_i + \beta_2 \text{FullyFlipped}_i + \varepsilon_i$$

Research question: Is there a relationship between teaching style and student score?

What are my null and alternative hypotheses, in terms of one or more model parameters?

Inference with linear models

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Research question: Is there a relationship between teaching style and student score?

$$H_0 : \beta_1 = \beta_2 = 0$$

$$H_A : \text{at least one of } \beta_1, \beta_2 \neq 0$$

What test would I use to test these hypotheses?

F tests

$$Score_i = \beta_0 + \beta_1 \text{SomeFlipped}_i + \beta_2 \text{FullyFlipped}_i + \varepsilon_i$$

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What are my degrees of freedom for the F test?

F tests for mixed effects models

$$Score_{ij} = \beta_0 + \beta_1 \text{SomeFlipped}_i + \beta_2 \text{FullyFlipped}_i + u_i + \varepsilon_{ij}$$

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F tests for mixed effects models

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Research question: Is there a relationship between teaching style and student score?

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Test: We will use an F test again

- + numerator df = number of parameters tested = 2
- + denominator df = ??

What *are* degrees of freedom?

Suppose we want to estimate the mean μ of a distribution. We observe n observations X_1, \dots, X_n , and calculate the sample mean

$$\bar{X} = \frac{X_1 + X_2 + \dots + X_n}{n}$$

Suppose we know the value of \bar{X} . How many of the values X_1, \dots, X_n are "free to vary" (i.e., can be any number they want)?

Example: simple linear regression

Observe $(X_1, Y_1), \dots, (X_n, Y_n)$ and calculate

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i$$

What are my degrees of freedom?

Denominator degrees of freedom for mixed models

$$Score_{ij} = \beta_0 + \beta_1 \text{SomeFlipped}_i + \beta_2 \text{FullyFlipped}_i + u_i + \varepsilon_{ij}$$

$$H_0 : \beta_1 = \beta_2 = 0 \quad H_A : \text{at least one of } \beta_1, \beta_2 \neq 0$$

Test: We will use an F test again

+ numerator df = number of parameters tested = 2

+ denominator df =

number of independent observations – number of parameters

Are all observations independent?

Bounds on the denominator degrees of freedom

$$Score_{ij} = \beta_0 + \beta_1 \text{SomeFlipped}_i + \beta_2 \text{FullyFlipped}_i + u_i + \varepsilon_{ij}$$

$$u_i \stackrel{iid}{\sim} N(0, \sigma_u^2) \quad \varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_\varepsilon^2)$$

$$\# \text{ groups} - p \leq \text{denominator df} \leq n - p$$

+ p = number of parameters in full model

+ n = total number of observations

Approximating the degrees of freedom

```
library(lme4)
library(lmerTest)
m1 <- lmer(score ~ style + (1|professor),
           data = teaching)
anova(m1)
```

```
## Type III Analysis of Variance Table with Satterthwaite's
##          Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## style  65.437   32.718      2     12   7.6949 0.007072 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
```

- ✚ The `lmerTest` package approximates degrees of freedom with *Satterthwaite's method* (details are beyond the scope of this course)
- ✚ This allows us to calculate (approximate) p-values

Why degrees of freedom matter

- + If we use the wrong degrees of freedom, we get the wrong p-value
- + Often this means our p-value is smaller than it should be (we overestimate the strength of evidence)

Using the correct degrees of freedom:

```
pf(7.69, 2, 12, lower.tail=F)
```

```
## [1] 0.007087398
```

If we just did $n - p$ (wrong):

```
pf(7.69, 2, 372, lower.tail=F)
```

```
## [1] 0.0005339106
```

Class activity

https://sta214-f22.github.io/class_activities/ca_lecture_28.html

Class activity

There are 1561 rentals in 43 neighborhoods. What are the lower and upper bounds on the denominator degrees of freedom?

Class activity

What is the approximate denominator df, using Satterthwaite's method?

Class activity

Do we have evidence for a relationship between overall satisfaction and price?

Class activity

$$Price_{ij} = \beta_0 + \beta_1 Satisfaction_{ij} + u_i + \varepsilon_{ij}$$

$$u_i \stackrel{iid}{\sim} N(0, \sigma_u^2) \quad \varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_\varepsilon^2)$$

where $Price_{ij}$ is the price of rental j in neighborhood i

What assumptions are we making in this mixed effects model?

Assumptions

$$Price_{ij} = \beta_0 + \beta_1 Satisfaction_{ij} + u_i + \varepsilon_{ij}$$

$$u_i \stackrel{iid}{\sim} N(0, \sigma_u^2) \quad \varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_\varepsilon^2)$$

+ Shape:

- + the overall relationship between satisfaction and price is linear
- + The slope is the *same* for each neighborhood

Assumptions

$$Price_{ij} = \beta_0 + \beta_1 Satisfaction_{ij} + u_i + \varepsilon_{ij}$$

$$u_i \stackrel{iid}{\sim} N(0, \sigma_u^2) \quad \varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_\varepsilon^2)$$

+ Independence:

- + random effects are independent
- + observations within neighborhoods are independent after accounting for the random effect (i.e., the random effect captures the correlation within neighborhoods)
- + observations from different neighborhoods are independent

Assumptions

$$Price_{ij} = \beta_0 + \beta_1 Satisfaction_{ij} + u_i + \varepsilon_{ij}$$

$$u_i \stackrel{iid}{\sim} N(0, \sigma_u^2) \quad \varepsilon_{ij} \stackrel{iid}{\sim} N(0, \sigma_\varepsilon^2)$$

- + **Normality:** Both $u_i \sim N(0, \sigma_u^2)$ and $\varepsilon_{ij} \sim N(0, \sigma_\varepsilon^2)$
- + **Constant variance:**
 - + ε_{ij} has the same variance σ_ε^2 regardless of satisfaction or neighborhood