Course Business

- Lab materials on Canvas

- Final project information will be posted on Canvas at 4:00 PM today
  - Final project: Analyze your own data
    - I can supply simulated data if needed—send me an intro & methods section for the data you’d like to analyze
  - In-class presentation: Last 2.5 weeks of class, beginning Nov. 9th
    - Sign up on Canvas for a time slot – first come, first served!
  - Final paper: Due on Canvas last day of class
  - Canvas will have more info. on requirements
Week 11.1: Growth Curve Analysis

Overview
- Reshaping Data
- Growth Curve Analysis
  - Time as a Predictor Variable
  - Quadratic & Higher Degrees
  - Random Slopes
  - Time-Variant & -Invariant Variables
  - Breakpoints
- Lab
Longitudinal Designs

Degrees of Improvement
Percentage of 20-24 year olds in year shown who have graduated from high school.

Source: Richard Mumane
Longitudinal Designs

• There are many methods available for analyzing longitudinal data
  • Aidan Wright’s class on Applied Longitudinal Data Analysis

• Mixed-effects models are one effective solution
  • Hierarchical models naturally account for longitudinal data
  • Include all of the other features we’ve looked at (multiple random effects, mix of categorical & continuous variables, non-normal DVs, etc.)
What kind of random-effects structure is this?
What kind of random-effects structure is this?
Two levels of nesting – sample schools, then sample students inside each school.
Now imagine we observed each student several different times
- e.g., midterm & final exam
Longitudinal Data as Hierarchical Data

LEVEL 3
Sampled SCHOOLS

LEVEL 2
Sampled STUDENTS

LEVEL 1
Sampled TIME POINTS

- This is just another level of nesting
  - Sample schools
  - Sample student within each school
  - Sample time points within each student
Longitudinal Designs

• Two big questions mixed-effects models can help us answer about longitudinal data:

1) What is the overall trajectory of change across time?
   ➢ Today

2) How does an observation at one time point relate to the next time point?
   ➢ Wednesday
Role of language input in early vocab acquisition

200 kids from lower SES families:
- 100 families given books to read to their kids
- 100 waitlisted controls

Vocab assessed every 2 months from 20 mos. to 28 mos.

Research questions:
- What is the general trajectory of vocabulary acquisition in these ages?
- How is this altered by our intervention?
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  - Breakpoints
- Lab
**Long vs. Wide Format**

- For `lmer()`, each observation needs its own row
- “long” format

---

<table>
<thead>
<tr>
<th>Child Reading</th>
<th>MonthsInStudy</th>
<th>VocabWords</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;chr&gt;</td>
<td>&lt;fct&gt;</td>
<td>&lt;int&gt;</td>
</tr>
<tr>
<td>---------------</td>
<td>--------------</td>
<td>------------</td>
</tr>
<tr>
<td>S0001 Yes</td>
<td>0</td>
<td>93</td>
</tr>
<tr>
<td>S0001 Yes</td>
<td>2</td>
<td>137</td>
</tr>
<tr>
<td>S0001 Yes</td>
<td>4</td>
<td>185</td>
</tr>
<tr>
<td>S0001 Yes</td>
<td>6</td>
<td>296</td>
</tr>
<tr>
<td>S0001 Yes</td>
<td>8</td>
<td>441</td>
</tr>
<tr>
<td>S0002 No</td>
<td>0</td>
<td>97</td>
</tr>
<tr>
<td>S0002 No</td>
<td>2</td>
<td>121</td>
</tr>
<tr>
<td>S0002 No</td>
<td>4</td>
<td>175</td>
</tr>
<tr>
<td>S0002 No</td>
<td>6</td>
<td>268</td>
</tr>
<tr>
<td>S0002 No</td>
<td>8</td>
<td>368</td>
</tr>
<tr>
<td>S0003 Yes</td>
<td>0</td>
<td>78</td>
</tr>
<tr>
<td>S0003 Yes</td>
<td>2</td>
<td>144</td>
</tr>
</tbody>
</table>

---

<table>
<thead>
<tr>
<th>Subject</th>
<th>WordPair</th>
<th>StudyTime</th>
<th>Strategy</th>
<th>Recalled</th>
<th>SourceConfusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>S1</td>
<td>Oval--Round</td>
<td>6</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Game--Monopoly</td>
<td>4</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Rabbit--Fast</td>
<td>3</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Sack--Bag</td>
<td>4</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Screen--Patio</td>
<td>5</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Scotch--Vodka</td>
<td>4</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Binder--Folder</td>
<td>3</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Holiday--Christmas</td>
<td>3</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Career--Job</td>
<td>4</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>S1</td>
<td>Appraise--Value</td>
<td>2</td>
<td>Elaborative</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
For `lmer()`, each observation needs its own row
- “long” format

Sometimes data comes to us in “wide” format
- Each repeated measure is a different *column* in the same row
- e.g., what SPSS uses
- `vocab.csv` is in this format
Long vs. Wide Format

- Tidyverse contains very easy functions for **pivoting** data between formats
  - `pivot_longer()`: To turn data *into* long format
  - `pivot_wider()`: To turn data *into* wide format
**pivot_longer()**

- Here is a look at our dataframe...

We want to turn into each of these columns into a separate row
pivot_longer()

- `vocab %>%
pivot_longer(cols=c('Month0', 'Month2', 'Month4', 'Month6', 'Month8')) -> vocab.p`
- Now we have five rows per child

We want to turn into each of these columns into a separate row.
pivot_longer()

- By default, R saves the original column name in a variable called "name", and the DV in a variable called "value"
  - Not very informative
- We can specify better names:
- `vocab %>% pivot_longer(cols=c('Month0', 'Month2', 'Month4', 'Month6', 'Month8'), names_to='MonthsInStudy', values_to='VocabWords')` -> `vocab.p`
pivot_longer()

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What we’d really like is to turn `MonthsIntoStudy` into a numeric variable.

- Currently, the values are “Month0,” “Month2,” etc., because those were the original column names.
- Since these all start with the same prefix (`Month`), `tidyverse` can automatically strip that out for us.

```r
vocab %>%
  pivot_longer(cols=c('Month0','Month2','Month4','Month6','Month8'),
               names_to='MonthsInStudy',
               names_prefix='Month',
               values_to='VocabWords')
```

---

<table>
<thead>
<tr>
<th>Child</th>
<th>Reading</th>
<th>MonthsInStudy</th>
<th>VocabWords</th>
</tr>
</thead>
<tbody>
<tr>
<td>S0001</td>
<td>Yes</td>
<td>Month0</td>
<td>93</td>
</tr>
<tr>
<td>S0001</td>
<td>Yes</td>
<td>Month2</td>
<td>137</td>
</tr>
<tr>
<td>S0001</td>
<td>Yes</td>
<td>Month4</td>
<td>185</td>
</tr>
<tr>
<td>S0001</td>
<td>Yes</td>
<td>Month6</td>
<td>296</td>
</tr>
<tr>
<td>S0001</td>
<td>Yes</td>
<td>Month8</td>
<td>441</td>
</tr>
<tr>
<td>S0002</td>
<td>No</td>
<td>Month0</td>
<td>97</td>
</tr>
</tbody>
</table>
pivot_longer()

- What we’d really like is to turn MonthsIntoStudy into a numeric variable
  - Currently, the values are "Month0," "Month2," etc., because those were the original column names
  - Since these all start with the same prefix (Month), tidyverse can automatically strip that out for us

- `vocab %>% pivot_longer(cols=c('Month0','Month2','Month4','Month6','Month8'), names_to='MonthsInStudy', names_prefix='Month', values_to='VocabWords')` -> vocab.p
pivot_longer()

- Now, we can use `as.numeric()` on this variable
- `vocab.p %>%
  mutate(MonthsInStudy = as.numeric(MonthsInStudy))` -> `vocab.p`
pivot_longer()

- Now, we can use as.numeric() on this variable
  - `vocab.p %>%
    mutate(MonthsInStudy = as.numeric(MonthsInStudy)) -> vocab.p`
Week 11.1: Growth Curve Analysis

Overview

Reshaping Data

- Growth Curve Analysis

Time as a Predictor Variable

- Quadratic & Higher Degrees
- Random Slopes
- Time-Variant & -Invariant Variables
- Breakpoints

- Lab
Role of language input in early vocab acquisition

200 kids from lower SES families:
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Vocab assessed every 2 months from 20 mos. to 28 mos.

Research questions:
- What is the general trajectory of vocabulary acquisition in these ages?
- How is this altered by our intervention?
**Longitudinal Designs**

- Two big questions mixed-effects models can help us answer about longitudinal data:

  1) What is the overall trajectory of change across time?
     - Today: *Growth curve analysis*

  2) How does an observation at one time point relate to the next time point?
     - Wednesday
Time as a Predictor Variable

• How does vocabulary change over time?

• The simple way to answer this question: Add time as a variable in our model
  • Nothing “special” about time as a predictor
**Time as a Predictor Variable**

- Let’s add the effect of time to our model
  - Here: `MonthsInStudy` (starting at 0)
  - Fixed effect because we’re interested in time effects

- `model1 <- lmer(VocabWords ~ 1 + MonthsInStudy + (1|Child), data=vocab)`

| Fixed effects:                                | Estimate | Std. Error | df  | t value | Pr(>|t|) |
|------------------------------------------------|----------|------------|-----|---------|----------|
| (Intercept)                                    | 51.1640  | 4.7212     | 416.7500 | 10.84   | <2e-16 *** |
| MonthsInStudy                                  | 34.8935  | 0.6767     | 799.0000 | 51.56   | <2e-16 *** |

- How would you interpret the two estimates?
  - **Intercept:**
  - **Slope:**
Time as a Predictor Variable

- Let’s add the effect of time to our model
  - Here: `MonthsInStudy` (starting at 0)
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- `model1 <- lmer(VocabWords ~ 1 + MonthsInStudy + (1|Child), data=vocab)`

- How would you interpret the two estimates?
  - **Intercept**: Average vocab ~51 words at start of study
  - **Slope**: Gain of about ~35 words per month
**Time as a Predictor Variable**

- **Not** necessary to have every time point represented
  - Don’t even have to be the same set of time points across participants

- Time **units** also don’t matter as long as they’re consistent
  - Could be hours, days, years …
Week 11.1: Growth Curve Analysis

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Quadratic & Higher Degrees

![Graph showing Vocab Words vs. Months In Study]
Quadratic & Higher Degrees

- We’ve been assuming a *linear* effect of time
Quadratic & Higher Degrees

• But, it looks like vocab growth may accelerate
  • Growth between 0 mo. and 2 mo. is much smaller than growth between 6 mo. and 8 mo.
  • Suggests a curve / quadratic equation
Quadratic & Higher Degrees

• Add *quadratic* effect \((\text{MonthsInStudy}^2)\):
  - `model.poly <- lmer(VocabWords ~ 1 + poly(MonthsInStudy,degree=2,raw=TRUE) + (1|Child), data=vocab.p)`

• *degree* \(= 2\) because we want \(\text{MonthsInStudy}^2\)
  - `poly()` automatically adds lower-order terms as well
    - i.e., the linear term \((\text{MonthsInStudy}^1)\)

• *raw* \(= \text{TRUE}\) to keep the original scale of the variables (time measured in months)
Quadratic & Higher Degrees

- Results:

- Implied equation (approximate):
  - VocabWords = 75 + 11*Months + 3*Months^2

- What are predicted values if…
  - Month=0?
  - Month=1?
  - Month=2?
Quadratic & Higher Degrees

- Results:

| Fixed effects:                           | Estimate | Std. Error | df | t value | Pr(>|t|) |
|-----------------------------------------|----------|------------|----|---------|----------|
| (Intercept)                             | 75.2597  | 5.0787     | 523.0423 | 14.819  | < 2e-16  *** |
| poly(MonthsInStudy, degree = 2, raw = TRUE)1 | 10.7978  | 2.2154     | 798.0000 | 4.874   | 1.32e-06 *** |
| poly(MonthsInStudy, degree = 2, raw = TRUE)2 | 3.0120   | 0.2655     | 798.0000 | 11.343  | < 2e-16  *** |

- Implied equation (approximate):
  - VocabWords = 75 + 11*Months + 3*Months^2

- What are predicted values if...
  - Month=0? VocabWords = 75 + (11*0) + (3*0^2) = 75
  - Month=1? VocabWords = 75 + (11*1) + (3*1^2) = 89
  - Month=2? VocabWords = 75 + (11*2) + (3*2^2) = 109

- Vocab growth is accelerating (larger change from month 1 to month 2 than from month 0 to month 1)
Different patterns of quadratic & linear effects in a GCA describe different curves.
• **Linear trend**: Is there an overall increase over time (+), decrease (-), or no change?

• **Quadratic trend**: Is the line curved up (+), down (-), or straight?
Quadratic & Higher Degrees

- The Yerkes-Dodson law (Yerkes & Dodson, 1908) describes the optimal level of physiological arousal to perform a task: Low arousal results in poor performance because you are not alert enough, medium arousal results in strong performance, and high arousal results in poor performance because you are too anxious.

Linear trend:

Quadratic trend:
The Yerkes-Dodson law (Yerkes & Dodson, 1908) describes the optimal level of physiological arousal to perform a task: Low arousal results in poor performance because you are not alert enough, medium arousal results in strong performance, and high arousal results in poor performance because you are too anxious.

Linear trend: NONE

Quadratic trend: NEGATIVE
Quadratic & Higher Degrees

• In adulthood, working memory declines the older you get (Park et al., 2002).

Linear trend:

Quadratic trend:
Quadratic & Higher Degrees

• In adulthood, working memory declines the older you get (Park et al., 2002).

  Linear trend: **NEGATIVE**

  Quadratic trend: **NONE**
Quadratic & Higher Degrees

• Aphasia is a neuropsychological disorder that disrupts speech, often resulting from a stroke. After initially acquiring aphasia, patients often experience rapid recovery in much of their language performance (dependent variable) as time (independent variable) increases. But, this recovery eventually slows down, and language performance doesn’t get much better no matter how much more time increases (e.g., Demeurisse et al., 1980).

Linear trend:

Quadratic trend:
Quadratic & Higher Degrees

• Aphasia is a neuropsychological disorder that disrupts speech, often resulting from a stroke. After initially acquiring aphasia, patients often experience rapid recovery in much of their language performance (dependent variable) as time (independent variable) increases. But, this recovery eventually slows down, and language performance doesn’t get much better no matter how much more time increases (e.g., Demeurisse et al., 1980).

Linear trend: POSITIVE
Quadratic trend: NEGATIVE
Quadratic & Higher Degrees

- Studies of practice and expertise (e.g., Logan, 1988) show that people learning to do a task—such as arithmetic—initially show a quick decrease in response time (dependent variable) as the amount of practice increases. However, eventually they hit the point where the task can’t possibly be done any faster, and response time reaches an asymptote and stops decreasing.

Linear trend:

Quadratic trend:
Quadratic & Higher Degrees

- Studies of practice and expertise (e.g., Logan, 1988) show that people learning to do a task—such as arithmetic—initially show a quick decrease in response time (dependent variable) as the amount of practice increases. However, eventually they hit the point where the task can’t possibly be done any faster, and response time reaches an asymptote and stops decreasing.

Linear trend: **NEGATIVE**

Quadratic trend: **POSITIVE**

![Graph showing linear and quadratic trends](image)
Quadratic & Higher Degrees

- Could go up to even higher degrees ($\text{Time}^3, \text{Time}^4 \ldots$)
  - $\text{degree}=3$ if highest exponent is 3

- Degree minus 1 = Number of bends in the curve

![Graphs of quadratic and higher degree functions](image-url)
Quadratic & Higher Degrees

• **Maximum** degree of polynomial: # of time points minus 1
  • Example: 2 time points perfectly fit by a line (degree 1). Nothing left for a quadratic term to explain.

• But, don’t want to **overfit**
  • Probably not the case that the real underlying (population) trajectory has 6 bends in it

• What degree **should** we include?
  • Theoretical considerations
  • If comparing conditions, look at mean trajectory across conditions (Mirman et al., 2008)
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- So far, we assume the same growth rate for all kids
  - Almost certainly not true!
- At level 2, we’re sampling kids both with different **starting points** (intercepts) and **growth rates** (slopes)
**Longitudinal Data: Random Slopes**

**RANDOM INTERCEPTS MODEL**

Kids vary in starting point, but all acquire vocabulary at the same rate over this period.

**WITH RANDOM SLOPES**

Allows rate of vocab acquisition to vary across kids (as well as intercept).
Longitudinal Data: Random Slopes

- Let's allow the `MonthsInStudy` effect to be **different for each** Child.

- `model.Slope <- lmer(VocabWords ~ 1 + poly(MonthsInStudy,degree=2,raw=TRUE) + (1 + poly(MonthsInStudy,degree=2,raw=TRUE)|Child), data=vocab.p)`
**Longitudinal Data: Random Slopes**

Random effects:
<table>
<thead>
<tr>
<th>Groups</th>
<th>Name</th>
<th>Variance</th>
<th>Std. Dev.</th>
<th>Corr</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child</td>
<td>(Intercept)</td>
<td>73.990</td>
<td>8.602</td>
<td></td>
</tr>
<tr>
<td></td>
<td>poly(MonthsInStudy, degree = 2, raw = TRUE)1</td>
<td>23.777</td>
<td>4.876</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>poly(MonthsInStudy, degree = 2, raw = TRUE)2</td>
<td>4.014</td>
<td>2.004</td>
<td>0.15 0.03</td>
</tr>
<tr>
<td>Residual</td>
<td></td>
<td>94.039</td>
<td>9.697</td>
<td></td>
</tr>
</tbody>
</table>

Number of obs: 1000, groups: Child, 200

Fixed effects:
| (Intercept)                                           | Estimate    | Std. Error  | df  | t value | Pr(>|t|) |
|--------------------------------------------------------|-------------|-------------|-----|---------|---------|
| (Intercept)                                            | 75.2597     | 0.8868      | 198.9954 | 84.87   | <2e-16 *** |
| poly(MonthsInStudy, degree = 2, raw = TRUE)1           | 10.7978     | 0.5148      | 199.0031 | 20.98   | <2e-16 *** |
| poly(MonthsInStudy, degree = 2, raw = TRUE)2           | 3.0120      | 0.1489      | 199.0011 | 20.23   | <2e-16 *** |

Substantial variability in the MonthsInStudy slope

SD of the slope across children is ~5 words

Mean slope is 11 words/mo, but some kids might have a slope of 6 or 16
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**Time-Variant & -Invariant Variables**

- We may want to include other (experimental or observational) variables in a GCA model:
  - e.g., our reading intervention

- **MonthsInStudy + Reading**
  - Effect of Reading *invariant across time*
  - Can only affect the intercept (parallel lines)

- **MonthsInStudy * Reading**
  - Effect of Reading *varies with time*
  - Can affect intercept & slope
**Time-Variant & -Invariant Variables**

- Fixed-effect results with the interaction:

| Estimate  | Std. Error   | df | t value | Pr(>|t|)  |
|-----------|--------------|----|---------|-----------|
| (Intercept) | 72.3809      | 1.2235 | 198.0059 | 59.159 | < 2e-16 ** ** ** |
| poly(MonthsInStudy, degree = 2, raw = TRUE)1 | 8.4231 | 0.6897 | 197.4460 | 12.213 | < 2e-16 ** ** ** |
| poly(MonthsInStudy, degree = 2, raw = TRUE)2 | 2.8679 | 0.2106 | 196.6498 | 13.617 | < 2e-16 ** ** ** |
| ReadingYes | 5.7577       | 1.7303 | 198.0061 | 3.328 | 0.00104 ** |
| poly(MonthsInStudy, degree = 2, raw = TRUE)1:ReadingYes | 4.7493 | 0.9754 | 197.4474 | 4.869 | 2.29e-06 ** ** ** |
| poly(MonthsInStudy, degree = 2, raw = TRUE)2:ReadingYes | 0.2882 | 0.2978 | 196.6906 | 0.968 | 0.33439 |

Effect of reading at time 0 (intercept): ~6 words

Also results in faster vocab growth (amplifies + Time effect)
- Linear growth rate for “No” group:
  - 8.4 words / month

- Linear growth rate for “Yes” group:
  - 8.4 + 4.7 = 13.1 words / month

No effect on curvature (quadratic term)

e.g., Huttenlocher et al., 1991
**Time-Variant & -Invariant Variables**

- Can be either:
  - **Time-Invariant Predictor:** *Same* across all time points within a subject
    - e.g., our intervention, race/ethnicity
    - Level 2 variables
  - **Time-Varying Predictor:** Varies even within a subject, from one time point to another
    - e.g., hours of sleep, mood
    - Level-1 variable

- Since R automatically figures out what’s a level-1 vs. level-2 variable, we don’t have to do anything special for either kind of variable
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Another possibility (in general) is a *qualitative change* in the trajectory at some point in the range of time observed

- e.g., age of majority, public policy changes, etc.

Include a **breakpoint**—a categorical variable that represents whether or not you’re above the point at which the change happens

```r
mydata %>%
  mutate(Year2015OrLater =
    ifelse(Year >= 2015, 1, 0)) -> mydata
```

New variable is:

- 0 before 2015
- 1 for 2015 onwards
Breakpoints

- Another possibility (in general) is a *qualitative change* in the trajectory at some point in the range of time observed
  - e.g., age of majority, public policy changes, etc.

- Include a **breakpoint**—a categorical variable that represents whether or not you’re above the point at which the change happens

- Main effect of breakpoint only – single shift downward (or upward) but same slope
- Main effect of breakpoint & an interaction – slope also changes
**Breakpoints**

- Can apply this technique to *any* continuous variables, not just time
  - e.g., above/below the poverty line

- As with higher-order polynomials, be wary of overfitting the data
  - Most effective if we have an a priori reason to expect a breakpoint somewhere
  - Or, use cross-validation to support a more exploratory analysis
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