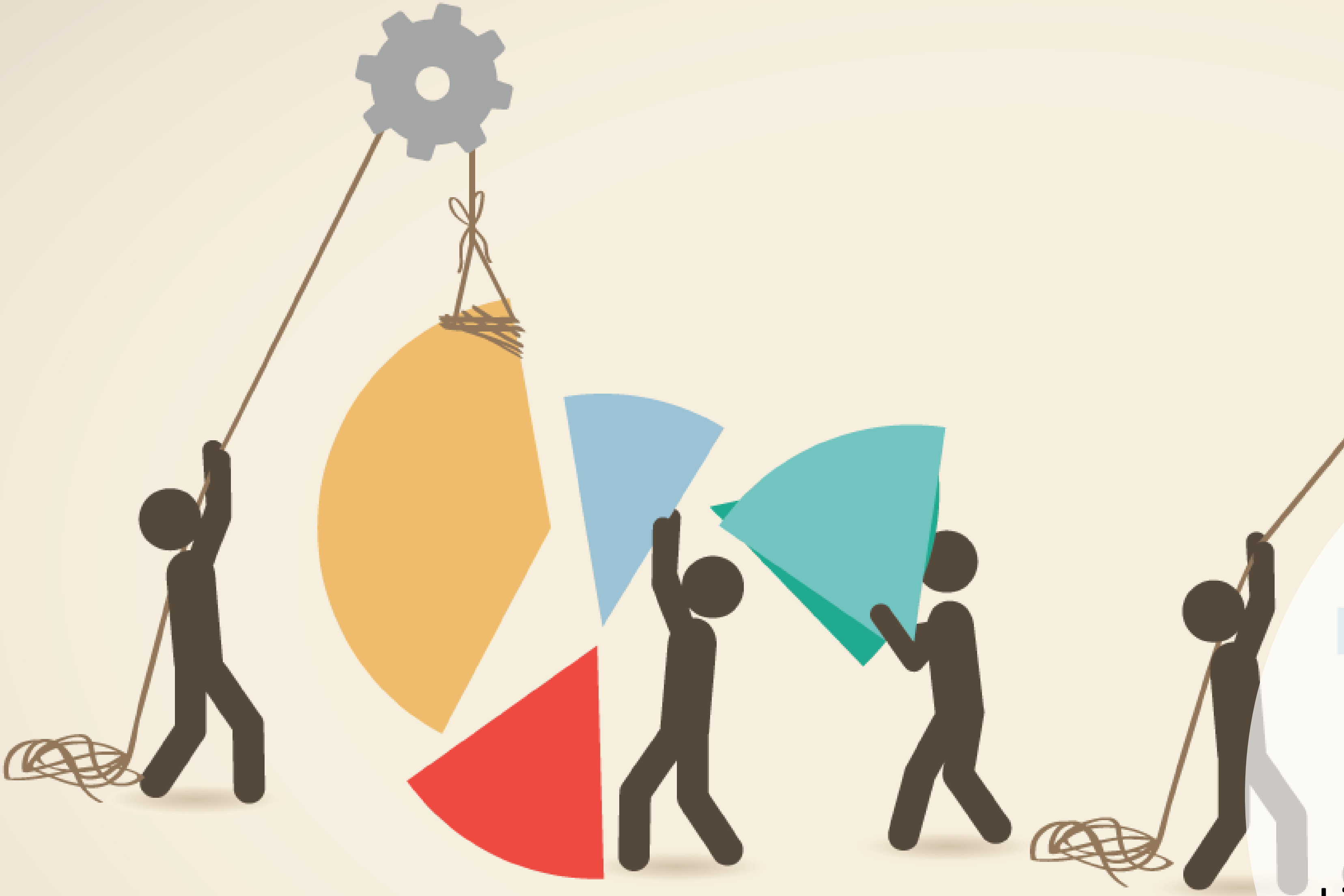
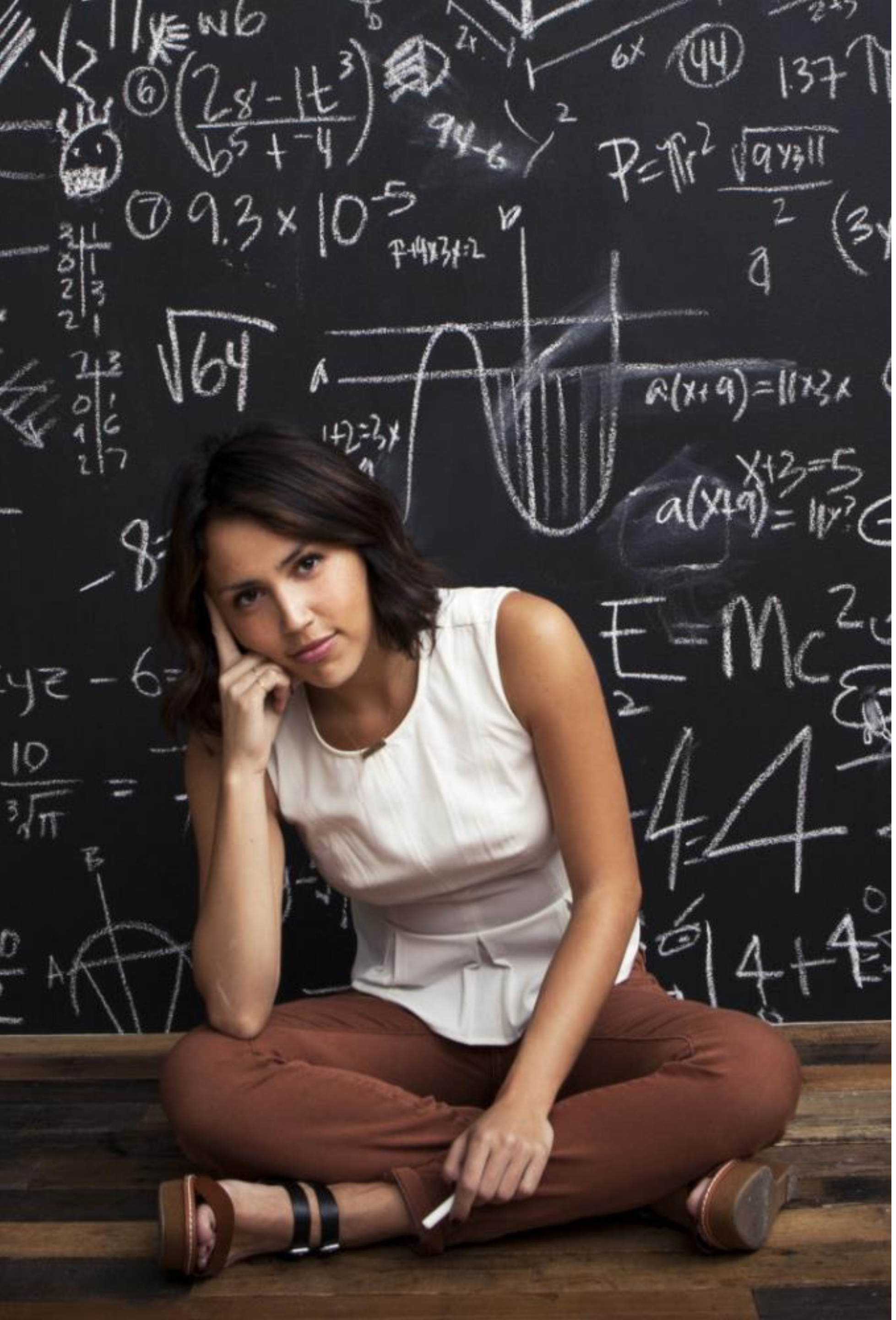


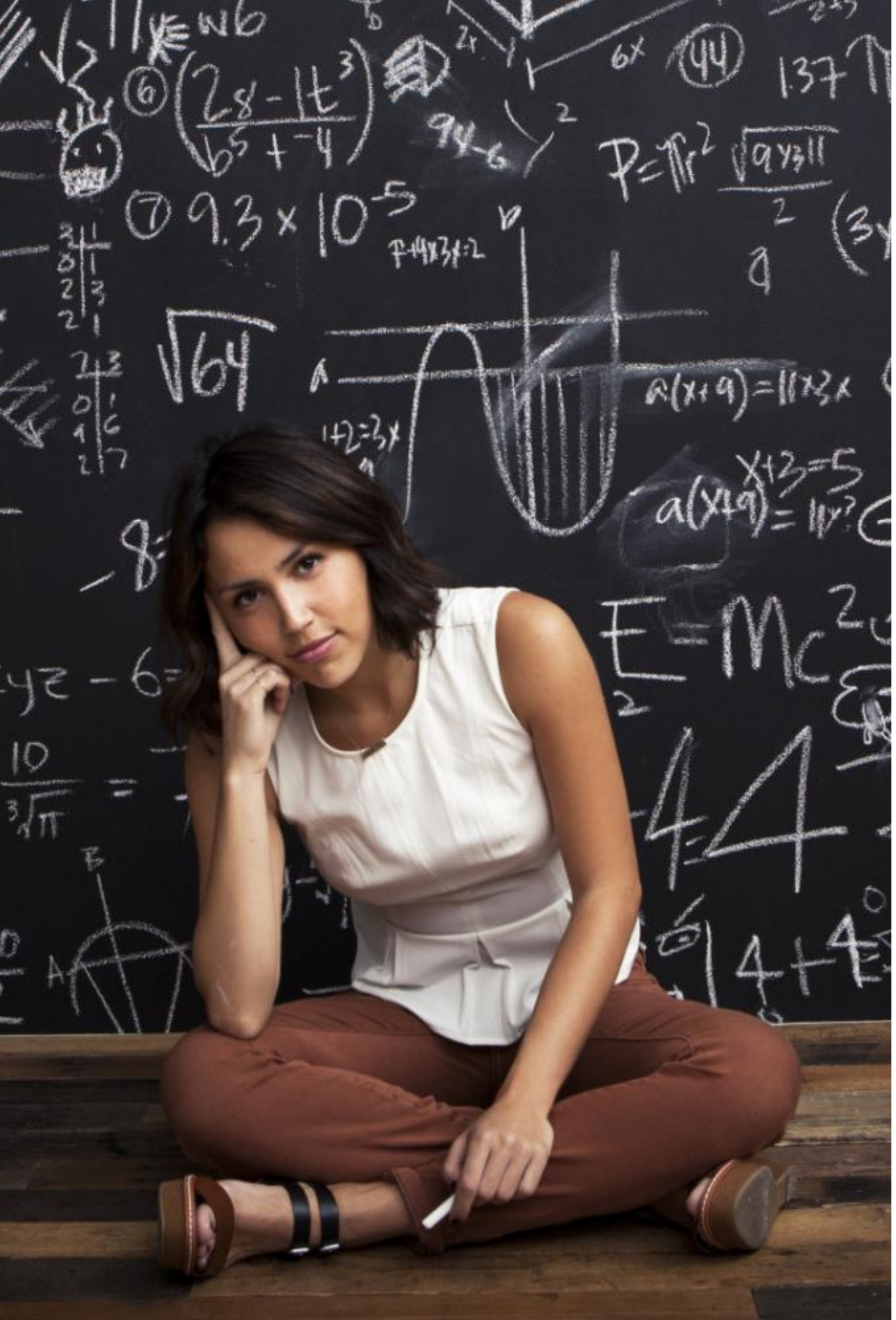
Adapting to the Modeling Revolution: A Guide to SEM & HLM

Lisa Fitton, Dr. Autumn McIlraith, Jessica Hooker, Dr. Nicole Sparapani, Dr. Carla Wood, & Dr. Suzanne Adlof



Disclosures

The authors have no conflicts of interest to report.



Outline

Introduction (Dr. Carla Wood)

Foundation of Statistics (Jessica Hooker)

Overview of Structural Equation Modeling (Dr. Nicole Sparapani)

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Valuing Variance in Data Collection (Lisa Fitton)

Discussion (Dr. Suzanne Adlof)

"No Field Left Behind"

- High stakes competition for external funding
- Multi-disciplinary nature of language and literacy research
- Diversity of methods
  - Variety of different lenses, angles
  - Strengthens confidence in findings

Next-generation scholars must be **good consumers and producers of research**, including a variety of rigorous research methods

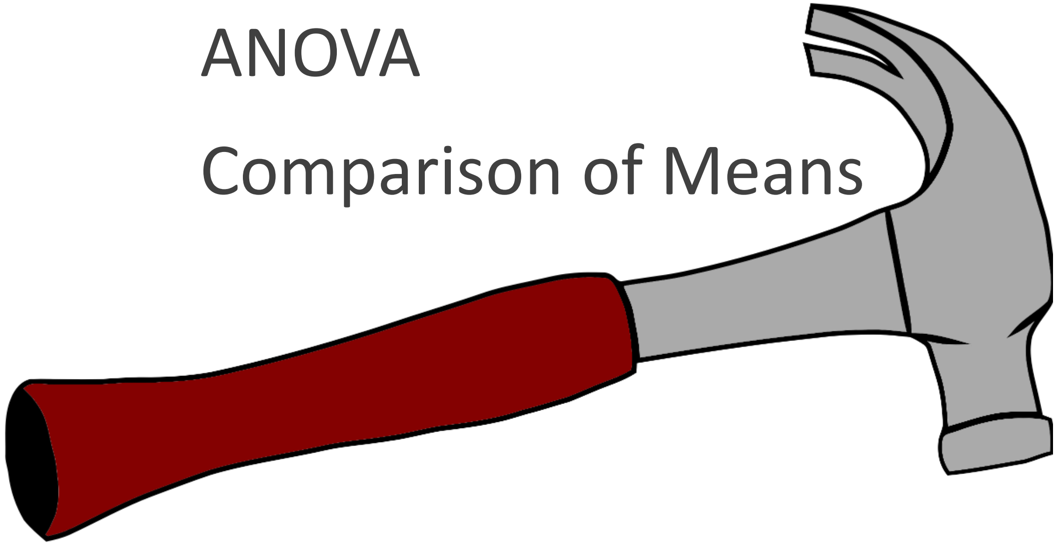
"Who Moved My Cheese?"

….Modeling Revolution?

Traditional training often includes only a few hammers

ANOVA

Comparison of Means



Correlational &

Regression

Revolution in research practices
includes national movement toward:

- Large data sets
- Randomization
- Large Scale Replication
- Advanced Methods: Multi-level modeling (HLM), SEM

We examined 2 years of 10 journals in Language and Literacy Research

JOURNALS

LSHSS	JREE
AJSLP	JEP
JSLHR	Reading and Writing
JCD	RRQ
JLD	SSR

DESCRIPTIVES

Average sample size

Proportion of different types of analyses

The extent to which random assignment and replication was utilized

Summary of Findings

LSHSS, AJSLP, JSLHR, CLD

Employed traditional methods
(58-92% of the time)

- Descriptive data
- ANOVAs
- Regression analyses

Low proportion of advanced methods (8%)

Lower sample sizes on average

RRQ, RW, JLD, JREE, SSR, JEP

Employed advanced methods more often

- Multi dimensional methods

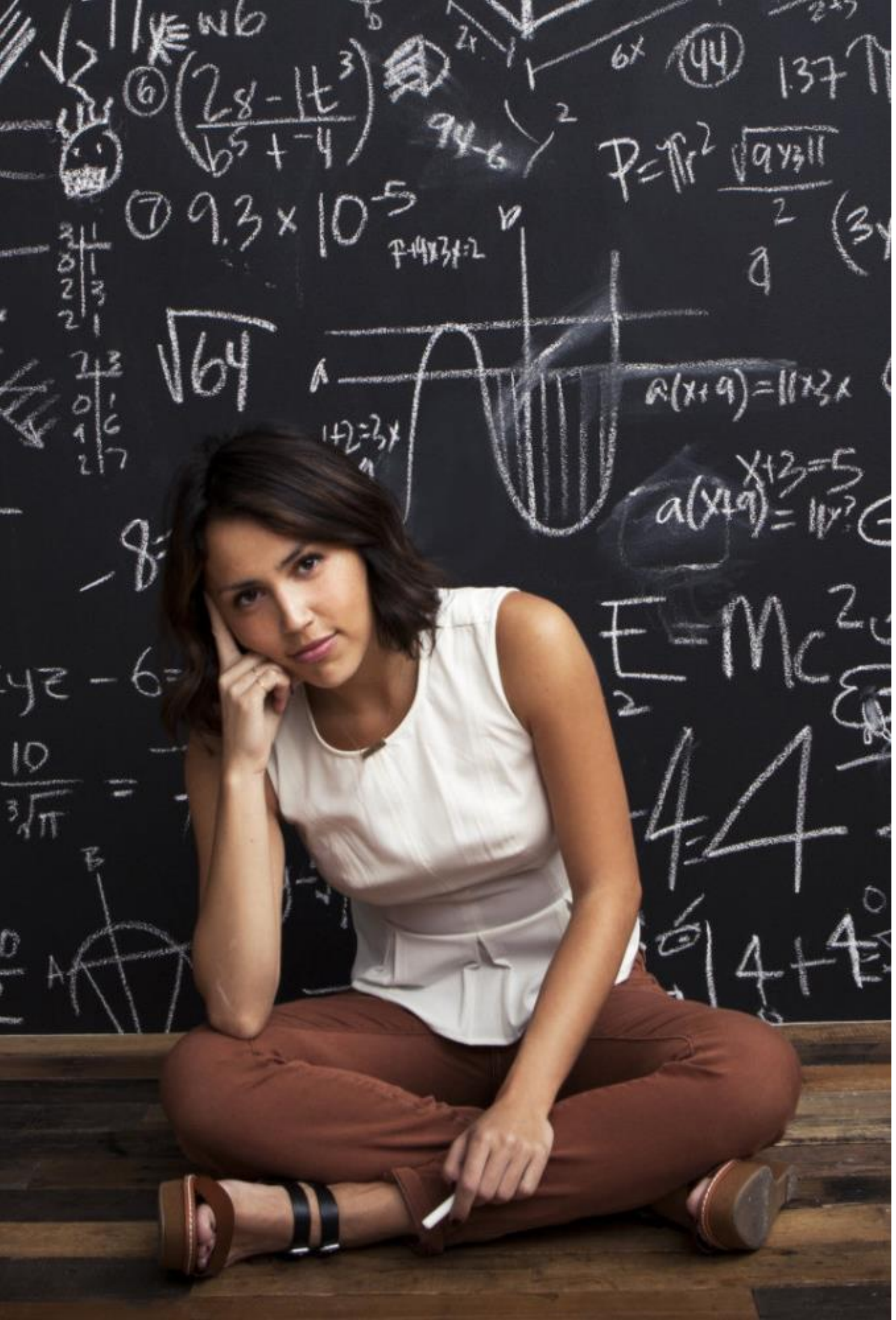
Included more than 50 participants

Research in our field must "keep up" with changing times and *rigor*

Real Life Challenges:

Prevalence of Small *n*	• Low incidence of populations of interest
Impracticality of Random Assignment	• Inherent participant characteristics
Ethical Considerations	• Ethical conflicts of RA to comparison vs treatment when early intervention is best
Infrastructure Weaknesses	• Lack of infrastructure to facilitate rigorous research methods

- To be good consumers and producers of a diverse range of methods we want to strive to….
  - **de-mystify advanced methods**
  - **build infrastructure for rigorous research**
  - **promote accessible continuing education**



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FOUNDATIONAL STATISTICS

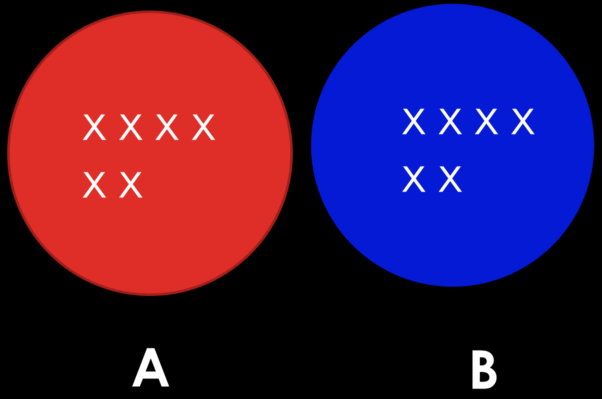
Σ σ^2 μ χ^2 ρ

Jessica Hooker, M.S., CF-SLP
Florida State University

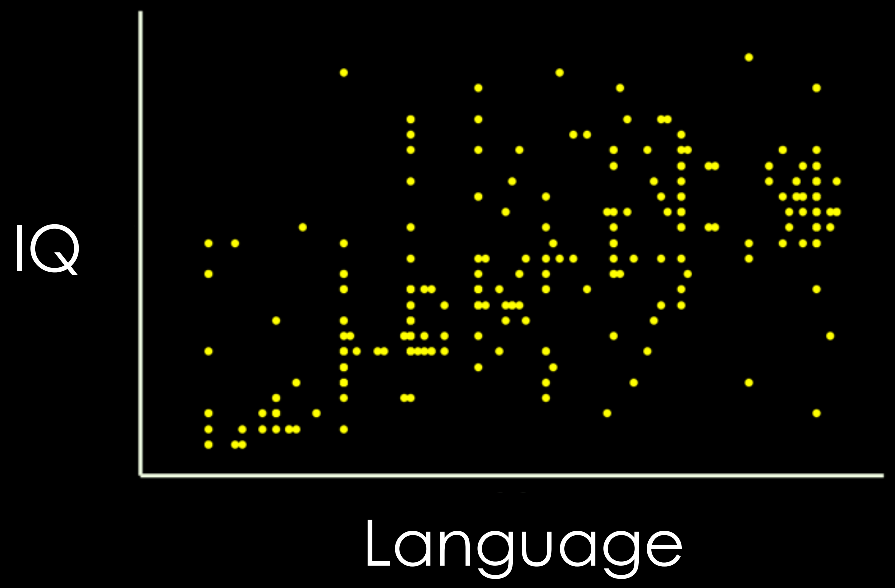
η^2 β ω ξ τ δ γ

An Important Distinction

Observational Data vs **Intervention Data**



CORRELATION: What it tells us



When X changes, does Y change in a consistent way across all of the changes in X?

Assumptions

Linearity

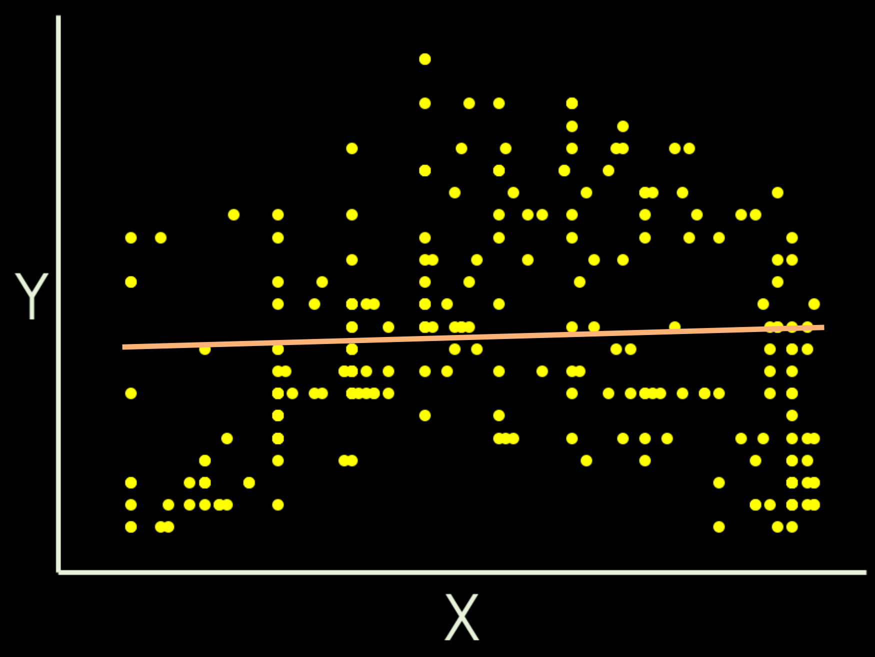
Continuous

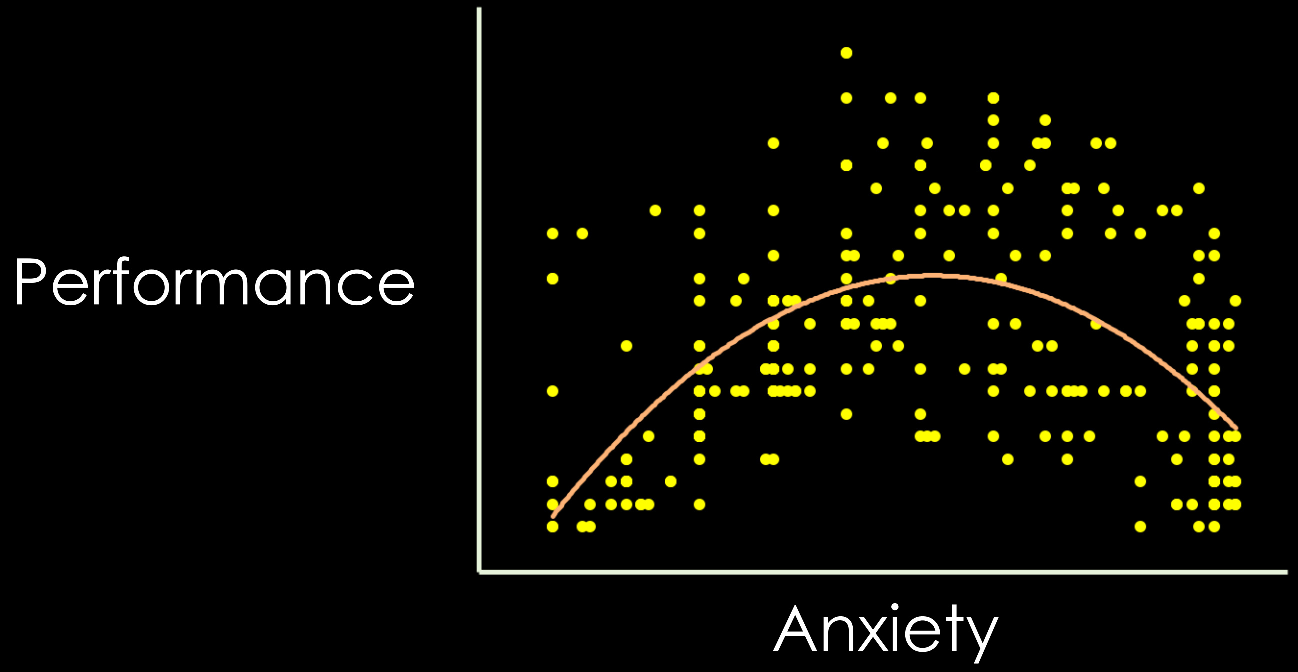
Independence

Normality

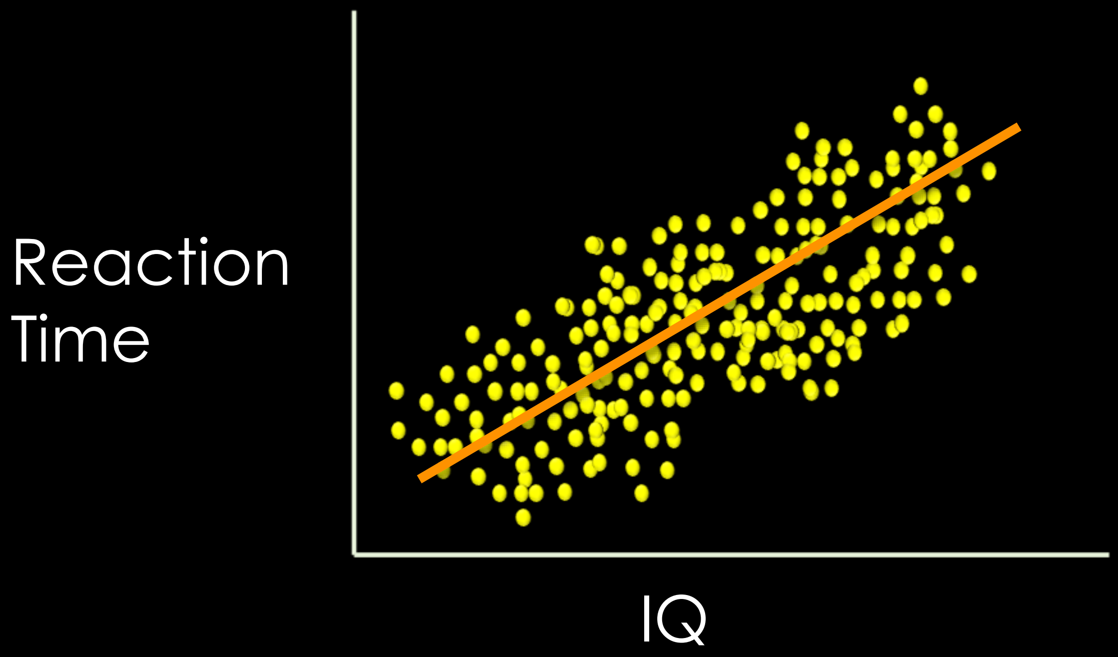
Outliers

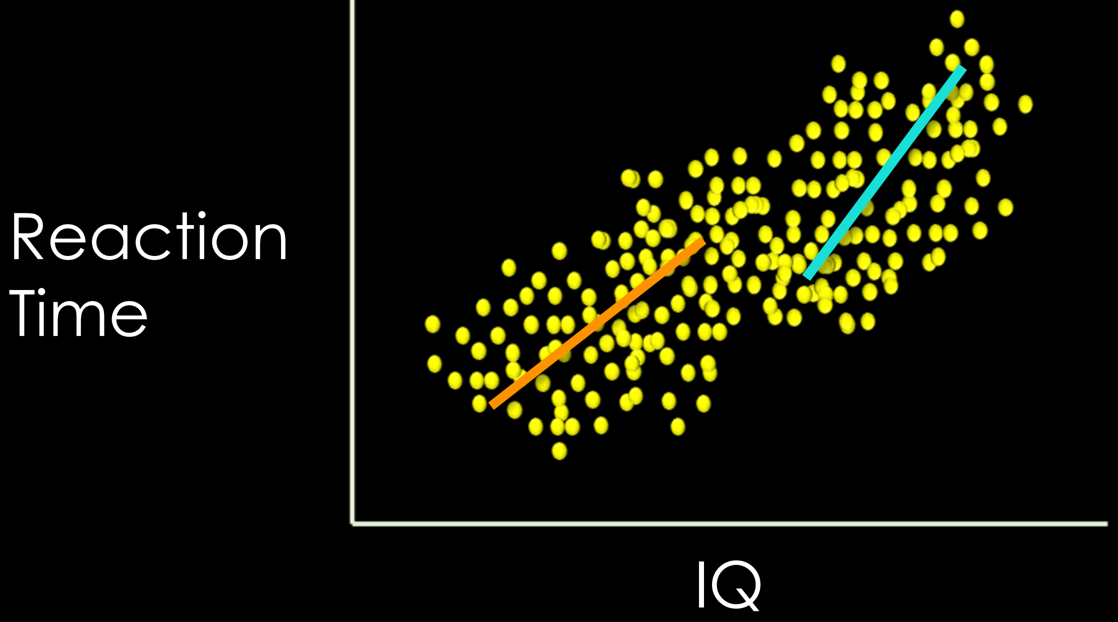
CORRELATION: What it doesn't tell us





CORRELATION:
What it doesn't tell us





CORRELATION:
What it doesn't tell us

CORRELATION

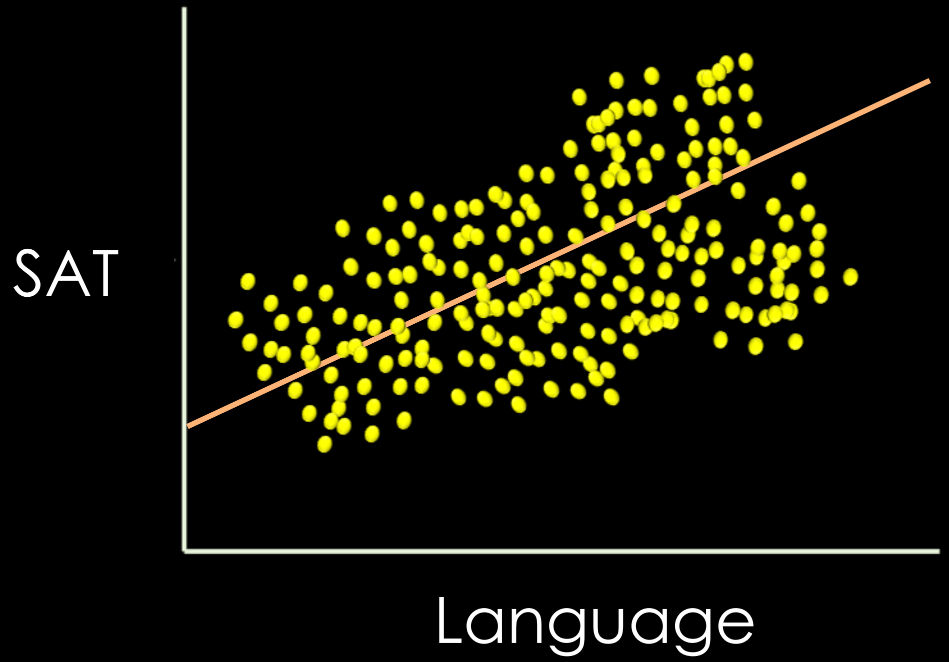
When it’s helpful

- Preliminary examinations
- Previously established relationships
- Small samples

When it’s not helpful

- Establishing causation
- Examining complex data
- Ruling out alternate explanations
- Non-linear relationships

REGRESSION: What it tells us

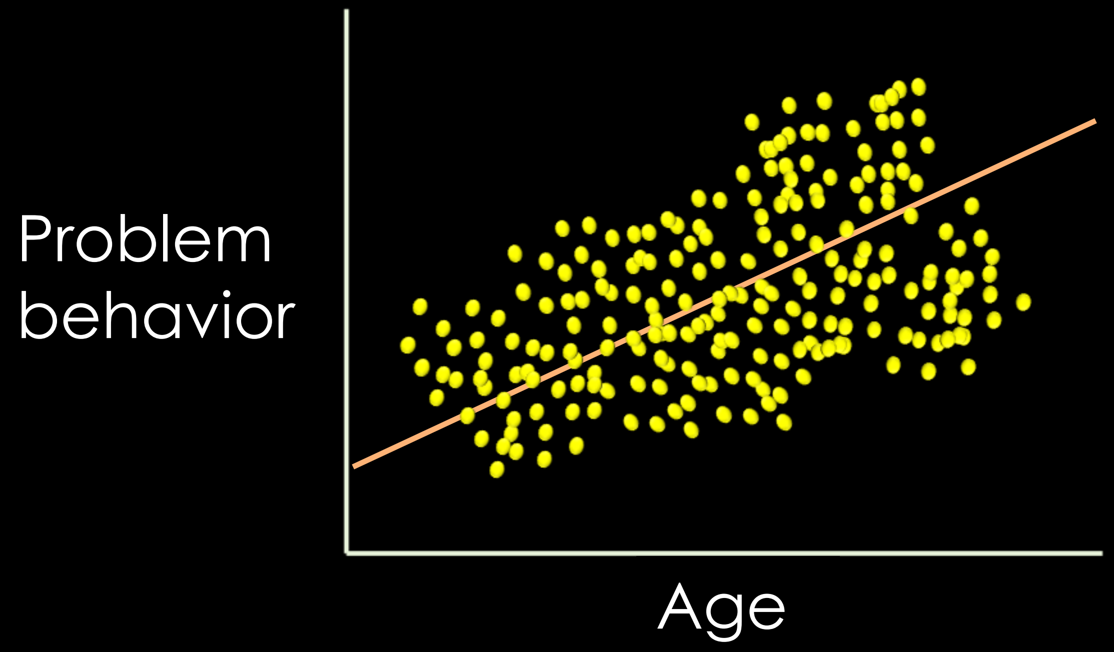


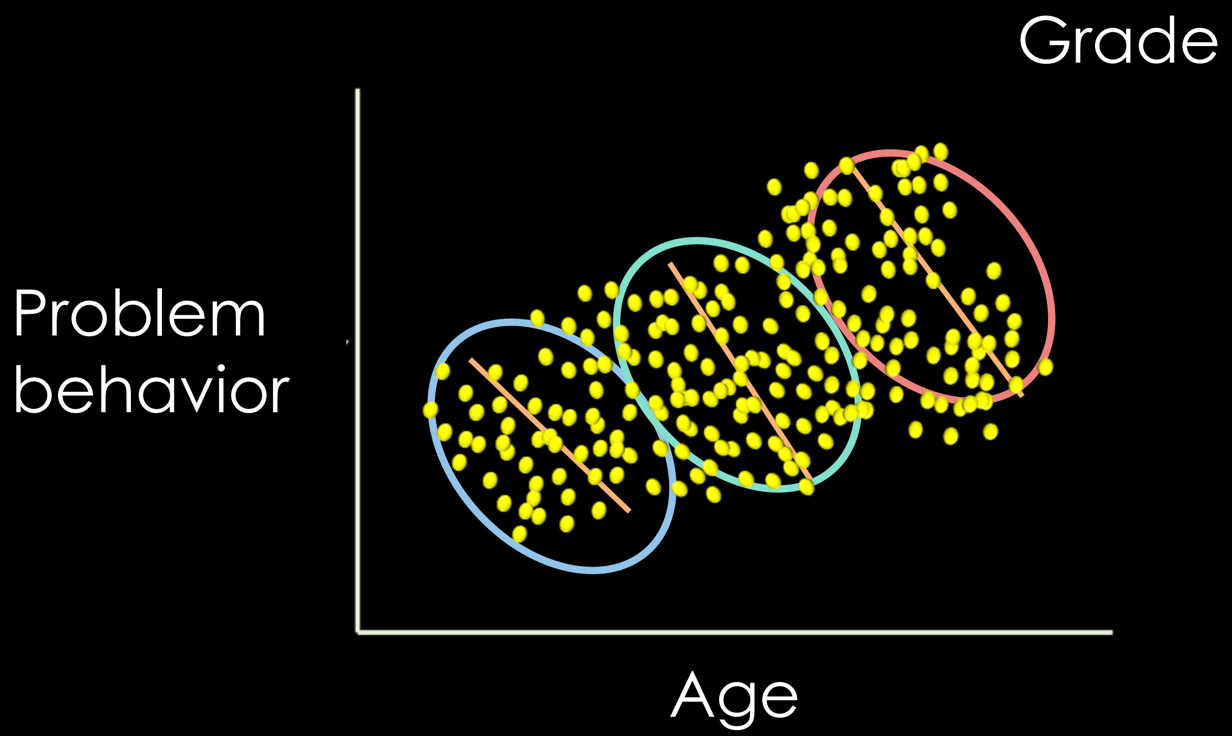
Can we use X to tell us something about Y?

Assumptions

Linearity
Normality
Independence

REGRESSION:
What it doesn't tell us



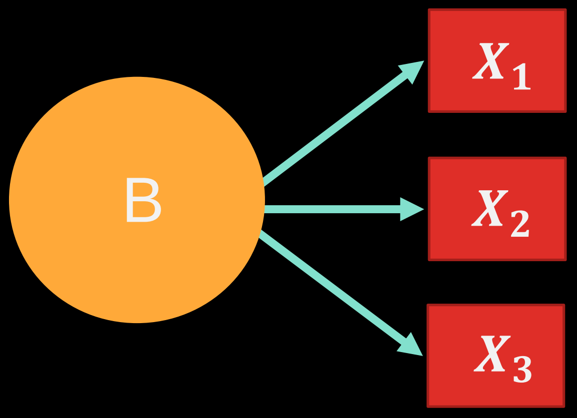


REGRESSION:
What it doesn't tell us

Measurement Error

True Score = Observed Score + Error

Latent Variables



REGRESSION

When it's helpful

- Confirming previously established relationships
- Establishing potential causality
- Identify unique contributors of variance
- Small samples

When it's not helpful

- Non-linear relationships
- The mean is not enough
- Measurement Error
- Latent variables
- Nested data structure

Assumptions

Power

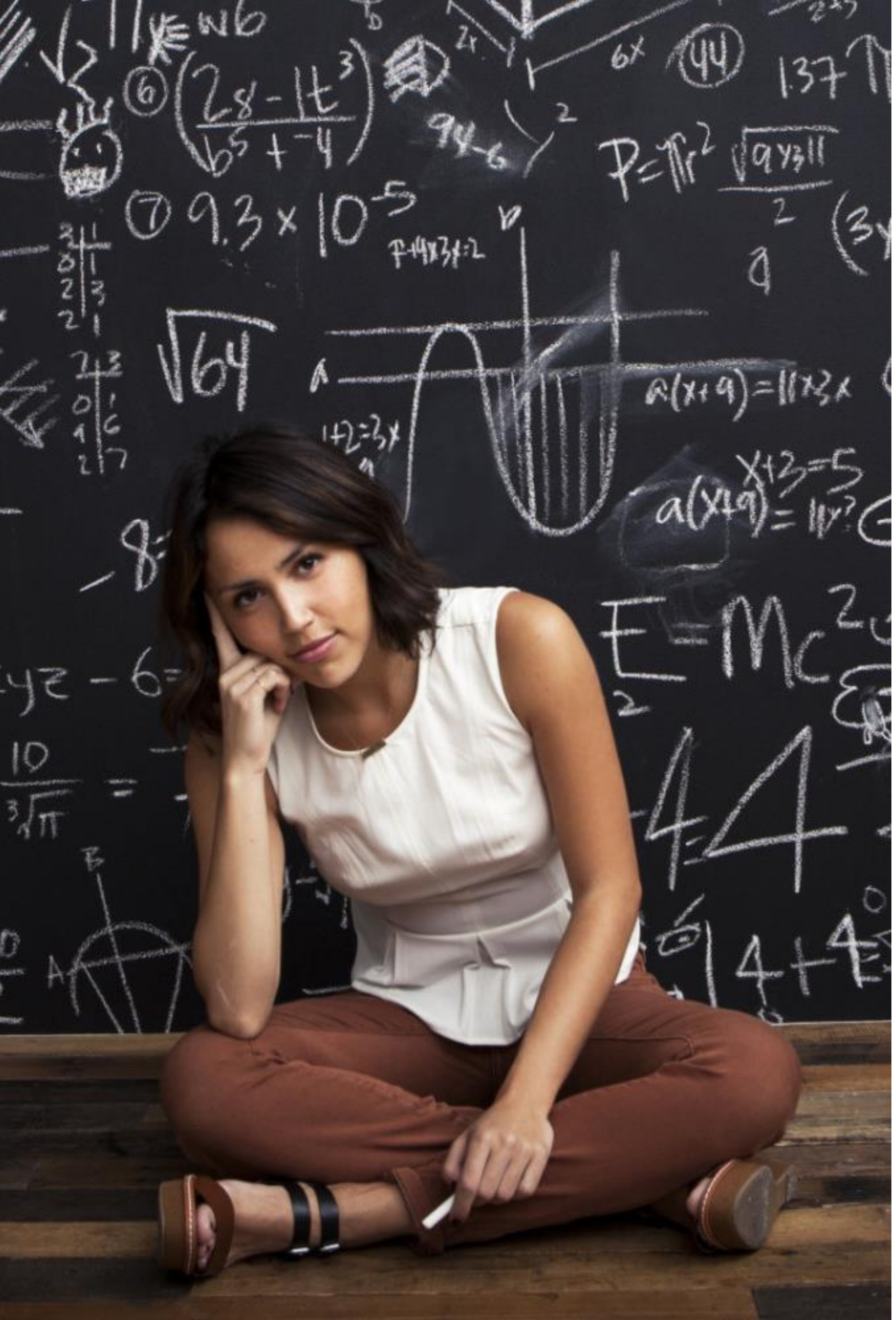
SAMPLE SIZE

Effect Size

Model

IMAGE ATTRIBUTIONS

By Peter (Own work) [Watching the Skyline (http://creativecommons.org/licenses/by-sa/3.0/), via Wikimedia Commons



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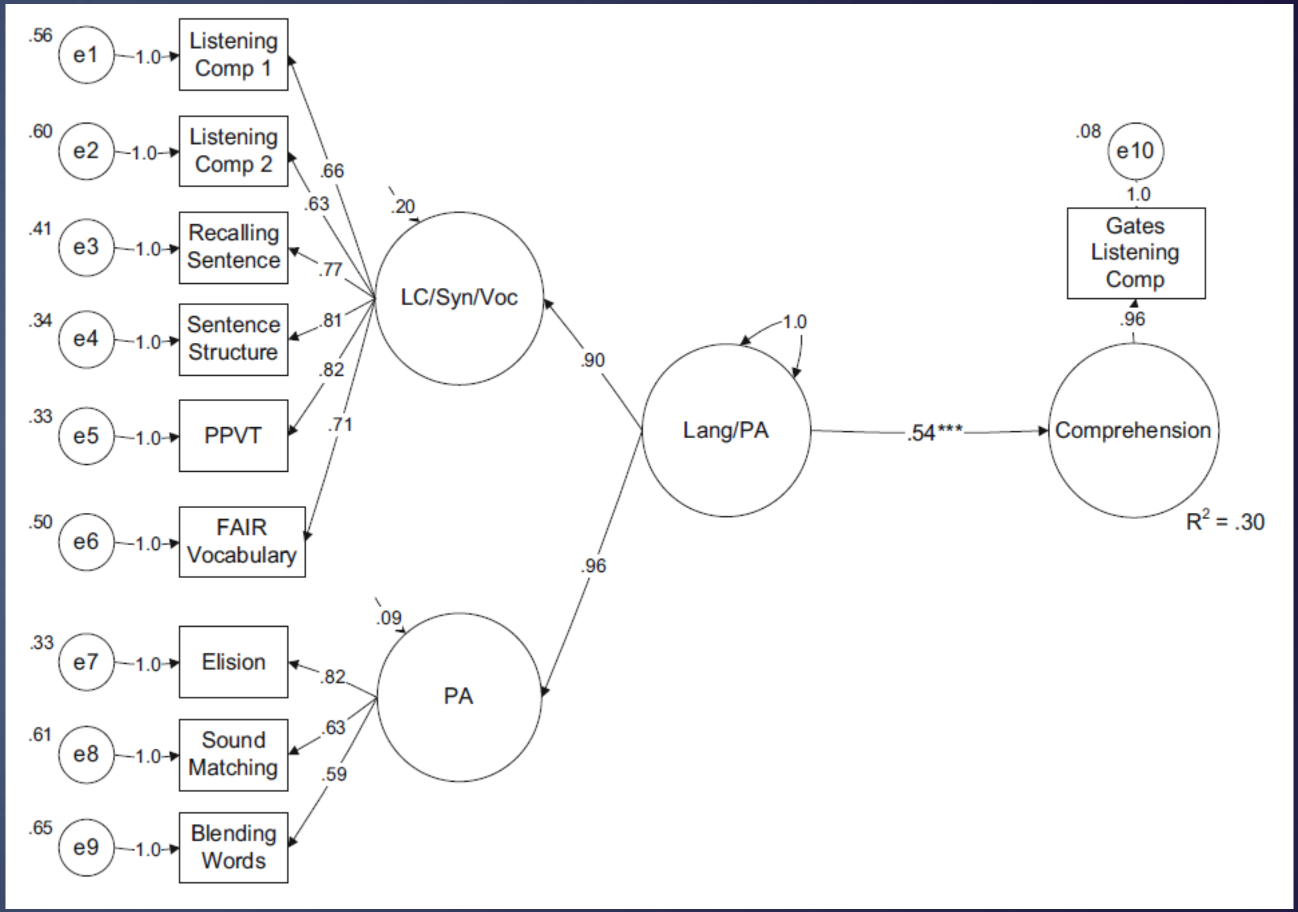
Introduction to Structural Equation Modeling

Nicole Sparapani, Ph.D., CCC-SLP
Assistant Professor
UC Davis School of Education, MIND Institute

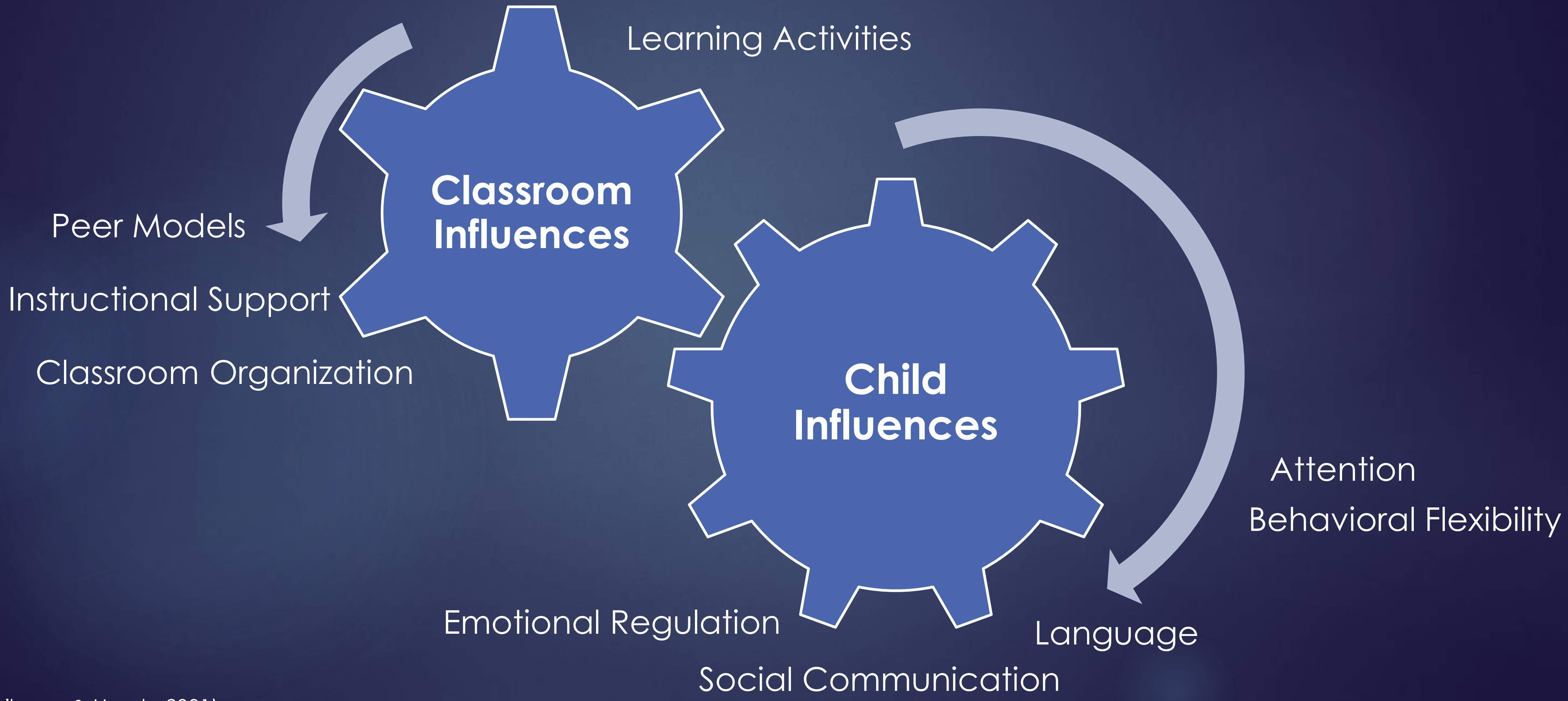
Learning Objectives

- What is Structural Equation Modeling (SEM)?
- What distinguishes SEM from other statistical techniques?
- What are the benefits of using SEM?



Foorman et al., 2015

Interest in understanding complex phenomena at one point in time or over a period of time



(Yoshikawa & Hsueh, 2001)

What are the dynamic relations among **classroom organization**, **social communication**, and **emotional regulation**?

Emotional Regulation

Social Communication

Mrs. B's class

Tommy

What are the dynamic relations among **classroom organization, social communication**, and **emotional regulation**?

Ms. H’s class

Emotional Regulation

Social Communication

Tommy

Why Use Structural Equation Modeling?

Structural equation modeling (SEM) is a statistical method that allows for the examination of **dynamic and interactive systems**—how each system interacts with and influences the other

Structural Equation Modeling (SEM)

- Fairly new statistical technique (1970) - became popular in the 90s
  - Refers to a family of related procedures
- Two new ideas in the field emerged
  - Modeling **of causal or predictive** relations
  - Constructs represented by **latent variables** rather than observed variables

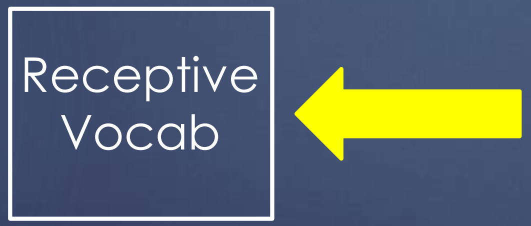
Combining these ideas led to 3 Major SEM techniques…

- Path Analysis
  - Modeling causal or predictive relations among **observed variables**
- **Confirmatory Factor Analysis (CFA)**
  - Modeling of non-causal (i.e., correlational) relations among **latent variables**
- Structural Equation Modeling (SEM)
  - Modeling of causal or predictive relations among **latent variables**

Latent Variables

What is a latent variable??

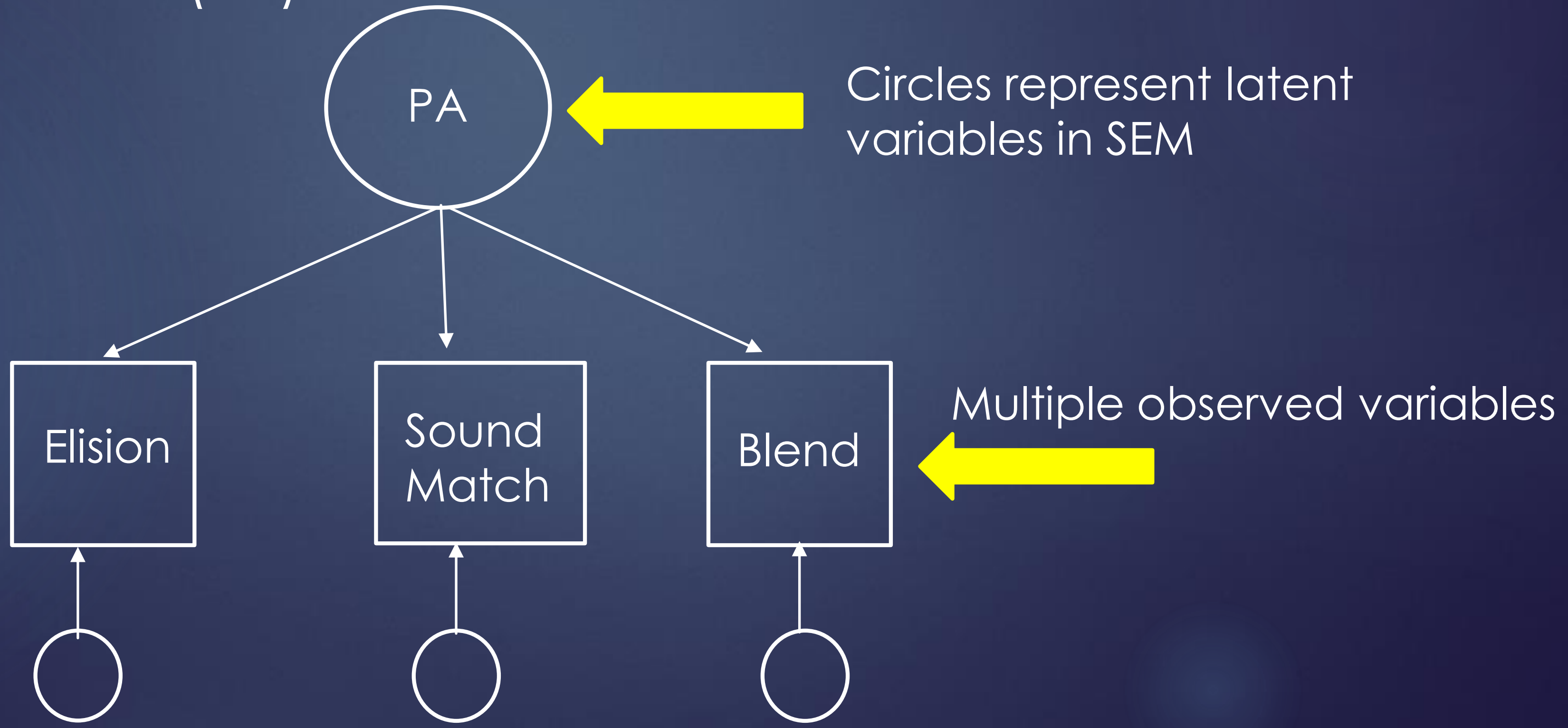
- **Observed variables**: Actual scores from assessments
  - Variables for which we have collected scores and entered in the data file
    - Example: PPVT test scores to measure receptive vocabulary



Squares represent observed variables in SEM

What is a latent variable??

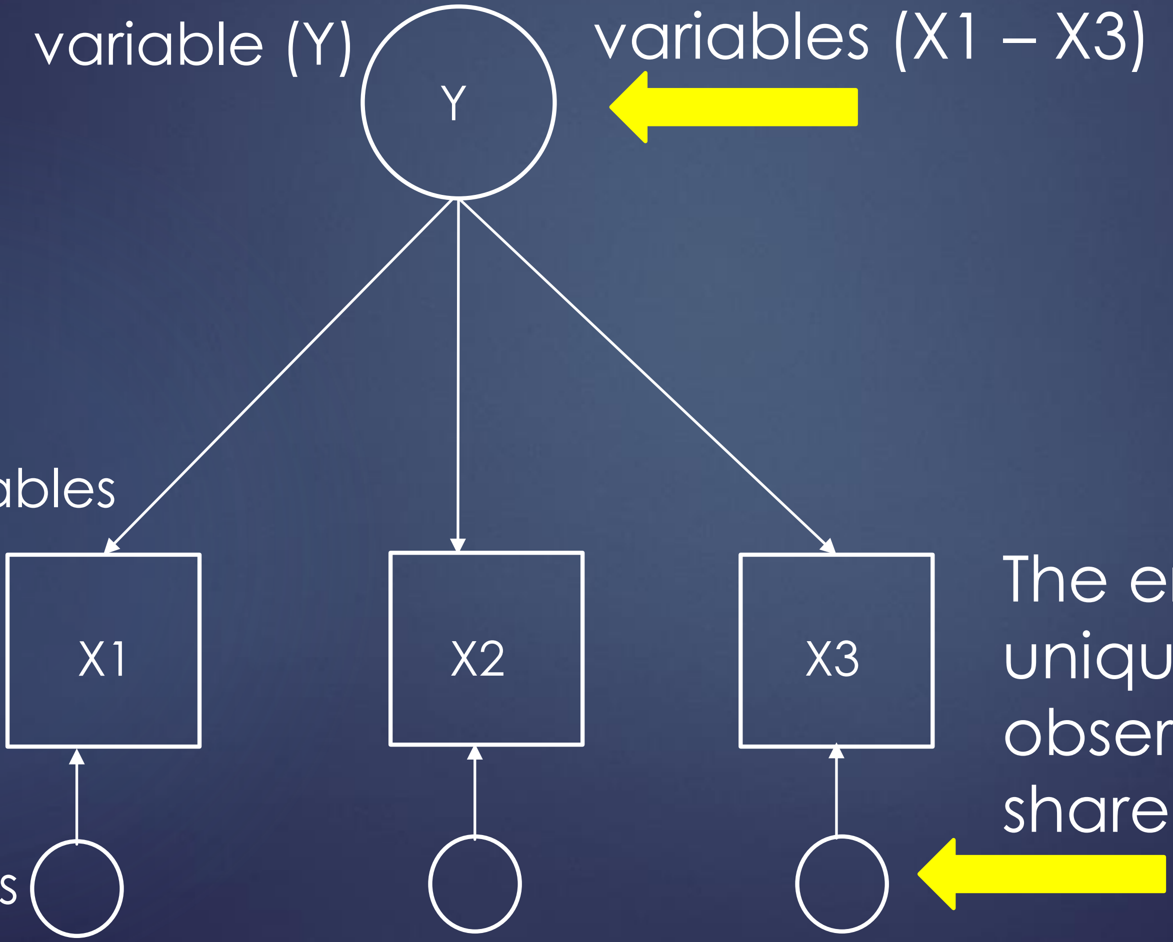
- **Latent variables:** Represent theoretical constructs of interests
  - Consists of multiple observed variables
    - Example: Multiple assessments and/or scores to measure phonological awareness skills (PA)



What is a latent variable?

Y represents the common or shared variance among the observed variables (X1 – X3)

1 latent variable (Y)



3 observed variables (X1 – X3)

3 error terms

The error terms represent the unique variance of each observed variable that is not shared with other variables

Confirmatory Factor Analysis (CFA)

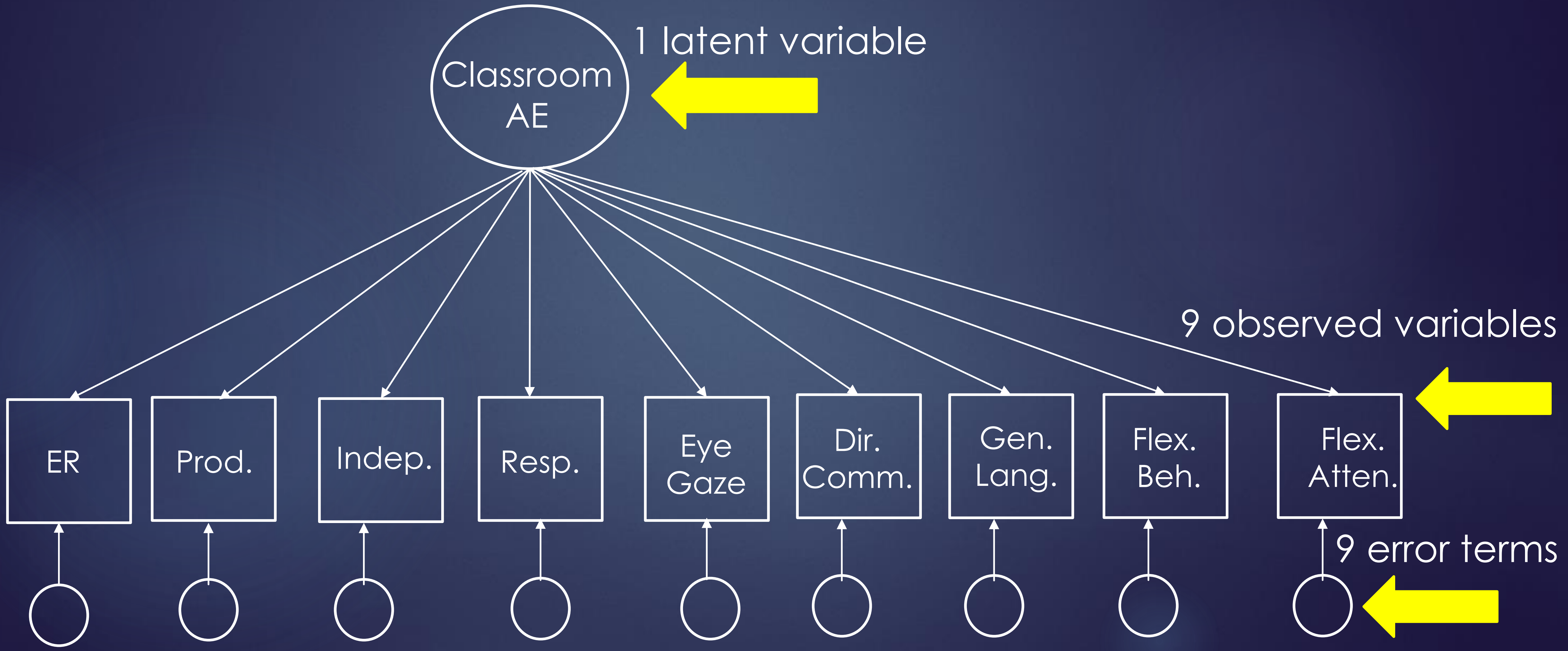
- **EXAMPLE.** Sparapani, N, Morgan, L., Reinhardt, V., Schatschneider, C., & Wetherby, A.M. (2016). Evaluation of classroom active engagement in elementary students with autism spectrum disorder. *Journal of Autism and Developmental Disorders*, 1–15

- Examined the components that comprised Classroom Active Engagement in children with ASD
  - Classroom video observations (PI: Wetherby)
  - 196 students with ASD (126 teachers)
  - Kindergarten–2nd grade

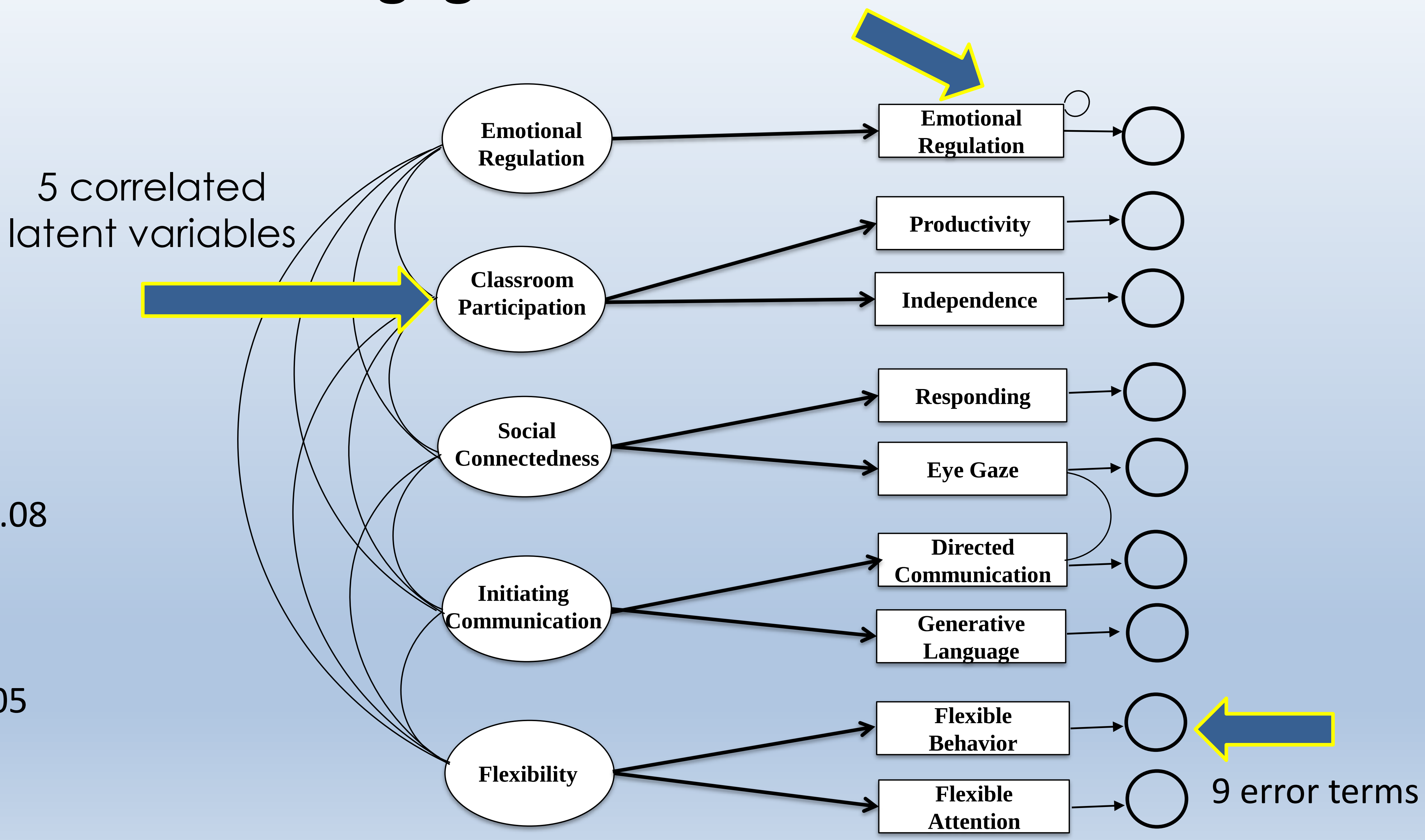
What is the latent factor structure of Classroom Active Engagement?

- **9 Observed Variables**
  - Emotional Regulation (ER)
  - Productivity
  - Independence
  - Responding
  - Eye Gaze
  - Directed Communication
  - Generative Language
  - Flexible Behavior
  - Flexible Attention

Examining the latent factor structure of Classroom Active Engagement?



Classroom Active Engagement



RMSEA: 0.08

CFI: 0.95

SRMR: 0.05

Summary

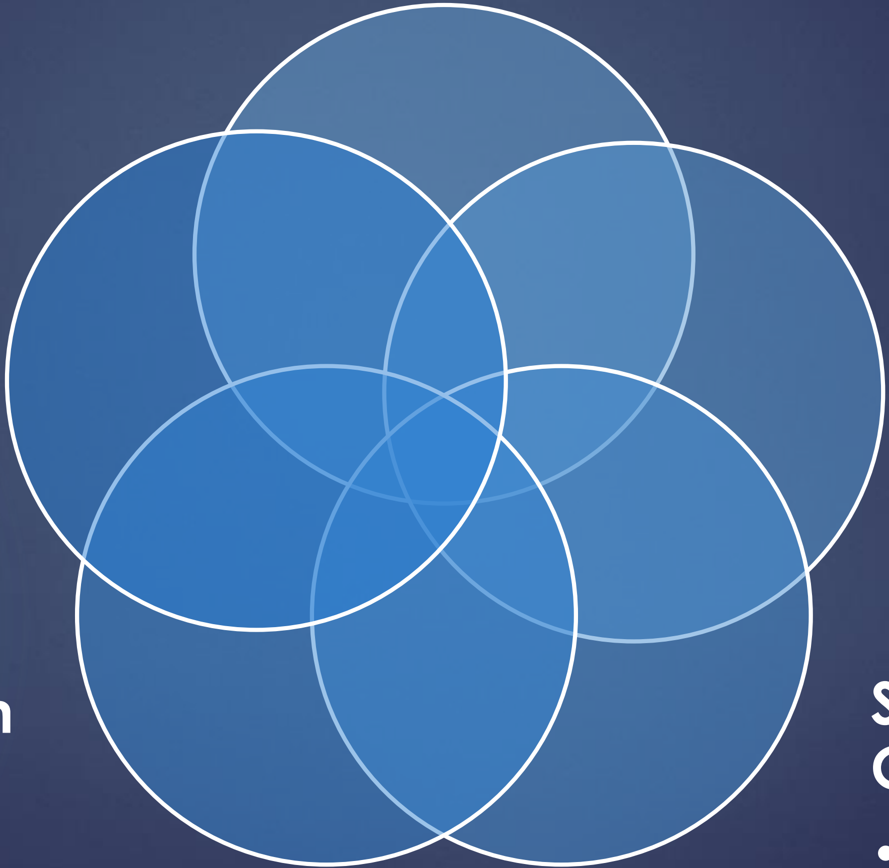
- **Confirmatory Factor Analysis**
  - Evaluate the factor structure of Classroom Active Engagement
- Support for a multi-component observational tool
- Classroom Active Engagement
  - 9 observed variables that comprise 5 latent variables (factors)

Emotional Regulation

- Emotional Regulation

Flexibility

- Flexible Behavior
- Flexible Attention



Classroom Participation

- Productivity
- Independence

Initiating Communication

- Directed Communication
- Generative Language

Social Connectedness

- Responding
- Eye Gaze

About Sample Size

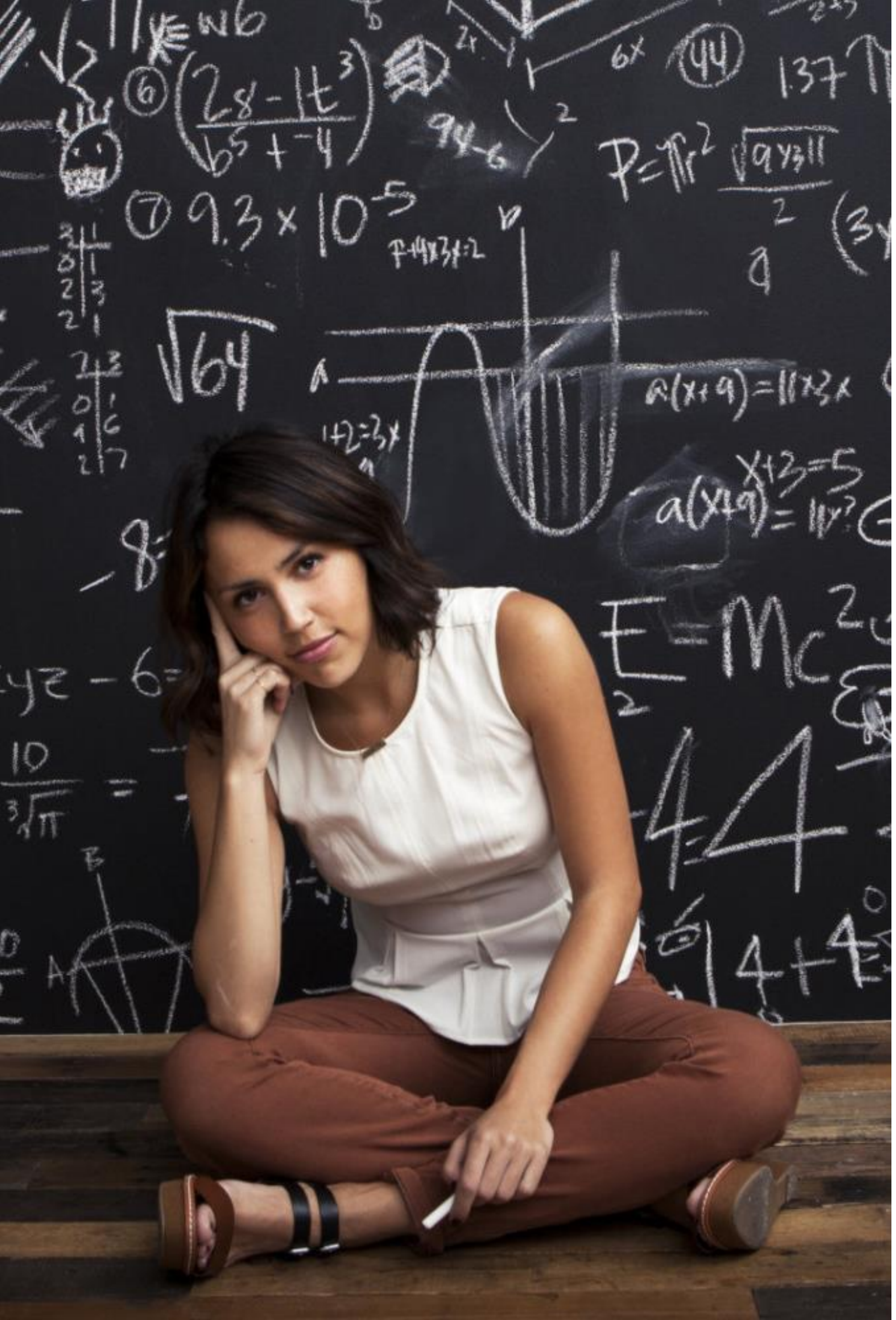
- SEM requires fairly large samples
  - Increase model complexity = increase sample
- Small samples may be problematic
  - Smaller samples may not be normally distributed
  - Results may not be accurate
- Consider the N:q rule (sample size to parameter ratio)
  - 20:1 (N = 400, parameters = 20)
  - 10:1 frequently observed
  - 5:1 (as ratio falls, so does trustworthiness of results…)

Benefits of Using SEM

- Flexibility. SEM "thinks" about research problems the way researchers do (test theoretical models)
- Constructs measured using **latent variables** rather than a single observed variable
- Explains as much variance as possible with the measurement model
- Simultaneously tests relations among variables while taking into account measurement error

Questions

Njsparapani@ucdavis.edu



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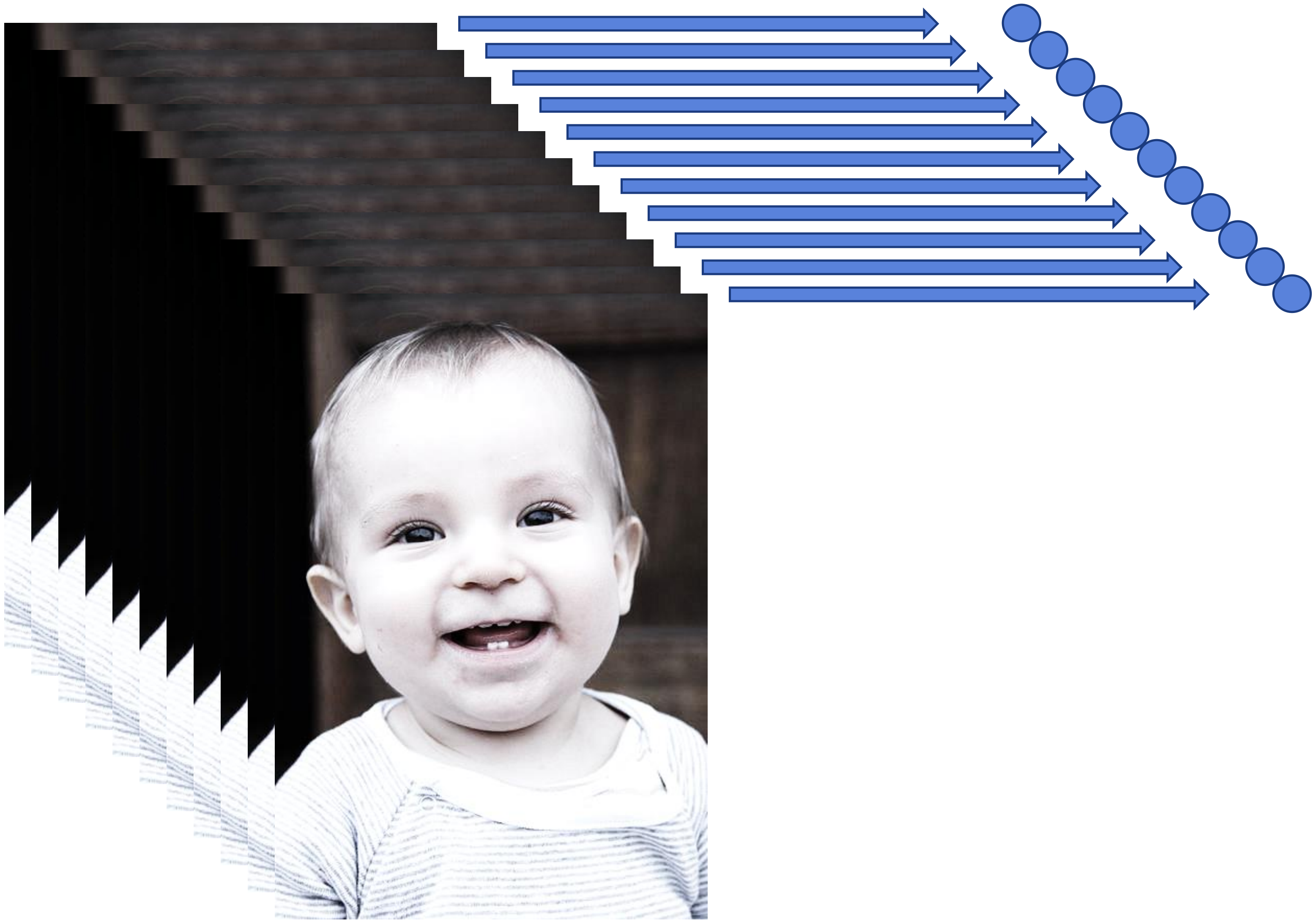
Overview of Hierarchical Linear Modeling (HLM)

Autumn L. McIlraith, Ph.D.
University of Houston

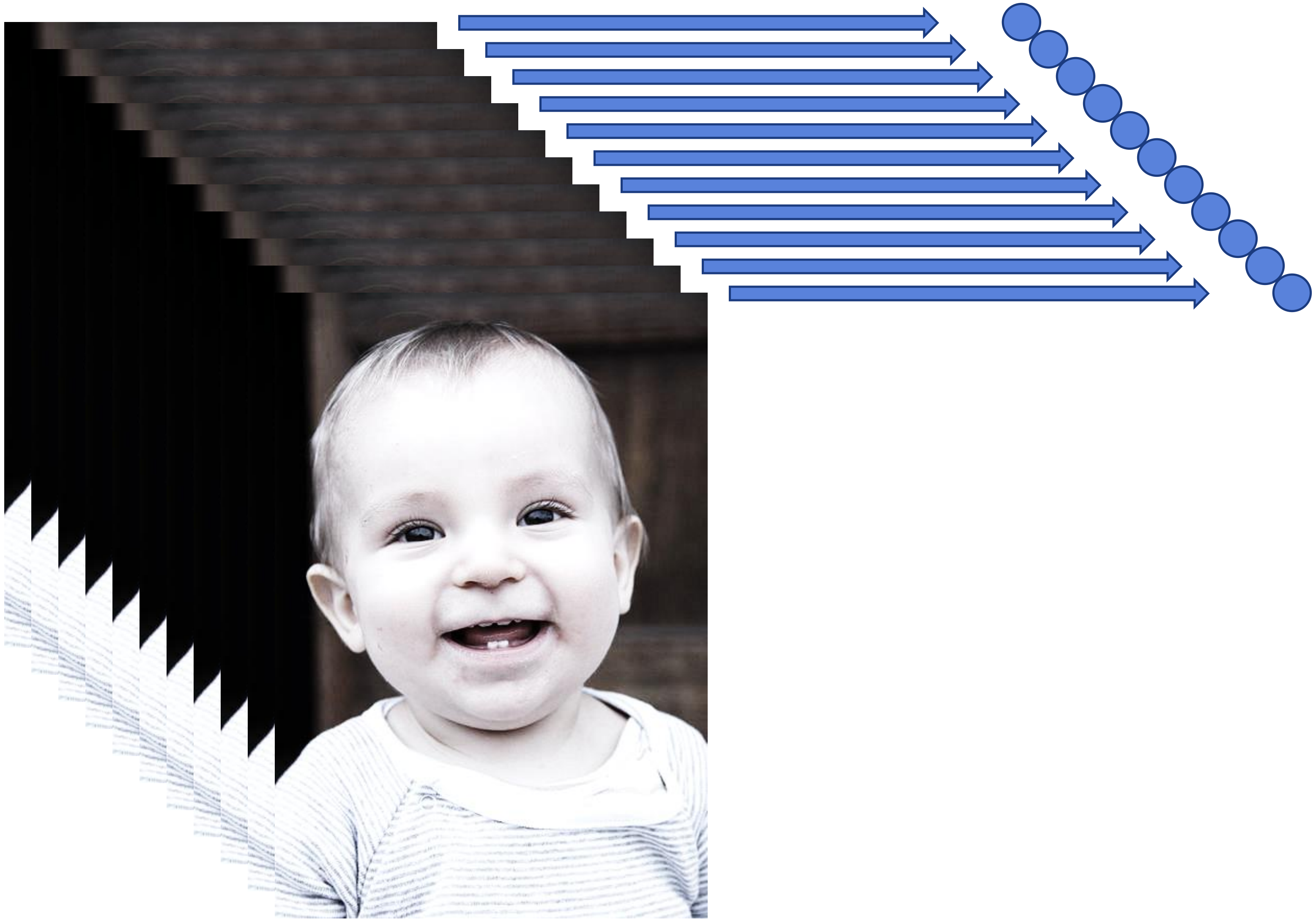
When is HLM appropriate?

When is HLM appropriate?

Test score



No HLM needed!

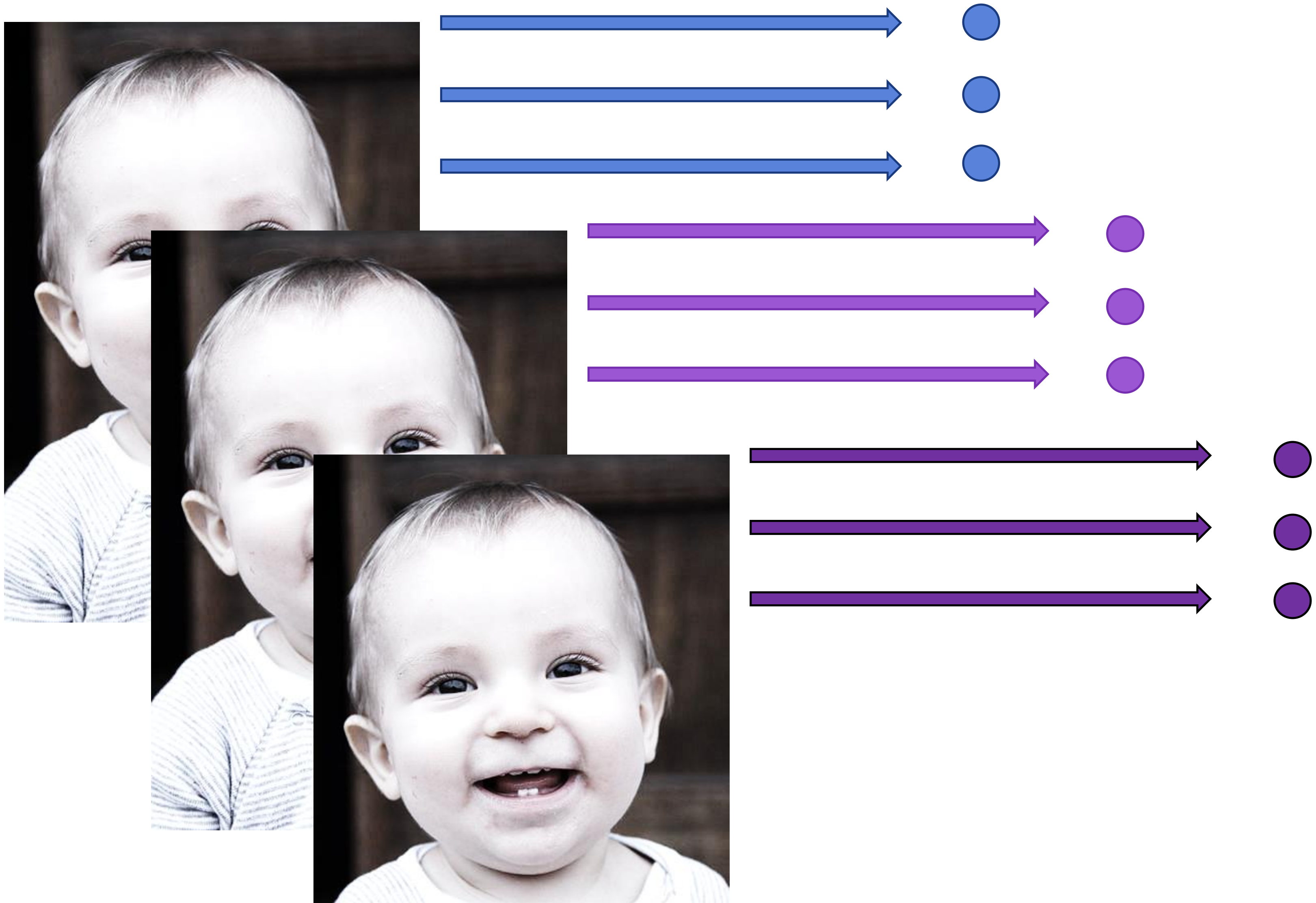


Independent observations

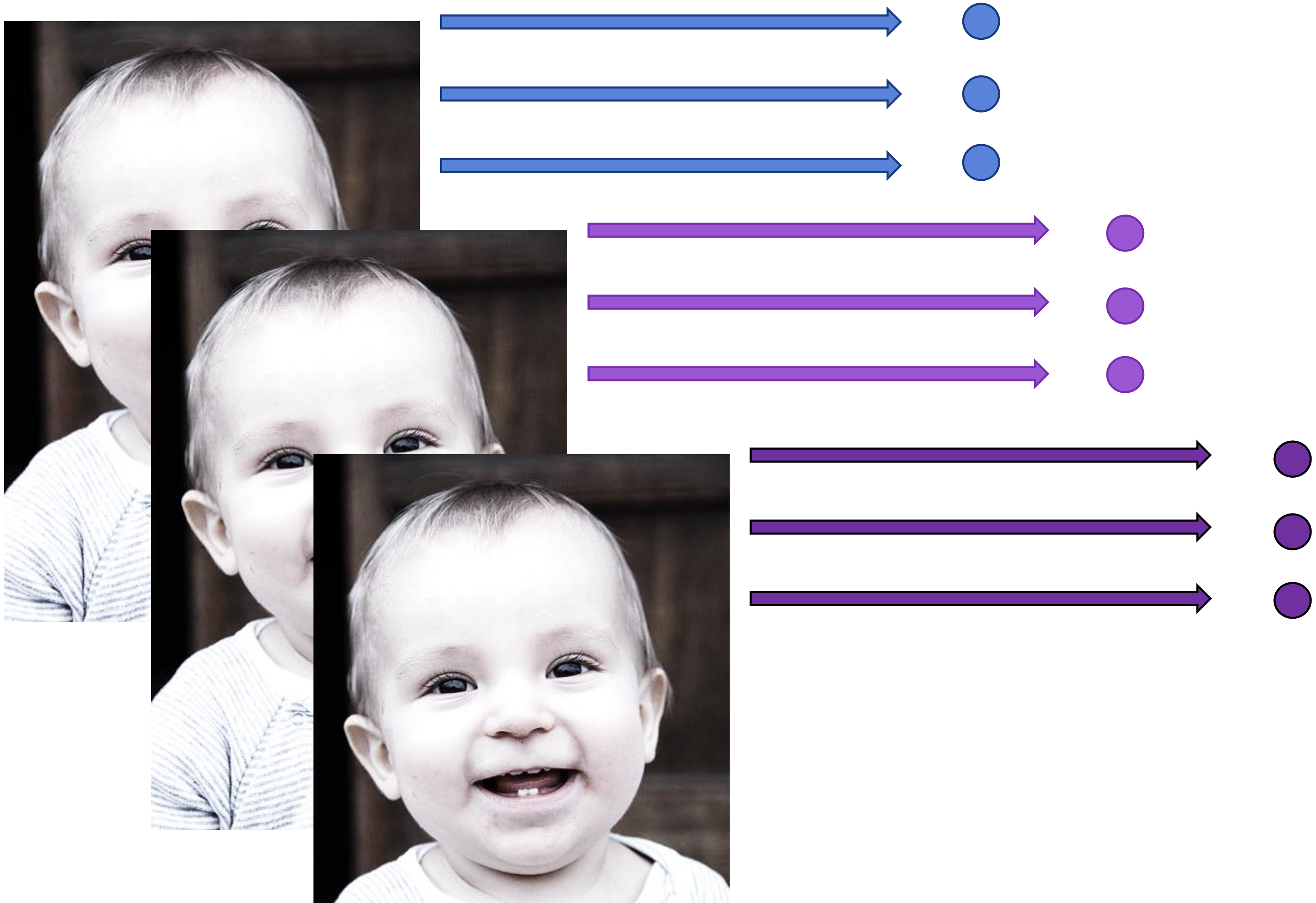
When is HLM appropriate?

When is HLM appropriate?

When is HLM appropriate?

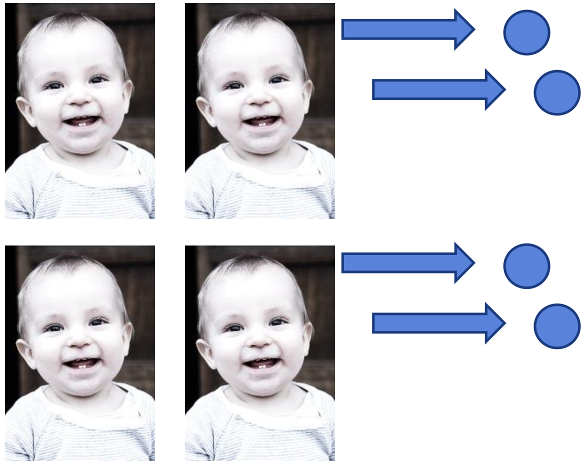


HLM is needed to account for dependency among observations



Dependent observations

What about other kinds of dependency?



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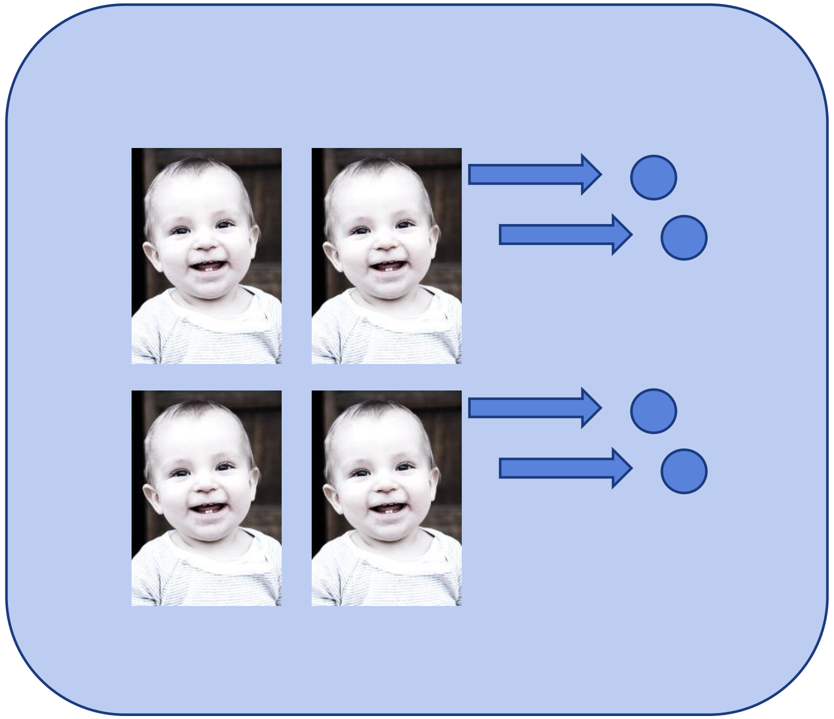

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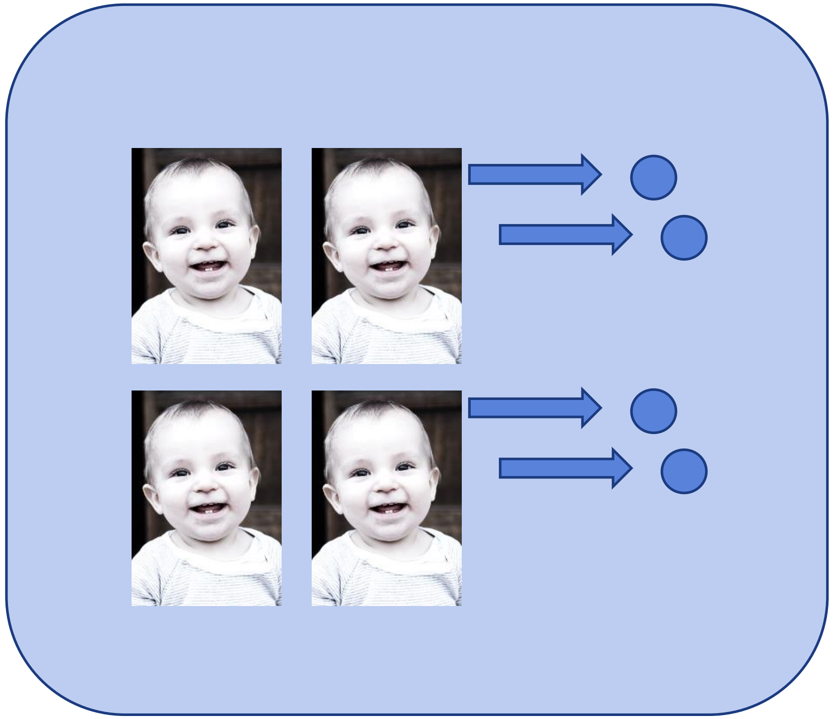
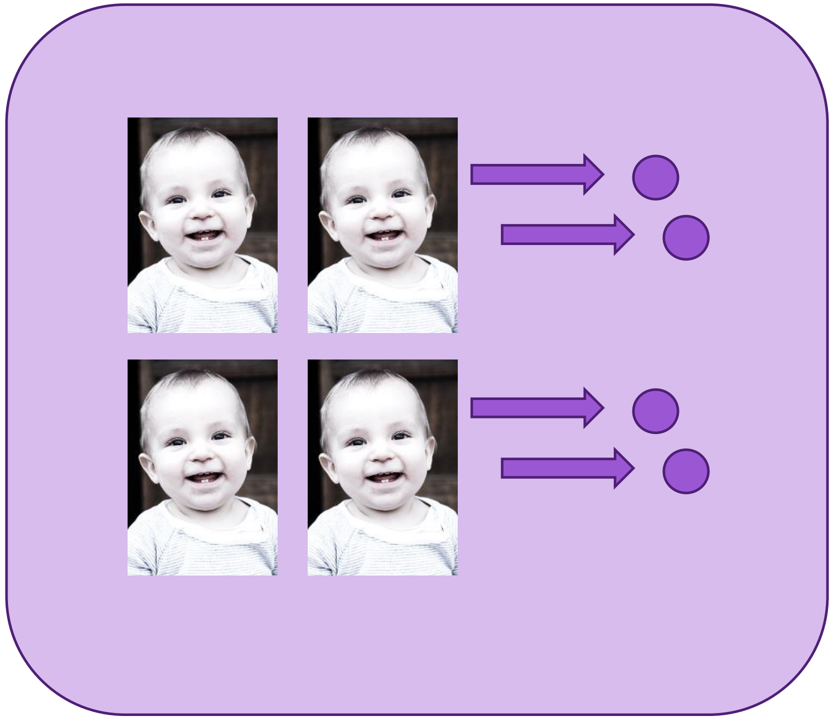
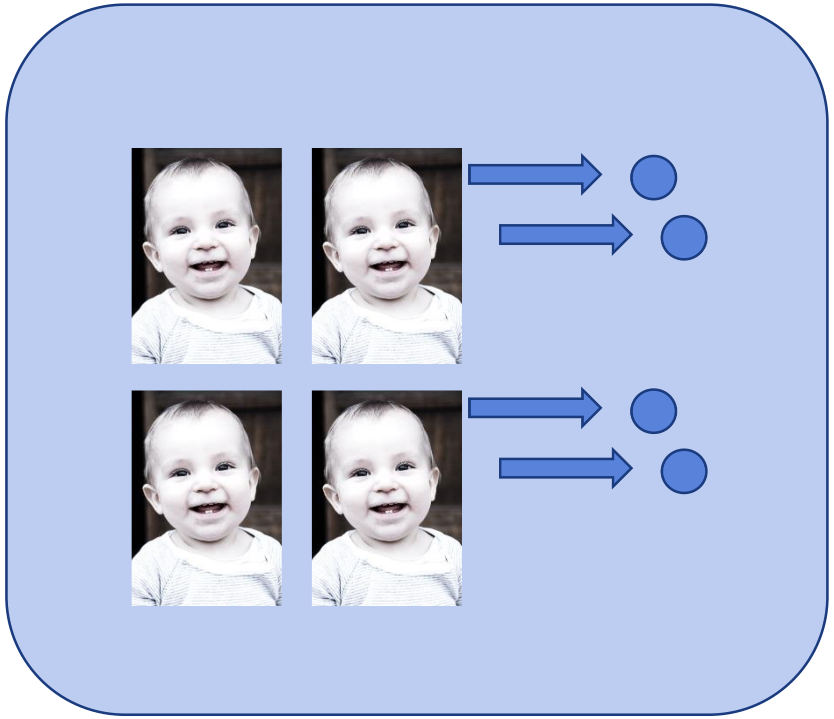
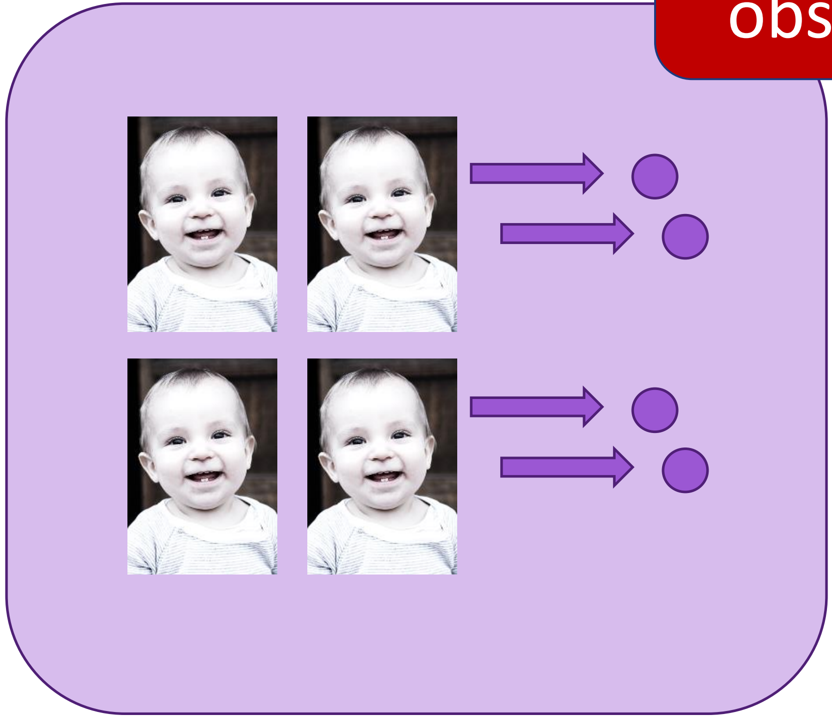


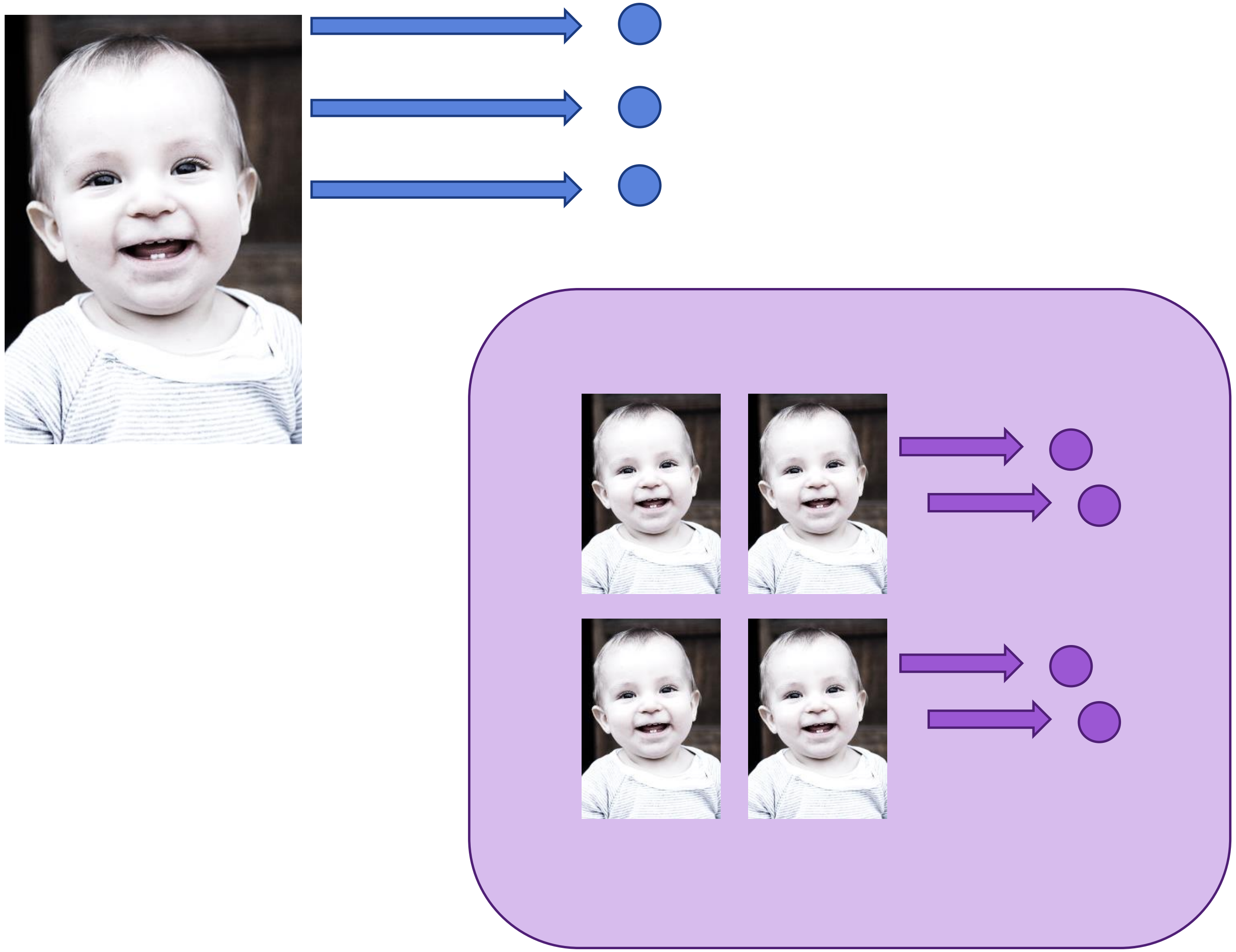


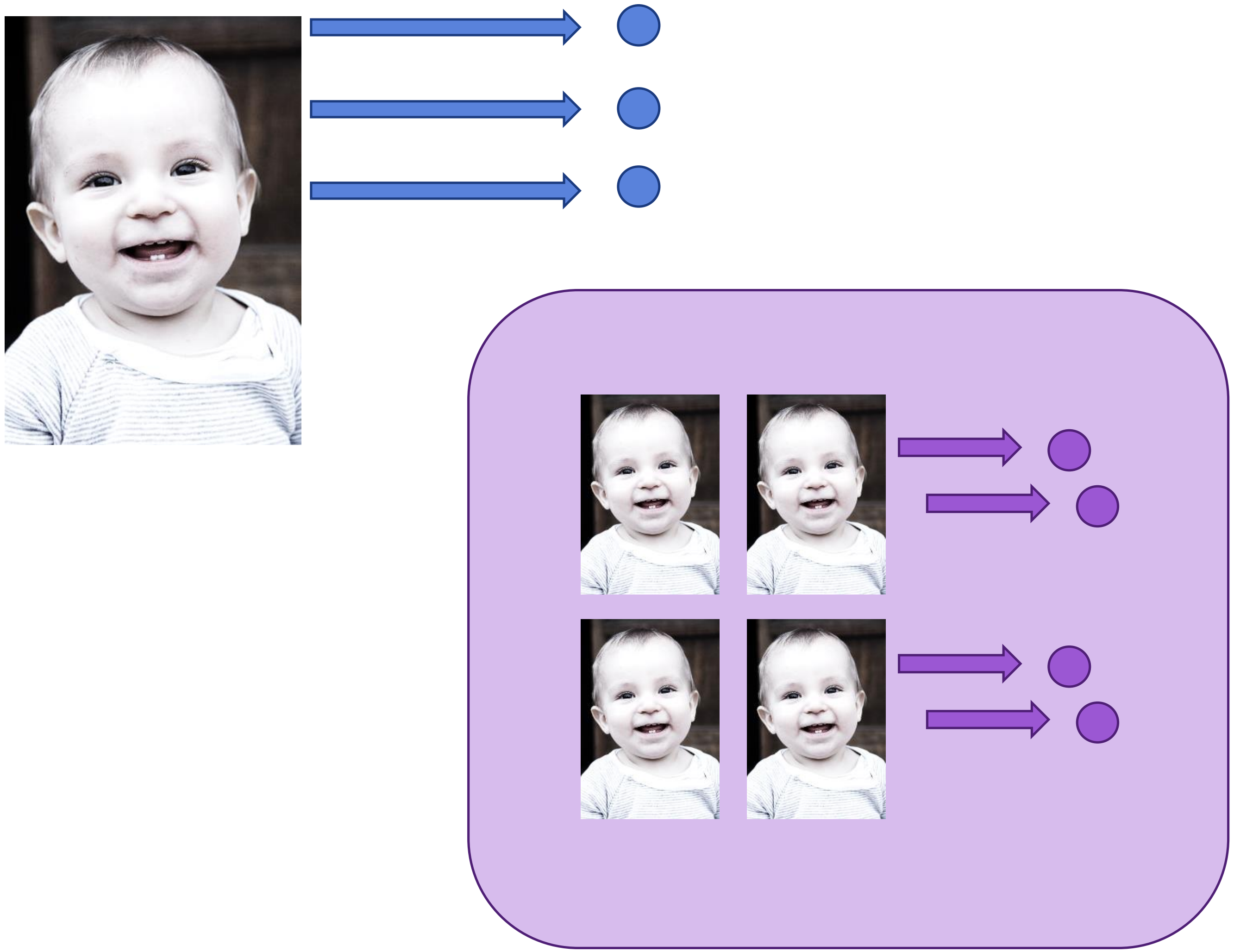
HLM works here too!



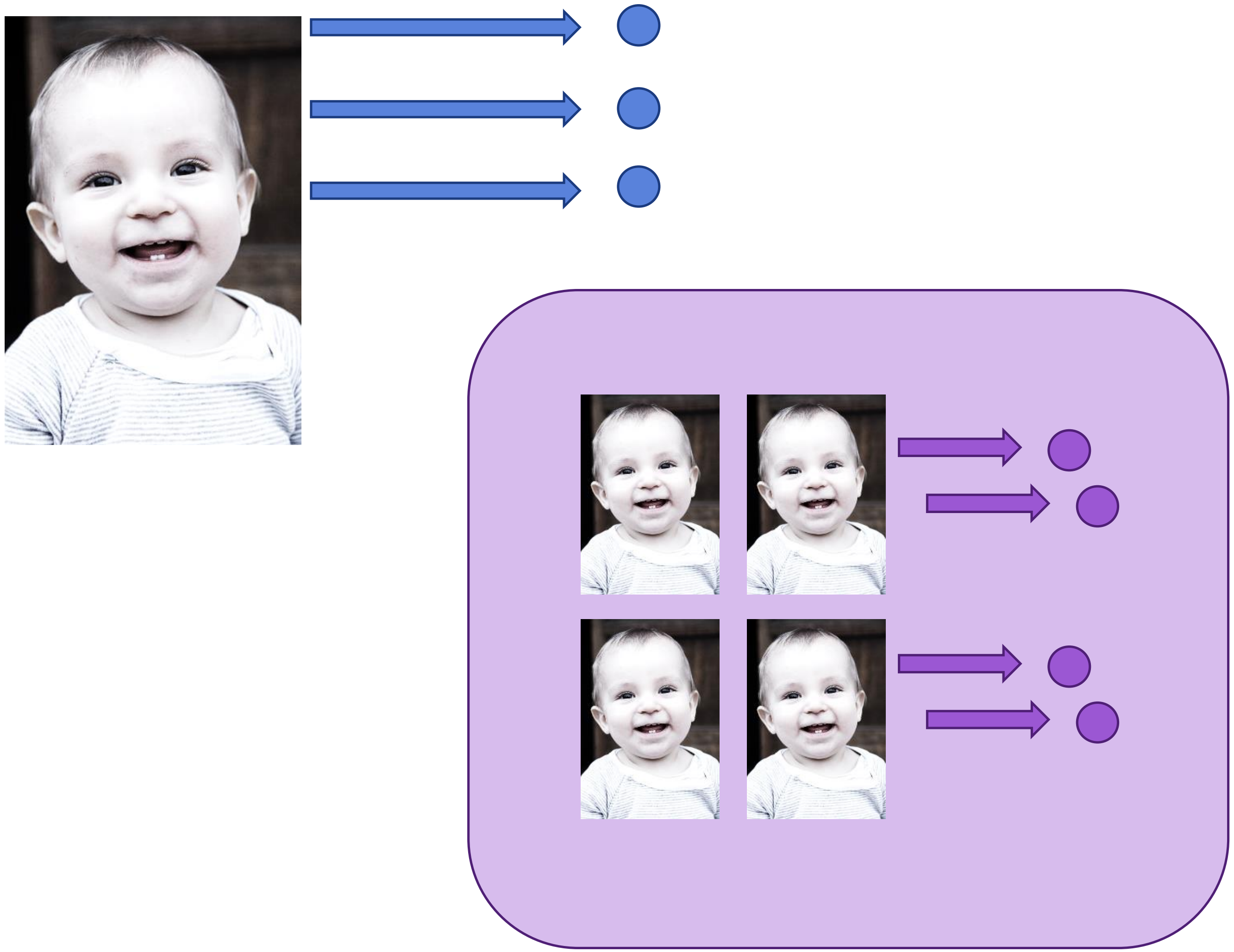


Dependent observations





clustering



clustering

nesting

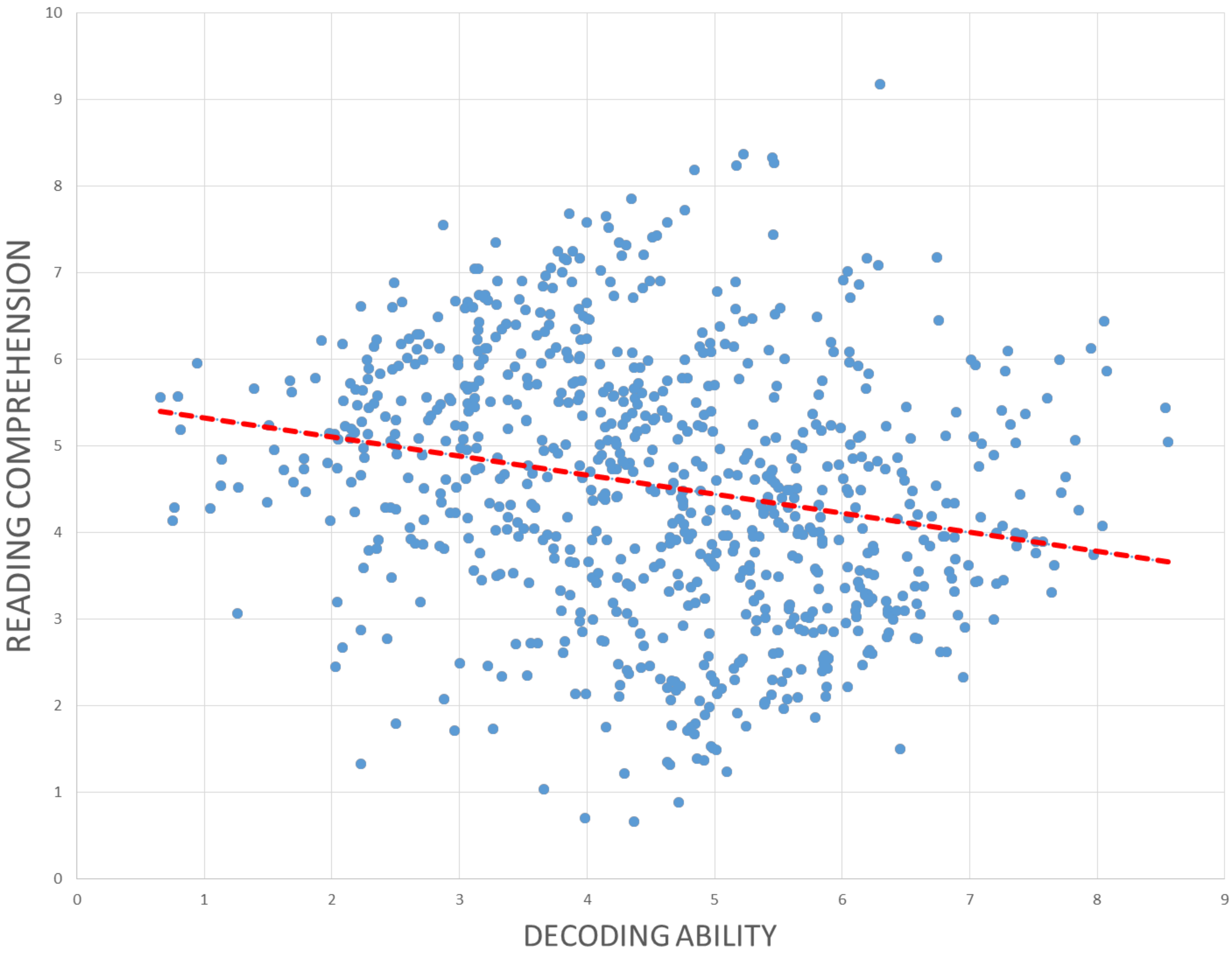
Why does dependency matter?

Why does dependency matter?

Violation of assumptions of many statistical tests

Can lead to inaccurate estimates of effects, less confidence in findings

Ignoring dependency can lead to ‘masking’ of real effects


READING COMPREHENSION
DECODING ABILITY
0
1
2
3
4
5
6
7
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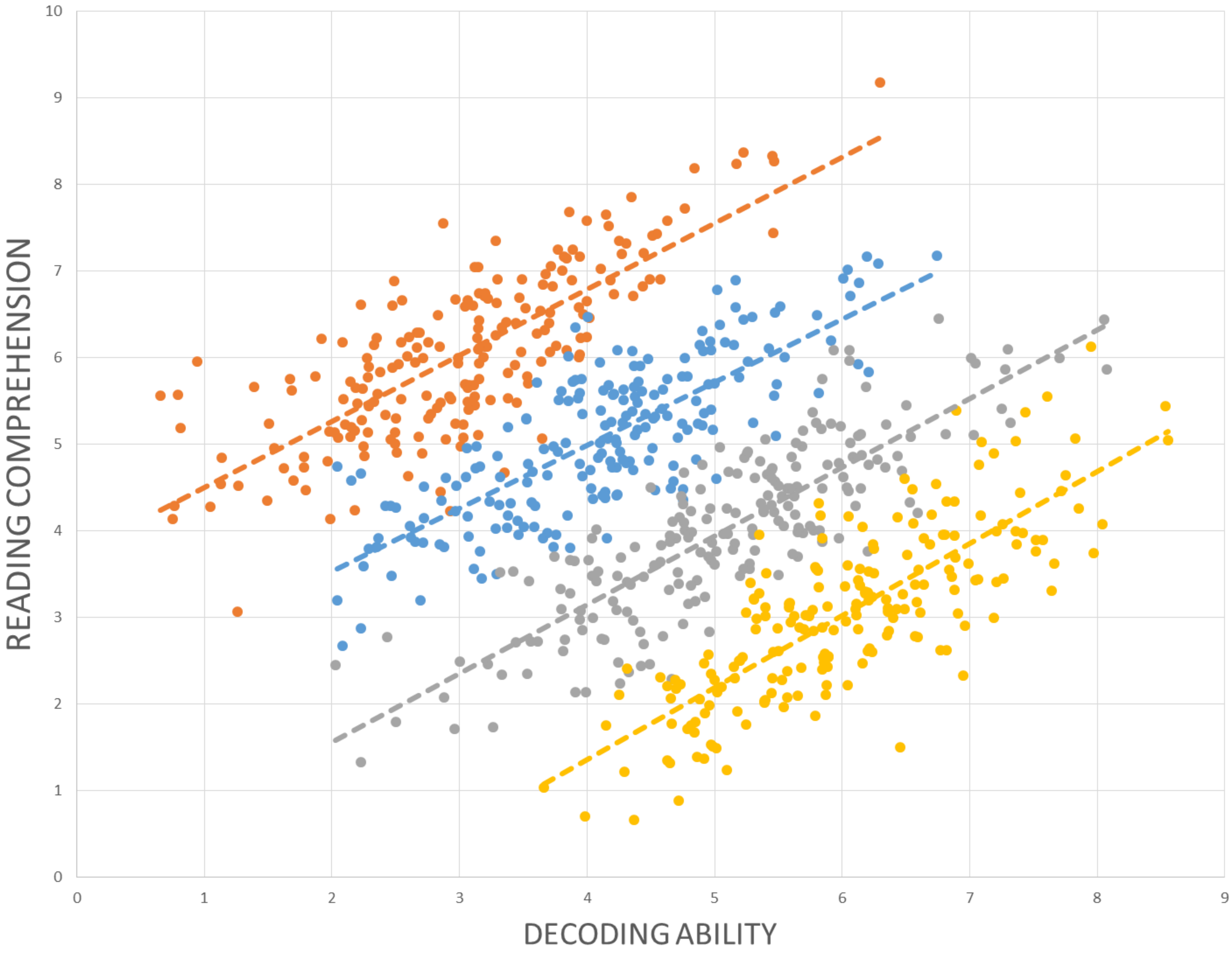
9
10



10
9
8
7
6
5
4
3
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1
0
READING COMPREHENSION
0
1
2
3
4
5
6
7
8
9
DECODING ABILITY

How can dependency of observations be handled?

How can dependency of observations be handled?

Robust standard errors

Repeated Measures analyses
(e.g., Repeated Measures ANOVA)

Hierarchical Linear Modeling

Structural Equation Modeling

How can dependency of observations be handled?

Robust standard errors

- Useful when you do not have hypotheses about the larger clusters, only the individuals
- More conservative with determining statistical significance, but does not change the estimated effects themselves.

Repeated Measures analyses
(e.g., Repeated Measures ANOVA)

Hierarchical Linear Modeling

Structural Equation Modeling

How can dependency of observations be handled?

Robust standard errors

Repeated Measures analyses
(e.g., Repeated Measures ANOVA)

- Useful with balanced data, categorical predictors, *observations nested within person*, and little to no missing data
- Tends to oversimplify the raw data patterns
- Often requires numerous post-hoc pairwise comparisons

Hierarchical Linear Modeling

Structural Equation Modeling

How can dependency of observations be handled?

Robust standard errors

Repeated Measures analyses
(e.g., Repeated Measures ANOVA)

Hierarchical Linear Modeling

- Can handle both categorical and continuous predictors
- Can handle unbalanced data, and missing data
- Can address hypotheses at the observation and cluster level

Structural Equation Modeling

How can dependency of observations be handled?

Robust standard errors

Repeated Measures analyses
(e.g., Repeated Measures ANOVA)

Hierarchical Linear Modeling

Structural Equation Modeling

- Conceptually, very similar to HLM
- Uses latent factors
- Useful with larger sample sizes

nesting

Level 1 ***nested within*** level 2

Level 1 (“micro”)	**Level 2 (“macro”)**
Participants	Classroom
Classrooms	School
Voters	District
Patients	Clinician
Time Points	Participant
Item responses	Item
Item responses	Participant

nesting

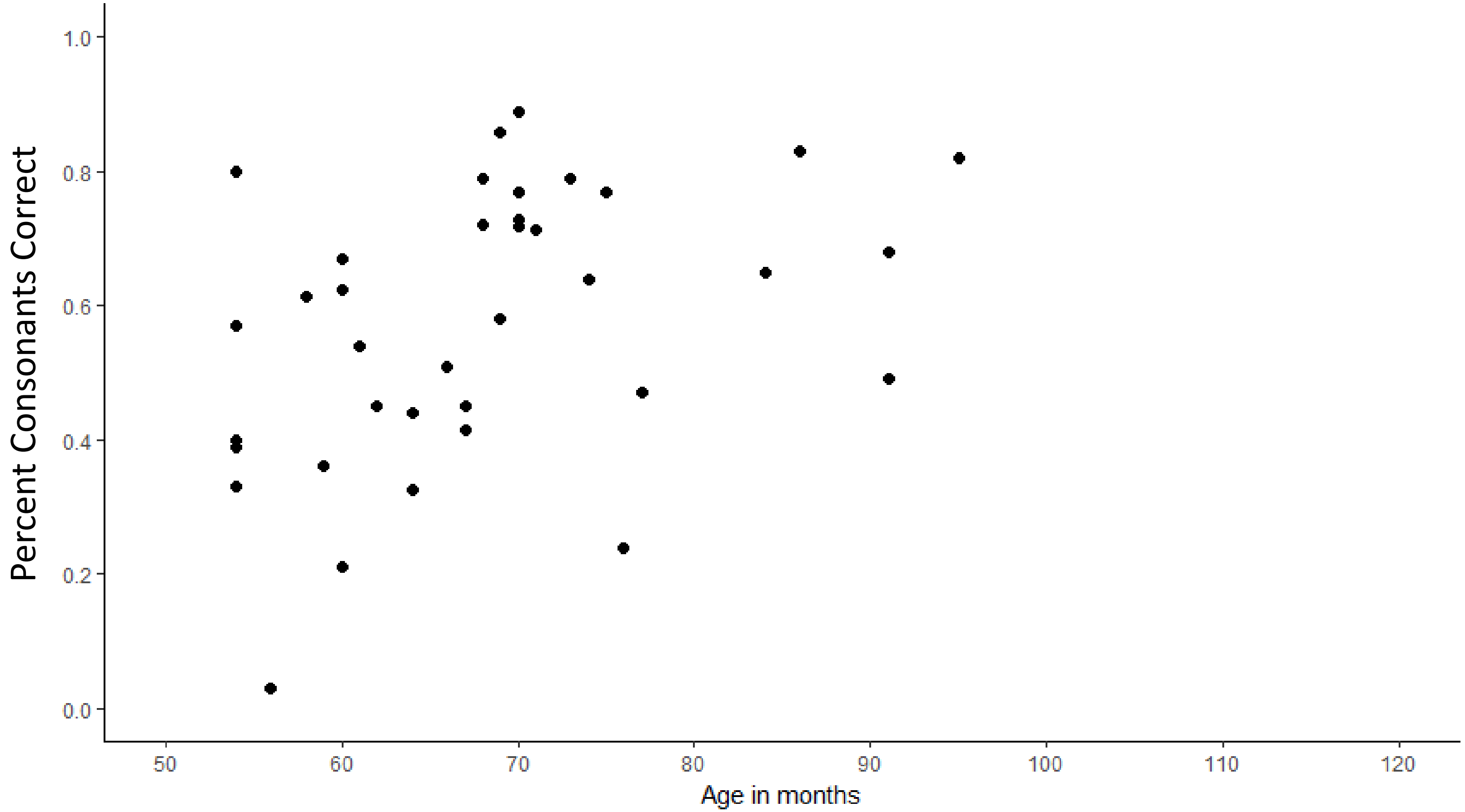
Level 1 ***nested within*** level 2

Level 1 ("micro")	Level 2 ("macro")
Participants	Classroom
Classrooms	School
Voters	District
Patients	Clinician
Time Points	Participant
Item responses	Item
Item responses	Participant

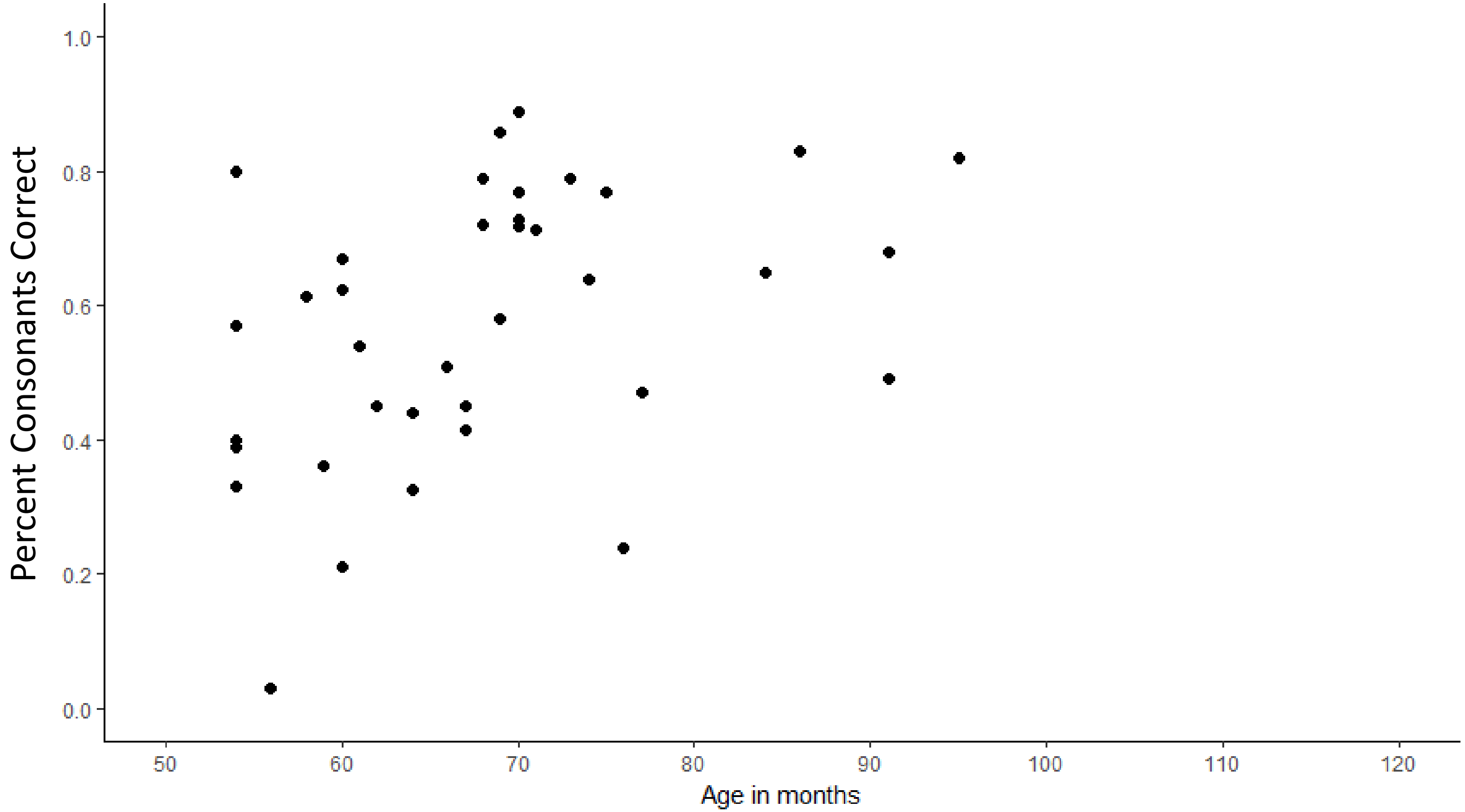
Some Level 2 groups are doing better than others…

Within each Level 2 group, some of the Level 1 units are doing better than others

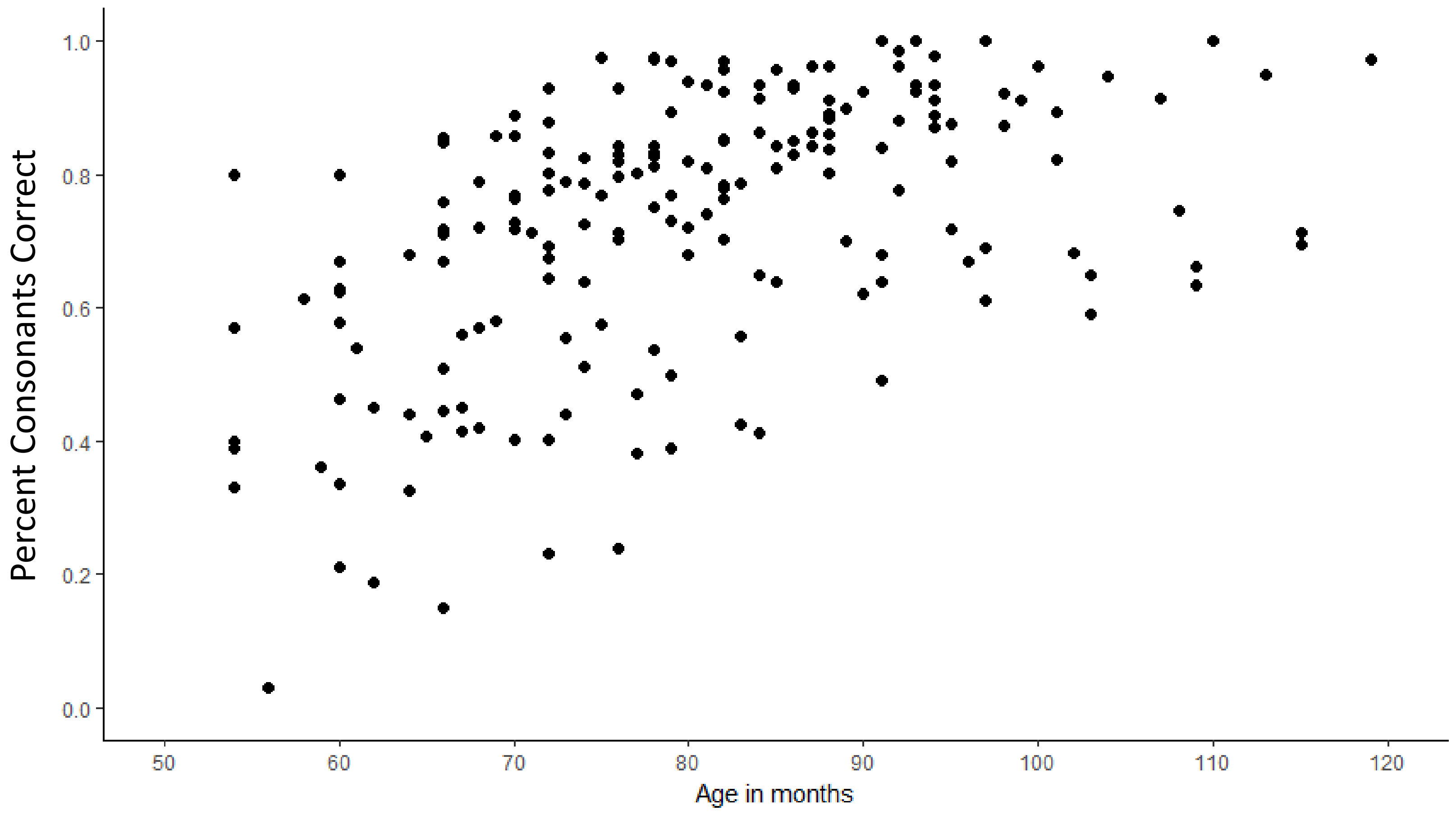
Let’s look at some real data…



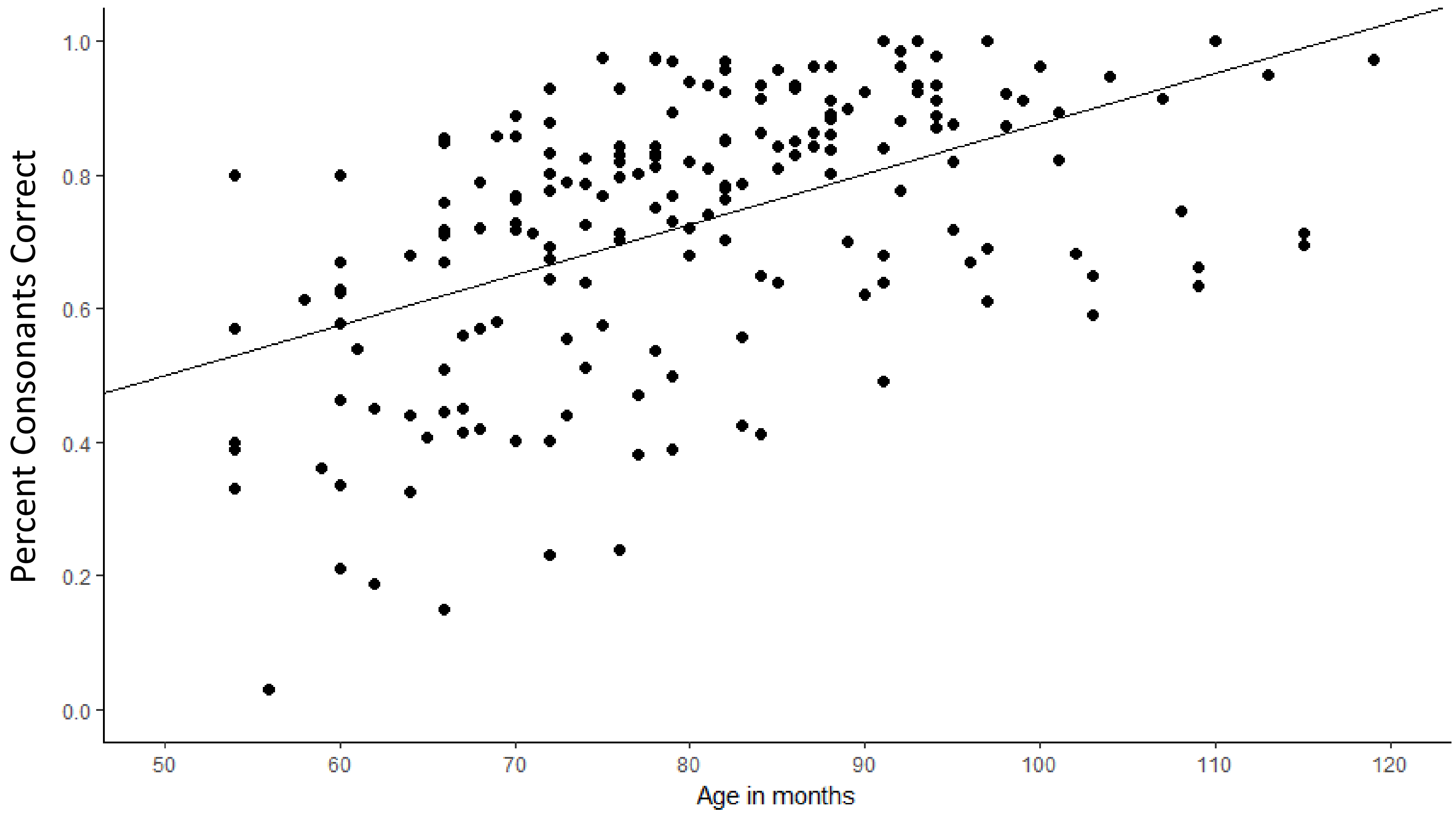
Scatterplot: Percent consonants correct (PCC), and age in months, for a sample of children with inconsistent speech sound errors



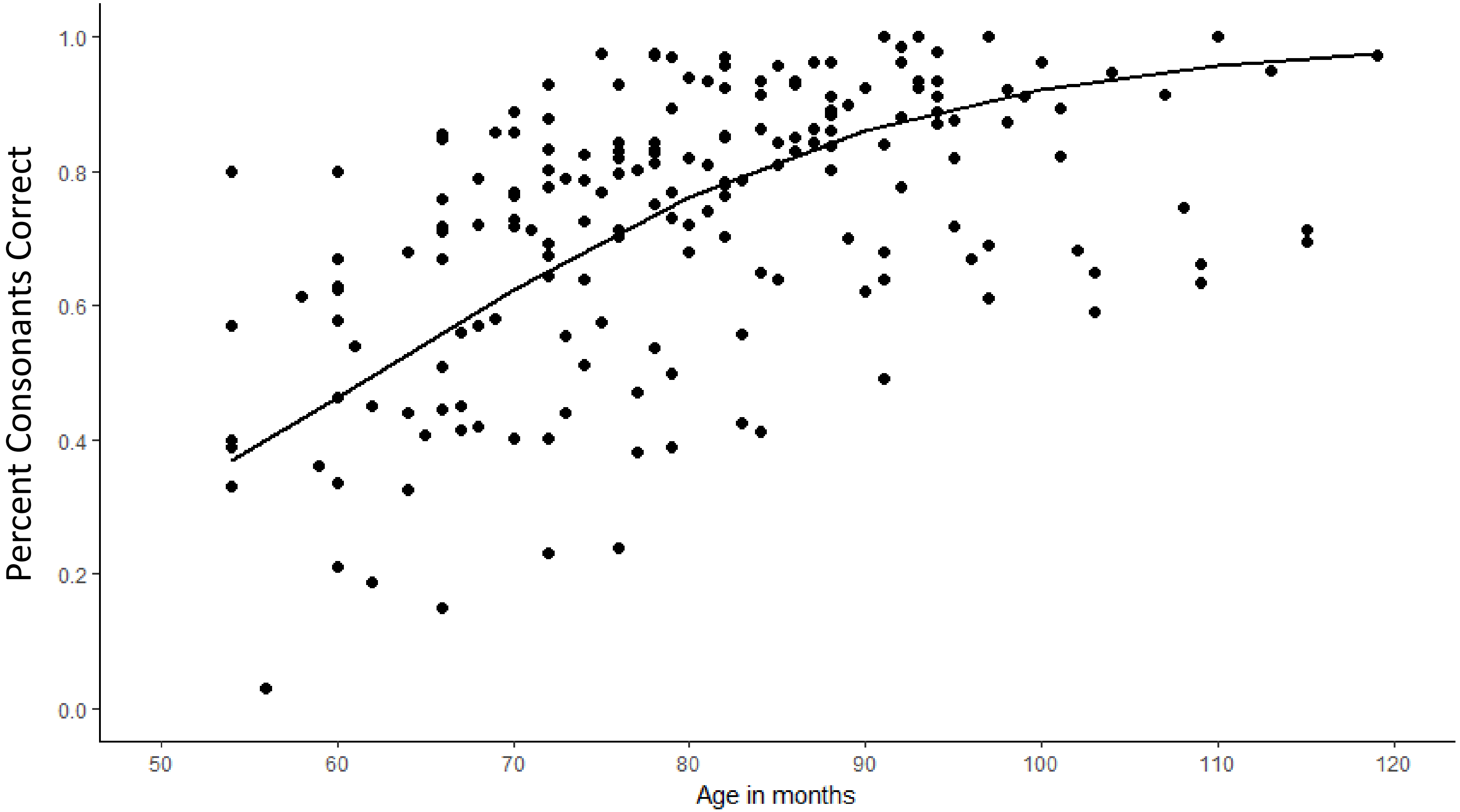
Measured at 5 different time points, separated by 6-month intervals

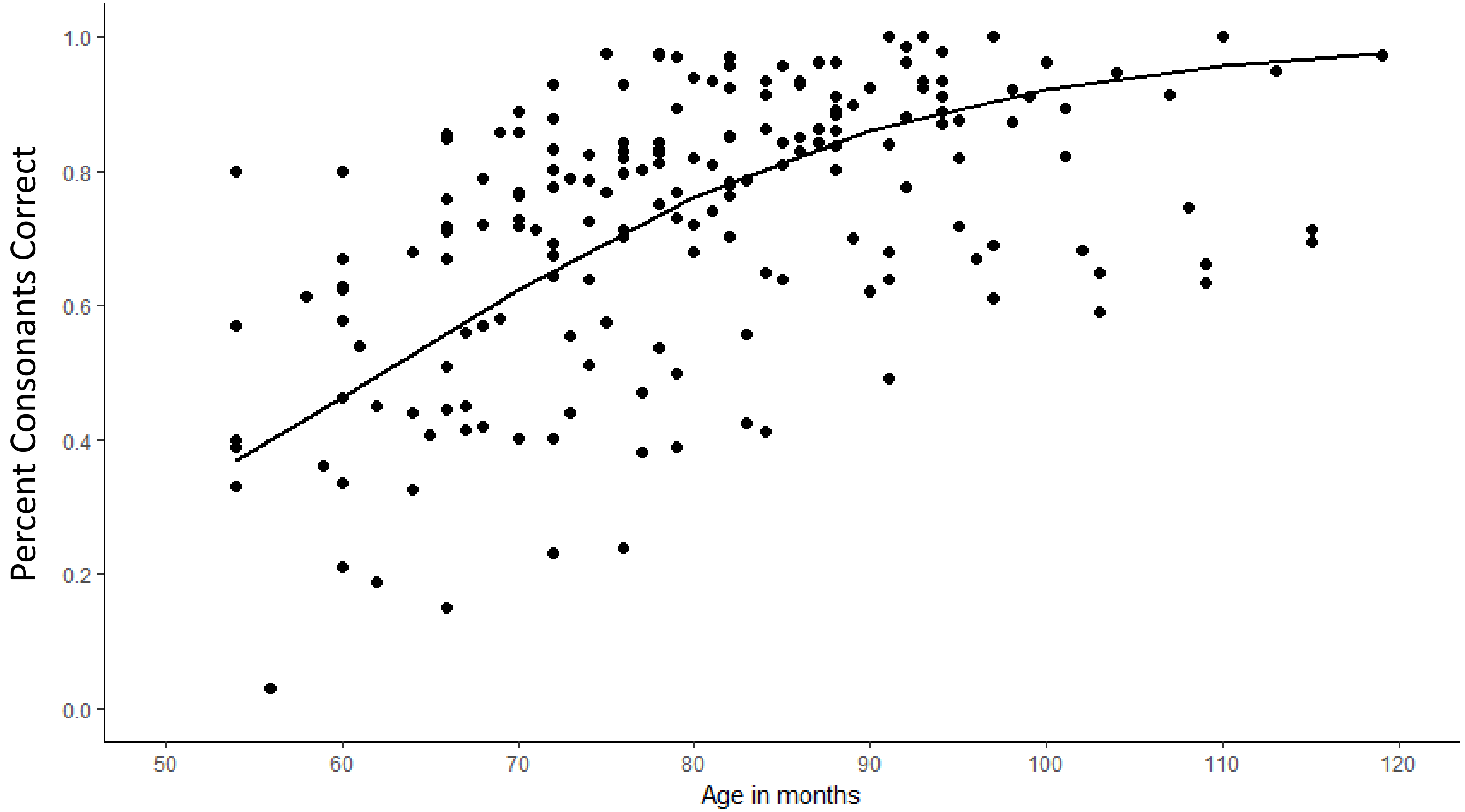


Linear model



Non-linear model (bounded by 0% and 100%)

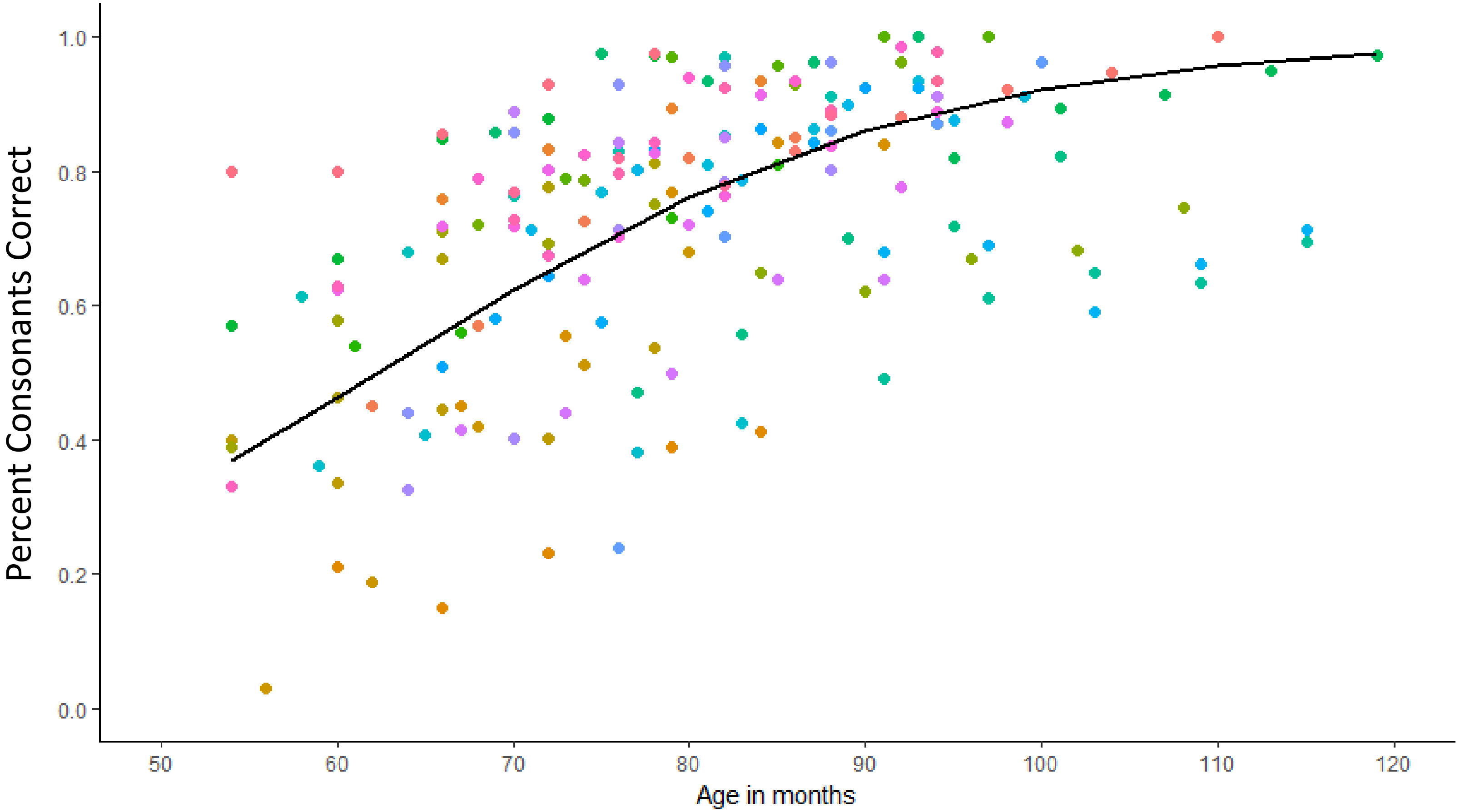




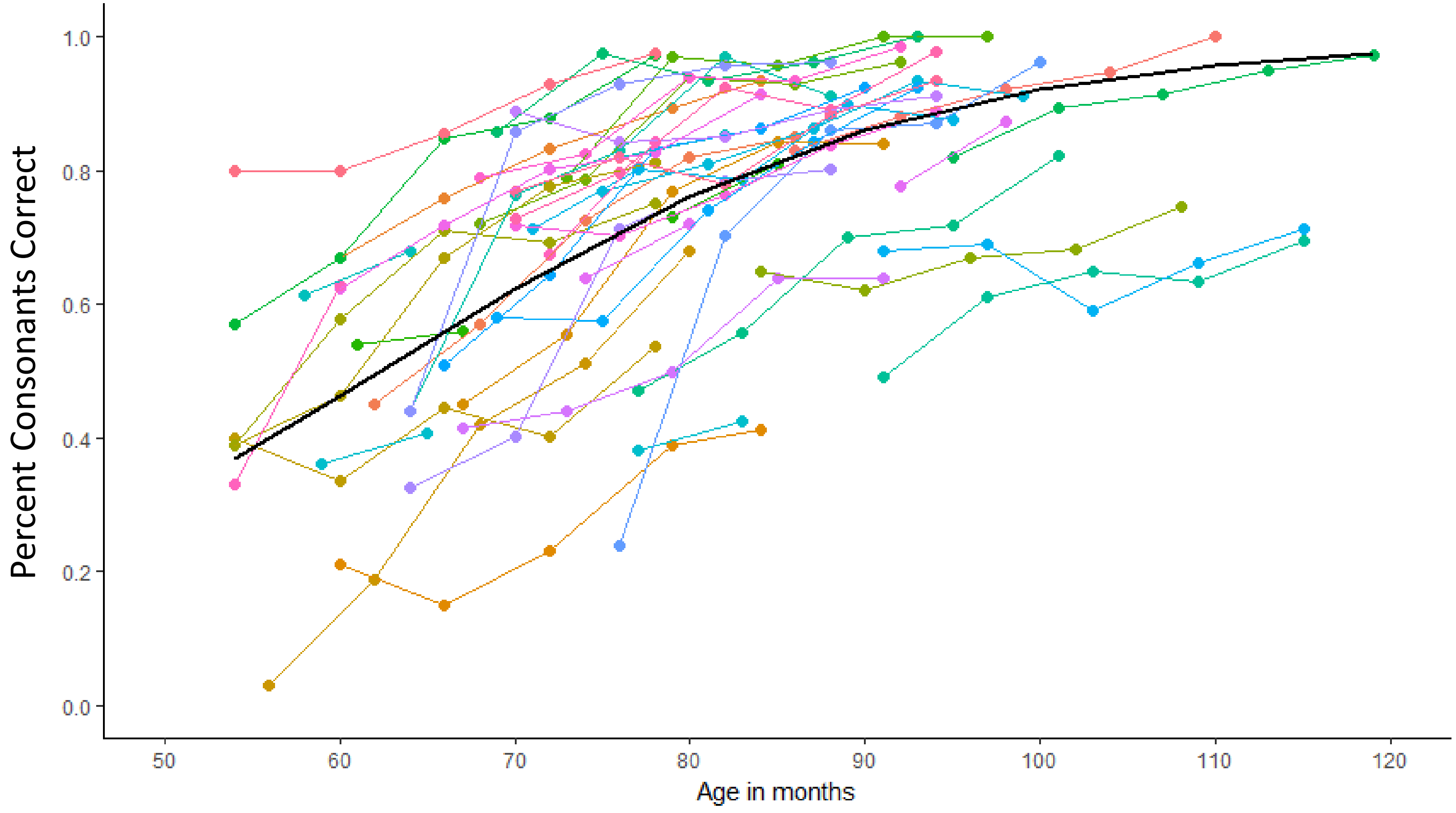
Does age predict PCC?

Yes, but there's a lot of error.

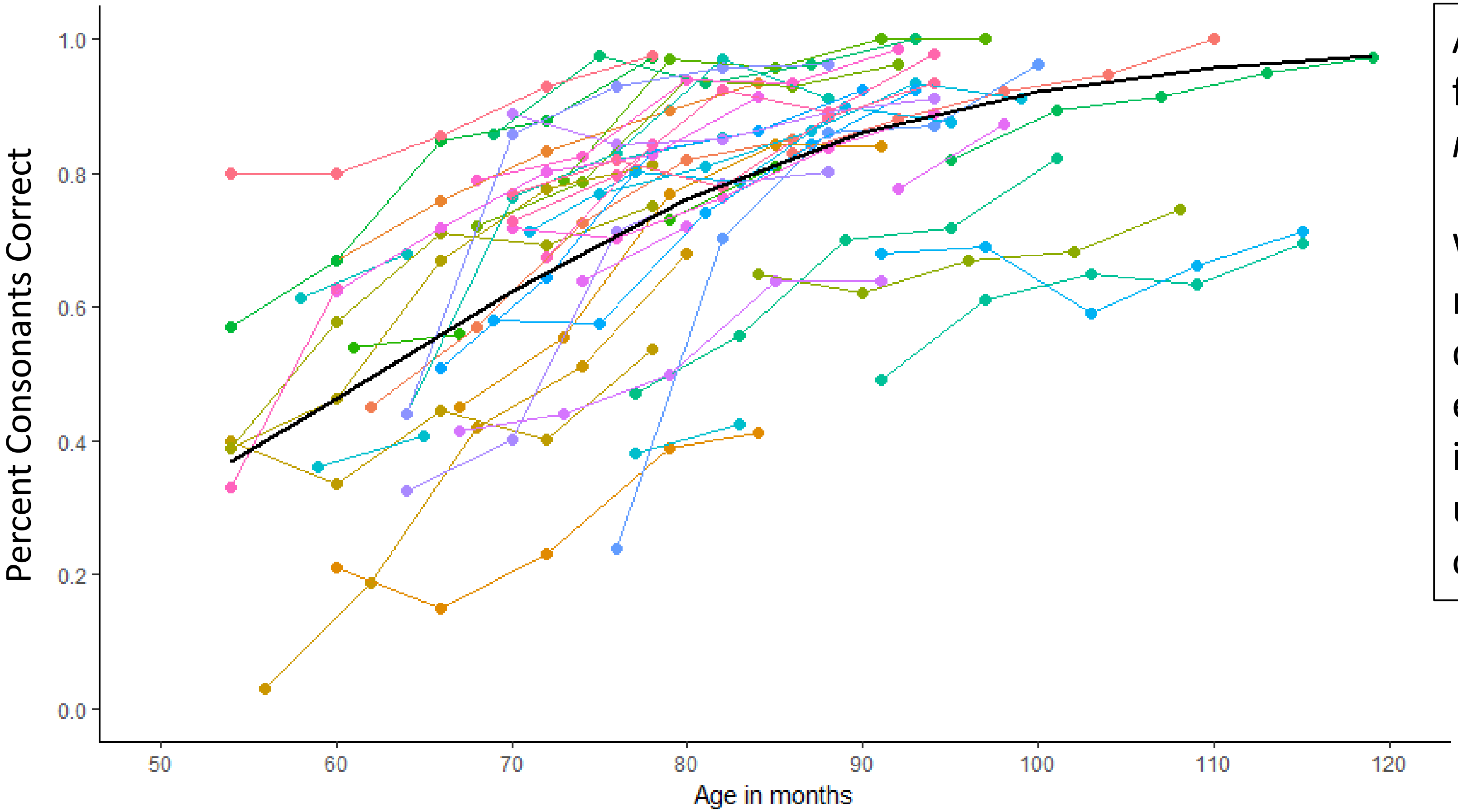
Color-coded by child



Color-coded by child

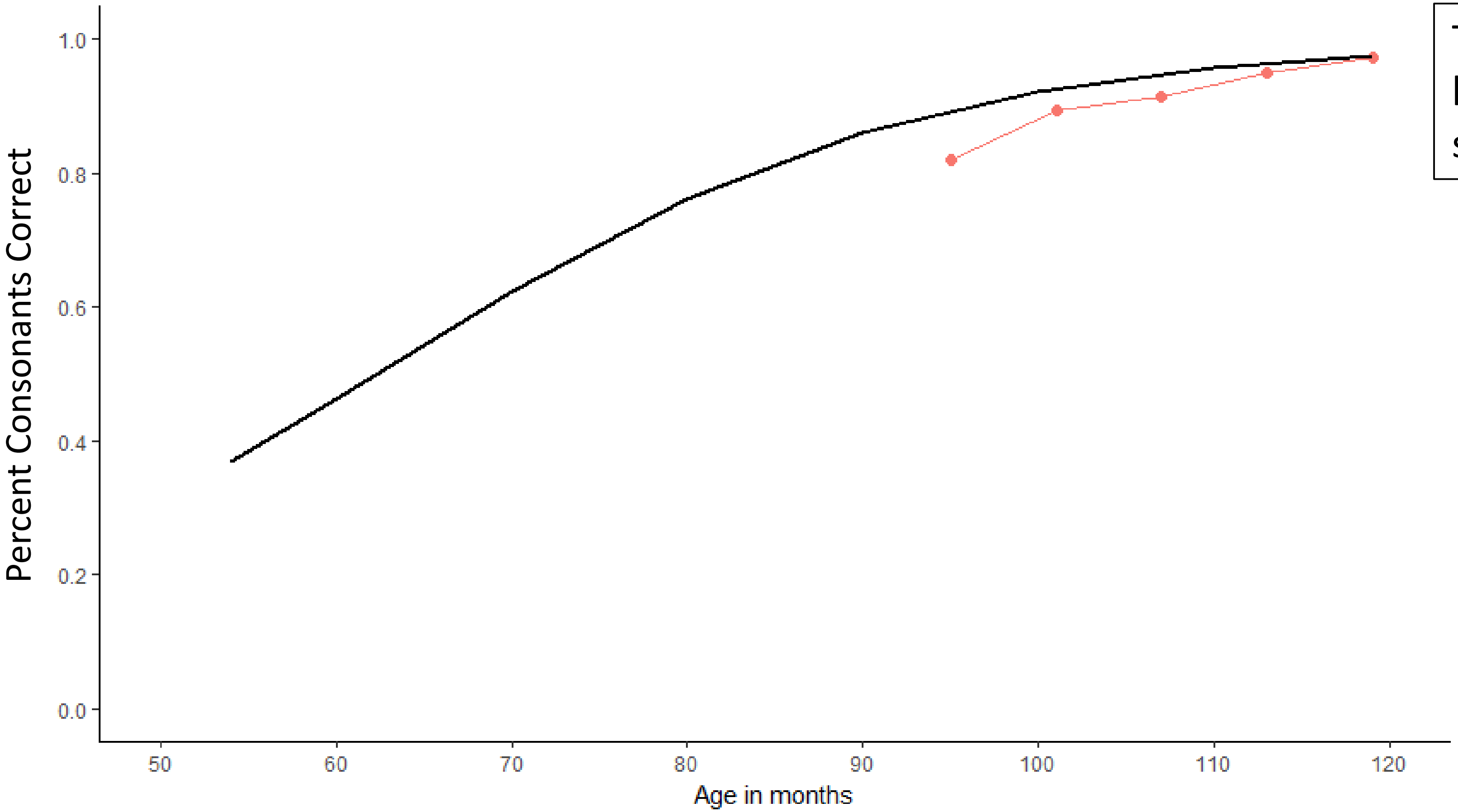


Color-coded by child

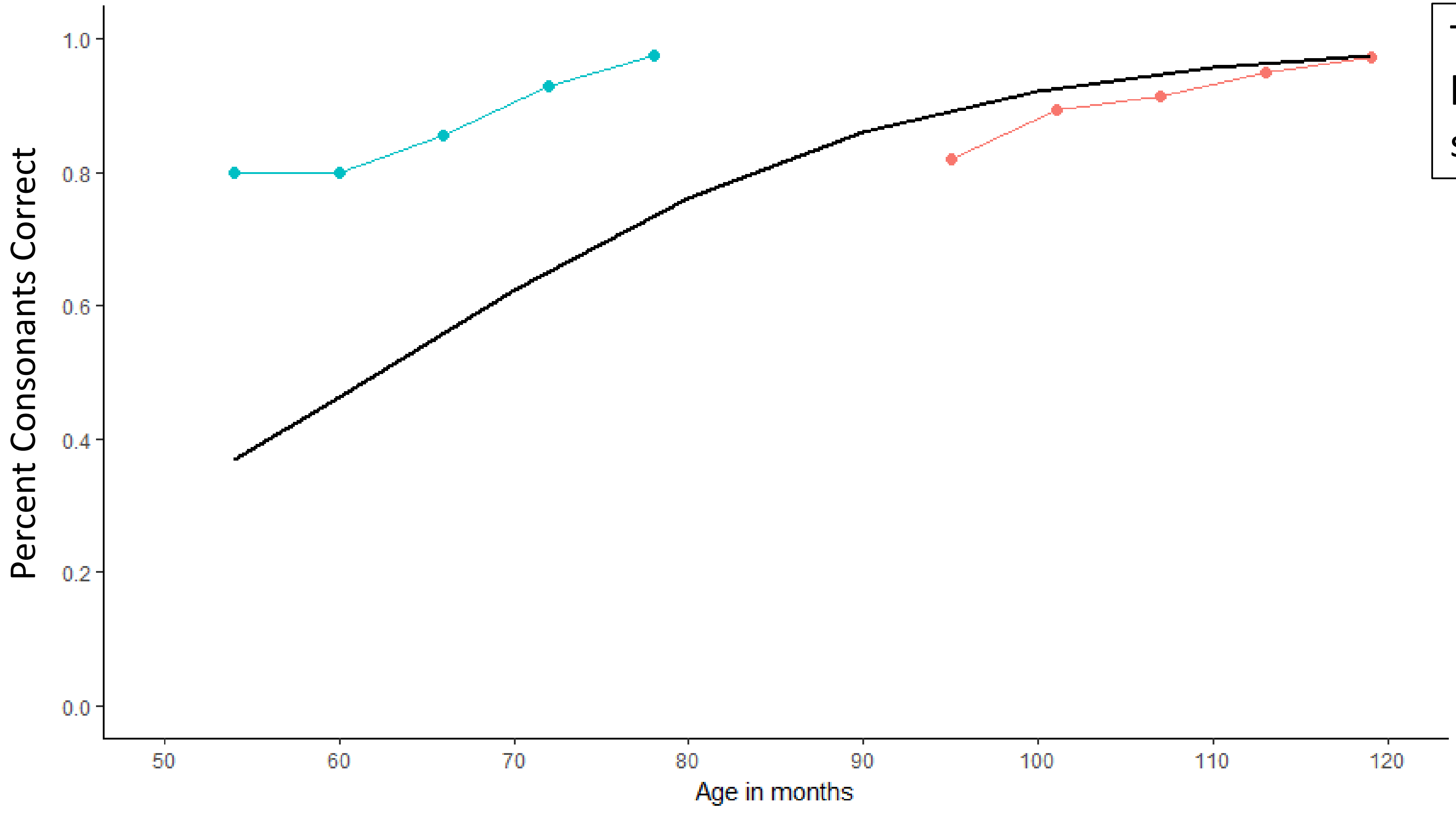


All the observations from a single child are *not* independent.

Without modeling the nested nature of the data, we are treating every observation as if it were unique and unrelated to the others.



The model predictions look pretty good for some children…



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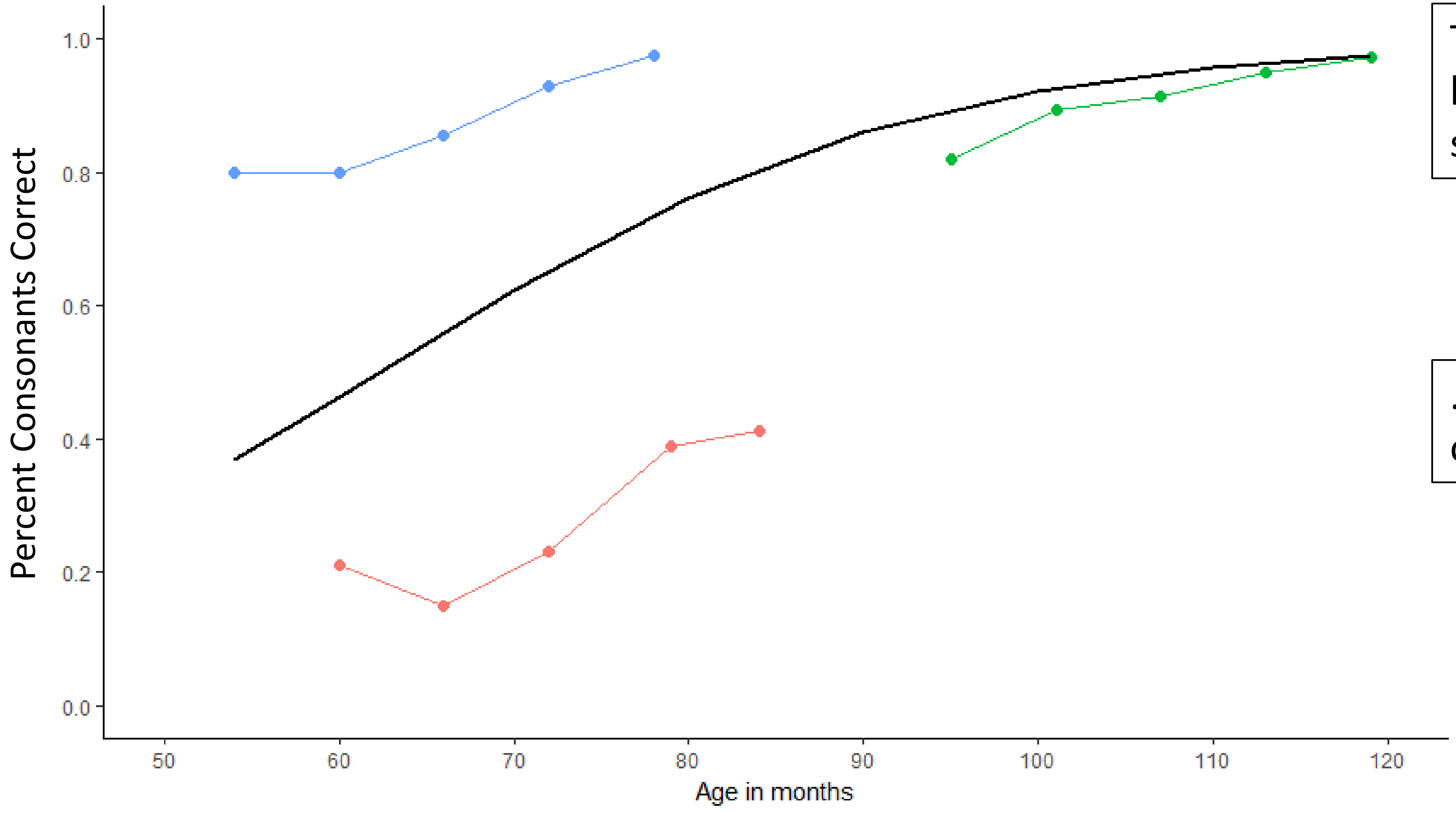
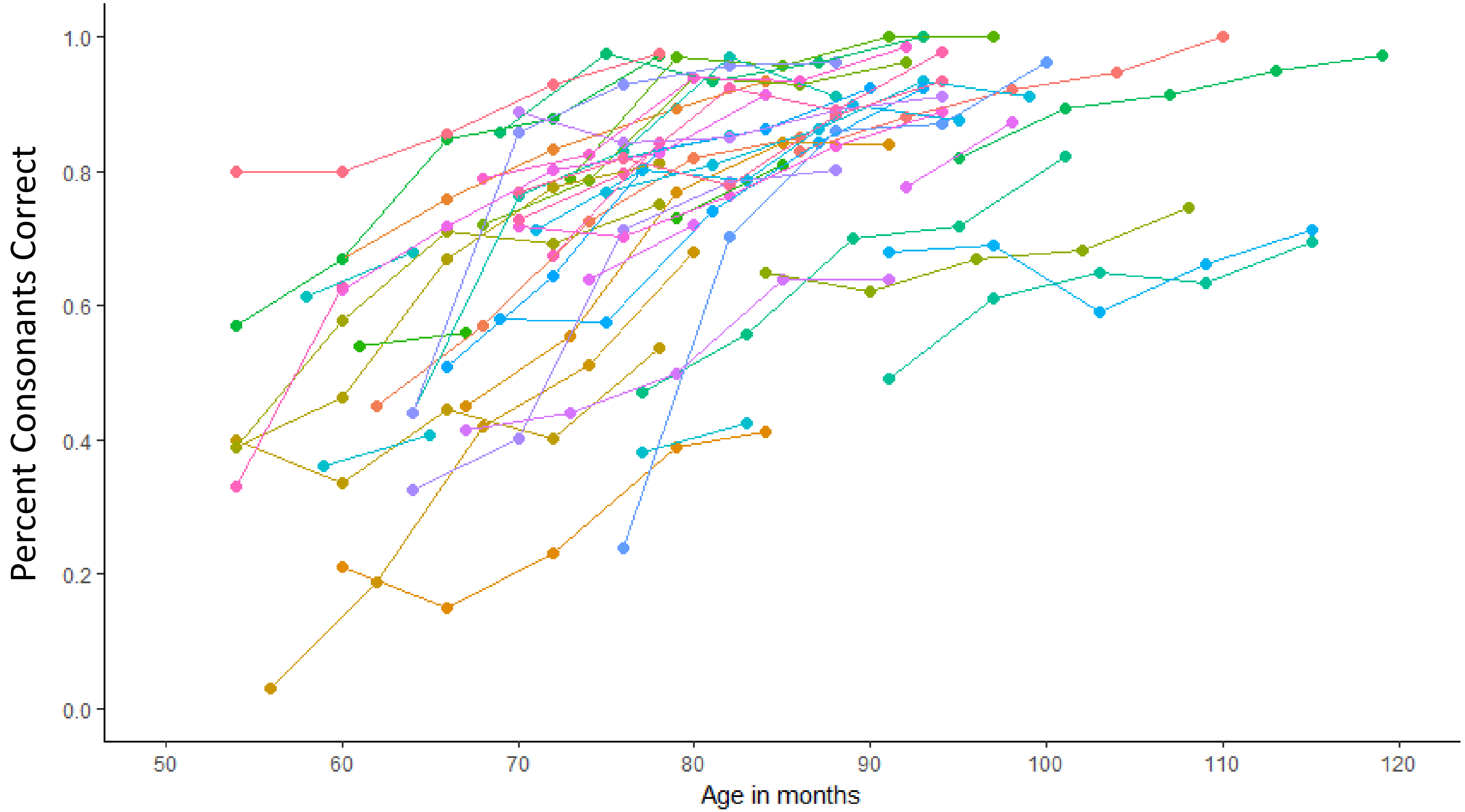


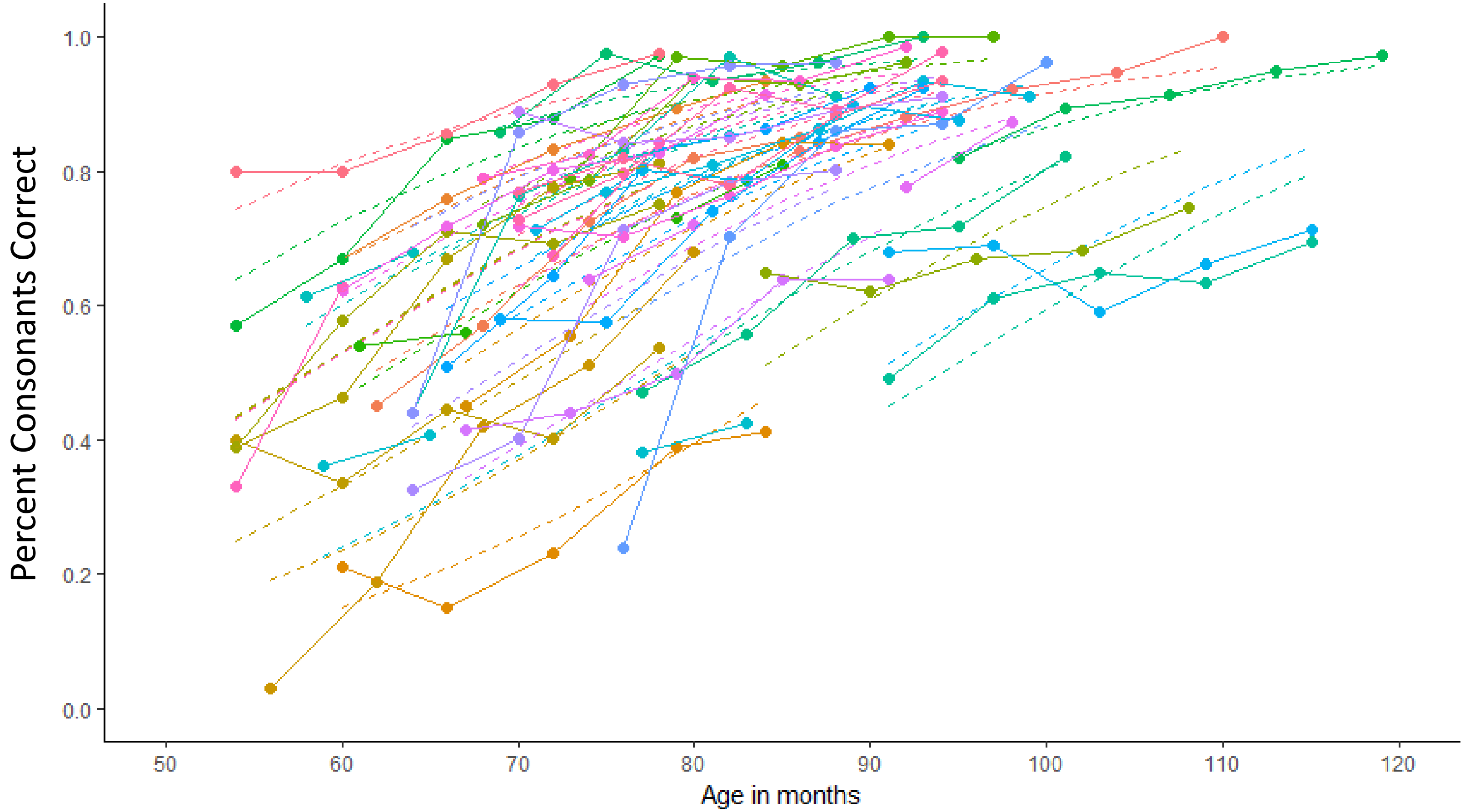
The model predictions look pretty good for some children…

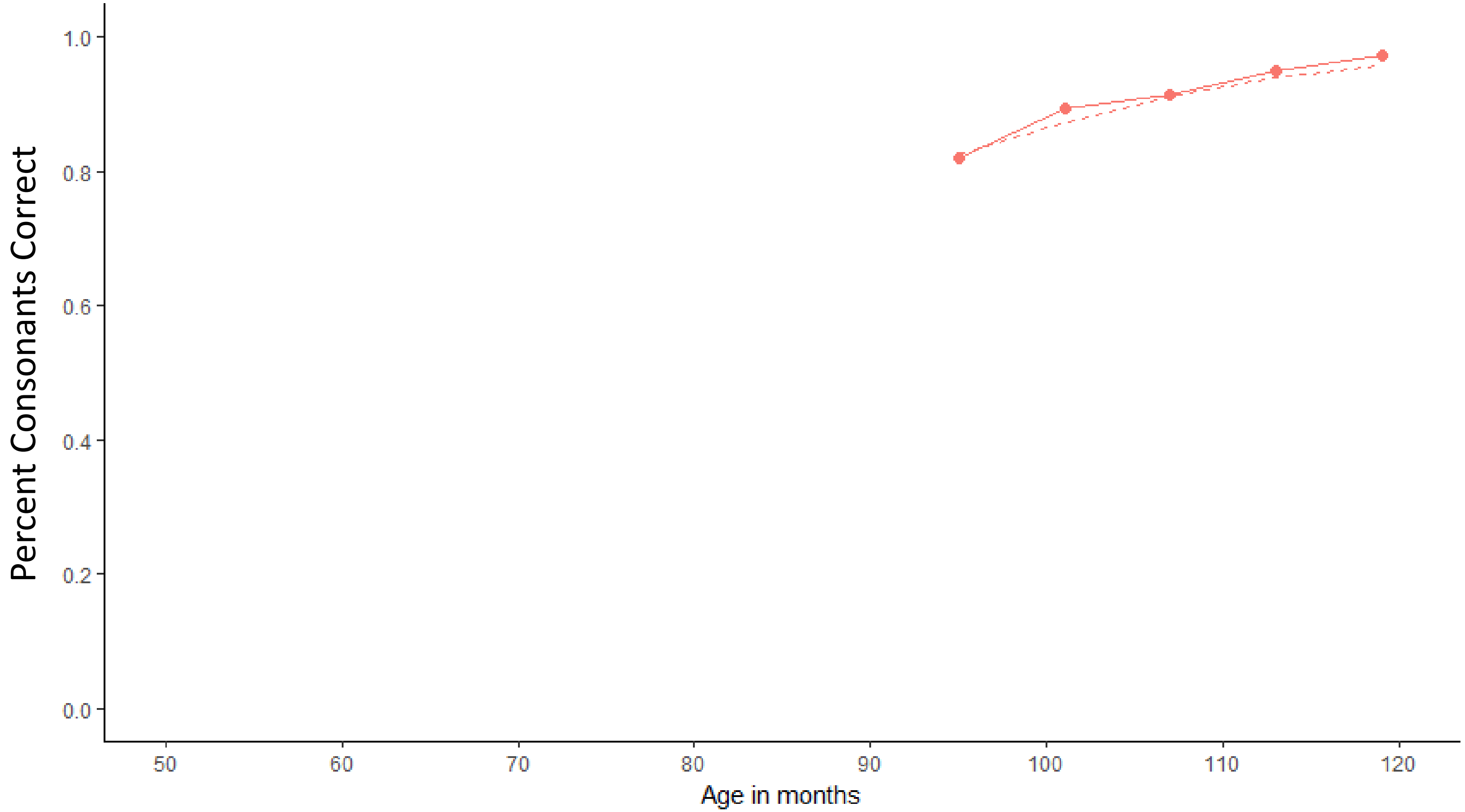
… but less so for others.

Now let's try HLM



Each child gets their own predicted pattern of growth




1.0
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Percent Consonants Correct
50
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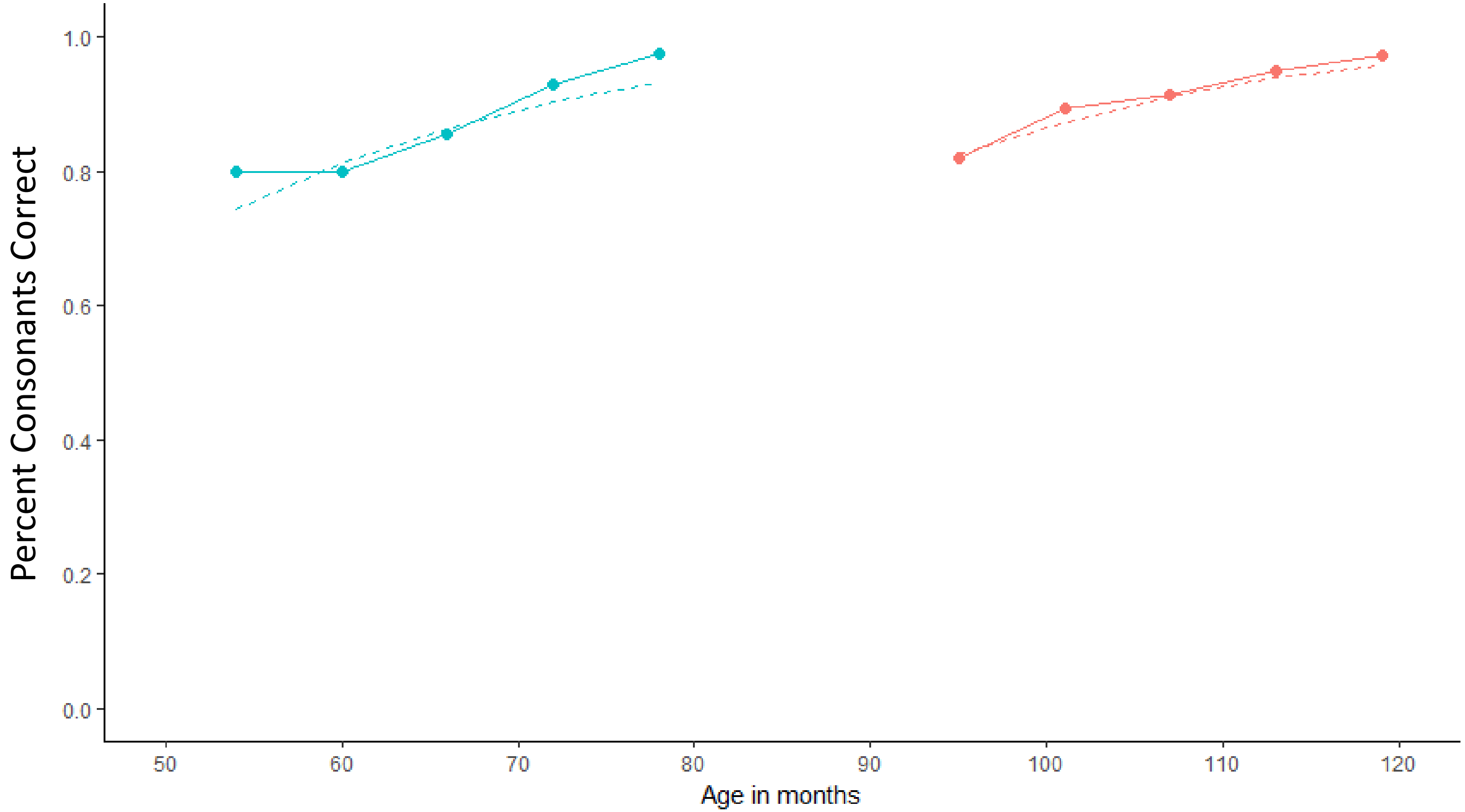
90
100
110
120
Age in months



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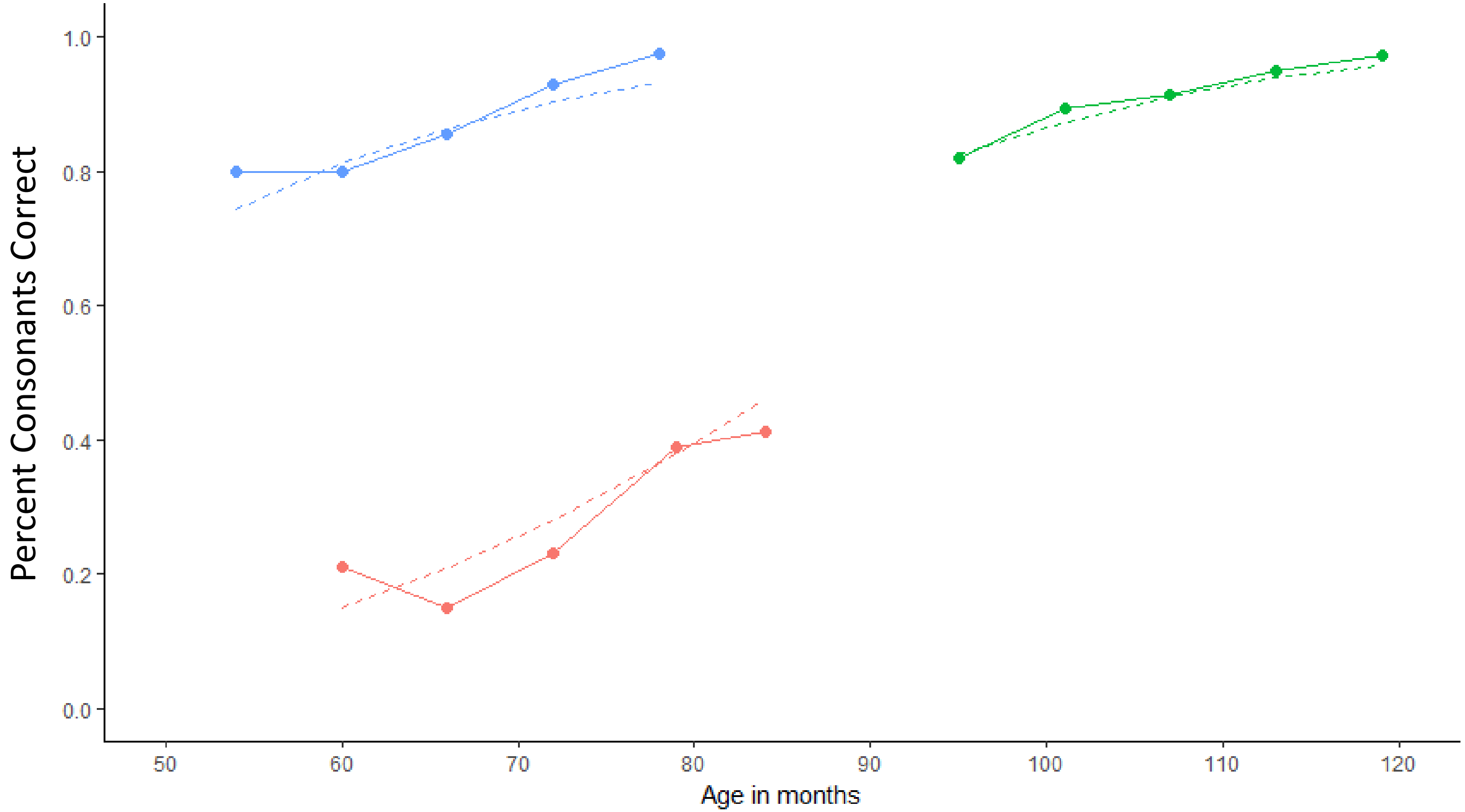
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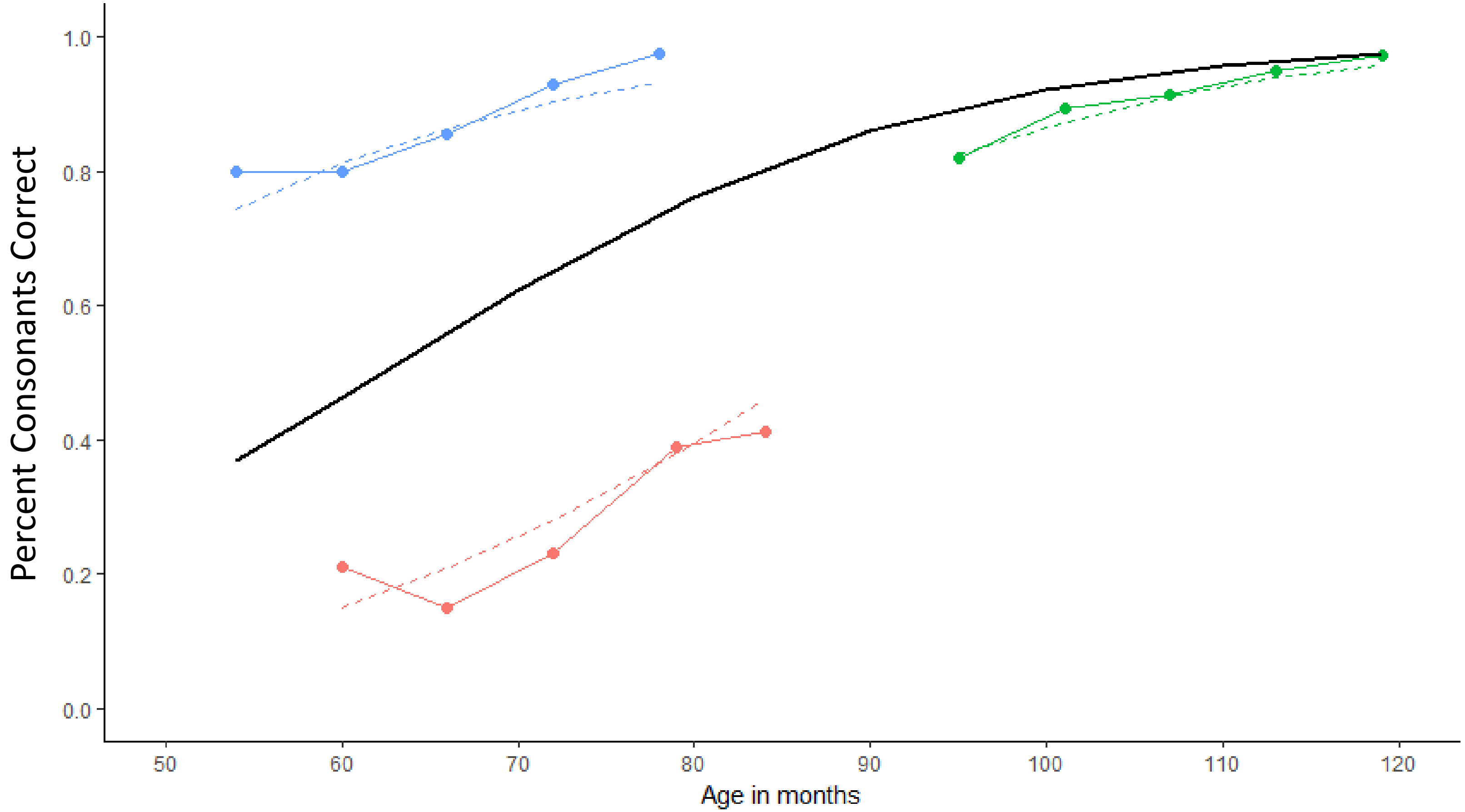

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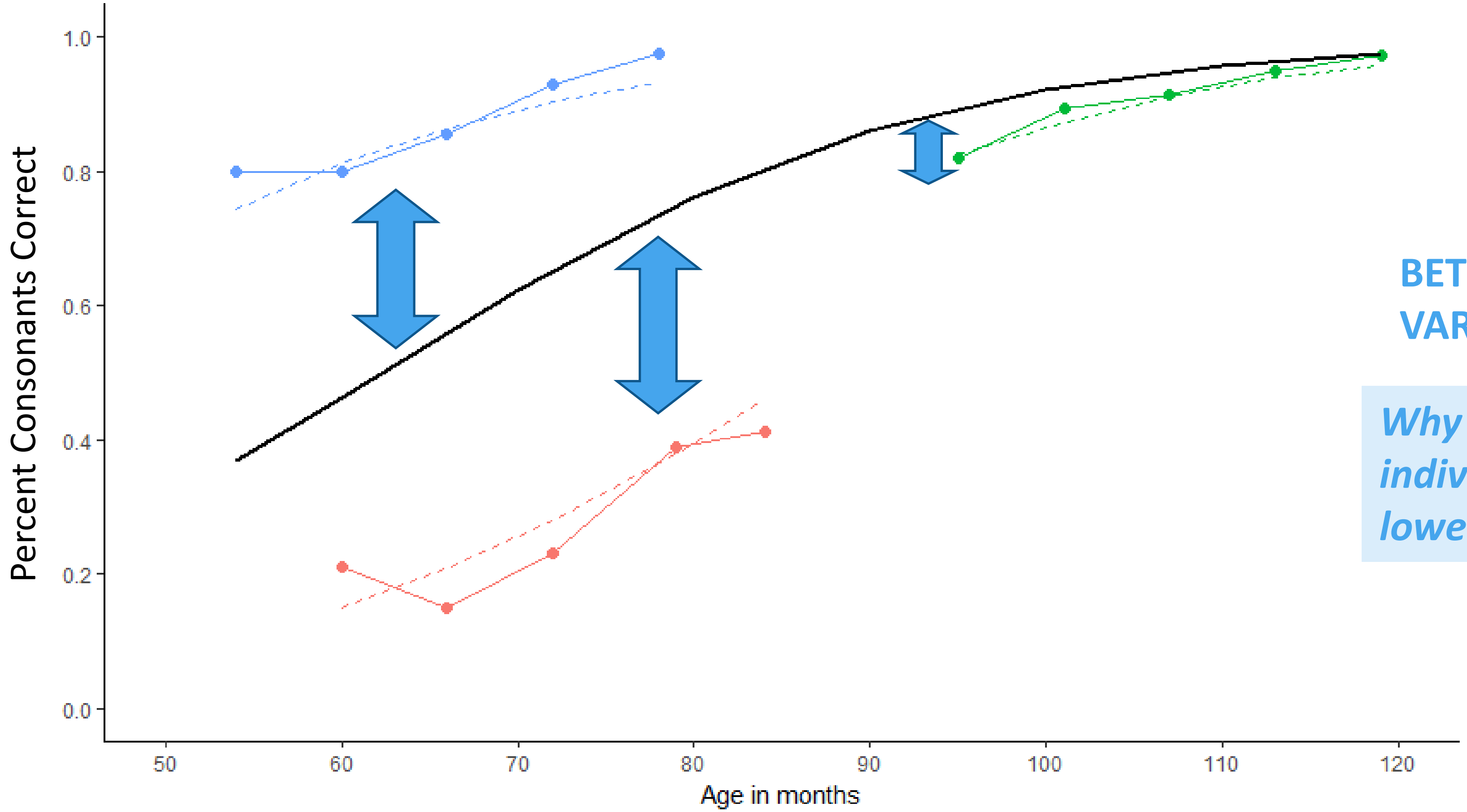
Two kinds of variance



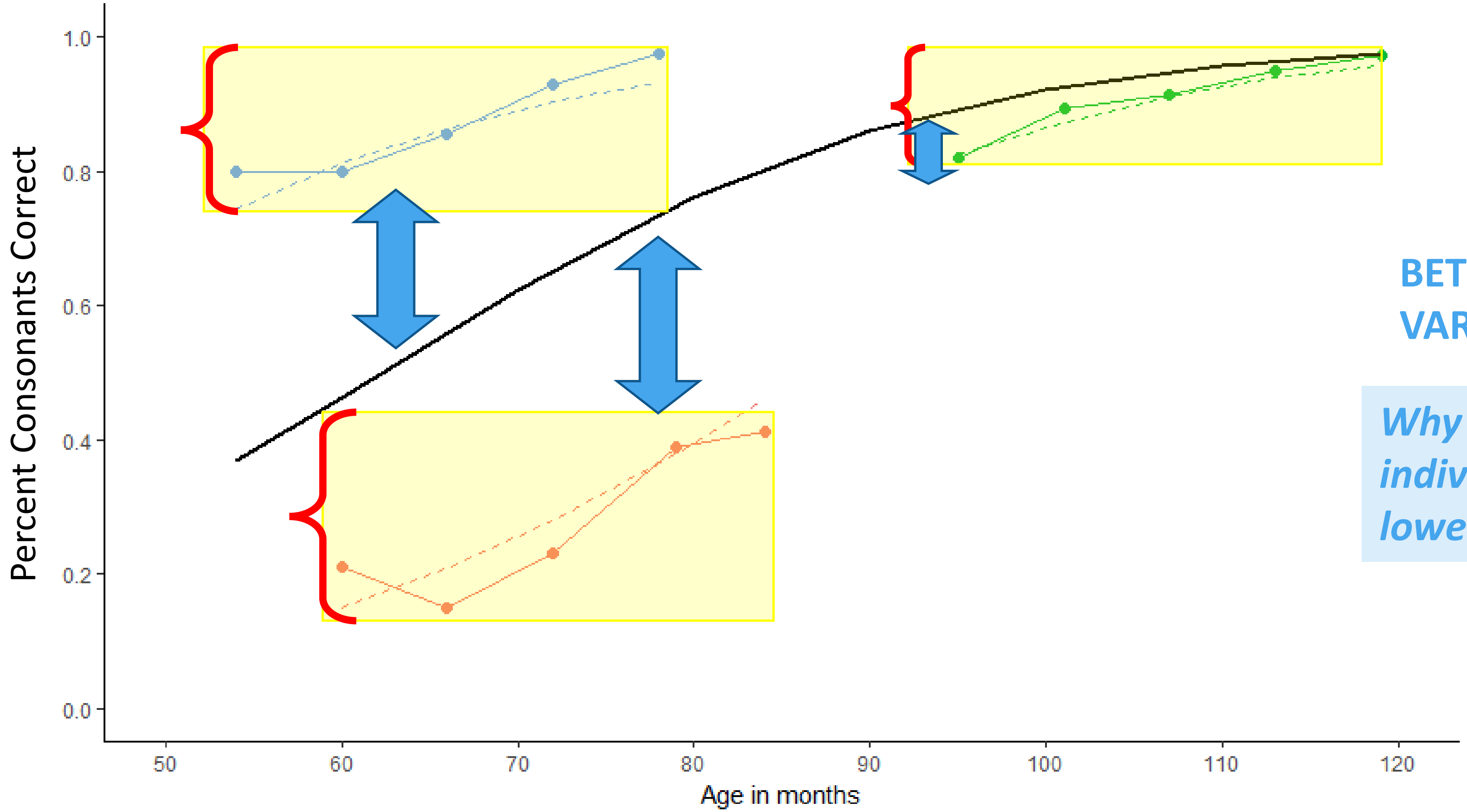
BETWEEN-PERSON VARIANCE

Why are some individuals higher or lower than others?

Two kinds of variance

WITHIN-PERSON VARIANCE

Why do scores differ within an individual?



BETWEEN-PERSON VARIANCE

Why are some individuals higher or lower than others?

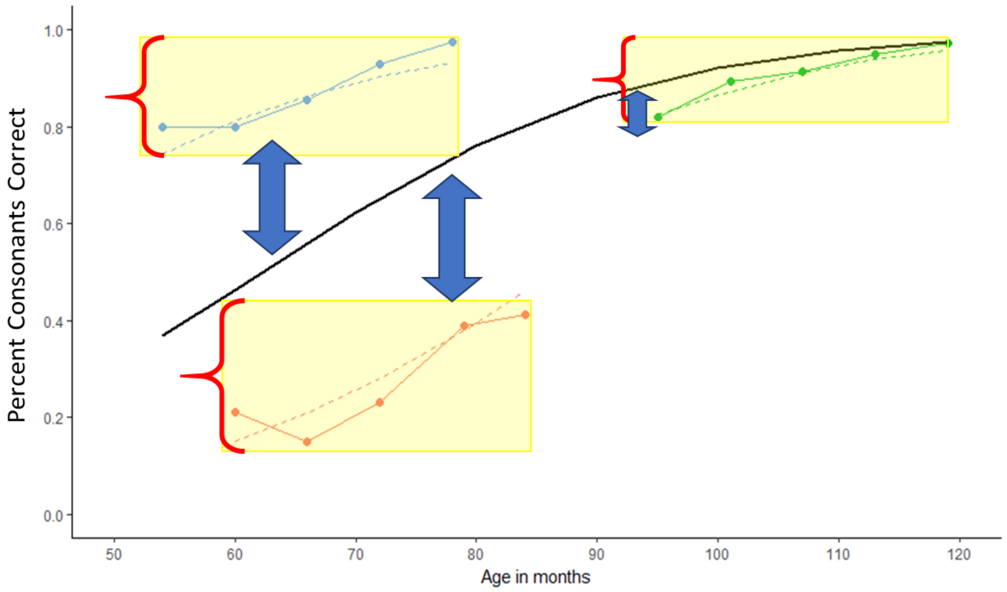
Two kinds of variance

WITHIN-PERSON VARIANCE

Why do scores differ within an individual?

In this model:

- **Age explains change within individuals**
- **We could add other predictors that differ within the individual: vocabulary at each timepoint?**



BETWEEN-PERSON VARIANCE

Why are some individuals higher or lower than others?

In this model:

- **We could add treatment history, SES, home environment: any variable that differs between individuals.**

A note on terminology

Fixed effects

- The same for everyone (a *fixed* value)
- Fixed Intercept
  - Overall starting point for everyone
- Fixed slope
  - Overall rate of change/growth/etc. for everyone
- A predictor *always* has a fixed effect

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A few examples

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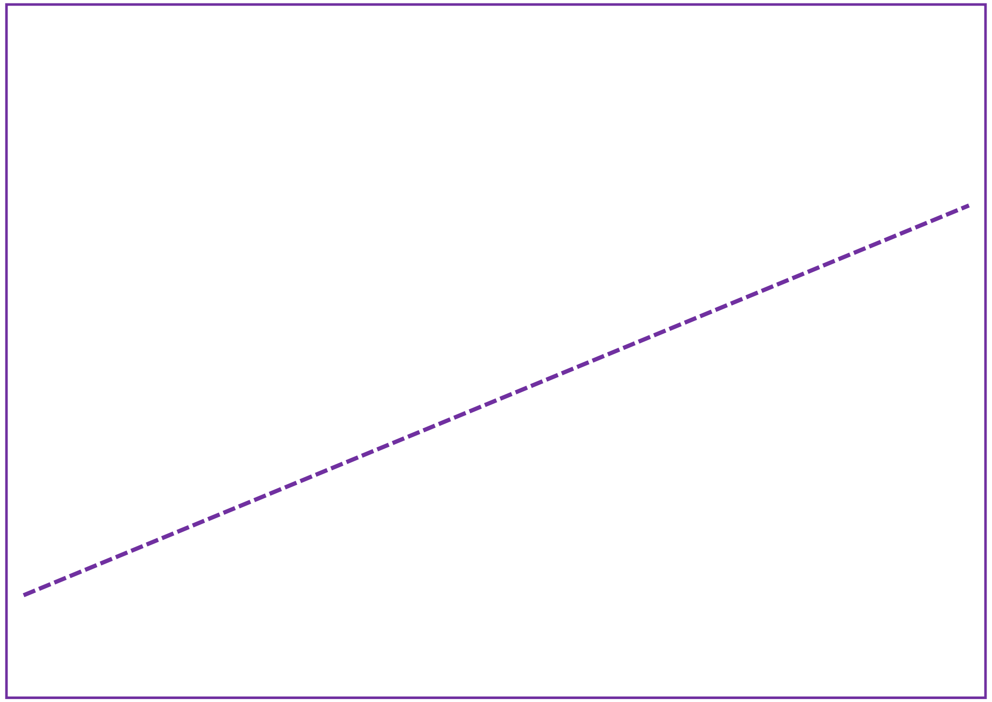

Fixed intercept + **Fixed slope**

A few examples

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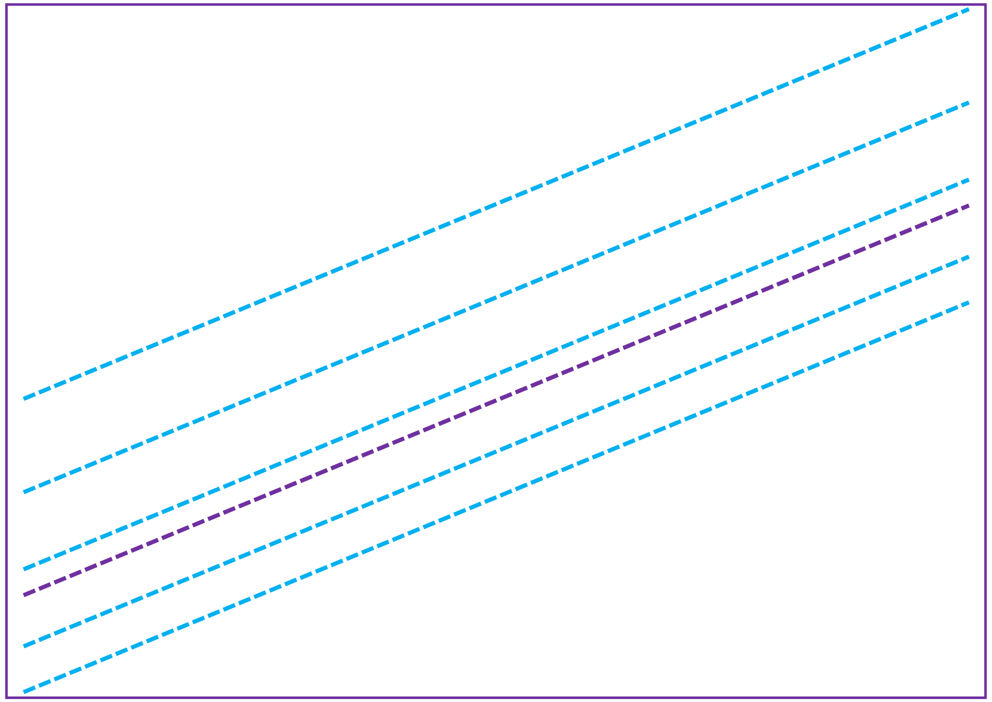

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Random intercept

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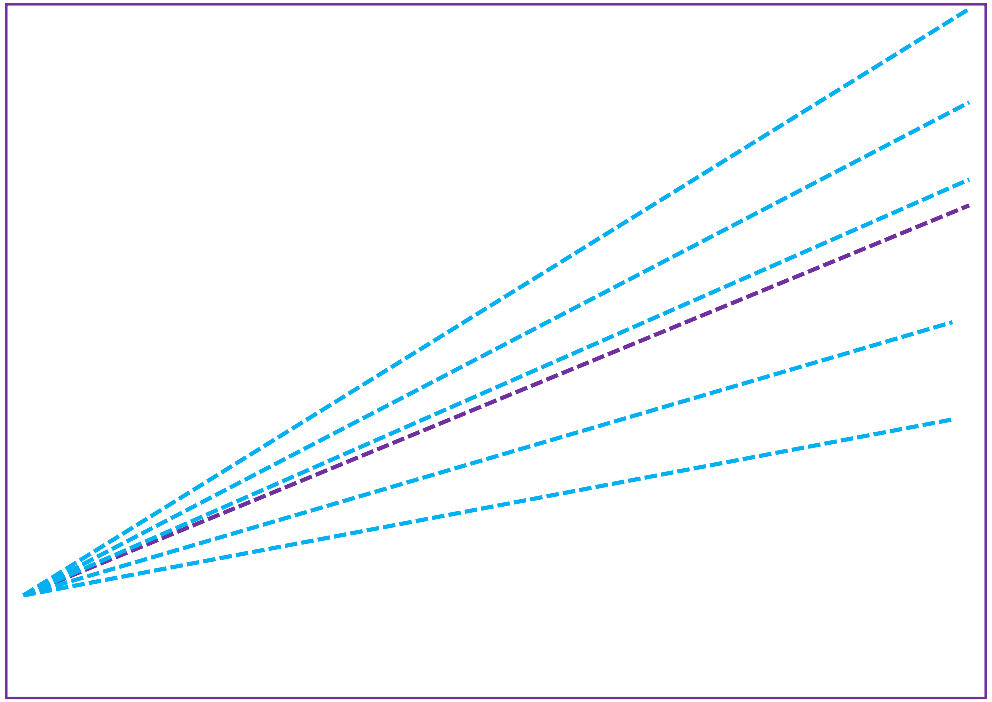

Fixed intercept + **Fixed slope**

Random slope

A few examples

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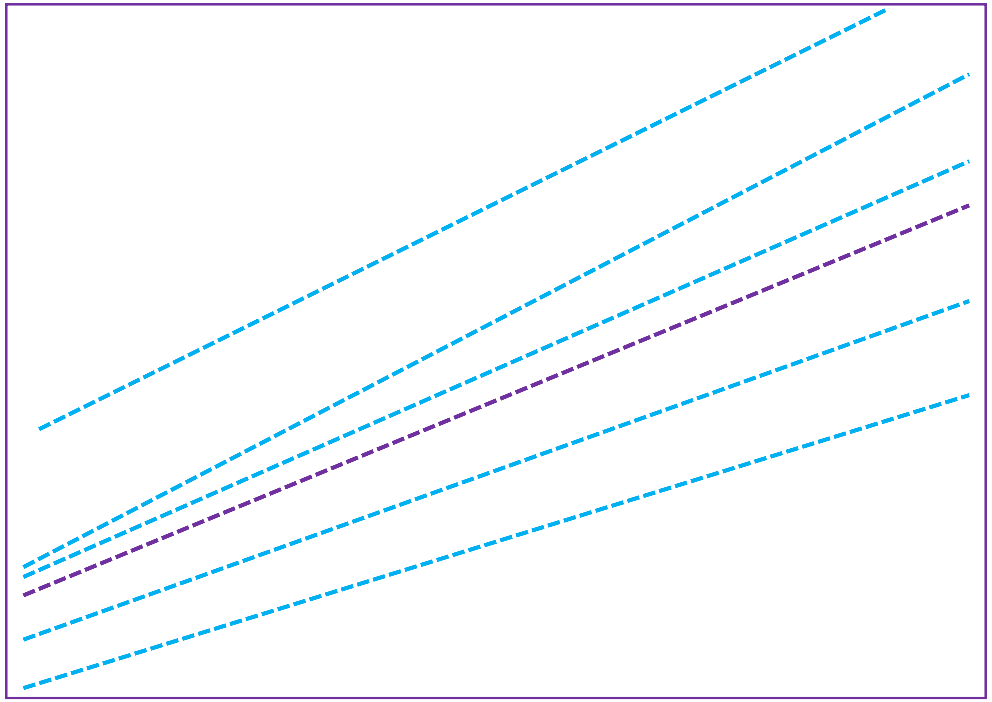

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Random intercept **Random slope**

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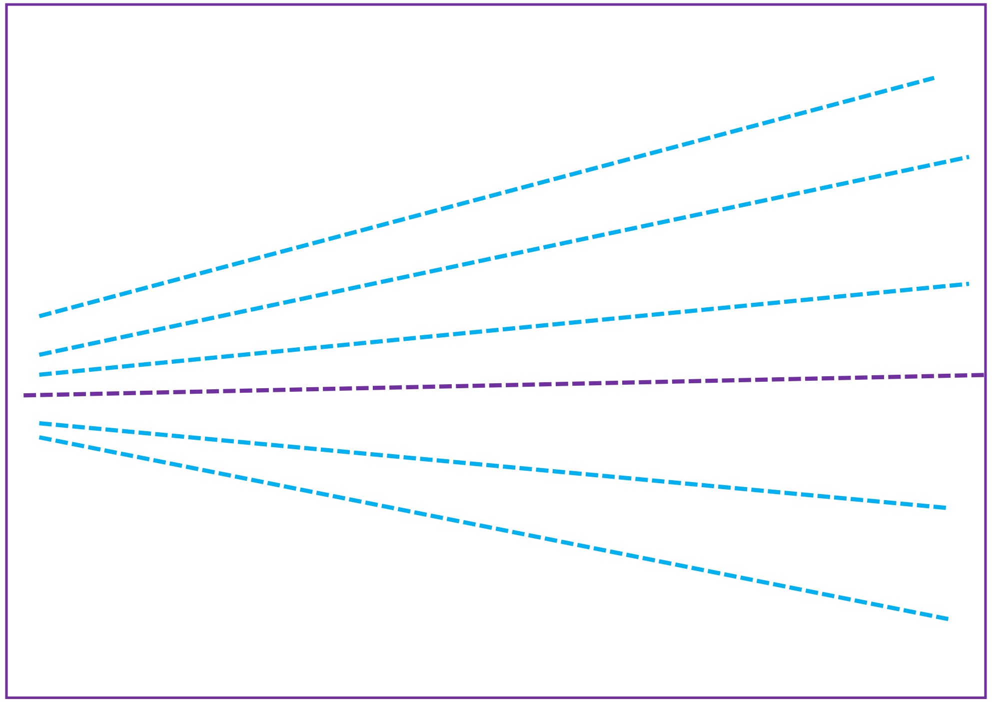

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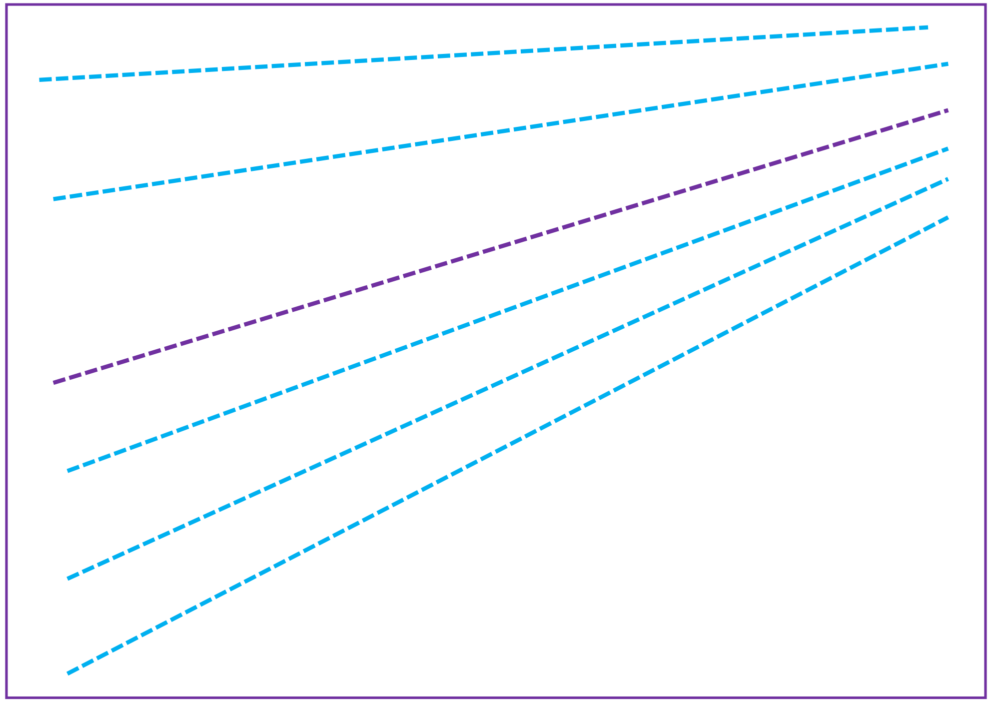

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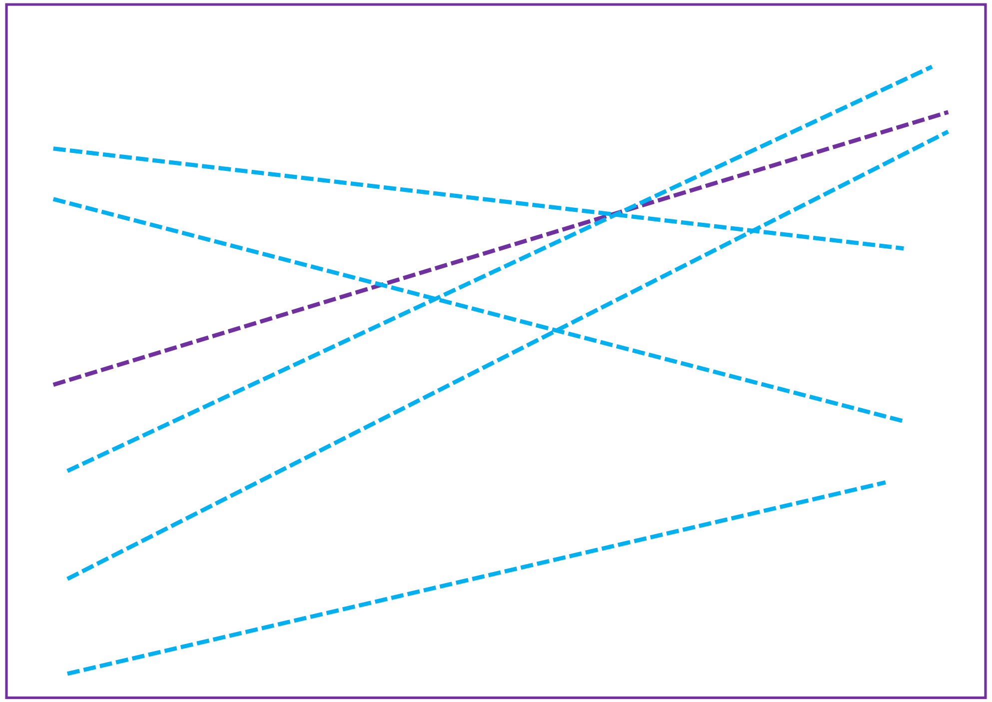

Fixed intercept + **Fixed slope**

Random intercept **Random slope**

Your turn…

What are your hypotheses? Are they about Level 1, or Level 2, or both?

Level 1 ***nested within*** level 2

Level 1 (“micro”)	Level 2 (“macro”)
Participants	Classroom
Classrooms	School
Voters	District
Patients	Clinician
Time Points	Participant
Item responses	Item
Item responses	Participant

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Level 1 ***nested within*** level 2

Level 1 ("micro")	Level 2 ("macro")
Participants	Classroom
Classrooms	School
Voters	District
Patients	Clinician
Time Points	Participant
Item responses	Item
Item responses	Participant

What is your Level 1?

- **How many Level 1 units total? How many within each larger unit?**
- **Do you have any Level 1 predictors?**
- **If you have timepoints as Level 1…**
  - **Do you have at least 3 timepoints per person?**

What is your Level 2?

- **How many Level 2 units do you have?**
- **What are your Level 2 predictors?**

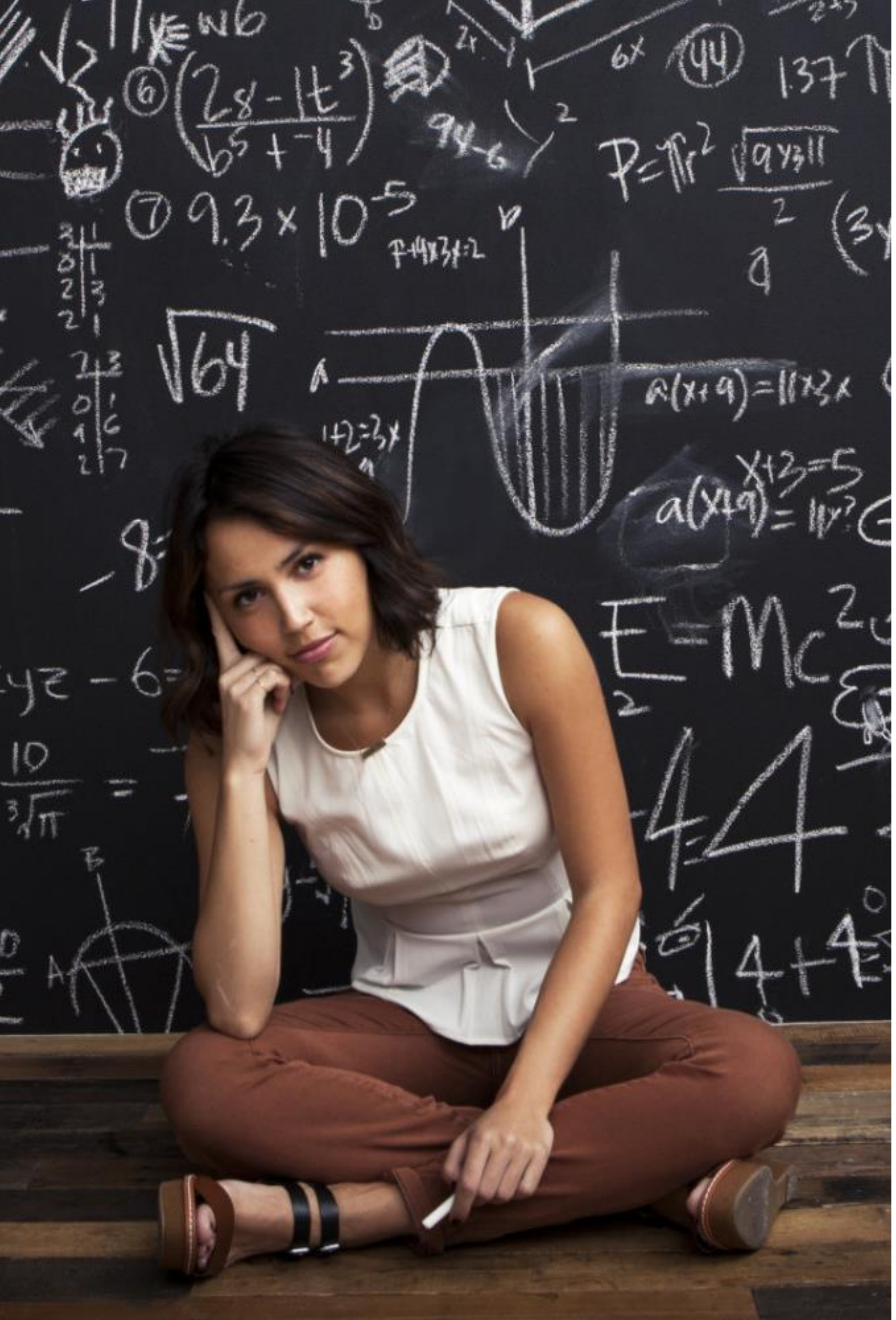
Is it more complicated than that?

- **More than 2 levels?**
- **Crossed rather than nested?**
- **Non-normal outcome variable?**

What to look for when reading a study that uses HLM

- Do the data have a nested structure?
- Are there at least 10 Level-2 units?
- How many models were examined, and why they were chosen?
- Were any variables centered? What kind of centering was used?
- Were there any outliers? How were they dealt with?
- How much missing data was there, and how was this addressed?
- What software was used? What estimation method was used? Did the model run properly?
- Are all parameter estimates provided for the interpreted models?
- Are standard errors or interval estimates provided?

Ferron, J., Hess, M. R., Hogarty, K. Y., Dedrick, R. F., Kromrey, J. D., Lang, T. R., & Niles, J. (April, 2004). *Hierarchical linear modeling: A review of methodological issues and applications.* Paper presented at the meeting of the American Educational Research Association, San Diego, CA.



Outline

Introduction (Dr. Carla Wood)

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The Value of Variance

Lisa Fitton, M.S., CCC-SLP

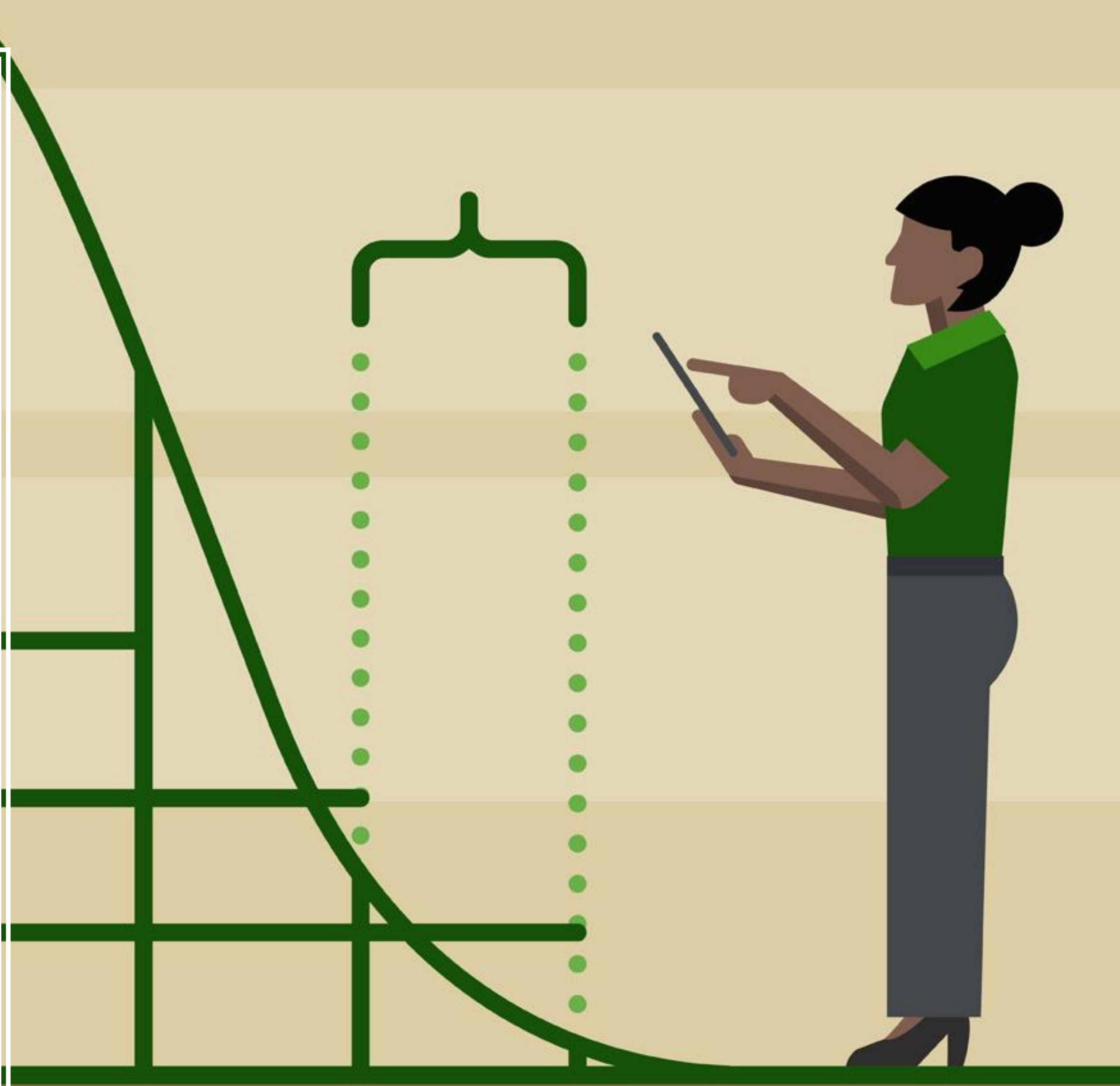
Florida State University

The Value of Variance

Avoid dichotomization whenever possible

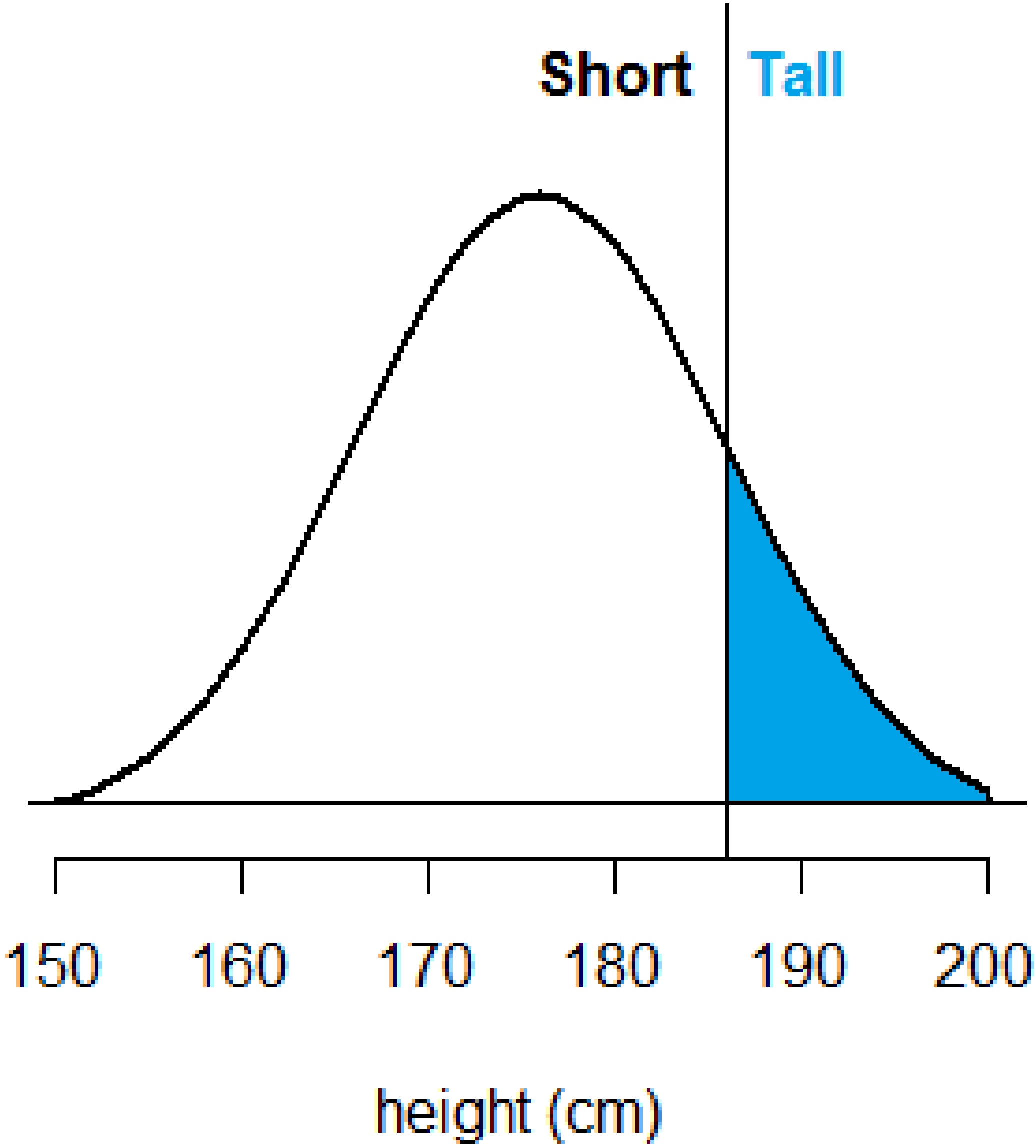
Supplement visual inspection of data with statistics

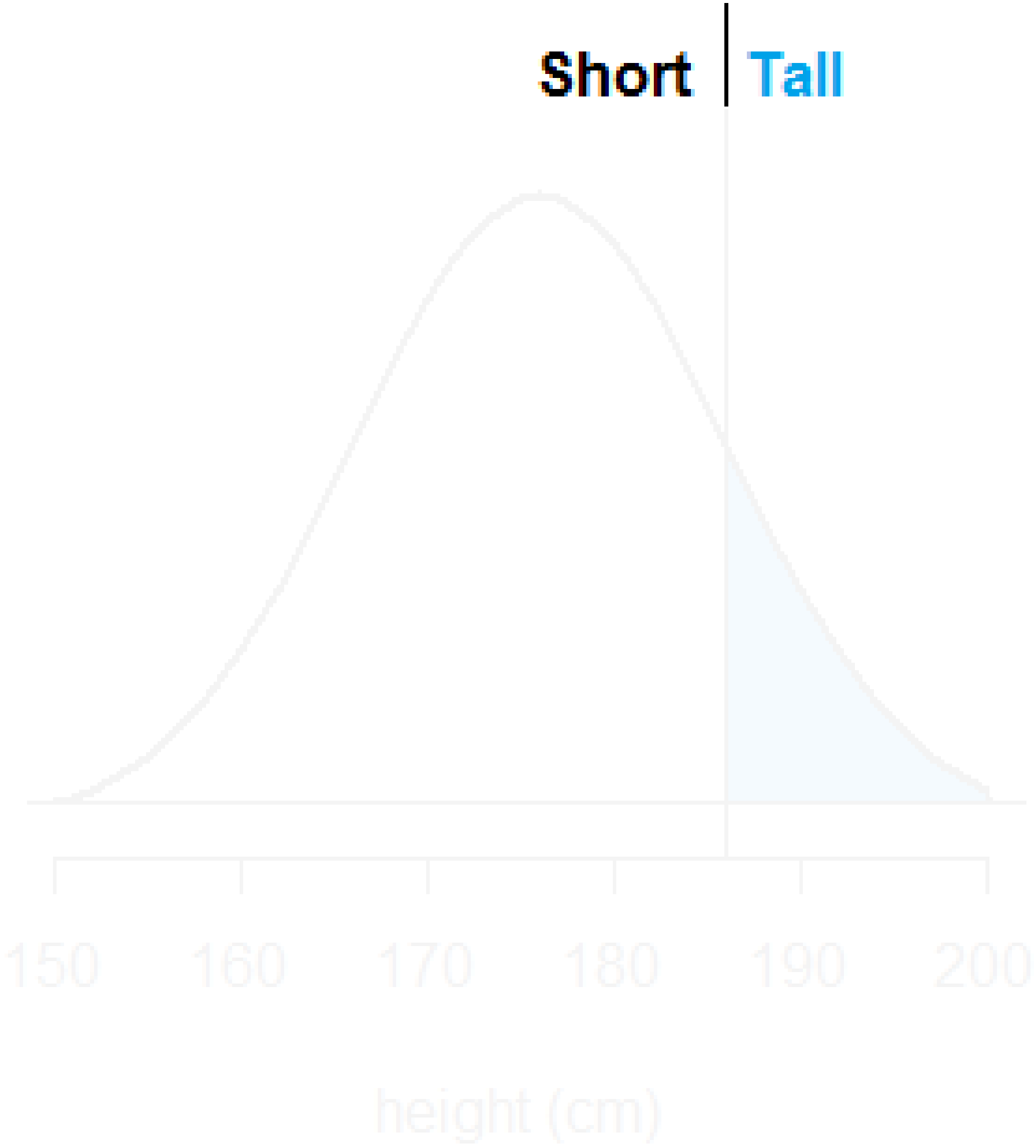
Plan in advance to make sure you have enough power to answer the question you want to ask



Avoid dichotomization whenever possible

What is dichotomization?


Short
Tall
150
160
170
180
190
200
height (cm)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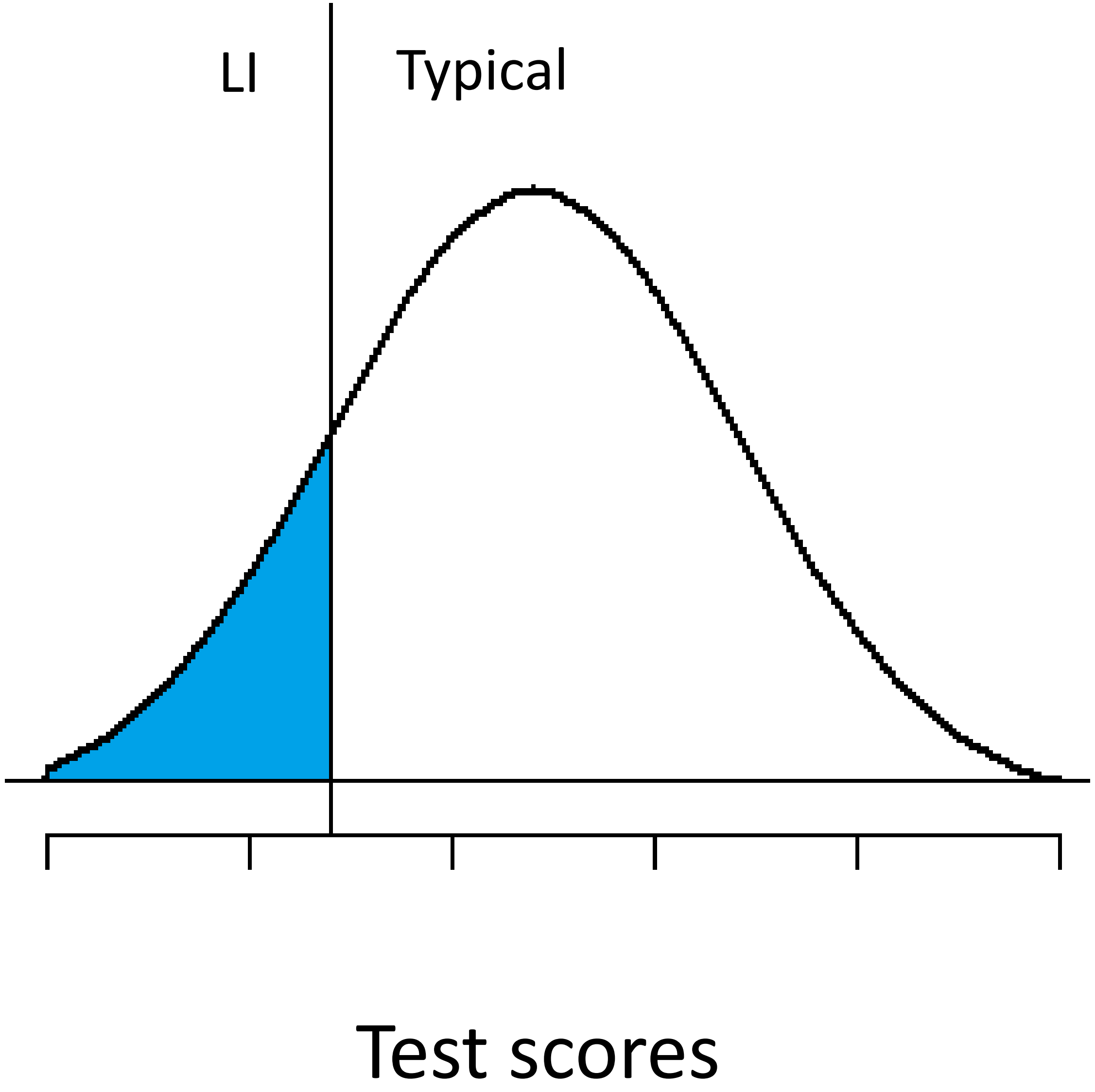
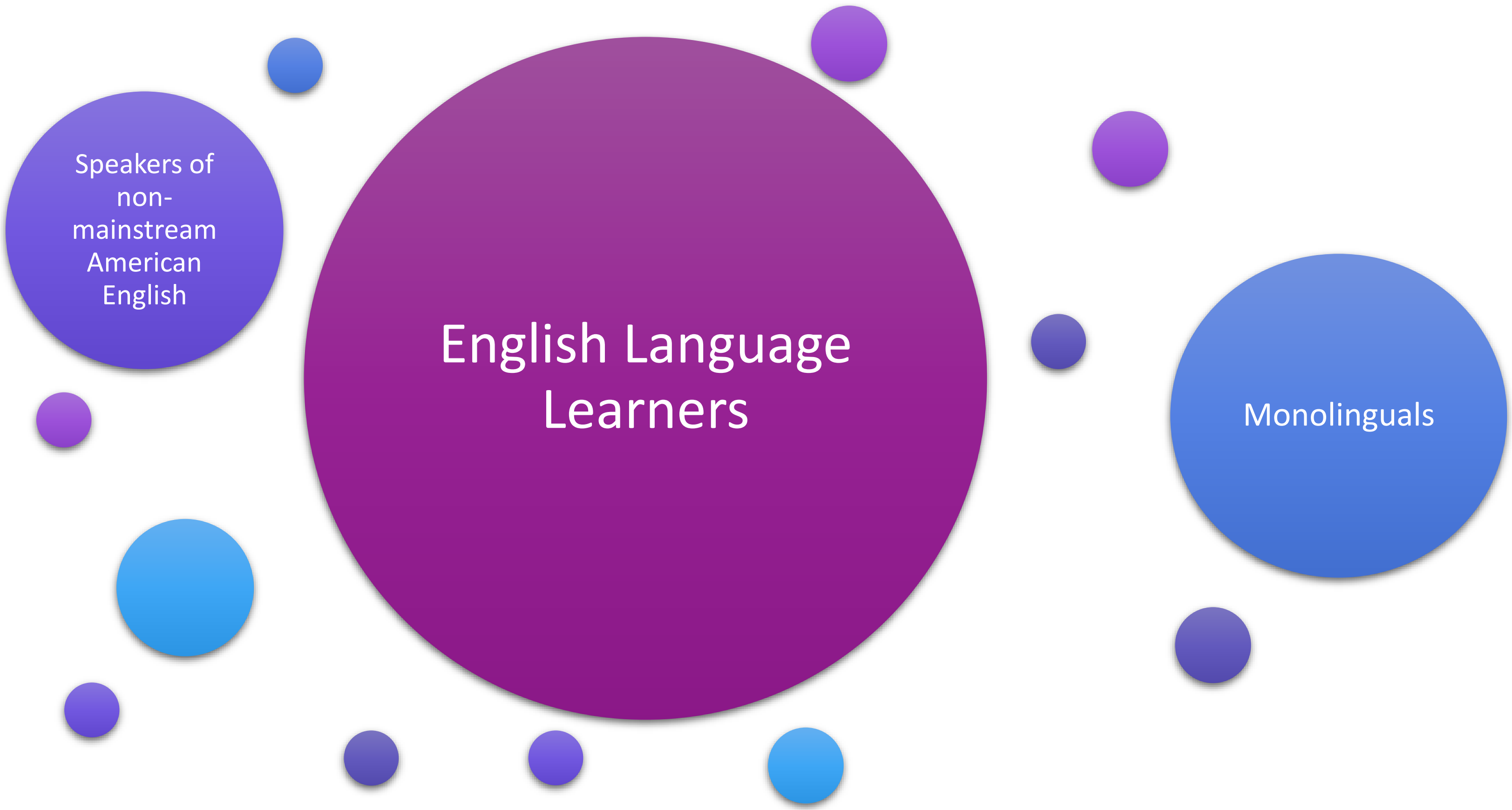
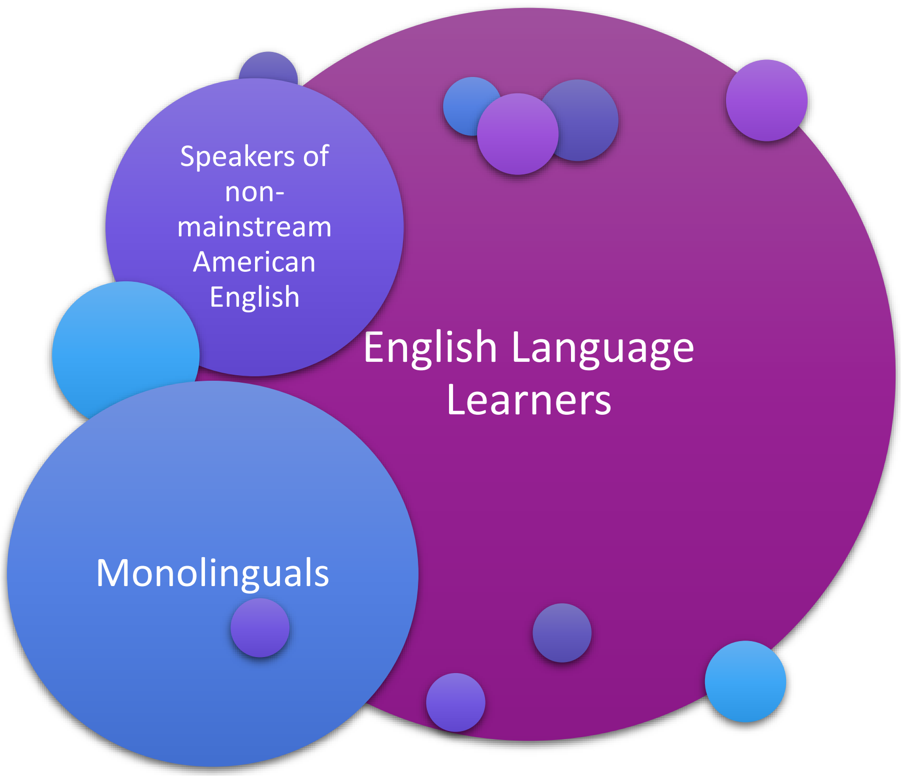

LI
Typical
Test scores



Avoiding Dichotomies



Avoiding Dichotomies

Dichotomization is Avoidable

Use continuous measures

Example: English proficiency instead of "ELL vs. Monolingual"

Continuum-based "grouping"

Native English speakers with only English input

Individuals with input in both English and another language

Non-English speakers with no English input

Dichotomization is Avoidable

Use continuous measures

Example: English proficiency instead of “ELL vs. Monolingual”

Dichotomization is Avoidable

Use continuous measures

Example: English proficiency instead of "ELL vs. Monolingual"

Reconsider the meaningfulness of the grouping

Is the grouping functionally important? Why are we grouping in research?

Dichotomization is Avoidable

Use continuous measures	Example: English proficiency instead of “ELL vs. Monolingual”
Reconsider the meaningfulness of the grouping	Is the grouping functionally important? Why are we grouping in research?
If a grouping is meaningful, focus on the functional difference rather than a cut score	Example: Instead of “LI vs. Typically-Developing”, consider “Receiving weekly intervention services vs. Not receiving extra educational services”

The Value of Variance

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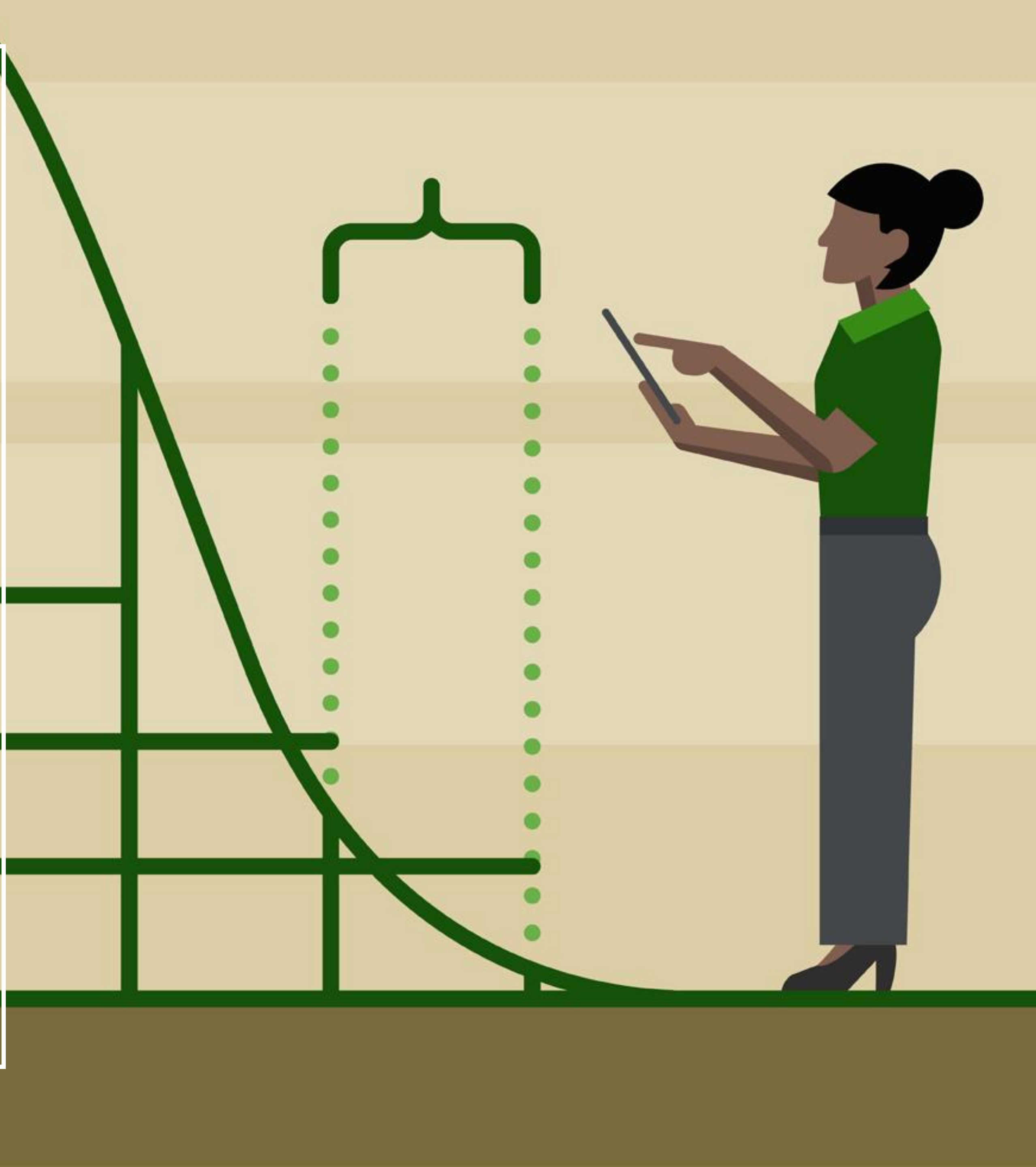
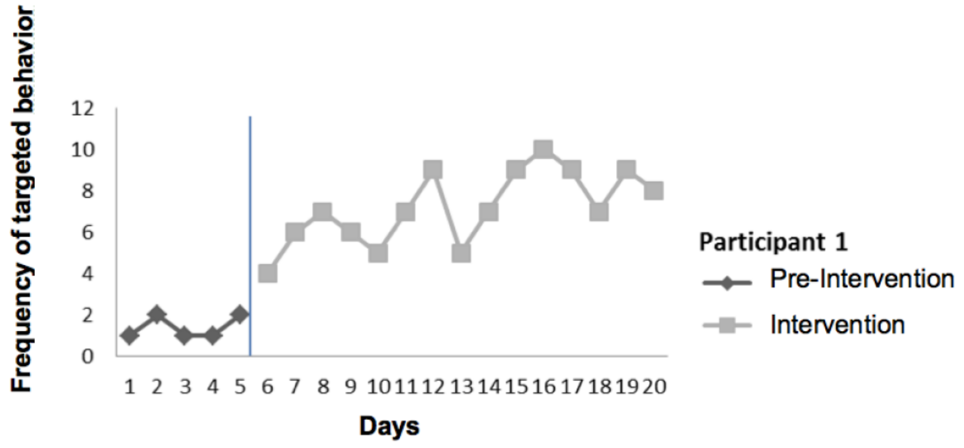
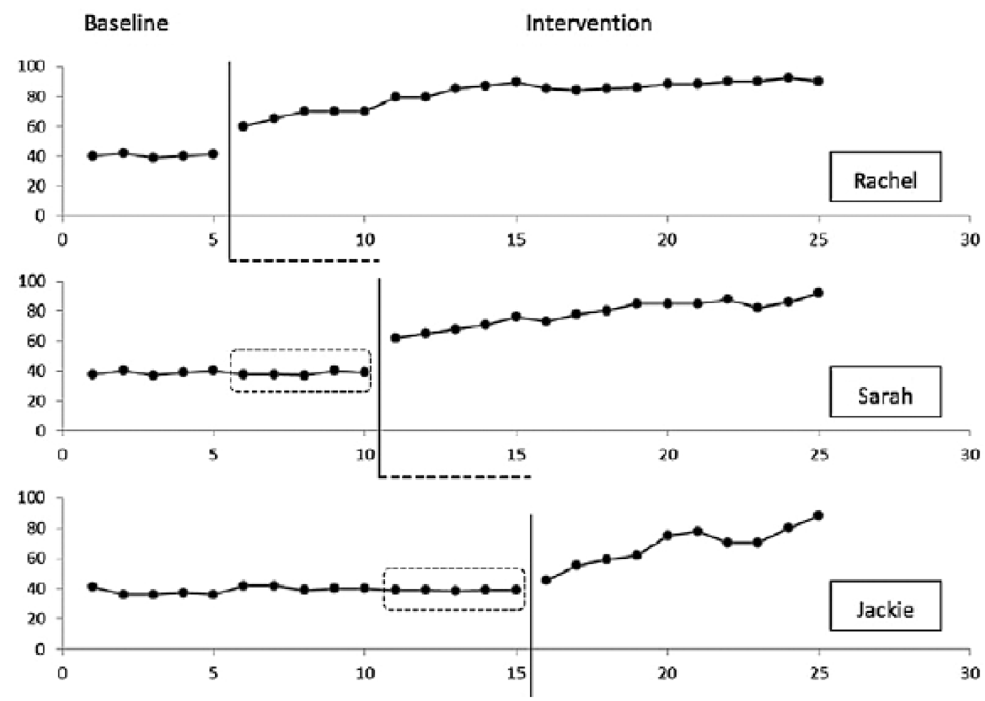


Visual Analysis in Single Case Research

Can be convincing and valid…
but is inherently subjective





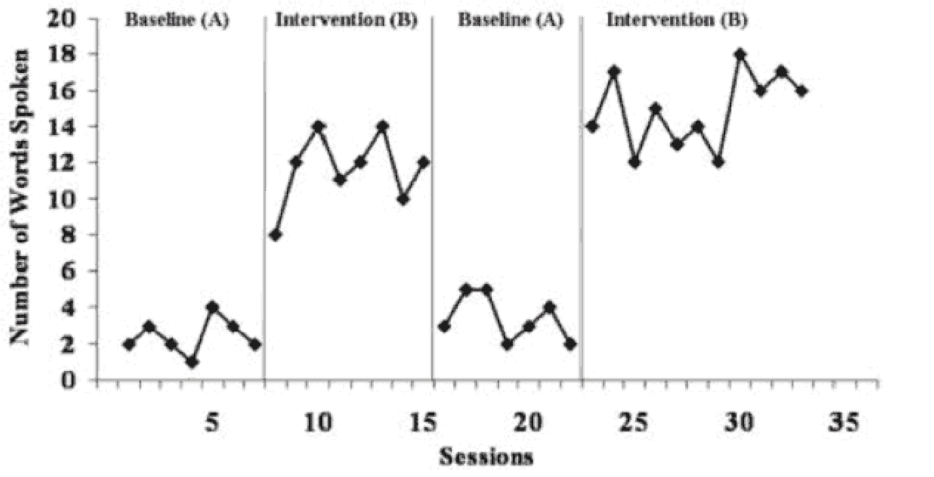


Figure 1. ABAB design: Hypothetical representation of child communication outcomes.

Single Case Research

Consider designing your single case study so that you can use hierarchical linear modeling (HLM)

- Allows for quantification of observed effects
- Allows for (some) examination of predictors

Single Case Research

More measurement time points = more power to detect overall effects

More participants = more power to detect predictors of outcomes

Augmenting Visual Analysis in Single-Case Research with Hierarchical Linear Modeling (Davis, Gagne, Fredrick, Alberto, Waugh, & Harrdorfer, 2013)

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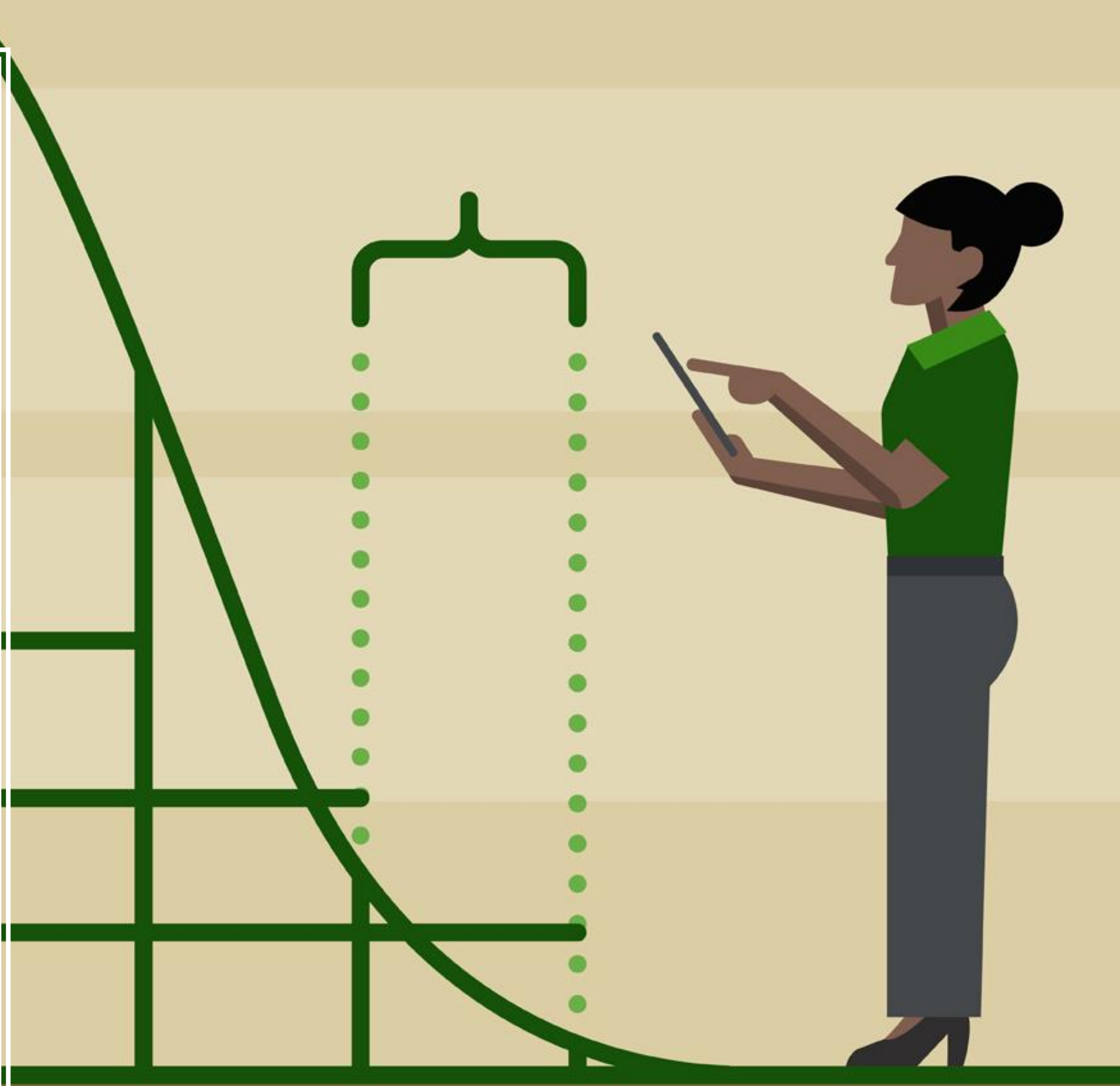

Planning in Advance for Statistics

Power	Power analyses to determine the sample size needed to answer your research questions
Talk	If planning to use a statistician, talk to him/her well in advance – an ounce of planning is worth a pound of cure
Design	Have your statistician involved in the design of the project
Discuss	Discuss data management early – what does he/she need to be sure that the planned analyses can be completed effectively?

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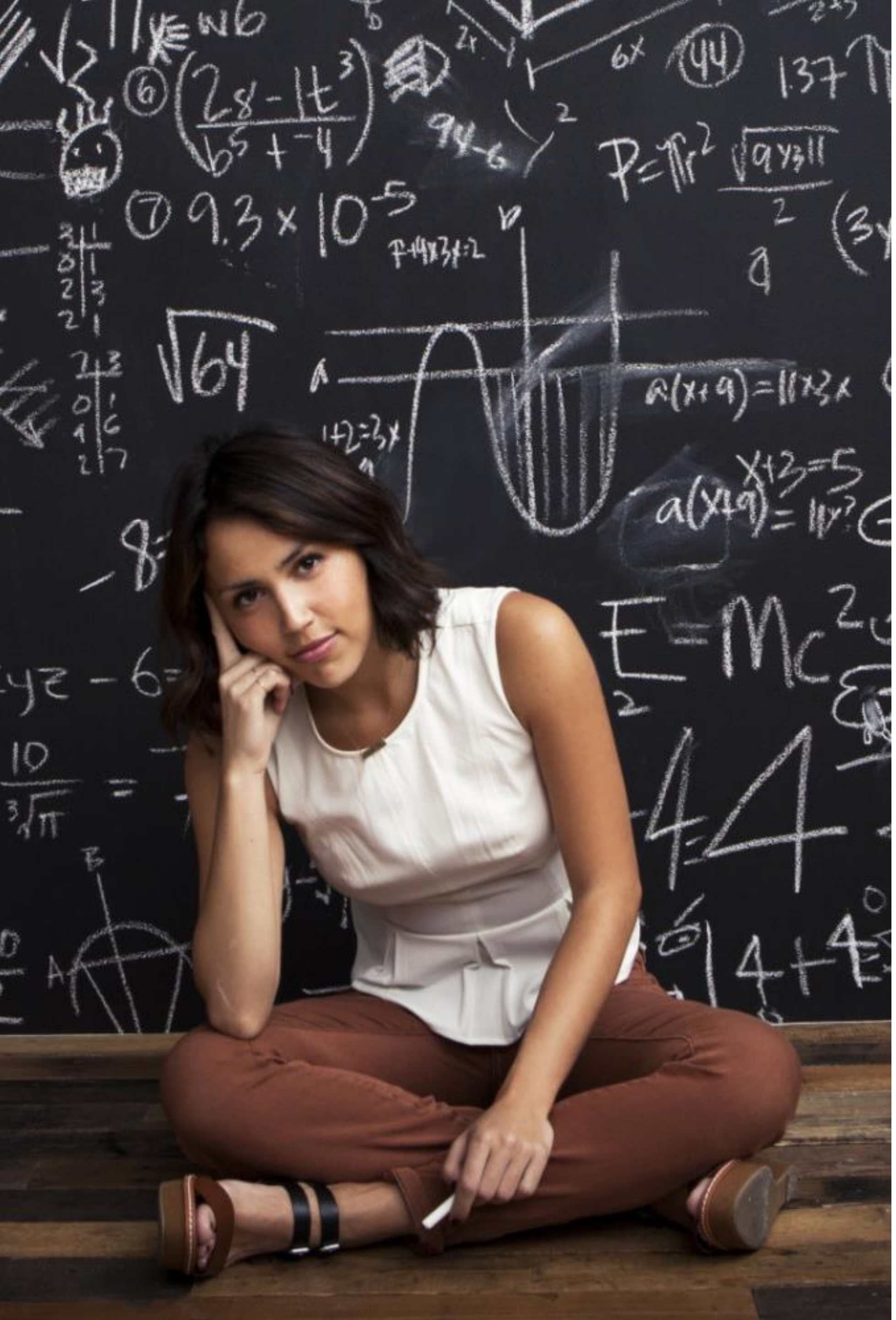

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