

Tips, tricks, and FAQs for getting started in longitudinal data analysis.

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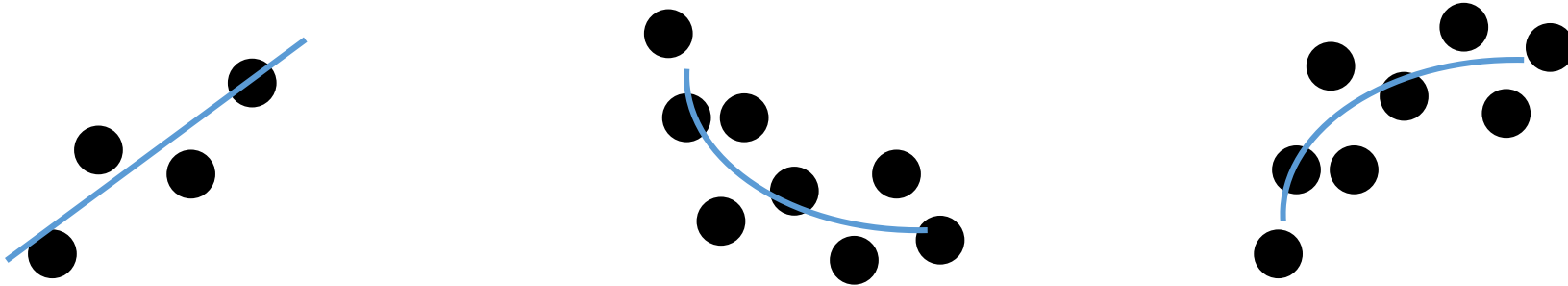
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1. Know your types of variables.

- **Static/ “Fixed”** variables are variables that keep the same value over the course of the study.
 - For most longitudinal studies, these are variable that vary between people but stay constant within a person (e.g., gender and age at start of study are example static variables).
 - Can be continuous or categorical.
- **Dynamic/ “Time Varying”** variables are variables that change value over the course of the study.
 - Our principle dynamic independent variable is Time (but this could be seconds, months, or years, depending on the resolution over your data).
 - Most of our dependent variables are also dynamic (i.e., we might have BBS, WMFT, or 10m WT scores at each time point).
 - Can be continuous or categorical.

2. How will you model time?



- Do most people tend to change linearly or non-linearly?
 - Is there a between-subjects variable associated with different change curves?
 - Exploratory data visualization is really helpful here and can inform subsequent model building.
- Remember that the more complicated your hypotheses about time, the more time-points you will need to collect.

3. What does zero mean in your model?

Continuous Variables

- Do you have an interpretable zero in your independent variables:
 - Age versus Onset days (Age = 0 doesn't make sense; Onset = 0 might).
- Have you mean-centered the variables in your model?
 - If all variables are mean-centered, you can interpret the effects of one variable "on average" across the other variables.
- Is there a separate value you want to center your variables on?
 - I.e., look at group differences at the end rather than beginning by making the terminal point the intercept.

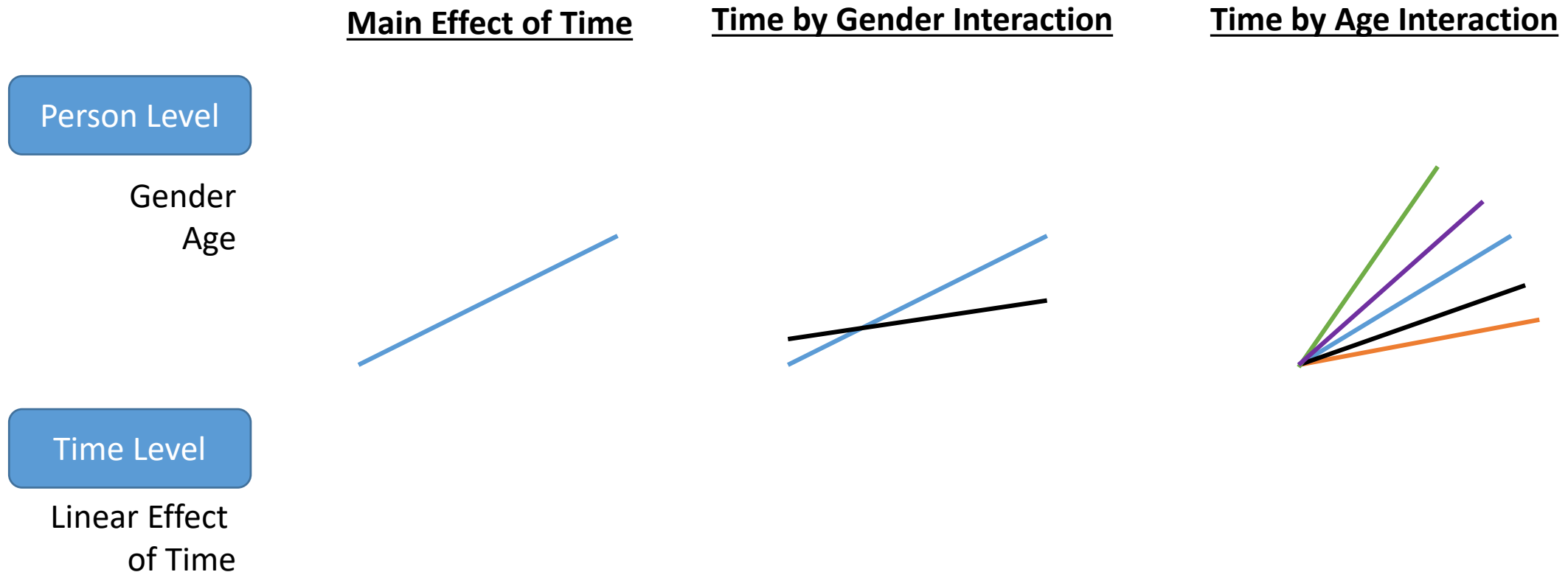
Categorical variables:

- Contrast coded versus dummy coded variables.
 - Contrast codes make zero the average, dummy codes make the reference group zero.

4. Levels of measurement

- Do you really have an interval level variable?
 - The errors that result from treating non-interval data as interval data actually get worse across time (e.g. FIM scores).
 - Especially anytime you break a scale into subscales!
 - Unequal differences in scale warp the shape of the time function.
- Look into Rasch Scaling as an approach to “intervalizing” ordinal data.
 - Pragmatically, check your residuals and the assumptions of the MLM.

5. What effects are you interested in?



- Often, we are interested in interactions between the person-level and the time-level, but we can also test main-effects and interactions within the person-level or within the time-level!

6. How do I compare between models?

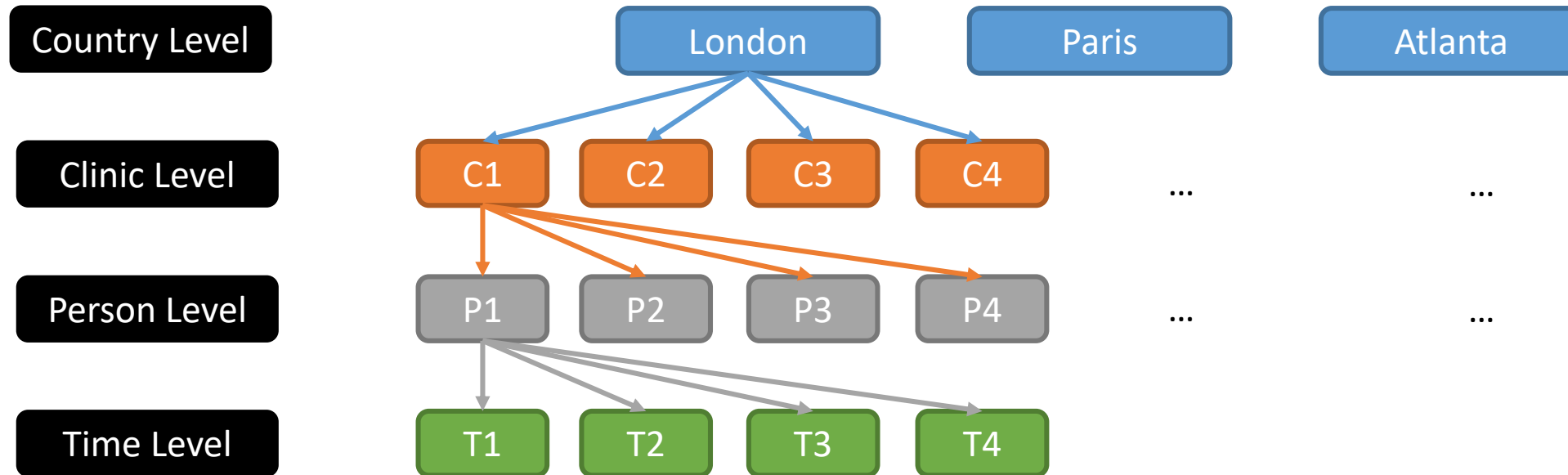
- Models can have different methods of estimation in order to fit their parameters:
 - ML – maximum likelihood estimation.
 - REML – restricted maximum likelihood estimation.
- Often we prefer ML to REML because it allows us to compare nested models using likelihood based methods like the change in deviance or the Akaike Information Criterion (AIC).
 - Deviance is a measure of the amount of error in a model, so lower deviance means a better model.
 - This can be tested statistically with the Wald Test of the change in deviance.
 - AIC is also a measure of error in a model, so lower AIC means a better model.
 - However, the AIC also introduces a penalty for the number of parameters in a model. This makes the AIC more conservative and helps prevent “over-fitting” of the model.

7. How do I statistically power a longitudinal study?

- Statistical power for multi-level models gets pretty complicated, so it is highly recommended that you talk to a statistical consultant. In preparation for that meeting, you'll want to be able to phrase your main narrative hypothesis as a statistical hypothesis like the following:
 - “I am interested in the main-effect of time.”
 - You will need to estimate how much you expect participants to change over time, estimate the average standard deviation at each time point, and the average correlation between time points.
 - “I am interested in the interaction of time and group.”
 - You will need to estimate all of the same information as above, but you will need to estimate it for each group.
- As a rule of thumb, increasing the number of ***time-points*** will improve power for effects at the time-level and person by time interactions.
 - Increasing the number of ***participants*** will improve power for effects at the person-level and person by time interactions.

8. What if I have multiple levels?

- Multi-level models can do that!
 - Let's say that you are running large international study...
 - Or combining data from lot's of different studies in secondary analysis...



9. What are Fixed-Effects and Random-Effects?

Remember the general concept of $DATA = MODEL + Error$.

This can be more elaborately written as:

$$y_{ij} = B_0 + U_{0j} + (B_1 + U_{1j}) * (TIME_{ij}) + \epsilon_{ij}$$

Thus, we have the following terms in our *DATA* (y_{ij} 's):

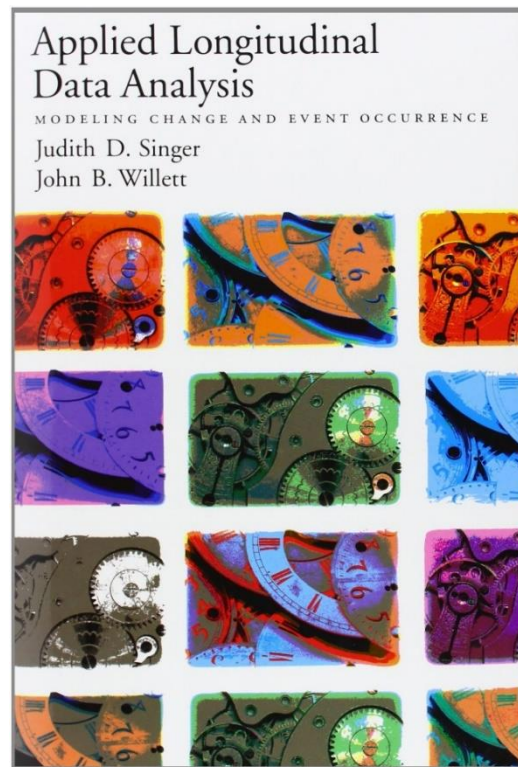
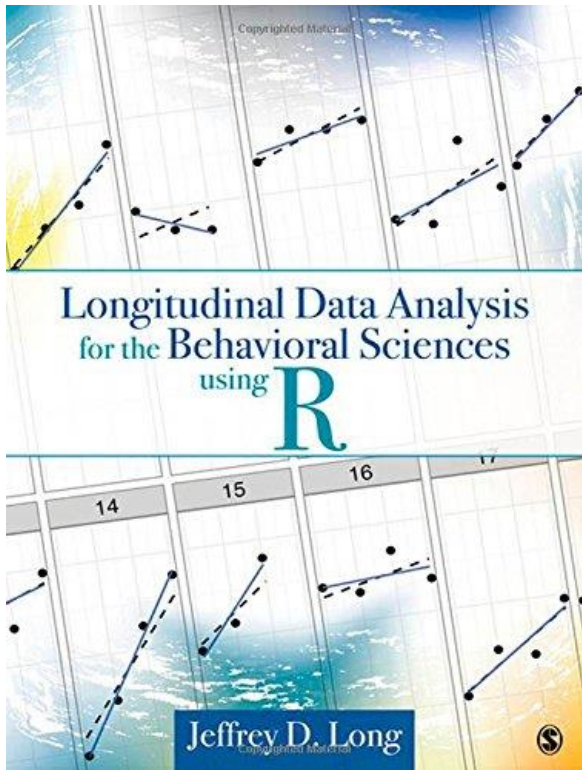
- The *MODEL* includes fixed effects and random effects.
- **Fixed-Effects** are the group-level B 's, these effects parallel the traditional main-effects and interactions that you have probably encountered in other statistical analyses.
- **Random-Effects** are the participant-level U_j 's that remove statistical dependency from our data. (This is bit of a simplification, but you can think of not including the appropriate random-effects like running a between-subjects ANOVA when you should be running a repeated-measures ANOVA.)
- The *ERRORS*, or more specifically *Random Errors* (ϵ_{ij} 's), are the difference between our *MODEL*'s predictions and the actual *DATA*.

10. Assumptions

- Normality
 - Does transforming the DV change the model?
 - Make it clear to readers that you tested transformed and raw DVs.
- Homoscedasticity
- Scale Invariance
 - Is there bias in the models predictions?
 - Explore methods for looking at measurement variance over time.
- Influential data points/sources
 - There are tools for checking Cook's Distances and VIFs in MLMs.
 - Influential data don't always show up in univariate plots/analyses.
 - See philosophical discussions about outliers and removing influential data points.
 - Run the model both ways and be transparent about what you did in your write-up.
- Floor/Ceiling Effects

11. How can I actually run my multi-level models?

- There are numerous texts to help and software packages to do it. They are all slightly different, but users need the same basic understanding of fixed-effects and random-effects to make sure models run correctly.



We will be using:



R and R Studio

- Packages:
 - lme4
 - ggplot
 - dplyr

But you can also use:



Most of what I will say has been said better in these resources!

12. Be up front about your limitations.

- Exploratory modelling.
 - You will test a lot of things you probably didn't plan on testing, but be transparent in the reporting of your analyses.
 - The dataset that generates a model/prediction cannot also be used to confirm that model/prediction.
- Are your results “robust” to the method of analysis?
 - A lot of issues about how you are modelling times, do you meet normality, or should exclude an influential data point can be addressed by running the model both ways.
 - Is the answer the same both time? Is a difference in the answer meaningful?