Cramming Sam's Tips for Chapter 20: Multilevel linear models

Multilevel models

- Multilevel models should be used to analyse data that have a hierarchical structure. For example, you might measure depression after psychotherapy. In your sample, patients will see different therapists within different clinics. This is a three-level hierarchy with depression scores from patients (level 1) nested within therapists (level 2) who are themselves nested within clinics (level 3).
- Hierarchical models are just like regression, except that you can allow parameters to vary (this is called a random effect). In ordinary regression, parameters generally are a fixed value estimated from the sample (a fixed effect).
- If we estimate a linear model within each context (e.g., the therapist or clinic) rather than the sample as a whole, then we can assume that the intercepts of these models vary (a random intercepts model), or that the slopes of these models differ (a random slopes model) or that both vary.
- We can compare different models by looking at the difference in the value of $-2LL$. Usually we would do this when we have changed only one parameter (added one new thing to the model).
- For any model we have to assume a covariance structure. For random intercepts models the default of variance components is fine, but when slopes are random an unstructured covariance structure is often assumed. When data are measured over time an autoregressive structure (AR1) is often assumed.

Multilevel models Output

- The *Information Criteria* table can be used to assess the overall fit of the model. The $-2LL$ can be tested for significance with *df* = the number of parameters being estimated. It is mainly used, though, to compare models that are the same in all but one parameter by testing the difference in $-2LL$ in the two models against *df* = 1 (if only one parameter has been changed). The AIC, AICC, CAIC and BIC can also be compared across models (but not tested for significance).
- The table of *Type III Tests of Fixed Effects* tells you whether your predictors significantly predict the outcome: look in the column labelled *Sig.* If the value is less than .05 then the

effect is significant.

- The table of *Estimates of Fixed Effects* gives us the regression coefficient for each effect and its confidence interval. The direction of these coefficients tells us whether the relationship between each predictor and the outcome is positive or negative.

- The table labelled *Estimates of Covariance Parameters* tells us about any random effects in the model. These values can tell us how much intercepts and slopes varied over our level 1 variable. The significance of these estimates should be treated cautiously. The exact labelling of these effects depends on which covariance structure you selected for the analysis.

Growth models

- Growth models are multilevel models in which changes in an outcome over time are modelled using potential growth patterns.

- These growth patterns can be linear, quadratic, cubic, logarithmic, exponential, or anything you like, really.

- The hierarchy in the data is that time points are nested within people (or other entities). As such, it's a way of analysing repeated-measures data that have a hierarchical structure.

- The *Information Criteria* table can be used to assess the overall fit of the model. The −2LL can be tested for significance with *df* = the number of parameters being estimated. It is mainly used, though, to compare models that are the same in all but one parameter by testing the difference in −2*LL* in the two models against *df* = 1 (if only one parameter has been changed). The AIC, AICC, CAIC and BIC can also be compared across models (but not tested for significance).

- The table of *Type III Tests of Fixed Effects* tells you whether the growth functions that you have entered into the model significantly predict the outcome: look in the column labelled *Sig.* If the value is less than .05 then the effect is significant.

- The table labelled *Estimates of Covariance Parameters* tells us about any random effects in the model. These values can tell us how much intercepts and slopes varied over our level 1 variable. The significance of these estimates should be treated cautiously. The exact labelling of these effects depends on which covariance structure you selected for the analysis.

- An autoregressive covariance structure, AR(1), is often assumed in time course data such as that in growth models.