

HLM

Hierarchical Linear Modeling

Lesson Three

Lesson Three Plan

- I. Review of I and II
- II Null Model
- III R-Squared in HLM
- IV Shrinkage and the Reliability of Estimates

The Model

$$Y_{ij} = \alpha_{0j} + \alpha_{1j}X_{1ij} + \alpha_{2j}X_{2ij} + \alpha_{3j}X_{3ij} + \epsilon_{ij} \quad \text{within}$$

$$\alpha_{0j} = \gamma_{00} + \gamma_{01}Z_{1j} + \gamma_{02}Z_{2j} + U_{0j}$$

$$\alpha_{1j} = \gamma_{10} + \gamma_{11}Z_{1j} + \gamma_{12}Z_{2j} + U_{1j} \quad \text{between}$$

$$\alpha_{2j} = \gamma_{20} + \gamma_{21}Z_{1j} + \gamma_{22}Z_{2j} + U_{2j}$$

$$\alpha_{3j} = \gamma_{30} + \gamma_{31}Z_{1j} + \gamma_{32}Z_{2j} + U_{3j}$$

Model Adequacy

First fit a model without any group-level (i.e. Z) variables:

	Effect Significant? (T-test)	Varies Significantly Across Groups (X^2 - test)	
a	No	No	Consider dropping from the model but consider its role in analysis
b	No	Yes	Retain as a random factor
c	Yes	No	Retain as a fixed factor
d	Yes	Yes	Retain as a random factor

In case b and d, you can then specify and test between-group models.

Null Model

The null model is useful at the outset to determine what proportion of the variance lies between groups.

$$Y_{ij} = \mu_{0j} + \epsilon_{ij} \quad (1)$$

$\epsilon_{ij} \sim \text{NID}(0, \sigma^2)$ within

$$\mu_{0j} = \mu_{00} + U_{0j} \quad (2)$$

$U_{0j} \sim \text{NID}(0, \sigma^2)$ between

Substituting (2) into (1) yields:

$$Y_{ij} = \mu_{00} + U_{0j} + \epsilon_{ij}$$

μ_{00} is the grand mean

U_{0j} is the group's deviation from the mean

ϵ_{ij} is the individual's deviation from the mean.

Notice that the variance of the outcome is:

$$\text{Var}(Y_{ij}) = \text{Var}(\text{💣}_{00} + U_{0j} + \text{📦}_{ij}) = \text{😊} + \text{👉}^2$$

This is equivalent to a one-way ANOVA model with random effects.

! produces point estimate and confidence interval for 💣_{00} .

! gives information about outcome variability at each level.

! allows you to calculate the intra-class correlation coefficient:

$$\text{👉} = \frac{\text{😊}}{\text{😊} + \text{👉}^2}$$

R-Squared

In OLS regression we can think of R-squared as the proportion of variance explained.

For example, if we started with a null model:

$$Y_i = \beta_0 + \varepsilon_i$$

Shrinkage and the Reliability of Estimates

see Raudenbush & Bryk (1986)

Within-Group Model:
$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{1ij} + \epsilon_{ij}$$
$$\epsilon_{ij} \sim N(0, \sigma^2)$$

we have j such equations, one for each group.

Between-Group Model: Assume no knowledge of group-level factors)

$$\beta_{0j} = \beta_{00}^* + U_{0j}$$
$$U_{0j} \sim N(0, \sigma_0^2)$$

σ_0^2 is the "true" parameter variance of β_{0j}

$$\beta_{1j} = \beta_{10}^* + U_{1j}$$
$$U_{1j} \sim N(0, \sigma_1^2)$$

- if we centred the data within schools we could have:

$$\beta_{1j} = \beta_{10} + U_{1j}$$

average
slope

$N(0, \sigma_1^2)$

T_1 is the “true” parameter variance of B_{1j}
 (i.e., variance of true outcome/SES slopes
 across schools)

- if we used OLS for each of the j within-group regressions, we would obtain "observed" slopes :

Observed = True + Sampling Error

$$\hat{\beta}_{1j} = \beta_{1j} + e_j$$

$N(0, V_j)$

where $V_j = \text{Variance}(\hat{\beta}_{1j} | \beta_{1j}) = \sigma^2 / \sum x^2$

- taking variances we get :

$$\begin{aligned} \text{Var}(\hat{\beta}_{0j}) &= \text{Var}(\beta_j) + \text{Var}(e_j) \\ &= \underbrace{\text{parameter}}_{\text{variance}} + \underbrace{V_j}_{\text{sampling variance}} \end{aligned}$$

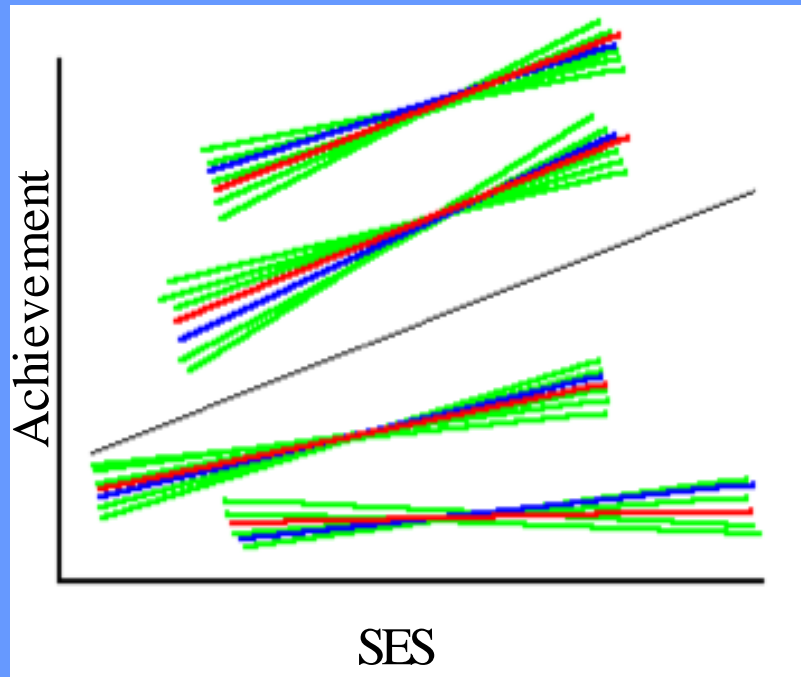
- Under Empirical Bayes :

$$\hat{\beta}_j^* = w_j \hat{\beta}_j + (1-w_j) \Phi_{10}^*$$

This is a weighted sum of the OLS slope and the mean slope for the population of schools

$$\text{where } \Phi_{10}^* = \frac{\sum w_j \beta_{1j}}{\sum w_j} \quad \text{and} \quad w_j = \frac{T}{T + V_j}$$

Like a classical test theory reliability



Φ_{10}

Alternate Slope

True slope ω_{1j}

[Their “true” variance is T]

Observed slope ω_{1j}

[Variance of observed slopes around their true slopes is V_j]

Empirical Bayes slopes

[A weighted average of the average slope and the average slope. \bullet_{10}^*]

The extent of “shrinkage” depends on the ratio $T/(T+V_j)$. When our within-group estimates are precise (large n_j and heterogeneous x), V_j is small, so the ratio $w_j = T/(T + V_j)$ approaches 1.0. Thus there is little shrinkage. But if V_j is large relative to T , w_j approaches 0. Then each $\hat{\mu}_{1j}$ is shrunk towards μ_{10} .