

EXTRA SLIDES

Model 2: Latent Regression LLTM + e

$$\text{logit}(\Pr(Y_{ip} = 1 | \theta_p)) = \theta_p - \delta_i \quad (1)$$

$$\delta_i = \sum_{k=0}^K \beta_k X_{ki} + \epsilon_i \quad \epsilon_i \sim N(0, \sigma_{\epsilon_i}^2) \quad (2)$$

$$\theta_p = \sum_{j=0}^J \vartheta_j Z_{pj} + \epsilon_p \quad \epsilon_p \sim N(0, \sigma_{\epsilon_p}^2) \quad (3)$$

Indices:

p = person

i = item

j = person covariate

k = item/text feature

→ Inclusion of ϵ_i in (2) relaxes the strict assumption of LLTM

→ However this model (cross classified, random effect model) takes a very long time to converge.

Model 3: Two-Stage Estimation of Latent Regression LLTM + e (Furr, 2017, a random-effects meta-regression model)

$$\text{logit}(\Pr(Y_{ip} = 1 | \theta_p)) = \theta_p - \delta_i \quad (1)$$

$$\delta_i = \sum_{k=0}^K \beta_k X_{ki} + u_i + \epsilon_i \quad (2)$$

$$u_i \sim N(0, \widehat{\text{var}}(\hat{\delta}_i))$$

$$\epsilon_i \sim N(0, \sigma_{\epsilon_i}^2)$$

Indices:

p = person

i = item

j = person covariate

k = item/text feature

u_i is residual related to uncertainty in the estimated item difficulty $\hat{\delta}_i$


u_i has known variance ($\widehat{\text{var}}(\hat{\delta}_i)$), which is the square of estimated std error of $\hat{\delta}_i$


$$\theta_p = \sum_{j=0}^J \vartheta_j Z_{pj} + \epsilon_p \quad \epsilon_p \sim N(0, \sigma_{\epsilon_p}^2) \quad (3)$$

Add interaction terms

→ Between the reader factor (vocabulary level) and the text- and item-predictors to explore the effect modification.

Level	Testlet 1	Testlet 2	Testlet 3	Testlet 4
1	<i>Blobfish</i>	<i>Frog</i>	<i>Sand Dollar</i>	<i>Sea Star</i>
2	<i>Bread</i>	<i>Corn</i>	<i>Gum</i>	<i>Rice</i>
3	<i>Cave Art</i>	<i>Dance</i>	<i>Rain Sticks</i>	<i>Singing Bowls</i>
4	<i>Dragon Boats</i>	<i>Kite Fighting</i>	<i>Stick Juggling</i>	<i>Tribal Masks</i>
5	<i>History of Sports</i>	<i>Injury in Sports</i>	<i>Science in Sports</i>	<i>Technology in Sports</i>
6	<i>Black Holes</i>	<i>Comets</i>	<i>Solar Flares</i>	<i>Space Junk</i>
7	<i>High-Speed Boats</i>	<i>Mars Rovers</i>	<i>Self-Driving Cars</i>	<i>Unmanned Planes</i>
8	<i>Dream Catchers</i>	<i>Fish Rubbing</i>	<i>Paper Cutting</i>	<i>Shadow Puppets</i>
9	<i>Fracking</i>	<i>Red Tide</i>	<i>Sailing Stones</i>	<i>Wildlife Crossings</i>
10	<i>Busby Berkeley</i>	<i>Duke Ellington</i>	<i>John Williams</i>	<i>Martha Graham</i>
11	<i>Bonsai</i>	<i>Dadaism</i>	<i>Kabuki</i>	<i>Mehndi</i>
12	<i>Coral Reefs</i>	<i>Deserts</i>	<i>Grasslands</i>	<i>Tundras</i>

 = link testlets (response data from 1st thru 5th testlets included)

 = non-link testlets (response data only from the 5th testlets included)

Each student took 5 testlets in a testing session

testlet administration order

Testlet 1

Testlet 2

Testlet 3

Testlet 4

Testlet 5

chosen based on student's vocab level

given adaptively based on performance on the previous testlet

randomly chosen from the test bank

Goal: make the best use of this segment of item responses

240 items given in 1st thru 4th testlets

240 items given in the 5th testlet

concurrent calibration with the Rasch model

6 link testlets were selected which had items **with least discrepancies in difficulty** between 1st-4th testlets vs. the 5th testlet

Model Comparisons

Pseudo-R² / Fit Index (Embretson, 1983)

where:

lnL= log-likelihood

$$\Delta^2 = \frac{\ln L_0 - \ln L_m}{\ln L_0 - \ln L_s}$$

indices:

0 = null model (constant difficulty for all items)

m = model to be evaluated (difficulty of item features are estimated)

s = saturated model (difficulty of all items are estimated)

AIC (Akaike, 1974) and BIC (Schwarz, 1978) were also used.