

# Item Parameter Interpretation and Model Fit

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# Talk Overview

- Here we evaluate the fit of a model
- Item level
  - Item parameter interpretation
- Test level
  - Goodness of fit of a DCM to a test

# **ITEM PARAMETER INTERPRETATION**

# Log-linear Cognitive Diagnosis Model

- The LCDM specifies the probability of a correct response as a function of a set of attributes and a Q-matrix:

$$P(X_{ij} = 1 | \mathbf{a}_i) = \frac{e^{\lambda_j^T \mathbf{h}(\mathbf{q}_j, \mathbf{a}_i)}}{1 + e^{\lambda_j^T \mathbf{h}(\mathbf{q}_j, \mathbf{a}_i)}}$$

- For an item, the LCDM has ANOVA-like parameters:

$$\lambda_j^T \mathbf{h}(\mathbf{q}_j, \mathbf{a}_i) = \lambda_{j,0} + \sum_{u=1}^K \lambda_{j,1,(u)} (\alpha_u q_{ju}) + \sum_{u=1}^K \sum_{v>u} \lambda_{j,2,(u,v)} (\alpha_{iu} \alpha_{iv} q_{ju} q_{jv}) + \dots$$

The diagram illustrates the ANOVA-like parameters of the LCDM. The equation is shown with red circles highlighting the terms  $\lambda_{j,0}$ ,  $\lambda_{j,1,(u)}$ ,  $\lambda_{j,2,(u,v)}$ , and the ellipsis. Red arrows point from boxes below to these terms:

- Intercepts** points to  $\lambda_{j,0}$ .
- Main Effects** points to  $\lambda_{j,1,(u)}$ .
- Two-Way Interactions** points to  $\lambda_{j,2,(u,v)}$ .
- Higher Interactions** points to the ellipsis.

# Interpreting LCDM Item Parameters

- Because of the multiple types of item parameters in the LCDM, interpretation of each varies
  - Follows a ANOVA/linear modeling approach
  - Intercepts
  - Main effects (when interactions aren't present)
  - Interactions (when present)
    - Then main effects

# Example Item

- To demonstrate parameter interpretation, we include Mplus output from an estimated example item
  - Measured two attributes (of three in Q-matrix)

## New/Additional Parameters

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
L6_0	-2.537	0.176	-14.385	0.000
L6_12	2.102	0.226	9.310	0.000
L6_13	2.151	0.218	9.851	0.000
L6_223	1.110	0.376	2.947	0.003

# Reading Mplus Output

## New/Additional Parameters

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
L6_0	-2.537	0.176	-14.385	0.000
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- L[i]\_[e][a1,...]
  - LCDM parameter
    - i – item number
    - e – type of effect (intercept=0, main effect = 1, two-way interaction = 2, ...)
    - a1,... - list of attributes to which effect applies

# Reading Mplus Output

## New/Additional Parameters

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- Estimate – LCDM parameter estimate
- S.E. – (Asymptotic) standard error of the estimate
- Est./S.E. – Test statistic for testing null hypothesis parameter is zero
- P-value – Approximate p-value for interaction parameters
  - NOT main effects



# LCDM Intercepts

- Estimated Intercept: -2.537 (0.176)
- Indicates the log-odds of a correct response for a non-master of all attributes
  - Here, non-masters have a very low probability of a correct response:  $\exp(-2.537)/1+\exp(-2.537) = 0.07$
- Hypothesis test is not important
  - Tests whether non-masters have a probability of a correct response of 0.5
- Problematic when very high
  - Difficult to identify other parameters

# Higher Order Model Parameters

- Interpretation of main effects and interactions proceeds sequentially:
- If interactions are present:
  - Examine highest level of interaction
    - If significantly different from zero, leave in model
    - If not, term can be omitted
- If interactions are not present:
  - Examine how far main effect is from zero

# Examining Interaction Parameters

- 2-way interaction parameter: 1.110 (0.376)
- P-value for parameter was 0.002
  - Indicates parameter is significantly different from zero
  - Candidate to leave in model
- Value indicates that there is an over-additive effect of mastering both attributes
  - Like a bonus for mastery of both attributes

# Interpreting Main Effects

- When significant interactions are present, main effects cannot be easily interpreted
  - Need to know *combination* of attributes mastered to fully describe item response function
- Main effects are still increase in log-odds of a correct response for mastery of an attribute
  - Just difficult to parse effect out of context

# Other Main Effect Concerns

- Because of lower bound, main effect hypothesis tests from Mplus are invalid near zero
  - So are model standard errors
- For items with one attribute:
  - Must rely on goodness of fit to determine if attribute is influential or sufficient for item fit

# General Modeling Tips

- High-level interactions are difficult to estimate in most samples
  - More than 2-way interactions may not be possible
- Modeling strategy:
  - Try all interactions
    - If model does not converge, limit to only 2-way interactions
  - Remove non-significant interactions from model
  - If all interactions and main effects for an attribute are close to zero:
    - Entry for attribute in Q-matrix can be removed
  - Double check with AIC/BIC as hypothesis test is approximate

# **ASSESSMENT OF MODEL FIT**

# Assessing Model Fit

- There is no one best way to assess fit in DCMs
- Techniques typically used can put into several general categories:
  - Absolute fit
    - Model based hypothesis tests
    - Entropy
  - Relative fit
    - Information criteria
  - Item fit



# Model Chi-Squared test

- For small numbers of items (10-15), the traditional Chi-Squared test of model fit can be used.
  - Test is invalid for too many items – sparse data
- Mplus gives this automatically
  - Omits when data are sparse

Chi-Square Test of Model Fit for the Binary  
and Ordered Categorical (Ordinal) Outcomes

## Pearson Chi-Square

Value	9.459
Degrees of Freedom	6
P-Value	0.1494

## Likelihood Ratio Chi-Square

Value	8.966
Degrees of Freedom	6
P-Value	0.1755

# (Relative) Entropy

- The entropy of a model is a measure of classification uncertainty.
  - It is an absolute fit statistic
- Mplus reports relative entropy
  - Value of 1.00 means all examinees classified with complete certainty (good fit)
  - Value of 0.00 means all examinees classified with equal probabilities for all classes (poor fit)

# Model Comparison: Information Criteria

- Used when comparing between two models, i.e.:
  - Two DCMs (LCDM v. DINA)
  - Two Q-matrices (4 attribute v. 5 attribute)
  - Two different models (IRT v. DCM)
- Mplus reports:
  - AIC
  - BIC
  - Sample size adjusted BIC
- All can be used
  - Smallest value is best

# Mplus Model Fit Output

## TESTS OF MODEL FIT

Loglikelihood

H0 Value	-331.764
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## Information Criteria

Number of Free Parameters	9
Akaike (AIC)	681.527
Bayesian (BIC)	708.130
Sample-Size Adjusted BIC	679.653
(n* = (n + 2) / 24)	
Entropy	0.754

# Item Fit Statistics

- The TECH10 option reports a degree of misfit for each
  - Item individually (Univariate)
  - Pair of two items (Bivariate)
- Uses Chi-squared test for misfit
  - Values for each item are distributed as Chi-square with 1 df (for binary items)
- Misfitting items can be investigated
  - Q-matrix can be changed
  - Items can be removed

# Univariate Fit

## UNIVARIATE MODEL FIT INFORMATION

Variable	Estimated Probabilities		
	H1	H0	Standard Residual
U1			
Category 1	0.472	0.472	0.000
Category 2	0.528	0.528	0.000
U2			
Category 1	0.514	0.514	0.000
Category 2	0.486	0.486	0.000
U3			
Category 1	0.739	0.739	0.000
Category 2	0.261	0.261	0.000
U4			
Category 1	0.563	0.563	0.000
Category 2	0.437	0.437	0.000

# Bivariate Fit

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## BIVARIATE MODEL FIT INFORMATION

Variable	Variable	Estimated Probabilities		Standardized Residual (z-score)
		H1	H0	
X9	X13			
Category 1	Category 1	0.048	0.038	2.722
Category 1	Category 2	0.107	0.116	-1.625
Category 2	Category 1	0.141	0.150	-1.458
Category 2	Category 2	0.705	0.695	1.134
Bivariate Pearson Chi-Square				11.659
Bivariate Log-Likelihood Chi-Square				11.228

## **CONCLUDING REMARKS**



# Concluding Remarks

- In this section, we discussed
  - Parameter interpretation
  - Modeling strategy for LCDM estimation
  - Model fit and comparison assessment
- More details contained in forthcoming book:
  - Diagnostic Measurement: Theory, Methods, and Applications (Rupp, Templin, & Henson, 2010)