Structural Models: Examining the Distribution of Attributes in Diagnostic Classification Models

Session 4

Session Overview

- Session 4 will provide an understanding of structural models used in DCMs
  - What they are: estimates of how attributes are distributed in a sample of examinees
  - How to summarize them: by attribute (marginal probabilities) and by attribute pairs (correlations)
  - Differing types of structural models
    - Mplus: log-linear structural models
    - Other methods not readily available in commercial software

Notation Used Throughout Session

- **Attributes**: $a = 1,\ldots, A$
- **Respondents**: $r = 1,\ldots,R$
- **Attribute Profiles**: $\boldsymbol{\alpha}_r = [\alpha_{r1}, \alpha_{r2},\ldots, \alpha_{rA}]$
  - α_{ra} is 0 or 1
- **Latent Classes**: $c = 1,\ldots,C$
  - We have $C = 2^A$ latent classes – one for each possible attribute profile
- **Items**: $i = 1,\ldots,I$
  - Restricted to dichotomous item responses (X_{ri} is 0 or 1)
- **Q-matrix**: Elements q_{ia} for an item i and attribute a
  - q_{ia} is 0 or 1

Session 4: Diagnostic Classification Structural Models

STRUCTURAL MODELS

DCM Structural Models

- Throughout the workshop, attribute profile base-rates have been mentioned as being influential in DCMs
  - Part of respondent diagnoses: the attribute “base rates”
  - Describes distribution of attribute profiles in a sample
    - Proportion of masters for any given attribute
    - Correlation of attributes

- The base-rates represent the probability any respondent has a given attribute profile

- For a test measuring *A* attributes, 2^A profiles are possible
  - The structural model provides the probability for each profile

DCMs are Constrained Latent Class Models

- Previously we’ve learned how different DCMs provide different parameterizations of the measurement component of the model
  - The LCDM – and which attributes are specified in the q-matrix
- In this session we’ll learn about the parameterization of the structural component of DCMs
  - Choice of structural model not dependent on the measurement component

Observed Data: Probability of observing examinee *r*’s vector of item responses to all *I* items

Measurement Component: Product of Conditional Item Response Probabilities (Item Responses are Independent)

$$P(\mathbf{X}_r = \mathbf{x}_r) = \sum_{c=1}^{C} \nu_c \prod_{i=1}^{I} \pi_{ic}^{x_{ir}} (1 - \pi_{ic})^{x_{ir}}$$

Structural component: Proportion of examinees in each class

DCM Structural Models – Defined

- The parameter for the structural model is ν_c
- Each attribute profile $\boldsymbol{\alpha}_c$ has one
- ν_c is the base-rate probability of attribute profile *c*:
$$\nu_c = P(\boldsymbol{\alpha}_c)$$
- The ECPE estimates of ν_c are shown to the right

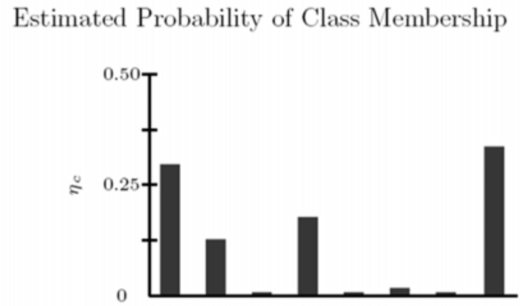
c	ν_c	$\boldsymbol{\alpha}_1$	$\boldsymbol{\alpha}_2$	$\boldsymbol{\alpha}_3$
1	0.30	0	0	0
2	0.13	0	0	1
3	0.01	0	1	0
4	0.18	0	1	1
5	0.01	1	0	0
6	0.02	1	0	1
7	0.01	1	1	0
8	0.34	1	1	1

Interpreting the Structural Model

- Because there are numerous ν_c parameters, interpretation is difficult
  - Useful for detecting attribute hierarchies
- Often, the ν_c parameters are re-expressed as:
  - The marginal probability an attribute is mastered in the population
  - The correlation between any two attributes
- Both can be computed using a frequency analysis weighted by ν_c

Attribute Pattern Probabilities

- Base-rate pattern of profiles mastered in sample indicates an attribute hierarchy
  - Lexical
  - Cohesive
  - Morphosyntatic
- Suggests information about second-language acquisition



Morphosyntactic					✓	✓	✓	✓
Cohesive			✓	✓			✓	✓
Lexical		✓		✓		✓		✓
Profile c	1	2	3	4	5	6	7	8
$\hat{\eta}_c$	0.30	0.13	0.01	0.18	0.01	0.02	0.01	0.34

SAS Structural Model Summary

- SAS can be used to compute summaries of the structural model parameters

```
DATA structural;
INPUT pattern eta alpha1 alpha2 alpha3;
DATALINES;
1 0.30074 0 0 0
2 0.12899 0 0 1
3 0.01192 0 1 0
4 0.17507 0 1 1
5 0.00874 1 0 0
6 0.01815 1 0 1
7 0.01079 1 1 0
8 0.34561 1 1 1
; RUN;

PROC FREQ DATA=structural;
WEIGHT eta;
TABLE alpha1-alpha3;
TABLE alpha1*alpha2 alpha1*alpha3 alpha2*alpha3/PLCORR;
RUN;

```

SAS Structural Model Summary

- For each attribute, marginally:

Proportion of Masters

The FREQ Procedure

alpha1	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	0.61672	61.67	0.61672	61.67
1	0.38327	38.33	0.99999	100.00

alpha2	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	0.45662	45.66	0.45662	45.66
1	0.54337	54.34	0.99999	100.00

alpha3	Frequency	Percent	Cumulative Frequency	Cumulative Percent
0	0.33218	33.22	0.33218	33.22
1	0.66781	66.78	0.99999	100.00

Marginal Attribute Summary

- You can also compute these from the table use a weighted sum
- Example: $P(\alpha_1) = .30(0) + .13(0) + .01(0) + .18(0) + .01(1) + .02(1) + .02(1) + .34(1) = .39$

c	ν_c	α_1	α_2	α_3
1	0.30	0	0	0
2	0.13	0	0	1
3	0.01	0	1	0
4	0.18	0	1	1
5	0.01	1	0	0
6	0.02	1	0	1
7	0.01	1	1	0
8	0.34	1	1	1

Proportion of Masters

- You can also compute these from the table use a weighted sum
- Example: $P(\alpha_1) = .30(0) + .13(0) + .01(0) + .18(0) + .01(1) + .02(1) + .02(1) + .34(1) = .39$

SAS Structural Model Summary

- For each pair of attributes:

Tetrachoric Correlation

```
alpha1     alpha2

Frequency|
Percent  |
Row Pct  |
Col Pct  |       0|       1|  Total
---------+--------+--------+
       0 | 0.4297 |  0.187 | 0.6167
         |  42.97 |  18.70 |  61.67
         |  69.68 |  30.32 |
         |  94.11 |  34.41 |
---------+--------+--------+
       1 | 0.0269 | 0.3564 | 0.3833
         |   2.69 |  35.64 |  38.33
         |   7.02 |  92.98 |
         |   5.89 |  65.59 |
---------+--------+--------+
Total     0.45662   0.54339  1.00001
            45.66     54.34   100.00

     Statistics for Table of alpha1 by alpha2

Statistic                          Value       ASE
---------------------------------------------------
Gamma                             0.9364    0.4250
Kendall's Tau-b                   0.6116    0.7014
Stuart's Tau-c                    0.5925    0.7344

Somers' D C|R                     0.6266    0.7161
Somers' D R|C                     0.5970    0.7326

Pearson Correlation               0.6116    0.7014
Spearman Correlation              0.6116    0.7014
Tetrachoric Correlation           0.8619    0.6355
```


Attribute Summary

- For the ECPE data, we have the following summary of attribute summary information

Attribute	Prop. Masters		Tetrachoric Correlation		
1. Morphosyntatic	0.383				
2. Cohesive	0.543		0.862		
3. Lexical	0.668		0.774	0.904	

- Such information is helpful in determining nature of attributes in a population of interest
  - Analogous to information about latent variables in CFA/MIRT

Differing Structural Models

- The structural model of a DCM has the potential to have an overwhelming number of parameters
  - For A attributes, total estimated: 2^A-1
    - All must sum to 1
    - ***Saturated model***
- Multiple structural models exist
  - All reduce the number of parameters
  - All use categorical data analysis techniques to model ν_c
- Analogous to latent variable covariance structure in structural equation modeling
  - Distribution of attributes is categorical, not continuous
  - Can help to determine nature of attribute relationships

Types of Structural Models

- **Log-linear model**
  - Models the natural logarithm of ν_c by the attributes in each profile
  - Allows for varying levels of complexity
    - Most: Saturated Model – full set of parameters
    - Least: Independent Attributes Model – no parameters
  - Implemented in Mplus and main focus of discussion today
- **Tetrachoric correlation model**
  - Provides an item factor model for latent attributes
  - Uses only bivariate information for pairs of attributes
  - Allows for covariance structures to be estimated
  - Not available in any software packages (see Templin & Henson, 2006)
- **Hierarchical factors model**
  - Special case of tetrachoric correlation model (see de la Torre & Douglas, 2004)
- **Mixture models**
  - Henson and Templin (2005): used to evaluate types of pathological gamblers
  - Also given by von Davier (2008)

LOG-LINEAR STRUCTURAL MODELS

The Logic Behind Log-Linear Models

- Log-linear models take the set of probabilities from the structural model and re-express them on the log scale

$$\mu_c = \log \nu_c$$

- Re-expression on the log scale is convenient as these terms can now be modeled (predicted) by other features in the model
  - The attributes themselves
  - Covariates (if any)
- Because of the re-expression, redundant terms can be removed from the model
  - Simplifying estimation, improving parsimony
- In a structural model, there are 2^A probabilities…but they all add up to 1.0
  - Therefore there can only be at most $2^A - 1$ log-linear model parameters

Log-Linear Structural Models

- The log-linear structural model is the easiest to implement
  - Due to its availability in Mplus (called a latent variable mean)

c	ν_c	μ_c	α_1	α_2	α_3
1	0.30	-1.2	0	0	0
2	0.13	-2.0	0	0	1
3	0.01	-4.6	0	1	0
4	0.18	-1.7	0	1	1
5	0.01	-4.6	1	0	0
6	0.02	-3.9	1	0	1
7	0.01	-4.6	1	1	0
8	0.34	-1.1	1	1	1

- μ_c is the natural logarithm of ν_c:

$$\mu_c = \log \nu_c$$

- We can convert from μ_c back to probabilities:

$$\nu_c = \frac{\exp(\mu_c)}{\sum_{i=1}^{2^A} \exp(\mu_i)}$$

Log-Linear Model Set Up

- It is important to remember that the structural model is a re-expression of the probability of any examinee having a given attribute pattern
  - The "saturated" log-linear model has as many parameters as possible (2^A – 1 for a test measuring *A* attributes)
- In our example, we have 3 attributes (8 probabilities, 7 of which must be estimated)
  - Mplus fixes the value of the last class to zero
- Our parameterization (and the Mplus implementation) will reflect this constraint
  - We will therefore omit what we will learn to be an intercept

Log-Linear Structural Model Notation

- Like the LCDM, the log-linear structural model parameters have several subscripts:

$$\gamma_{\boxed{e,}\boxed{(a_1,\dots)}}$$

- Subscript #1 – *e*: the level of the effect
  - 0 would be the intercept – but we won't have one
  - 1 is the main effect
  - 2 is the two-way interaction
  - 3 is the three-way interaction
- Subscript #2 – (a_1,…): the attributes the effect applies to
  - Same number of attributes listed as number in Subscript #2

Log-Linear Model for μ_c

- The structural model then uses an ANOVA-like model to predict the value of μ_c as a function of the attributes that are defined in attribute profile *c*
  - Shown for 3-attribute model (used in the ECPE)
  - Includes main effects, 2-way, and 3-way interactions
  - *All parameters must sum to zero for identifiability*
- The general model is given by:

Main effects

$$\mu_c = \gamma_{1,(1)}(\alpha_{c1}) + \gamma_{1,(2)}(\alpha_{c2}) + \gamma_{1,(3)}(\alpha_{c3})$$
$$+\gamma_{2,(1,2)}(\alpha_{c1})(\alpha_{c2}) + \gamma_{2,(1,3)}(\alpha_{c1})(\alpha_{c3}) + \gamma_{2,(2,3)}(\alpha_{c2})(\alpha_{c3})$$
$$+\gamma_{3,(1,2,3)}(\alpha_{c1})(\alpha_{c2})(\alpha_{c3})$$

2-way and 3-way interactions

Log-Linear Model Explained

- Because not all attribute profiles include all attributes, only some terms get used to predict each value of μ_c

- For attribute profile 1: $\boldsymbol{\alpha}_1 = [\alpha_{11} = 0; \alpha_{12} = 0; \alpha_{13} = 0]$:

$$\mu_1 = \gamma_{1,(1)}(0) + \gamma_{1,(2)}(0) + \gamma_{1,(3)}(0)$$
$$+\gamma_{2,(1,2)}(0)(0) + \gamma_{2,(1,3)}(0)(0) + \gamma_{2,(2,3)}(0)(0)$$
$$+\gamma_{3,(1,2,3)}(0)(0)(0)$$

  - As all attributes are zero, the predicted value of $\mu_1 = 0$

- Although this may seem counter-intuitive, this is our constraint
  - We only get 7 parameters, not 8
  - The value of μ_1 is relative – the probability ν_1 depends on the other terms in the model

Log-Linear Model Explained

- For attribute profile 2: $\boldsymbol{\alpha}_2 = [\alpha_{21} = 0; \alpha_{22} = 0; \alpha_{23} = 1]$:

$$\mu_2 = \gamma_{1,(1)}(0) + \gamma_{1,(2)}(0) + \boxed{\gamma_{1,(3)}}(1)$$
$$+\gamma_{2,(1,2)}(0)(0) + \gamma_{2,(1,3)}(0)(0) + \gamma_{2,(2,3)}(0)(0)$$
$$+\gamma_{3,(1,2,3)}(0)(0)(0)$$

  - The main effect of attribute 3 only applies

$$\mu_3 = \gamma_{1,(3)}$$

Log-Linear Model Explained

- For attribute profile 6: $\boldsymbol{\alpha}_6 = [\alpha_{61} = 1; \alpha_{62} = 0;\ \alpha_{63} = 1]$:

$$\mu_6 = \boxed{\gamma_{1,(1)}}(1) + \gamma_{1,(2)}(0) + \boxed{\gamma_{1,(3)}}(1)$$
$$+\gamma_{2,(1,2)}(0)(0) + \boxed{\gamma_{2,(1,3)}}(1)(1) + \gamma_{2,(2,3)}(0)(0)$$
$$+\gamma_{3,(1,2,3)}(0)(0)(0)$$

  - The main effects of attribute 1 and attribute 3, and interaction between attributes 1 and 3 apply

$$\mu_6 = \gamma_{1,(1)} + \gamma_{1,(3)} + \gamma_{2,(1,3)}$$

Log-Linear Model Explained

- For attribute profile 8: $\boldsymbol{\alpha}_8 = [\alpha_{11} = 1; \alpha_{12} = 1; \alpha_{13} = 1]$:

$$\mu_8 = \boxed{\gamma_{1,(1)}}(1) + \boxed{\gamma_{1,(2)}}(1) + \boxed{\gamma_{1,(3)}}(1)$$
$$+\boxed{\gamma_{2,(1,2)}}(1)(1) + \boxed{\gamma_{2,(1,3)}}(1)(1) + \boxed{\gamma_{2,(2,3)}}(1)(1)$$
$$+\boxed{\gamma_{3,(1,2,3)}}(1)(1)(1)$$

  - All parameters apply

$$\mu_8 = \gamma_{1,(1)} + \gamma_{1,(2)} + \gamma_{1,(3)} + \gamma_{2,(1,2)} + \gamma_{2,(1,3)} + \gamma_{2,(2,3)} + \gamma_{3,(1,2,3)}$$

Interpretations of Model Parameters

- The log-linear model with ALL main effects and interactions is statistically equivalent to the saturated structural model
- Two-way interactions are analogous to bivariate correlations in categorical models
  - Higher-level interactions represent higher level of characteristics of attribute distribution (i.e., skewness, kurtosis, etc…)
- Models without interactions imply uncorrelated attributes
  - Main effects are essentially attribute base-rates
- Models without main effects or interactions assume all attribute profiles are equally likely
- Higher order interactions can be removed if not significantly different from zero

LOG-LINEAR STRUCTURAL MODELS IN MPLUS

Implementing Log-Linear Structural Models with Mplus

- Implementation of log-linear structural models in Mplus is much like implementation of the LCDM
  - Labeling parameters
  - Creating new parameters
  - Expressing the labeled parameters as a function of the new parameters through model constraints

- Note: if no structural model is specified, the Mplus default is the saturated structural model

Our Previous Analysis

- From our ECPE analysis, we initially get the output for our structural model:

```
FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON THE ESTIMATED MODEL

   Latent
  Classes

     1        878.76793          0.30074
     2        376.91420          0.12899
     3         34.82866          0.01192
     4        511.56563          0.17507
     5         25.53117          0.00874
     6         53.03067          0.01815
     7         31.51099          0.01078
     8       1009.85074          0.34560
```

c	ν_c	$\boldsymbol{\alpha}_1$	$\boldsymbol{\alpha}_2$	$\boldsymbol{\alpha}_3$
1	0.30	0	0	0
2	0.13	0	0	1
3	0.01	0	1	0
4	0.18	0	1	1
5	0.01	1	0	0
6	0.02	1	0	1
7	0.01	1	1	0
8	0.34	1	1	1

Categorical Latent Variable Means Output

- From our ECPE analysis, a there was a section of output that we overlooked:

```
Categorical Latent Variables

 Means
    C#1             -0.139      0.112     -1.242      0.214
    C#2             -0.986      0.240     -4.101      0.000
    C#3             -3.367      1.325     -2.541      0.011
    C#4             -0.680      0.162     -4.208      0.000
    C#5             -3.678      0.861     -4.270      0.000
    C#6             -2.947      0.626     -4.706      0.000
    C#7             -3.467      0.751     -4.619      0.000
```

- You will note, Mplus only gives 7 of these
- The last class "mean" is fixed to zero in Mplus
  - We will have to build code to get around this

The Interplay Between Latent Variable Means and Class Probabilities

- The latent variable means are directly related to the class probabilities using the conversion formula:

$$\nu_c = \frac{\exp(\mu_c)}{\sum_{i=1}^{2^A} \exp(\mu_i)}$$

- Under the spreadsheet for this session, the conversion from μ_c to ν_c is shown
- Our next step is to implement the log-linear structural model as a series of main effects and interactions

Mplus Syntax for Log-Linear Structural Model

- The Mplus syntax must be modified to add the log-linear structural model
  - Labeling parameters
  - Creating new parameters
  - Expressing the labeled parameters as a function of the new parameters through model constraints

Labeling Parameters

- Under the MODEL: section, the latent class means are accessed and labeled using the following syntax:

```
%OVERALL%
[C#1] (M1); !profile [000]
[C#2] (M2); !profile [001]
[C#3] (M3); !profile [010]
[C#4] (M4); !profile [011]
[C#5] (M5); !profile [100]
[C#6] (M6); !profile [101]
[C#7] (M7); !profile [110]
```

- Goes under %OVERALL% command
- The parameter goes in brackets (Mplus syntax for means)
- The name of the class (here C) is the name used under the CLASSES = C(8); line, in the VARIABLE: section
- Our labels are M1 – M7 (arbitrary names, but must be unique)
  - There are only 7 – the 8th cannot be specified as it is fixed to zero

Creating New Parameters

- The next step is to create the set of new log-linear structural model parameters

```
MODEL CONSTRAINT:

!STRUCTURAL MODEL PORTION;
!define structural model parameters:
NEW(G_11*1 G_12*1 G_13*1 G_212*-1 G_213*-1 G_223*-1 G_3123*0);
```

- These go under MODEL CONSTRAINT
- The labels are arbitrary (our follow LCDM labels)
- The * after the labels sets the starting values
  - Not necessary, but can help speed convergence

Expressing Labels as Functions of New Parameters

- The syntax for expressing the M1-M7 labeled parameters as our log-linear parameters can be complicated
  - The issue is the last class being 0 by default
  - We must subtract our model's last class from all other classes
  - This makes it so $\mu_1 = 0$ – as specified in our model

```
!from structural model specification table:
!intercept:
M1=-(G_11+G_12+G_13+G_212+G_213+G_223+G_3123); !profile [000];
M2=G_13-(G_11+G_12+G_13+G_212+G_213+G_223+G_3123); !profile [001];
M3=G_12-(G_11+G_12+G_13+G_212+G_213+G_223+G_3123); !profile [010];
M4=G_12+G_13+G_223-(G_11+G_12+G_13+G_212+G_213+G_223+G_3123); !profile [011];
M5=G_11-(G_11+G_12+G_13+G_212+G_213+G_223+G_3123); !profile [100];
M6=G_11+G_13+G_213-(G_11+G_12+G_13+G_212+G_213+G_223+G_3123); !profile [101];
M7=G_11+G_12+G_212-(G_11+G_12+G_13+G_212+G_213+G_223+G_3123); !profile [110];
```

Mplus Syntax from SAS Macro

- The SAS macro can assist somewhat in the building of syntax:

```
* Use structural model(0=N,1=Y);                   %LET structon=      0;
* Order of interaction in structural model; %LET structorder=   2;
```

- Set structon = 1
- If you want only two way interactions, set structorder = 2

- Note: the syntax created by the macro will exceed 90 characters per line (the Mplus limit)
  - So you will have to go through the input file by hand to fix this before running Mplus

Log-Linear Model for ECPE

- To demonstrate the log-linear model, we again present our ECPE data
  - Full model (all parameters)

```
Categorical Latent Variables

 Means
    C#1              -0.139      0.112     -1.242      0.214
    C#2              -0.986      0.240     -4.101      0.000
    C#3              -3.367      1.325     -2.541      0.011
    C#4              -0.680      0.162     -4.208      0.000
    C#5              -3.678      0.861     -4.270      0.000
    C#6              -2.947      0.626     -4.706      0.000
    C#7              -3.467      0.751     -4.619      0.000

 New/Additional Parameters
    G_11             -3.539      0.872     -4.059      0.000
    G_12             -3.228      1.377     -2.344      0.019
    G_13             -0.847      0.219     -3.865      0.000
    G_212             3.439      1.901      1.809      0.070
    G_213             1.577      1.066      1.479      0.139
    G_223             3.534      1.268      2.787      0.005
    G_3123           -0.797      2.077     -0.384      0.701
```

Investigating Log-Linear Structural Model Parameters

- To further investigate these parameters, we return to the Excel worksheet for this section of the workshop
- Go to the tab labeled "Saturated Log-linear Model"

Removal of Non-Significant Parameters

- The saturated model indicated the three-way structural model interaction was non-significant
- In theory, we can remove this parameter without greatly changing the fit of the model

```
!STRUCTURAL MODEL PORTION;
!define structural model parameters:
NEW(G_11*1 G_12*1 G_13*1 G_212*-1 G_213*-1 G_223*-1);

!from structural model specification table:
!intercept:
M1=-(G_11+G_12+G_13+G_212+G_213+G_223); !profile [000];
M2=G_13-(G_11+G_12+G_13+G_212+G_213+G_223); !profile [001];
M3=G_12-(G_11+G_12+G_13+G_212+G_213+G_223); !profile [010];
M4=G_12+G_13+G_223-(G_11+G_12+G_13+G_212+G_213+G_223); !profile [011];
M5=G_11-(G_11+G_12+G_13+G_212+G_213+G_223); !profile [100];
M6=G_11+G_13+G_213-(G_11+G_12+G_13+G_212+G_213+G_223); !profile [101];
M7=G_11+G_12+G_212-(G_11+G_12+G_13+G_212+G_213+G_223); !profile [110];
```

Mplus Output Comparison

Full Model:

FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON THE ESTIMATED MODEL

Latent Classes		
1	878.76793	0.30074
2	376.91420	0.12899
3	34.82866	0.01192
4	511.56563	0.17507
5	25.53117	0.00874
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Categorical Latent Variables

Means				
C#1	-0.139	0.112	-1.242	0.214
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C#7	-3.467	0.751	-4.619	0.000
New/Additional Parameters				
G_11	-3.539	0.872	-4.059	0.000
G_12	-3.228	1.377	-2.344	0.019
G_13	-0.847	0.219	-3.865	0.000
G_212	3.439	1.901	1.809	0.070
G_213	1.577	1.066	1.479	0.139
G_223	3.534	1.268	2.787	0.005
G_3123	-0.797	2.077	-0.384	0.701

Reduced Model:

FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASSES
BASED ON THE ESTIMATED MODEL

Latent Classes		
1	866.58065	0.29657
2	375.80161	0.12861
3	47.21435	0.01616
4	513.62256	0.17578
5	30.19872	0.01033
6	45.91228	0.01571
7	26.64068	0.00912
8	1016.02915	0.34772

Categorical Latent Variables

Means				
C#1	-0.159	0.103	-1.545	0.122
C#2	-0.995	0.231	-4.298	0.000
C#3	-3.069	0.691	-4.441	0.000
C#4	-0.682	0.162	-4.222	0.000
C#5	-3.516	0.539	-6.522	0.000
C#6	-3.097	0.629	-4.921	0.000
C#7	-3.641	0.590	-6.171	0.000
New/Additional Parameters				
G_11	-3.357	0.524	-6.405	0.000
G_12	-2.910	0.722	-4.028	0.000
G_13	-0.835	0.214	-3.907	0.000
G_212	2.784	0.608	4.577	0.000
G_213	1.254	0.583	2.152	0.031
G_223	3.222	0.638	5.049	0.000

Session 4: Diagnostic Classification Structural Models

CONCLUDING REMARKS

Session 4 – Take-home Points

- DCM Structural Models describe the distribution of attributes
  - Means
  - Correlations
  - Overall structure

- Log-linear structural models are implemented in Mplus
  - Provide great flexibility in terms of number of parameters
  - Allow for ability to detect higher order structures
    - Attribute hierarchies
  - Allow for potential to model attributes using covariates