# Mplus estimators: MLM and MLR

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First Mplus User meeting – October 27th 2010 Utrecht University, the Netherlands

(with a few corrections, 10 July 2017)

#### NOTE: 2 corrections on slide 2 and 7 (and again on slide 18):

• slide 2 (and 18):

$$W = 2D'(\hat{\Sigma}^{-1} \otimes \hat{\Sigma}^{-1})D$$

should be

W 
$$=rac{1}{2}D'(\hat{\Sigma}^{-1}\otimes\hat{\Sigma}^{-1})D$$

• slide 7 (and 18):

$$U = (W^{-1} - W^{-1}\Delta(\Delta'W^{-1}\Delta)^{-1}\Delta'W^{-1})$$

should be

$$U = (W - W\Delta(\Delta'W\Delta)^{-1}\Delta'W)$$

#### **Estimator: ML**

- default estimator for many model types in Mplus
- likelihood function is derived from the multivariate normal distribution
- standard errors are based on the covariance matrix that is obtained by inverting the information matrix
- in Mplus versions 1–4, the default was to use the *expected* information matrix:

$$\begin{split} n \mathrm{Cov}(\hat{\theta}) &= A^{-1} \\ &= (\Delta' W \Delta)^{-1} \end{split}$$

- $\Delta$  is a jacobian matrix and W is a function of  $\Sigma^{-1}$
- if no meanstructure:

$$\Delta = \partial \hat{\Sigma} / \partial \hat{\theta}'$$

$$W = \frac{1}{2} D' (\hat{\Sigma}^{-1} \otimes \hat{\Sigma}^{-1}) D$$

• in Mplus versions 5–6, the default is the *observed* information matrix (because the default: TYPE=GENERAL MISSING H1):

$$\begin{split} n \text{Cov}(\hat{\theta}) &= A^{-1} \\ &= [-\text{Hessian}]^{-1} \\ &= \left[ -\partial F(\hat{\theta})/(\partial \hat{\theta} \partial \hat{\theta}') \right]^{-1} \end{split}$$

where  $F(\theta)$  is the function that is minimized

- overall model evaluation is based on the likelihood-ratio (LR) statistic (chi-square test):  $T_{ML}$ 
  - (minus two times the) difference between loglikelihood of user-specified model  $H_0$  and unrestricted model  $H_1$
  - equals (in Mplus)  $2 \times n$  times the minimum value of  $F(\theta)$
  - test statistics follows (under regularity conditions) a chi-square distribution
  - Mplus calls this the "Chi-Square Test of Model Fit"

### What if the data are NOT normally distributed?

- in the real world, data may never be normally distributed
- two types:
  - categorical and/or limited-dependent outcomes: binary, ordinal, nominal, counts, censored (WLSMV, logit/probit)
  - continuous outcomes, not normally distributed: skewed, too flat/too peaked (kurtosis), . . .
- in many situations, the ML parameter estimates are still consistent (if the model is identified and correctly specified)
- in fewer situations, the ML procedure can still provide reliable inference (SE's and test statistics), but it is hard to identify these conditions empirically
- in practice, we may prefer *robust* procedures

## Three classes of robust procedures in the SEM literature

- ML estimation with 'robust' standard errors, and a 'robust' test statistic for model evaluation
  - bootstrapped SE's, and bootstrapped test statistic
  - Satorra-Bentler corrections (Mplus: estimator=MLM)
  - Huber/Pseudo ML/sandwich corrections (Mplus: estimator=MLR)
- GLS (Mplus: estimator=WLS) with a weight matrix (Γ) based on the 4thorder moments of the data
  - Asymptotically Distribution Free (ADF) estimation (Browne, 1984)
  - only works well with large/huge sample sizes
- case-robust or outlier-robust methods: cases lying far from the center of the data cloud receive smaller weights, affecting parameter estimates, SE's and model evaluation
  - only available in EQS(?)

#### **Estimator MLM**

• Mplus 6 User's Guide page 533:

"MLM – maximum likelihood parameter estimates with standard errors and a mean-adjusted chi-square test statistic that are robust to non-normality. The MLM chi-square test statistic is also referred to as the Satorra-Bentler chi-square."

- parameter estimates are standard ML estimates
- · standard errors are robust to non-normality
  - standard errors are computed using a sandwich-type estimator:

$$n\text{Cov}(\hat{\theta}) = A^{-1}BA^{-1}$$
$$= (\Delta'W\Delta)^{-1}(\Delta'W\Gamma W\Delta)(\Delta'W\Delta)^{-1}$$

- A is usually the expected information matrix (but not in Mplus)
- references: Huber (1967), Browne (1984), Shapiro (1983), Bentler (1983), ...

- chi-square test statistic is robust to non-normality
  - test statistic is 'scaled' by a correction factor

$$T_{SB} = T_{ML}/c$$

- the scaling factor c is computed by:

$$c = tr \left[ U\Gamma \right] / \mathrm{df}$$

where

$$U = (W - W\Delta(\Delta'W\Delta)^{-1}\Delta'W)$$

- correction method described by Satorra & Bentler (1986, 1988, 1994)
- estimator MLM: for complete data only

(DATA: LISTWISE=ON)

#### **Estimator MLR**

• Mplus 6 User's Guide page 533:

MLR – maximum likelihood parameter estimates with standard errors and a chi-square test statistic (when applicable) that are robust to non-normality and non-independence of observations when used with TYPE=COMPLEX. The MLR standard errors are computed using a sandwich estimator. The MLR chi-square test statistic is asymptotically equivalent to the Yuan-Bentler T2\* test statistic.

• parameter estimates are standard ML estimates

- standard errors are robust to non-normality
  - standard errors are computed using a (different) sandwich approach:

$$n\text{Cov}(\hat{\theta}) = A^{-1}BA^{-1}$$
  
=  $A_0^{-1}B_0A_0^{-1} = C_0$ 

where

$$A_0 = -\sum_{i=1}^{n} \frac{\partial \log L_i}{\partial \hat{\theta} \, \partial \hat{\theta}'} \quad \text{(observed information)}$$

and

$$B_0 = \sum_{i=1}^{n} \left( \frac{\partial \log L_i}{\partial \hat{\theta}} \right) \times \left( \frac{\partial \log L_i}{\partial \hat{\theta}} \right)'$$

- for both complete and incomplete data
- Huber (1967), Gourieroux, Monfort & Trognon (1984), Arminger & Schoenberg (1989)

- chi-square test statistic is robust to non-normality
  - test statistic is 'scaled' by a correction factor

$$T_{MLR} = T_{ML}/c$$

- the scaling factor c is (usually) computed by

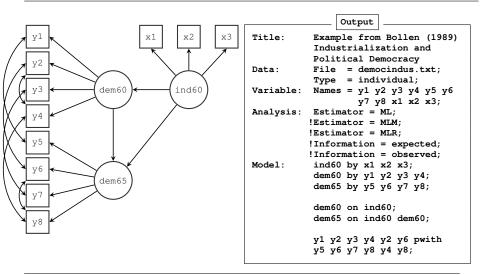
$$c = tr[M]$$

where

$$M = C_1(A_1 - A_1\Delta(\Delta'A_1\Delta)^{-1}\Delta'A_1)$$

- $A_1$  and  $C_1$  are computed under the unrestricted  $(H_1)$  model
- correction method described by Yuan & Bentler (2000)
- information matrix (A) can be observed or expected
- for complete data, the MLR and MLM corrections are asymptotically equivalent

### Example: Industrialization and Political Democracy (Bollen, 1989) N=75



# Mplus 6.1 output: estimator = ML, information = observed

			Output	<b>᠄</b> │		
Chi-Squa	are Test of	Model Fit		_		
	Value			38.125		
	Degrees	of Freedom		35		
	P-Value			0.3292		
					Two-Tailed	
		Estimate	S.E.	Est./S.E.	P-Value	
IND60	BY					
X1		1.000	0.000	999.000	999.000	
X2		2.180	0.139	15.685	0.000	
х3		1.819	0.152	11.949	0.000	
DEM60	BY					
Y1		1.000	0.000	999.000	999.000	
Y2		1.257	0.185	6.775	0.000	
¥3		1.058	0.148	7.131	0.000	
Y4		1.265	0.151	8.391	0.000	
DEM65	BY					
¥5		1.000	0.000	999.000	999.000	
¥6		1.186	0.171	6.920	0.000	
¥7		1.280	0.160	7.978	0.000	
Y8		1.266	0.163	7.756	0.000	

# Mplus 6.1 output: estimator = ML, information = expected

			Output	:		
Chi-Squa	re Test of	Model Fit				
	Value			38.125		
	Degrees	of Freedom		35		
	P-Value			0.3292		
					Two-Tailed	
		Estimate	S.E.	Est./S.E.	P-Value	
IND60	вч					
X1		1.000	0.000	999.000	999.000	
X2		2.180	0.139	15.742	0.000	
х3		1.819	0.152	11.967	0.000	
DEM60	BY					
Y1		1.000	0.000	999.000	999.000	
Y2		1.257	0.182	6.889	0.000	
¥3		1.058	0.151	6.987	0.000	
Y4		1.265	0.145	8.722	0.000	
DEM65	BY					
Y5		1.000	0.000	999.000	999.000	
¥6		1.186	0.169	7.024	0.000	
¥7		1.280	0.160	8.002	0.000	
Y8		1.266	0.158	8.007	0.000	

# Mplus output: estimator = MLM, information = expected

		Outpu			
hi-Squa	are Test of Model Fi	.t			
	Value		40.536*		
	Degrees of Freedo	om	35		
	P-Value		0.2393		
	Scaling Correction	n Factor	0.941		
	for MLM				
			•	Two-Tailed	
	Estimat	e S.E.	Est./S.E.	P-Value	
IND60	ВУ				
X1	1.00	0.000	999.000	999.000	
X2	2.18	0.126	17.251	0.000	
х3	1.81	.9 0.128	14.212	0.000	
DEM60	BY				
Y1	1.00	0.000	999.000	999.000	
Y2	1.25	0.137	9.193	0.000	
Y3	1.05	8 0.133	7.971	0.000	
Y4	1.26	55 0.119	10.585	0.000	
DEM65	BY				
¥5	1.00	0.000	999.000	999.000	
¥6	1.18	0.171	6.947	0.000	
¥7	1.28	0.166	7.706	0.000	
Y8	1.26	6 0.174	7.289	0.000	

## Mplus output: estimator = MLR, information = observed

			Output	·] ———		
Chi-Squa	re Test of Mod	del Fit				
	Value			41.401*		
	Degrees of E	reedom		35		
	P-Value			0.2114		
	Scaling Corr for MLR	rection Fa	ctor	0.921		
					Two-Tailed	
	Es	stimate	S.E.	Est./S.E.	P-Value	
IND60	ву					
X1		1.000	0.000	999.000	999.000	
X2		2.180	0.145	15.044	0.000	
х3		1.819	0.140	12.950	0.000	
DEM60	BY					
Y1		1.000	0.000	999.000	999.000	
Y2		1.257	0.150	8.392	0.000	
Y3		1.058	0.130	8.107	0.000	
Y4		1.265	0.146	8.661	0.000	
DEM65	BY					
Y5		1.000	0.000	999.000	999.000	
¥6		1.186	0.181	6.541	0.000	
¥7		1.280	0.173	7.415	0.000	
Y8		1.266	0.189	6.685	0.000	

### Mplus output: estimator = MLR, information = expected

			Output	<u> </u>		
Chi-Squa	are Test of	Model Fit				
	Value			40.936*		
	Degrees o	f Freedom		35		
	P-Value			0.2261		
	Scaling C	orrection Fa	actor	0.931		
	for MLR	L				
					Two-Tailed	
		Estimate	S.E.	Est./S.E.	P-Value	
IND60	BY					
X1		1.000	0.000	999.000	999.000	
X2		2.180	0.144	15.185	0.000	
х3		1.819	0.139	13.070	0.000	
DEM60	BY					
Y1		1.000	0.000	999.000	999.000	
Y2		1.257	0.140	8.964	0.000	
<b>Y3</b>		1.058	0.134	7.882	0.000	
Y4		1.265	0.127	9.972	0.000	
DEM65	BY					
Y5		1.000	0.000	999.000	999.000	
¥6		1.186	0.171	6.926	0.000	
¥7		1.280	0.166	7.694	0.000	
Y8		1.266	0.171	7.399	0.000	

# What about other software: EQS

- main developer: Peter Bentler
- in EQS 6.1, you can request robust SE's and test statistics (METHOD=ML, ROBUST)
- you can switch between the observed and expected information matrix (SE=OBS, or SE=FISHER)
- if the data is complete, you get:
  - robust standard errors
  - a Satorra-Bentler-scaled chi-square statistic
  - should be similar to Mplus estimator MLM
- if the data is incomplete, you get:
  - robust standard errors
  - Yuan-Bentler-scaled chi-square statistic
  - should be similar to Mplus estimator MLR

# 1. Mplus estimator MLM is NOT identical to EQS

- both SE's and the value of the Satorra-Bentler scaled test statistic are computed differently
- · formula standard errors:

$$n\operatorname{Cov}(\hat{\theta}) = (\Delta'W\Delta)^{-1}(\Delta'W\Gamma W\Delta)(\Delta'W\Delta)^{-1}$$

• formula Satorra-Bentler scaling factor:

$$c = tr \left[ U\Gamma \right] / \mathrm{df}$$

where

$$U = (\mathbf{W} - \mathbf{W}\Delta(\Delta'\mathbf{W}\Delta)^{-1}\Delta'\mathbf{W})$$

• however (if no meanstructure):

$$W = \frac{1}{2}D'(\hat{\Sigma}^{-1} \otimes \hat{\Sigma}^{-1})D \quad \text{(EQS)}$$
 
$$W = \frac{1}{2}D'(S^{-1} \otimes S^{-1})D \quad \text{(MPLUS)}$$

## Satorra-Bentler: Mplus variant

		Out	tput			
Lavaan (0.4-4) com	nverged nor	mally aft	er 95 ite	rations		
Estimator				ML	Robust	
Minimum Function	n Chi-squar	e		38.125	40.536	
Degrees of free	dom			35	35	
P-value				0.329	0.239	
Scaling correct:	ion factor				0.941	
for the Sator:	ra-Bentler	correctio	n (Mplus	variant)		
	Estimate	Std.err	<b>Z-value</b>	P(> z )		
Latent variables:						
ind60 =~						
<b>x</b> 1	1.000					
<b>x</b> 2	2.180	0.126	17.251	0.000		
<b>x</b> 3	1.819	0.128	14.212	0.000		
dem60 =~						
<b>y1</b>	1.000					
y2	1.257	0.137	9.193	0.000		
у3	1.058	0.133	7.971	0.000		
у4	1.265	0.119	10.585	0.000		
dem65 =~						
<b>y</b> 5	1.000					
у6	1.186	0.171				
у7	1.280					
у8	1.266	0.174	7.289	0.000		

#### **Satorra-Bentler: EQS variant**

Output Lavaan (0.4-4) converged normally after 91 iterations Estimator ML Robust Minimum Function Chi-square 37.617 40.512 Degrees of freedom 35 35 P-value 0.350 0.240 Scaling correction factor 0.929 for the Satorra-Bentler correction Estimate Std.err Z-value P(>|z|) Latent variables:  $ind60 = \sim$ x1 1.000 x2 2.180 0.143 15.287 0.000 **x**3 1.819 0.138 13.158 0.000  $dem60 = \sim$ 1.000 y1 1.257 0.139 9.024 0.000 y2 0.133 7.936 0.000 у3 1.058 y4 1.265 0.126 10.039 0.000  $dem65 = \sim$ v5 1.000 y6 1.186 0.170 6.973 0.000 у7 1.280 0.165 7.746 0.000 1.266 0.170 7.448 0.000 v8

# Satorra-Bentler in Mplus: use MLR with expected information

		Ou	tput			
Lavaan (0.4-4) c	converged nor	mally aft	er 95 ite	rations		
Estimator				ML	Robust	
Minimum Functi	on Chi-squar	е		38.125	40.936	
Degrees of fre	edom			35	35	
P-value				0.329	0.226	
Scaling correct for the MLR					0.931	
	Estimate	Std.err	<b>Z-value</b>	P(> z )		
Latent variables	s:					
ind60 =~						
x1	1.000					
<b>x</b> 2	2.180	0.144	15.185	0.000		
<b>x</b> 3	1.819	0.139	13.070	0.000		
dem60 =~						
y1	1.000					
y2	1.257	0.140	8.964	0.000		
у3	1.058	0.134	7.882	0.000		
y4	1.265	0.127	9.972	0.000		
dem65 =~						
y5	1.000					
у6	1.186	0.171	6.926	0.000		
<b>y</b> 7	1.280	0.166	7.694	0.000		
у8	1.266	0.171	7.399	0.000		

## 2. Mplus estimator MLR is NOT identical to EQS

- · SE's are ok
- the value of the Yuan-Bentler scaled test statistic is computed differently
- formula Yuan-Bentler scaling factor:

$$c = tr[M]$$

where

$$M = C_1(A_1 - A_1\Delta(\Delta'A_1\Delta)^{-1}\Delta'A_1)$$

• however, Mplus uses:

$$\operatorname{tr}(M) = tr(B_1 A_1^{-1}) - tr(B_0 A_0^{-1})$$

• but: asymptotically equivalent

• Mplus 6 User's Guide page 533:

MLR – maximum likelihood parameter estimates with standard errors and a chi-square test statistic (when applicable) that are robust to non-normality and non-independence of observations when used with TYPE=COMPLEX. The MLR standard errors are computed using a sandwich estimator. The MLR chi-square test statistic is asymptotically equivalent to the Yuan-Bentler T2\* test statistic.

• Mplus 3 User's Guide page 401:

MLR – maximum likelihood parameter estimates with standard errors and a chi-square test statistic (when applicable) that are robust to non-normality and non-independence of observations when used with TYPE=COMPLEX. The MLR standard errors are computed using a sandwich estimator. The MLR chi-square test statistic is also referred to as the Yuan-Bentler T2\* test statistic.

#### **Conclusions**

robust estimators in Mplus are similar, but not identical to EQS

- Mplus is not 'wrong', but uses different formulas
- in small samples, the differences can be substantial
- Mplus Users should be aware of the differences
- statisticians should study the differences
- we need open-source software (hint: http://lavaan.org)

### Thank you for your attention