

Psychology 454: Latent Variable Modeling

Using lavaan to model structure

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Outline

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 - Example from Bollen, 1989
- 2 EFA and CFA of the structure
 - Try a confirmatory model
- 3 Structural models
 - A simple model - no correlated residuals
 - A more complicated model – correlated residuals
- 4 Adding constraints
 - Compare to LISREL example
 - But remember, arrows can be reversed!

CFA confirms structure; SEM tests for “causality”

- We have examined the use of Confirmatory Factor Models for testing:
 - quality of measures (e.g., congeneric measurement models)
 - equivalence of measures over time or form (e.g., factor invariance models).
- Structural models combine measurement models with regression models
 - Regressions may be of observed variables but more typically, of latent variables.
 - In this case, the modeling is essentially just correcting for attenuation.
 - But can also add in additional fitting parameters to estimate correlations between residuals.
- Whenever discussing “causality” we need to remember the interchangeability of directional arrows.
 - Causality is not tested in any particular model. Causality reflects relative plausibility of alternative models.

Examples from lavaan version .4-6

.4-6 was released 2/14/11

```
install.packages("lavaan", repos="http://www.da.ugent.be", type="source")
library(lavaan)
data(`PoliticalDemocracy`)'
```

Industrialization And Political Democracy Dataset

Description

The "famous" Industrialization and Political Democracy dataset. This dataset is used throughout Bollen's 1989 book (see pages 12, 17, 36 in chapter 2, pages 228 and following in chapter 7, pages 321 and following in chapter 8).

The dataset contains various measures of political democracy and industrialization in developing countries.

Usage

A data frame of 75 observations of 11 variables.

```
y1 Expert ratings of the freedom of the press in 1960
y2 The freedom of political opposition in 1960
y3 The fairness of elections in 1960
y4 The effectiveness of the elected legislature in 1960
y5 Expert ratings of the freedom of the press in 1965
y6 The freedom of political opposition in 1965
y7 The fairness of elections in 1965
y8 The effectiveness of the elected legislature in 1965
x1 The gross national product (GNP) per capita in 1960
x2 The inanimate energy consumption per capita in 1960
x3 The percentage of the labor force in industry in 1960
```

Example from Bollen, 1989

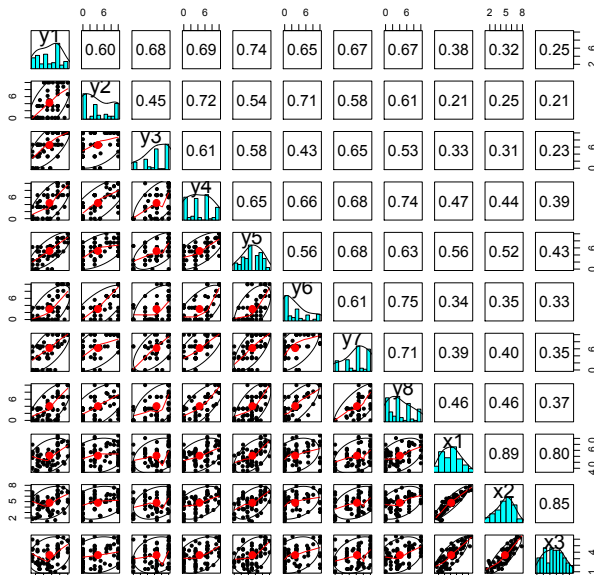
Basic descriptive statistics

```
> describe(PoliticalDemocracy)
```

	var	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
y1	1	75	5.46	2.62	5.40	5.46	3.11	1.25	10.00	8.75	-0.09	-1.10	0.30
y2	2	75	4.26	3.95	3.33	4.09	4.94	0.00	10.00	10.00	0.32	-1.44	0.46
y3	3	75	6.56	3.28	6.67	6.92	4.94	0.00	10.00	10.00	-0.59	-0.62	0.38
y4	4	75	4.45	3.35	3.33	4.33	4.94	0.00	10.00	10.00	0.12	-1.16	0.39
y5	5	75	5.14	2.61	5.00	5.23	3.71	0.00	10.00	10.00	-0.23	-0.68	0.30
y6	6	75	2.98	3.37	2.23	2.51	3.31	0.00	10.00	10.00	0.89	-0.34	0.39
y7	7	75	6.20	3.29	6.67	6.47	4.94	0.00	10.00	10.00	-0.55	-0.63	0.38
y8	8	75	4.04	3.25	3.33	3.82	4.40	0.00	10.00	10.00	0.45	-0.88	0.37
x1	9	75	5.05	0.73	5.08	5.03	0.82	3.78	6.74	2.95	0.25	-0.66	0.08
x2	10	75	4.79	1.51	4.96	4.85	1.53	1.39	7.87	6.49	-0.35	-0.46	0.17
x3	11	75	3.56	1.41	3.57	3.53	1.51	1.00	6.42	5.42	0.08	-0.86	0.16

Example from Bollen, 1989

A splom plot of the democracy data



Example from Bollen, 1989

The LISREL model of the data – note the correlated residuals

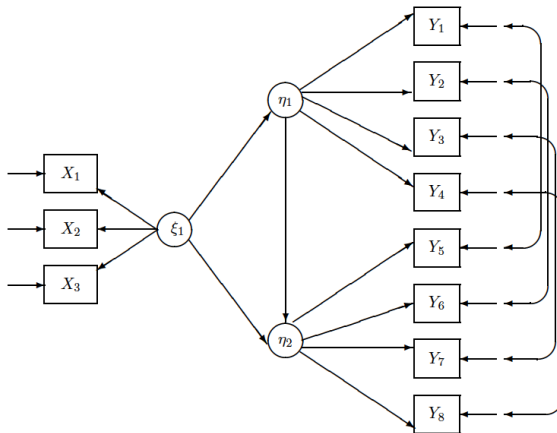


Figure 2: Panel Model of Democracy and Industrialization

Fitting as a simple measurement model – no structure

```
f3 <- fa(PoliticalDemocracy,3)
Factor Analysis using method = minres
Call: fa(r = PoliticalDemocracy, nfactors = 3)
Standardized loadings based upon correlation matrix
```

	MR1	MR2	MR3	h2	u2
y1	-0.05	0.20	0.75	0.78	0.219
y2	-0.09	0.76	0.10	0.66	0.345
y3	-0.01	-0.08	0.84	0.61	0.388
y4	0.12	0.48	0.37	0.72	0.278
y5	0.24	0.09	0.65	0.71	0.290
y6	0.04	0.91	-0.06	0.78	0.217
y7	0.07	0.31	0.53	0.66	0.336
y8	0.14	0.62	0.21	0.73	0.269
x1	0.90	-0.09	0.15	0.87	0.133
x2	0.96	0.01	0.00	0.94	0.065
x3	0.90	0.09	-0.13	0.78	0.223

	MR1	MR2	MR3
SS loadings	2.80	2.71	2.73
Proportion Var	0.25	0.25	0.25
Cumulative Var	0.25	0.50	0.75


```
With factor correlations of
```

	MR1	MR2	MR3
MR1	1.00	0.38	0.41
MR2	0.38	1.00	0.72
MR3	0.41	0.72	1.00

This is not the desired model. For it groups by content rather than time.

With goodness of fit statistics

Although it fits pretty well.

Test of the hypothesis that 3 factors are sufficient.

The degrees of freedom for the null model are 55 and the objective function was 9.74
with Chi Square of 677.07

The degrees of freedom for the model are 25 and the objective function was 0.43

The root mean square of the residuals is 0.02

The df corrected root mean square of the residuals is 0.03

The number of observations was 75 with Chi Square = 29.01 with prob < 0.26

Tucker Lewis Index of factoring reliability = 0.985

RMSEA index = 0.061 and the 90 % confidence intervals are 0.059 0.069

BIC = -78.93

Fit based upon off diagonal values = 1

Measures of factor score adequacy

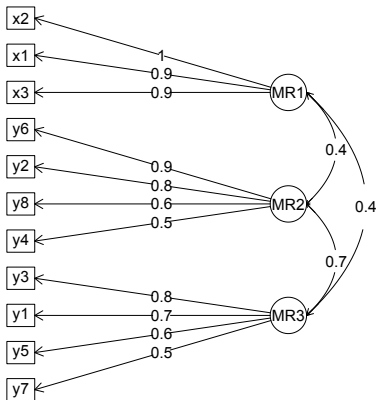
	MR1	MR2	MR3
Correlation of scores with factors	0.98	0.95	0.95
Multiple R square of scores with factors	0.96	0.90	0.90
Minimum correlation of possible factor scores	0.92	0.81	0.79

But this is not the model we wanted to fit!

The exploratory factor solution is pretty, but not what we want

Factors are forming based upon content rather than temporal relation.

Factor Analysis



Two ways of estimating χ^2

- There are two ways to calculate χ^2 , both are available in *lavaan* as options
 - The sem, LISREL, EQS, or AMOS way is to use a “Wishart” distribution based upon covariance matrix calculated with N-1 observations.
 - The MPlus way is to use N. (The normal approach to maximum likelihood estimation.)
 - “N” is used as a multiplier to compute both standard errors and test statistics. One advantage of the ‘normal’ approach is that it extends naturally to the missing-data case. The ‘wishart’ approach does not apply to missing data, and software programs tend to ‘switch’ to the normal approach if any data is missing.” (Rosseel, personal communication, 2/14/11).
- As of 2/14/11, (version .4-6) cfa and sem can do either approach. Specify the likelihood=“wishart” or “normal”.

Try a confirmatory model

CFA model of the data - is not very good

```
mod.cfa <- '
# latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + y2 + y3 + y4
  dem65 =~ y5 + y6 + y7 + y8'
cfa.fit <- cfa(mod.cfa,data=PoliticalDemocracy,
               std.ov=TRUE,std.lv=TRUE)
summary(cfa.fit,fit.measures=TRUE)
```

model converged normally after 38 iterations using ML

Minimum Function Chi-square	72.462
Degrees of freedom	41
P-value	0.0018

Chi-square test baseline model:

Minimum Function Chi-square	730.654
Degrees of freedom	55
P-value	0.0000

Full model versus baseline model:

Comparative Fit Index (CFI)	0.953
Tucker-Lewis Index (TLI)	0.938

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-835.991
Loglikelihood unrestricted model (H1)	-799.760

Akaike (AIC)	1721.982
Bayesian (BIC)	1779.919

Root Mean Square Error of Approximation:

RMSEA	0.101
90 Percent Confidence Interval	0.061 0.139
P-value RMSEA <= 0.05	0.021

Standardized Root Mean Square Residual:

SRMR	0.055
------	-------

Try a confirmatory model

With parameters of

	Estimate	Std.err	Z-value	P(> z)					
Latent variables:									
ind60 =~									
x1	0.913	0.088	10.339	0.000					
x2	0.967	0.085	11.428	0.000	Variances:				
x3	0.866	0.091	9.477	0.000	x1	0.152	0.036	4.180	0.000
dem60 =~					x2	0.052	0.031	1.689	0.091
y1	0.750	0.086	8.676	0.000	x3	0.236	0.046	5.174	0.000
y2	0.675	0.090	7.462	0.000	y1	0.282	0.057	4.910	0.000
y3	0.626	0.093	6.747	0.000	y2	0.417	0.076	5.479	0.000
y4	0.763	0.086	8.902	0.000	y3	0.496	0.088	5.662	0.000
dem65 =~					y4	0.257	0.054	4.731	0.000
y5	0.130	0.113	1.150	0.250	y5	0.350	0.065	5.351	0.000
y6	0.126	0.110	1.149	0.251	y6	0.382	0.070	5.456	0.000
y7	0.132	0.115	1.150	0.250	y7	0.325	0.062	5.252	0.000
y8	0.137	0.119	1.150	0.250	y8	0.279	0.056	5.019	0.000
Regressions:					ind60	1.000			
dem60 ~					dem60	1.000			
ind60	0.501	0.143	3.511	0.000	dem65	1.000			
dem65 ~									
ind60	0.895	0.827	1.082	0.279					
dem60	5.017	4.485	1.119	0.263					

Try a confirmatory model

Find the fits with “Wishart” distribution

```

mod.cfa <- '
# latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + y2 + y3 + y4
  dem65 =~ y5 + y6 + y7 + y8'
cfa.fit <- cfa(mod.cfa,data=PoliticalDemocracy,
               std.ov=TRUE,std.lv=TRUE,
               likelihood='wishart')
summary(cfa.fit,fit.measures=TRUE)

```

Lavaan (0.4-6) converged normally after 36 iterations

Number of observations	75	Number of free parameters	25
Estimator	ML	Akaike (AIC)	1733.056
Minimum Function Chi-square	71.495	Bayesian (BIC)	1790.993
Degrees of freedom	41	Sample-size adjusted Bayesian (BIC)	1712.200
P-value	0.002	Root Mean Square Error of Approximation:	
		RMSEA	0.100
Chi-square test baseline model:		90 Percent Confidence Interval	0.059 0.137
Minimum Function Chi-square	720.912	P-value RMSEA <= 0.05	0.025
Degrees of freedom	55	Standardized Root Mean Square Residual:	
P-value	0.000	SRMR	0.055

Full model versus baseline model:

Comparative Fit Index (CFI)	0.954
Tucker-Lewis Index (TLI)	0.939

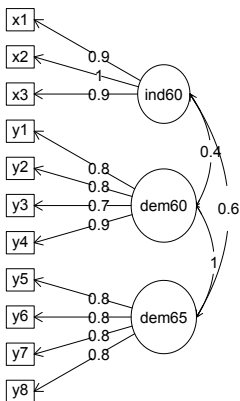
Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-841.528
Loglikelihood unrestricted model (H1)	-805.297

Try a confirmatory model

CFA of the model

Confirmatory structure



Structural models versus Confirmatory Factor models

- The CFA models are just glorified factor models – pure measurement.
 - Typically with fewer parameters because the cross loadings are ignored.
 - Cross loadings can be specified if needed (because of poor fit).
- Structural models combine the measurement models of cfa with regression.
 - The use of regression implies causal paths.
 - Always need to examine direction of these paths. Is the model plausible.

A simple model - no correlated residuals

The most simple model: Industrialization -> Democracy

```
mod.sem0 <- '
# latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem65 =~ y5 + y6 + y7 + y8
# regressions
  dem65 ~ ind60 '

sem.fit <- cfa(mod.sem0,data=PoliticalDemocracy,
               std.ov=TRUE,std.lv=TRUE)
summary(sem.fit,fit.measures=TRUE)
```

Lavaan (0.4-6) converged normally after 28 iterations

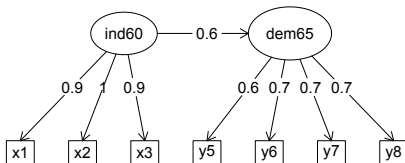
Number of observations	75
Estimator	ML
Minimum Function Chi-square	20.862
Degrees of freedom	13
P-value	0.076
Chi-square test baseline model:	
Minimum Function Chi-square	426.897
Degrees of freedom	21
P-value	0.000
Full model versus baseline model:	
Comparative Fit Index (CFI)	0.981
Tucker-Lewis Index (TLI)	0.969
RMSEA	0.090
90 Percent Confidence Interval	0.000 0.158
P-value RMSEA <= 0.05	0.173
Standardized Root Mean Square Residual:	
SRMR	0.054

A simple model - no correlated residuals

The most simple model: Industrialization leads to Democracy

```
lavaan.diagram(sem.fit,lr=FALSE,e.size=.2)
```

Structural model



A simple model - no correlated residuals

Consider a simple model, one causal factor, two dependent time points

```
mod.sem1 <- '
# latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + y2 + y3 + y4
  dem65 =~ y5 + y6 + y7 + y8
# regressions
  dem60 ~ ind60
  dem65 ~ ind60 + dem60'
sem.fit <- cfa(mod.sem1,data=PoliticalDemocracy,std.ov=TRUE)
summary(sem.fit,fit.measures=TRUE)
lavaan.diagram(sem.fit,cut=0,lr=FALSE)

lavaan (0.4-6) converged normally after 34 iterations
   Number of observations              75
   Estimator                          ML
   Minimum Function Chi-square         72.462
   Degrees of freedom                   41
   P-value                             0.002

Chi-square test baseline model:
   Minimum Function Chi-square         730.654
   Degrees of freedom                   55
   P-value                             0.000

Full model versus baseline model:
   Comparative Fit Index (CFI)         0.953
   Tucker-Lewis Index (TLI)           0.938

Root Mean Square Error of Approximation:
   RMSEA                              0.101
   90 Percent Confidence Interval      0.061 0.139
   P-value RMSEA <= 0.05              0.021

Standardized Root Mean Square Residual:
   SRMR                               0.055
```

Examine the residuals

```
> resid(sem.fit,type="normalized")
```

```
$cov
```

	x1	x2	x3	y1	y2	y3	y4	y5	y6	y7	y8
x1	0.000										
x2	-0.004	0.000									
x3	-0.018	0.012	0.000								
y1	0.274	-0.389	-0.698	0.000							
y2	-0.840	-0.685	-0.731	-0.285	0.000						
y3	0.301	0.045	-0.425	0.593	-0.672	0.000					
y4	0.896	0.537	0.438	-0.237	0.462	0.017	0.000				
y5	1.170	0.685	0.339	0.524	-0.409	0.167	-0.173	0.000			
y6	-0.445	-0.558	-0.388	0.018	0.870	-0.898	0.003	-0.483	0.000		
y7	-0.232	-0.323	-0.361	-0.017	-0.209	0.618	-0.060	0.145	-0.239	0.000	
y8	0.249	-0.012	-0.314	-0.242	-0.178	-0.417	0.174	-0.370	0.625	0.130	0.000

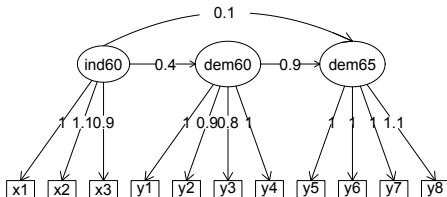
```
$mean
```

x1	x2	x3	y1	y2	y3	y4	y5	y6	y7	y8
0	0	0	0	0	0	0	0	0	0	0

A simple model - no correlated residuals

Show the structure

Structural model



Correlate some of the residuals

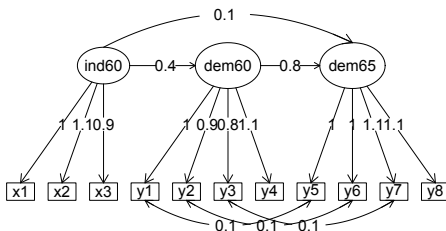
```
mod.sem2 <- '
# latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + y2 + y3 + y4
  dem65 =~ y5 + y6 + y7 + y8
# regressions
dem60 ~ ind60
dem65 ~ ind60 + dem60
y1 ~~ y5
y2 ~~ y6
y3 ~~ y7
y4 ~~ y8'
fit2 <- sem(mod.sem2, data=PoliticalDemocracy, std.ov=TRUE)
summary(fit2, fit.measures=TRUE)
lavaan.diagram(fit2, cut=0, lr=FALSE)
```

Minimum Function Chi-square	50.835
Degrees of freedom	37
P-value	0.064
Chi-square test baseline model:	
Minimum Function Chi-square	730.654
Degrees of freedom	55
P-value	0.000
Full model versus baseline model:	
Comparative Fit Index (CFI)	0.980
Tucker-Lewis Index (TLI)	0.970
Root Mean Square Error of Approximation:	
RMSEA	0.071
90 Percent Confidence Interval	0.000 0.115
P-value RMSEA <= 0.05	0.234
Standardized Root Mean Square Residual:	
SRMR	0.050

A more complicated model – correlated residuals

Correlated residuals

Structural model



Examine the residuals

```
resid(fit2)
```

```
> resid(fit2)
```

```
$cov
```

	x1	x2	x3	y1	y2	y3	y4	y5	y6	y7	y8
x1	0.000										
x2	-0.001	0.000									
x3	-0.003	0.002	0.000								
y1	0.042	-0.037	-0.073	0.001							
y2	-0.097	-0.080	-0.085	-0.021	0.001						
y3	0.041	0.011	-0.045	0.106	-0.074	0.003					
y4	0.104	0.058	0.045	-0.032	0.049	-0.003	-0.001				
y5	0.165	0.100	0.053	0.004	-0.013	0.067	0.005	0.002			
y6	-0.060	-0.074	-0.053	0.033	-0.007	-0.090	0.000	-0.049	-0.006		
y7	-0.030	-0.041	-0.045	0.038	-0.006	-0.005	-0.001	0.042	-0.039	-0.004	
y8	0.018	-0.016	-0.051	-0.009	-0.017	-0.039	0.000	-0.045	0.064	0.000	0.001

```
$mean
```

x1	x2	x3	y1	y2	y3	y4	y5	y6	y7	y8
0	0	0	0	0	0	0	0	0	0	0

A more complicated model – correlated residuals

Consider the modification indices

```
modificationIndices(fit2)
```

	lhs	op	rhs	mi	epc	sepc.lv	sepc.all
1	ind60	=	x1	NA	NA	NA	NA
2	ind60	=	x2	0.000	0.000	0.000	0.000
3	ind60	=	x3	0.000	0.000	0.000	0.000
4	ind60	=	y1	1.951	-0.128	-0.117	-0.118
...							
7	ind60	=	y4	3.760	0.179	0.163	0.164
8	ind60	=	y5	6.346	0.264	0.241	0.243
...							
26	dem65	=	y1	0.108	0.169	0.130	0.131
27	dem65	=	y2	0.617	-0.410	-0.316	-0.319
28	dem65	=	y3	0.423	-0.357	-0.275	-0.278
29	dem65	=	y4	0.744	0.456	0.351	0.354
30	dem65	=	y5	NA	NA	NA	NA
...							
73	y2	~~	y3	1.333	-0.061	-0.061	-0.062
74	y2	~~	y4	5.668	0.113	0.113	0.115
75	y2	~~	y5	0.560	0.035	0.035	0.035
...							
95	y6	~~	y7	0.495	-0.032	-0.032	-0.032
96	y6	~~	y8	8.813	0.132	0.132	0.133
97	y7	~~	y7	0.000	0.000	0.000	0.000
...							
109	dem65	~	ind60	0.000	0.000	0.000	0.000
110	ind60	~	dem60	NA	NA	NA	NA
111	ind60	~	dem65	NA	NA	NA	NA

Even more correlated residuals

```
mod.sem3<- '
# latent variable definitions
  ind60 =~ x1 + x2 + x3
  dem60 =~ y1 + y2 + y3 + y4
  dem65 =~ y5 + y6 + y7 + y8
# regressions
dem60 ~ ind60
dem65 ~ ind60 + dem60
y1 ~~ y5
y2 ~~ y4 + y6
y3 ~~ y7
y4 ~~ y8
y6 ~~ y8'
fit3 <- sem(mod.sem3, data=PoliticalDemocracy,std.ov=TRUE)
summary(fit3, fit.measures=TRUE)
lavaan.diagram(fit3,cut=0,lr=FALSE)
```

Lavaan (0.4-6) converged normally after 46 iterations

Number of observations	75
Estimator	ML
Minimum Function Chi-square	38.125
Degrees of freedom	35
P-value	0.329

Chi-square test baseline model:

Minimum Function Chi-square	730.654
Degrees of freedom	55
P-value	0.000

Root Mean Square Error of Approximation:

RMSEA	0.035
90 Percent Confidence Interval	0.000 0.092
P-value RMSEA <= 0.05	0.611

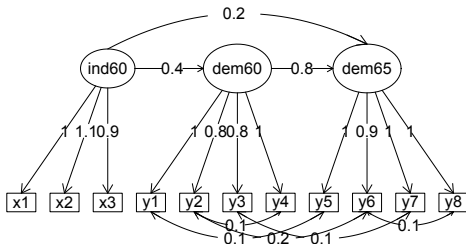
Standardized Root Mean Square Residual:

SRMR	0.044
------	-------

A more complicated model – correlated residuals

The very modified model

Structural model

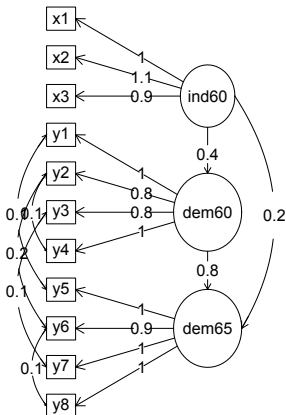


A more complicated model – correlated residuals

The very modified model – another way

```
lavaan.diagram(fit3,cut=0)
```

Structural model



A model with constraints at time 2 as well as correlated residuals

```
## The industrialization and Political Democracy Example
```

```
## Bollen (1989), page 332
```

```
model <- '
```

```
  # latent variable definitions
```

```
    ind60 =~ x1 + x2 + x3
```

```
    dem60 =~ y1 + y2 + y3 + y4
```

```
    dem65 =~ y5 + equal("dem60=~y2")*y6
```

```
          + equal("dem60=~y3")*y7
```

```
          + equal("dem60=~y4")*y8
```

```
  # regressions
```

```
    dem60 ~ ind60
```

```
    dem65 ~ ind60 + dem60
```

```
  # residual correlations
```

```
    y1 ~~ y5
```

```
    y2 ~~ y4 + y6
```

```
    y3 ~~ y7
```

```
    y4 ~~ y8
```

```
    y6 ~~ y8
```

```
fit <- sem(model, data=PoliticalDemocracy)
```

```
summary(fit, fit.measures=TRUE)
```

```
  Minimum Function Chi-square
```

```
  Degrees of freedom
```

```
  P-value
```

```
Chi-square test baseline model:
```

```
  Minimum Function Chi-square
```

```
  Degrees of freedom
```

```
  P-value
```

```
40.179
```

```
38
```

```
0.374
```

```
730.654
```

```
55
```

```
0.000
```

```
Full model versus baseline model:
```

```
  Comparative Fit Index (CFI)
```

```
  Tucker-Lewis Index (TLI)
```

```
Loglikelihood and Information Criteria:
```

```
  Loglikelihood user model (H0)
```

```
  Loglikelihood unrestricted model (H1)
```

```
  Number of free parameters
```

```
  Akaike (AIC)
```

```
  Bayesian (BIC)
```

```
  Sample-size adjusted Bayesian (BIC)
```

```
Root Mean Square Error of Approximation:
```

```
  RMSEA
```

```
  90 Percent Confidence Interval
```

```
  P-value RMSEA <= 0.05
```

```
Standardized Root Mean Square Residual:
```

```
  SRMR
```

```
0.997
```

```
0.995
```

```
-1548.818
```

```
-1528.728
```

```
28
```

```
3153.636
```

```
3218.526
```

```
3130.277
```

```
0.028
```

```
0.000 0.087
```

```
0.665
```

```
0.056
```

Constrained model with parameter values

Information		Expected Covariances:							
Standard Errors		Standard							
		Estimate	Std.err	Z-value	P(> z)	y1 ~~			
Latent variables:						y5	0.583	0.356	1.637
ind60 =~						y2 ~~			0.102
x1		1.000				y4	1.440	0.689	2.092
x2		2.180	0.138	15.751	0.000	y6	2.183	0.737	2.960
x3		1.818	0.152	11.971	0.000	y3 ~~			0.003
dem60 =~						y7	0.712	0.611	1.165
y1		1.000				y4 ~~			0.244
y2		1.191	0.139	8.551	0.000	y8	0.363	0.444	0.817
y3		1.175	0.120	9.755	0.000	y6 ~~			0.414
y4		1.251	0.117	10.712	0.000	y8	1.372	0.577	2.378
dem65 =~						Variances:			
y5		1.000				x1	0.081	0.019	4.182
y6		1.191				x2	0.120	0.070	1.729
y7		1.175				x3	0.467	0.090	5.177
y8		1.251				y1	1.855	0.433	4.279
Regressions:						y2	7.581	1.366	5.549
dem60 ~						y3	4.956	0.956	5.182
ind60		1.471	0.392	3.750	0.000	y4	3.224	0.723	4.458
dem65 ~						y5	2.313	0.479	4.831
ind60		0.600	0.226	2.661	0.008	y6	4.968	0.921	5.393
dem60		0.865	0.075	11.554	0.000	y7	3.560	0.710	5.018
						y8	3.308	0.704	4.701
						ind60	0.449	0.087	5.175
						dem60	3.875	0.866	4.477
						dem65	0.164	0.227	0.725
									0.469

Standardized solution

```
> standardizedSolution(fit)
```

	lhs	op	rhs	est	est.std	est.std.all
1	ind60	=~	x1	1.000	0.670	0.920
2	ind60	=~	x2	2.180	1.460	0.973
3	ind60	=~	x3	1.818	1.218	0.872
4	dem60	=~	y1	1.000	2.201	0.850
5	dem60	=~	y2	1.191	2.621	0.690
6	dem60	=~	y3	1.175	2.586	0.758
7	dem60	=~	y4	1.251	2.754	0.838
8	dem65	=~	y5	1.000	2.154	0.817
9	dem65	=~	y6	1.191	2.565	0.755
10	dem65	=~	y7	1.175	2.530	0.802
11	dem65	=~	y8	1.251	2.694	0.829
12	dem60	~	ind60	1.471	0.448	0.448
13	dem65	~	ind60	0.600	0.187	0.187
14	dem65	~	dem60	0.865	0.884	0.884
15	y1	~~	y5	0.583	0.583	0.085
16	y2	~~	y4	1.440	1.440	0.115
17	y2	~~	y6	2.183	2.183	0.169
18	y3	~~	y7	0.712	0.712	0.066
19	y4	~~	y8	0.363	0.363	0.034
20	y6	~~	y8	1.372	1.372	0.124
21	x1	~~	x1	0.081	0.081	0.154
22	x2	~~	x2	0.120	0.120	0.053
23	x3	~~	x3	0.467	0.467	0.239
24	y1	~~	y1	1.855	1.855	0.277
25	y2	~~	y2	7.581	7.581	0.525
26	y3	~~	y3	4.956	4.956	0.426
27	y4	~~	y4	3.224	3.224	0.298
28	y5	~~	y5	2.313	2.313	0.333
29	y6	~~	y6	4.968	4.968	0.430
30	y7	~~	y7	3.560	3.560	0.357
31	y8	~~	y8	3.308	3.308	0.313
32	ind60	~~	ind60	0.449	1.000	1.000
33	dem60	~~	dem60	3.875	0.800	0.800
34	dem65	~~	dem65	0.164	0.035	0.035

Lisrel example

```

model <- '
# latent variable definitions
ind60 =~ x1 + x2 + x3
dem60 =~ y1 + y2 + y3 + y4
dem65 =~ y5 + equal("dem60=~y2")*y6
      + equal("dem60=~y3")*y7
      + equal("dem60=~y4")*y8

# regressions
dem60 ~ ind60
dem65 ~ ind60 + dem60
# residual correlations
y1 ~~ y5
y2 ~~ y6
y3 ~~ y7
y4 ~~ y8'
fit <- sem(model, data=PoliticalDemocracy,
  likelihood='wishart')
summary(fit, fit.measures=TRUE)

```

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	-1561.202
Loglikelihood unrestricted model (H1)	-1534.265
Number of free parameters	26
Akaike (AIC)	3174.405
Bayesian (BIC)	3234.659
Sample-size adjusted Bayesian (BIC)	3152.714

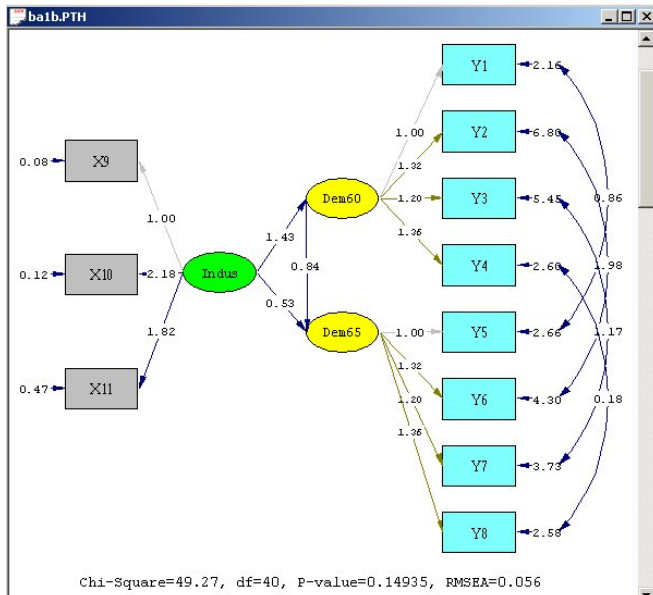
Root Mean Square Error of Approximation:

Lavaan (0.4-6) converged normally after 88 iterations	RMSEA	0.066
Number of observations	75	90 Percent Confidence Interval
Estimator	ML	0.000 0.110
Minimum Function Chi-square	53.156	P-value RMSEA <= 0.05
Degrees of freedom	40	0.277
P-value	0.080	Standardized Root Mean Square Residual:
Chi-square test baseline model:	SRMR	0.061
Minimum Function Chi-square	720.912	
Degrees of freedom	55	
P-value	0.000	
Full model versus baseline model:		
Comparative Fit Index (CFI)	0.980	

					variances:				
					y1	~~			
Latent variables:	Estimate	Std.err	Z-value	P(> z)	y5	~~	0.862	0.370	2.327
ind60 =~					y2	~~			0.020
x1	1.000				y6	~~	1.978	0.786	0.012
x2	2.180	0.140	15.620	0.000	y3	~~			
x3	1.819	0.153	11.888	0.000	y7	~~	1.171	0.638	0.066
dem60 =~					y4	~~			
y1	1.000				y8	~~	0.179	0.478	0.708
y2	1.318	0.149	8.869	0.000	Variances:				
y3	1.203	0.133	9.034	0.000	x1		0.083	0.020	0.000
y4	1.363	0.128	10.686	0.000	x2		0.122	0.071	0.089
dem65 =~					x3		0.473	0.092	0.000
y5	1.000				y1		2.157	0.454	0.000
y6	1.318				y2		6.799	1.265	0.000
y7	1.203				y3		5.452	1.021	0.000
y8	1.363				y4		2.601	0.669	0.000
Regressions:					y5		2.664	0.515	0.000
dem60 ~					y6		4.301	0.841	0.000
ind60	1.427	0.381	3.747	0.000	y7		3.729	0.724	0.000
dem65 ~					y8		2.576	0.620	0.000
ind60	0.525	0.215	2.445	0.014	ind60		0.455	0.088	0.000
dem60	0.845	0.071	11.850	0.000	dem60		3.659	0.845	0.000
					dem65		0.367	0.199	0.064

Compare to LISREL example

LISREL output



But remember, arrows can be reversed!

Reverse causation: Democracy leads to industrialization

```
model <- '
# latent variable definitions
ind60 =~ x1 + x2 + x3
dem60 =~ y1 + y2 + y3 + y4
dem65 =~ y5 + equal("dem60=~y2")*y6
      + equal("dem60=~y3")*y7
      + equal("dem60=~y4")*y8

# regressions
ind60 ~ dem60
dem65 ~ ind60 + dem60
# residual correlations
y1 ~~ y5
y2 ~~ y6
y3 ~~ y7
y4 ~~ y8'
fit <- sem(model, data=PoliticalDemocracy,
  likelihood='wishart')
summary(fit, fit.measures=TRUE)
```

Lavaan (0.4-6) converged normally after 90 iterations

Number of observations	75
Estimator	ML
Minimum Function Chi-square	53.156
Degrees of freedom	40
P-value	0.080
Chi-square test baseline model:	
Minimum Function Chi-square	720.912
Degrees of freedom	55
P-value	0.000
Full model versus baseline model:	
Comparative Fit Index (CFI)	0.980