

Psychology 454: Latent Variable Modeling SEM over time Changes in structure, changes in means

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Outline

- 1 Two time points-invariant
 - create the data
 - Exploratory Factor Models
 - Confirmatory models using lavaan
- 2 Two time points- changes
 - Create the data
 - EFA
 - CFA
- 3 Detecting change
- 4 Modeling change with growth curves
- 5 Traits and States

Measuring structure at two (or more) time points

- ① Is the structure the same
 - Structural Invariance (is the graph the same)
 - Measurement invariance (are the loadings the same)
 - Strong measurement invariance (are the item intercepts the same?)
 - Measuring change
- ② Do the means change (is there growth)
 - This is the means of the latent trait, not the means of the items
- ③ Do the latent traits correlate across two or more occasions?
 - Just two occasions, can not separate trait from state effects
 - With > 2 occasions, can examine trait and state effects
- ④ Compare several different simulations

Create some basic data and add in some change

```
> set.seed(42)
> fx <- matrix(c(.8,.7,.6,rep(0,6),.8,.7,.6),ncol=2)
> fx
      [,1] [,2]
[1,]  0.8  0.0
[2,]  0.7  0.0
[3,]  0.6  0.0
[4,]  0.0  0.8
[5,]  0.0  0.7
[6,]  0.0  0.6
> Phi <- matrix(c(1,.6,.6,1),ncol=2)
> Phi
      [,1] [,2]
[1,]  1.0  0.6
[2,]  0.6  1.0
> x.model <- sim(fx=fx,Phi=Phi,mu=c(0,1),n=250)
> x <- x.model$observed
> structure.diagram(fx,Phi,lr=FALSE,e.size=.3,main="A basic two time model")
> describe(x,skew=FALSE)

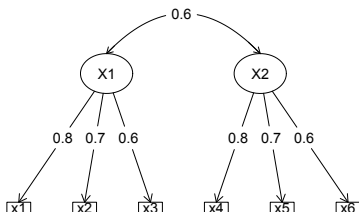
> pairs.panels(x,pch=".")
```

	var	n	mean	sd	median	trimmed	mad	min	max	range	se
V1	1	250	-0.01	0.94	-0.06	-0.02	1.00	-2.74	2.62	5.36	0.06
V2	2	250	0.04	0.98	0.11	0.06	0.99	-2.76	2.41	5.17	0.06
V3	3	250	-0.02	0.99	-0.03	-0.04	1.07	-2.32	2.84	5.17	0.06
V4	4	250	0.81	0.98	0.80	0.82	1.01	-2.03	3.29	5.32	0.06
V5	5	250	0.66	1.01	0.61	0.68	0.92	-2.89	3.72	6.61	0.06
V6	6	250	0.54	1.01	0.54	0.54	1.01	-2.42	3.71	6.13	0.06

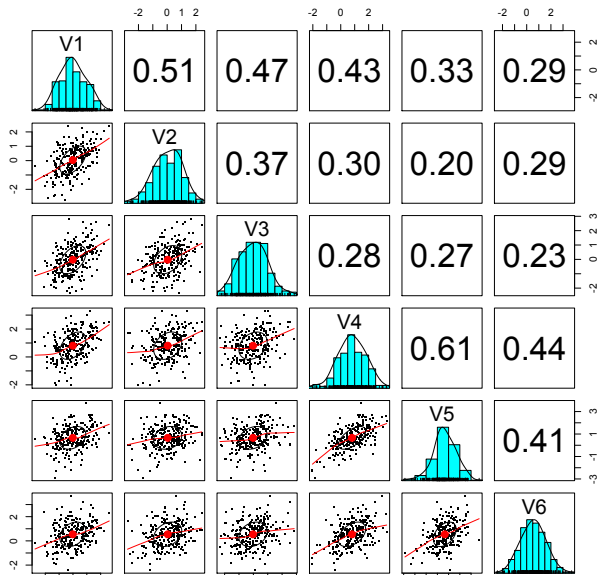
- 1 Set the random seed
- 2 Create a one factor structure
- 3 Put in some change
- 4 Show the structural model
- 5 Describe it
- 6 Show the splom (with small pch)

A basic two occasion trait model

A basic two time model



Splom of 6 basic variables



Multiple models

- ① Ignore time, are the data congeneric?
 - Are they all measures of the same thing?
 - This is a one factor model
- ② Include time, do we recover a correlation across time?
 - Try a two factor model
 - Plot the resulting structure

A one factor model

```
> fa(x)
```

```
Factor Analysis using method = minres
```

```
Call: fa(r = x)
```

```
Standardized loadings (pattern matrix)
```

```
based upon correlation matrix
```

	MR1	h2	u2
V1	0.64	0.41	0.59
V2	0.51	0.26	0.74
V3	0.50	0.25	0.75
V4	0.75	0.56	0.44
V5	0.66	0.43	0.57
V6	0.56	0.31	0.69

	MR1
SS loadings	2.22
Proportion Var	0.37

```
Test of the hypothesis that 1 factor is sufficient.
```

```
The degrees of freedom for the null model are 15
and the objective function was 1.58
with Chi Square of 388.97
```

```
The degrees of freedom for the model are 9
and the objective function was 0.3
```

```
The root mean square of the residuals (RMSR) is 0.07
The df corrected root mean square of the
residuals is 0.12
```

```
The number of observations was 250
with Chi Square = 73.6 with prob < 3e-12
```

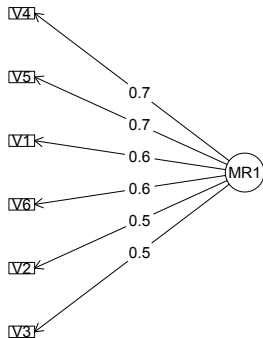
```
Tucker Lewis Index of factoring reliability = 0.711
RMSEA index = 0.171 and the
90 % confidence intervals are 0.135 0.206
BIC = 23.91
```

```
Fit based upon off diagonal values = 0.94
Measures of factor score adequacy
```

	MR1
Correlation of scores with factors	0.89
Multiple R square of scores with factors	0.79
Minimum correlation of possible factor scores	0.59

Fit a one factor model to the data

A one factor model



Try a two factor solution

```
> fa(x,2)
```

```
Loading required package: GPArotation
Factor Analysis using method = minres
Call: fa(r = x, nfactors = 2)
```

```
Standardized loadings (pattern matrix)
based upon correlation matrix
```

	MR1	MR2	h2	u2
V1	0.05	0.76	0.62	0.38
V2	-0.06	0.69	0.43	0.57
V3	0.04	0.55	0.33	0.67
V4	0.75	0.08	0.64	0.36
V5	0.81	-0.07	0.59	0.41
V6	0.47	0.12	0.30	0.70

	MR1	MR2
SS loadings	1.49	1.43
Proportion Var	0.25	0.24
Cumulative Var	0.25	0.49
Proportion Explained	0.51	0.49
Cumulative Proportion	0.51	1.00

```
With factor correlations of
```

	MR1	MR2
MR1	1.00	0.57
MR2	0.57	1.00

```
Measures of factor score adequacy
```

	MR1	MR2
Correlation of scores with factors	0.89	0.87
Multiple R square of scores with factors	0.80	0.77
Minimum correlation of possible factor scores	0.59	0.53

```
Test of the hypothesis that 2 factors are sufficient.
```

```
The degrees of freedom for the null model are 15
and the objective function was 1.58
with Chi Square of 388.97
```

```
The degrees of freedom for the model are 4
and the objective function was 0.02
```

```
The root mean square of the residuals (RMSR) is 0.02
The df corrected root mean square of
the residuals is 0.04
```

```
The number of observations was 250
with Chi Square = 5.87 with prob < 0.21
```

```
Tucker Lewis Index of factoring reliability = 0.981
RMSEA index = 0.045 and the
90 % confidence intervals are NA 0.112
```

```
BIC = -16.21
```

```
Fit based upon off diagonal values = 1
```

Compare the two solutions

Factor Analysis using method = minres

Call: fa(r = x)

Standardized loadings (pattern matrix)

based upon correlation matrix

	MR1	h2	u2
V1	0.64	0.41	0.59
V2	0.51	0.26	0.74
V3	0.50	0.25	0.75
V4	0.75	0.56	0.44
V5	0.66	0.43	0.57
V6	0.56	0.31	0.69

MR1

SS loadings 2.22

Proportion Var 0.37

Factor Analysis using method = minres

Call: fa(r = x, nfactors = 2)

Standardized loadings (pattern matrix)

based upon correlation matrix

	MR1	MR2	h2	u2
V1	0.05	0.76	0.62	0.38
V2	-0.06	0.69	0.43	0.57
V3	0.04	0.55	0.33	0.67
V4	0.75	0.08	0.64	0.36
V5	0.81	-0.07	0.59	0.41
V6	0.47	0.12	0.30	0.70

MR1 MR2

SS loadings 1.49 1.43

Proportion Var 0.25 0.24

Cumulative Var 0.25 0.49

Proportion Explained 0.51 0.49

Cumulative Proportion 0.51 1.00

With factor correlations of

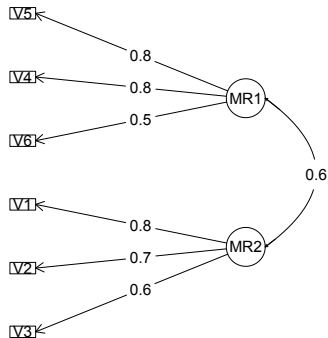
MR1 MR2

MR1 1.00 0.57

MR2 0.57 1.00

EFA two factor solution

Factor Analysis



Now try three different sems (using lavaan)

- ① Two correlated factors, free loadings
- ② Two correlated factors, equal loadings across occasions
- ③ Two correlated factors, all loadings equal

A simple sem with a standardized solution

```
#factor model
mod2f <- F1 =~ V1 + V2 + V3
          F2 =~ V4 + V5 + V6
          #correlation between factors
          F1 ~~F2# now fit it and summarize it
> fit <- sem(mod2f, data=x.df,std.lv=TRUE)
> summary(fit, fit.measures=TRUE)
> standardizedSolution(fit)
```

	lhs	op	rhs	est.std	se	z	pvalue
1	F1	=~	V1	0.819	NA	NA	NA
2	F1	=~	V2	0.618	NA	NA	NA
3	F1	=~	V3	0.579	NA	NA	NA
4	F2	=~	V4	0.835	NA	NA	NA
5	F2	=~	V5	0.720	NA	NA	NA
6	F2	=~	V6	0.552	NA	NA	NA
7	F1	~~	F2	0.607	NA	NA	NA

lavaan fit statistics

lavaan (0.4-14) converged normally after 16 iterations

Root Mean Square Error of Approximation:

Number of observations	250	RMSEA		0.026
		90 Percent Confidence Interval	0.000	0.081
Estimator	ML	P-value RMSEA <= 0.05		0.699
Minimum Function Chi-square	9.341			
Degrees of freedom	8	Standardized Root Mean Square Residual:		
P-value	0.314			
		SRMR		0.029

Chi-square test baseline model:

Parameter estimates:

Minimum Function Chi-square	395.026			
Degrees of freedom	15	Information		Expected
P-value	0.000	Standard Errors		Standard

Full model versus baseline model:

Estimate Std.err Z-value P(>|z|)

Latent variables:

Comparative Fit Index (CFI)	0.996	F1 =~				
Tucker-Lewis Index (TLI)	0.993	V1	0.768	0.062	12.363	0.000
		V2	0.604	0.065	9.313	0.000
		V3	0.569	0.066	8.672	0.000

Loglikelihood and Information Criteria:

F2 =~

Loglikelihood user model (H0)	-1909.112	V4	0.818	0.062	13.296	0.000
Loglikelihood unrestricted model (H1)	-1904.441	V5	0.727	0.064	11.346	0.000
		V6	0.558	0.066	8.472	0.000

Number of free parameters	13					
Akaike (AIC)	3844.224	Covariances:				
Bayesian (BIC)	3890.003	F1 ~~				
Sample-size adjusted Bayesian (BIC)	3848.791	F2	0.607	0.062	9.861	0.000

Create two new models with some equality constraints

```

> mod2fa <- F1 =~ a*V1 + b*V2 + c*V3
               F2 =~ a*V4 + b*V5 + c*V6
               F1 ~~F2
> fit2a <- sem(mod2fa,data=x.df,std.lv=TRUE)
> summary(fit2a,fit.measures=TRUE)

> mod2fe <- F1 =~ a*V1 + a*V2 + a*V3
               F2 =~ a*V4 + a*V5 + a*V6
               F1 ~~F2
> fit2e <- sem(mod2fe,data=x.df,std.lv=TRUE)
> summary(fit2e,fit.measures=TRUE)

```


Equal across time

lavaan (0.4-14) converged normally after 15 iterations

Root Mean Square Error of Approximation:

Number of observations	250	RMSEA	0.017
Estimator	ML	90 Percent Confidence Interval	0.000 0.070
Minimum Function Chi-square	11.797	P-value RMSEA <= 0.05	0.801
Degrees of freedom	11		
P-value	0.379	Standardized Root Mean Square Residual:	

Chi-square test baseline model:	SRMR	0.044
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Minimum Function Chi-square	395.026	Parameter estimates:	
Degrees of freedom	15		
P-value	0.000	Information	Expected
		Standard Errors	Standard

Full model versus baseline model:

			Estimate	Std.err	Z-value	P(> z)
Comparative Fit Index (CFI)	0.998	Latent variables:				
Tucker-Lewis Index (TLI)	0.997	F1 =~				
		V1 (a)	0.793	0.046	17.162	0.000
Loglikelihood and Information Criteria:		V2 (b)	0.669	0.047	14.116	0.000
		V3 (c)	0.564	0.048	11.819	0.000
Loglikelihood user model (H0)	-1910.340	F2 =~				
Loglikelihood unrestricted model (H1)	-1904.441	V4 (a)	0.793	0.046	17.162	0.000
		V5 (b)	0.669	0.047	14.116	0.000
Number of free parameters	10	V6 (c)	0.564	0.048	11.819	0.000
Akaike (AIC)	3840.679					
Bayesian (BIC)	3875.894	Covariances:				
Sample-size adjusted Bayesian (BIC)	3844.193	F1 =~				
		F2	0.606	0.061	9.869	0.000

All loadings equal

```
> summary(fit2e,fit.measures=TRUE)
```

lavaan (0.4-14) converged normally after 12 iterations

Root Mean Square Error of Approximation:

Number of observations	250	RMSEA		0.062
		90 Percent Confidence Interval	0.024	0.097
Estimator	ML	P-value RMSEA <= 0.05		0.260
Minimum Function Chi-square	25.457			
Degrees of freedom	13	Standardized Root Mean Square Residual:		
P-value	0.020	SRMR		0.071

Chi-square test baseline model:

Parameter estimates:

Minimum Function Chi-square	395.026	Information		Expected
Degrees of freedom	15	Standard Errors		Standard
P-value	0.000			

Full model versus baseline model:

Estimate Std.err Z-value P(>|z|)

Latent variables:

Comparative Fit Index (CFI)	0.967	F1 =~					
Tucker-Lewis Index (TLI)	0.962	V1	(a)	0.686	0.033	20.987	0.000
		V2	(a)	0.686	0.033	20.987	0.000
		V3	(a)	0.686	0.033	20.987	0.000

Loglikelihood and Information Criteria:

F2 =~

Loglikelihood user model (H0)	-1917.169	V4	(a)	0.686	0.033	20.987	0.000
Loglikelihood unrestricted model (H1)	-1904.441	V5	(a)	0.686	0.033	20.987	0.000
		V6	(a)	0.686	0.033	20.987	0.000

Number of free parameters	8						
Akaike (AIC)	3850.339	Covariances:					
Bayesian (BIC)	3878.510	F1 ~~					
Sample-size adjusted Bayesian (BIC)	3853.150	F2		0.624	0.063	9.909	0.000

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Create the data

Create a data set with non-invariant factor loadings

```
> set.seed(42)
> fx <- matrix(c(.8,.7,.6,rep(0,6),.6,.7,.8),ncol=2)
> fx
      [,1] [,2]
[1,]  0.8  0.0
[2,]  0.7  0.0
[3,]  0.6  0.0
[4,]  0.0  0.6
[5,]  0.0  0.7
[6,]  0.0  0.8
> Phi <- matrix(c(1,.6,.6,1),ncol=2)
> Phi
> set.seed(42)
> x.model <- sim(fx=fx,Phi=Phi,mu=c(0,1),n=250)
> x <- x.model$observed
> structure.diagram(fx,Phi,lr=FALSE,e.size=.3,main="A basic two time model")
> describe(x,skew=FALSE)
```

	var	n	mean	sd	median	trimmed	mad	min	max	range	se
V1	1	250	0.02	0.99	0.01	0.03	1.02	-2.64	2.76	5.40	0.06
V2	2	250	-0.02	0.96	-0.01	-0.03	0.94	-2.66	3.12	5.78	0.06
V3	3	250	0.02	0.97	-0.06	0.01	0.95	-2.74	2.41	5.15	0.06
V4	4	250	0.61	0.99	0.59	0.65	0.99	-3.26	3.15	6.41	0.06

One factor model

```
> fin <- fa(x)
> fin
```

Factor Analysis using method = minres

Call: fa(r = x)

Standardized loadings (pattern matrix) based upon correlation matrix

	MR1	h2	u2
V1	0.59	0.35	0.65
V2	0.56	0.31	0.69
V3	0.48	0.23	0.77
V4	0.54	0.29	0.71
V5	0.69	0.48	0.52
V6	0.72	0.52	0.48

	MR1
SS loadings	2.18
Proportion Var	0.36

Test of the hypothesis that 1 factor is sufficient.

The degrees of freedom for the null model are 15
 and the objective function was 1.58
 with Chi Square of 389.85
 The degrees of freedom for the model are 9
 and the objective function was 0.33

The root mean square of the residuals (RMSR) is 0.07
 The df corrected root mean square of the residuals is
 The number of observations was 250 with Chi Square =

Tucker Lewis Index of factoring reliability = 0.684
 RMSEA index = 0.179 and the 90 % confidence interval.
 BIC = 30.24

Fit based upon off diagonal values = 0.93
 Measures of factor score adequacy

	MR1
Correlation of scores with factors	0.89
Multiple R square of scores with factors	0.79
Minimum correlation of possible factor scores	0.57

Two factor model

```
> f2n <- fa(x,2)
> f2n
```

Factor Analysis using method = minres

Call: fa(r = x, nfactors = 2)

Standardized loadings (pattern matrix) based upon correlation matrix

	MR1	MR2	h2	u2
V1	-0.01	0.79	0.62	0.38
V2	-0.01	0.73	0.53	0.47
V3	0.15	0.40	0.25	0.75
V4	0.51	0.07	0.30	0.70
V5	0.79	-0.03	0.60	0.40
V6	0.80	0.02	0.65	0.35

	MR1	MR2
SS loadings	1.58	1.37
Proportion Var	0.26	0.23
Cumulative Var	0.26	0.49
Proportion Explained	0.53	0.47
Cumulative Proportion	0.53	1.00

With factor correlations of

	MR1	MR2
MR1	1.00	0.54
MR2	0.54	1.00

Correlation of scores with factors	0.90	0.88
Multiple R square of scores with factors	0.80	0.77
Minimum correlation of possible factor scores	0.61	0.54

Test of the hypothesis that 2 factors are sufficient.

The degrees of freedom for the null model are 15
and the objective function was 1.58
with Chi Square of 389.85

The degrees of freedom for the model are 4
and the objective function was 0

The root mean square of the residuals (RMSR) is 0.01
The df corrected root mean square of the residuals is
The number of observations was 250 with
Chi Square = 4.7 with prob < 0.32

Tucker Lewis Index of factoring reliability = 0.993
RMSEA index = 0.028 and the 90 % confidence interval.
BIC = -17.39
Fit based upon off diagonal values = 1
Measures of factor score adequacy

MR1 MR2

Compare the two solutions

Factor Analysis using method = minres

Call: fa(r = x)

Standardized loadings (pattern matrix)

based upon correlation matrix

	MR1	h2	u2
V1	0.59	0.35	0.65
V2	0.56	0.31	0.69
V3	0.48	0.23	0.77
V4	0.54	0.29	0.71
V5	0.69	0.48	0.52
V6	0.72	0.52	0.48

	MR1
SS loadings	2.18
Proportion Var	0.36

Factor Analysis using method = minres

Call: fa(r = x, nfactors = 2)

Standardized loadings (pattern matrix)

based upon correlation matrix

	MR1	MR2	h2	u2
V1	-0.01	0.79	0.62	0.38
V2	-0.01	0.73	0.53	0.47
V3	0.15	0.40	0.25	0.75
V4	0.51	0.07	0.30	0.70
V5	0.79	-0.03	0.60	0.40
V6	0.80	0.02	0.65	0.35

	MR1	MR2
SS loadings	1.58	1.37
Proportion Var	0.26	0.23
Cumulative Var	0.26	0.49
Proportion Explained	0.53	0.47
Cumulative Proportion	0.53	1.00

With factor correlations of

	MR1	MR2
MR1	1.00	0.54
MR2	0.54	1.00

CFA 2 correlated factors

```
> y.df <- data.frame(y)
> fitn<- sem(mod2f,data=y.df,std.lv=TRUE)
> summary(fitn, fit.measures=TRUE)
```

Root Mean Square Error of Approximation:

	RMSEA	0.000
	90 Percent Confidence Interval	0.000 0.000
	P-value RMSEA <= 0.05	0.994

lavaan (0.4-14) converged normally after 17 iterations

Number of observations 250

Estimator

Minimum Function Chi-square 2.552

Degrees of freedom 8

P-value 0.959

ML Standardized Root Mean Square Residual:

SRMR 0.014

Chi-square test baseline model:

Parameter estimates:

Minimum Function Chi-square

341.309

Degrees of freedom

15

P-value

0.000

Information

Standard Errors

Expected

Standard

Full model versus baseline model:

Latent variables:

Comparative Fit Index (CFI)

1.000

Tucker-Lewis Index (TLI)

1.031

Estimate Std.err Z-value P(>|z|)

F1 =~

V1

0.750 0.063 11.880 0.000

V2

0.725 0.065 11.160 0.000

V3

0.621 0.066 9.410 0.000

Loglikelihood and Information Criteria:

F2 =~

V4

0.585 0.074 7.896 0.000

V5

0.610 0.068 8.950 0.000

V6

0.700 0.066 10.545 0.000

Loglikelihood user model (H0)

-1952.265

Loglikelihood unrestricted model (H1)

-1950.989

Number of free parameters

13

Akaike (AIC)

3930.530

Bayesian (BIC)

3976.309

Sample-size adjusted Bayesian (BIC)

3935.09

Covariances:

F1 ~~

F2

0.607 0.067 9.067 0.000

Are the factors measurement invariant? Well, maybe.

```
> summary(fitn2a,fit.measures=TRUE)
```

Root Mean Square Error of Approximation:

	RMSEA	0.000
lavaan (0.4-14) converged normally after 14 iterations	90 Percent Confidence Interval	0.000 0.051
	P-value RMSEA <= 0.05	0.946

Number of observations

250

Standardized Root Mean Square Residual:

Estimator

ML

Minimum Function Chi-square

8.093

SRMR

0.049

Degrees of freedom

11

P-value

0.705

Parameter estimates:

Chi-square test baseline model:

Information

Standard Errors

Expected

Standard

Minimum Function Chi-square

341.309

Degrees of freedom

15

P-value

0.000

Estimate Std.err Z-value P(>|z|)

Latent variables:

F1 =~

Full model versus baseline model:

V1

(a)

0.686

0.050

13.774

0.000

V2

(b)

0.675

0.049

13.834

0.000

Comparative Fit Index (CFI)

1.000

V3

(c)

0.657

0.048

13.677

0.000

Tucker-Lewis Index (TLI)

1.012

F2 =~

V4

(a)

0.686

0.050

13.774

0.000

V5

(b)

0.675

0.049

13.834

0.000

Loglikelihood and Information Criteria:

V6

(c)

0.657

0.048

13.677

0.000

Loglikelihood user model (H0)

-1955.036

Loglikelihood unrestricted model (H1)

-1950.989

Covariances:

F1 ~~

Number of free parameters

10

F2

0.610

0.067

9.089

0.000

Akaike (AIC)

3930.072

Bayesian (BIC)

3965.286

Variances:

Create the original data set again

```

> fx <- matrix(c(.8,.7,.6,rep(0,6),.8,.7,.6),ncol=2)
> x.model <- sim(fx=fx,Phi=Phi,mu=c(0,1),n=250)
> x <- x.model$observed
> x.df <- data.frame(x)

> describe(x,skew=FALSE)
  var   n mean   sd median trimmed  mad   min  max range   se
V1   1 250 0.02 0.99  -0.01  -0.01  1.04 -2.38  3.26  5.64 0.06
V2   2 250 0.13 1.07   0.03   0.11  1.08 -2.53  3.65  6.19 0.07
V3   3 250 0.03 1.03   0.05   0.02  0.97 -2.68  3.12  5.80 0.07
V4   4 250 0.87 1.04   0.90   0.85  1.03 -1.63  3.61  5.24 0.07
V5   5 250 0.73 0.97   0.76   0.75  0.90 -2.36  3.29  5.65 0.06
V6   6 250 0.65 1.00   0.67   0.64  1.03 -2.58  3.17  5.75 0.06

```

Model change in the items

```
mod2fc <- F1 =~ a*V1 + b* V2 + c*V3
          F2 =~ a* V4 + b*V5 +c* V6
          #correlation between factors
          F2 ~ F1      #the regression
fit2c <- sem(mod2fc,data=x.df,meanstructure=TRUE)
summary(fit2c,fit.measures=TRUE)
```

frame

Root Mean Square Error of Approximation:										
lavaan (0.4-14) converged normally after 23 iterations										
		RMSEA					0.016			
		90 Percent Confidence Interval				0.000		0.071		
Number of observations		250	P-value RMSEA <= 0.05						0.793	
MLStandardized Root Mean Square Residual:										
Estimator										
Minimum Function Chi-square		10.616								
Degrees of freedom		10	SRMR						0.032	
P-value		0.388								
Parameter estimates:										
Chi-square test baseline model:										
		Information						Expected		
Minimum Function Chi-square		406.795	Standard Errors						Standard	
Degrees of freedom		15								
P-value		0.000			Estimate	Std.err	Z-value	P(> z)		
Latent variables:										
Full model versus baseline model:										
		F1 =~								
		V1	(a)	1.000						
Comparative Fit Index (CFI)		0.998	V2	(b)	0.925	0.076	12.243	0.000		
Tucker-Lewis Index (TLI)		0.998	V3	(c)	0.816	0.072	11.386	0.000		
		F2 =~								
		V4	(a)	1.000						
		V5	(b)	0.925	0.076	12.243	0.000			
		V6	(c)	0.816	0.072	11.386	0.000			
Loglikelihood and Information Criteria:										
Loglikelihood user model (H0)		-1952.674								
Loglikelihood unrestricted model (H1)		-1947.365								
Regressions:										
Number of free parameters		17	F2 ~							
Akaike (AIC)		3939.347	F1		0.644	0.075	8.593	0.000		
Bayesian (BIC)		3999.212								
Sample-size adjusted Bayesian (BIC)		3945.320	Intercepts:							

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With the intercepts

Intercepts:

V1	0.021	0.063	0.332	0.740
V2	0.135	0.066	2.033	0.042
V3	0.032	0.066	0.482	0.630
V4	0.865	0.065	13.294	0.000
V5	0.729	0.062	11.696	0.000
V6	0.649	0.063	10.369	0.000
F1	0.000			
F2	0.000			

Variances:

V1	0.383	0.060
V2	0.576	0.068
V3	0.670	0.071
V4	0.486	0.065
V5	0.481	0.061
V6	0.596	0.065
F1	0.613	0.088
F2	0.319	0.063

Try fitting a moments model

```

mod2fc <- F1 =~ a*V1 + b* V2 + c*V3
          F2 =~ a* V4 + b*V5 +c* V6
          means = ~ F1 + F2 + 1*V1 +1*V2+1*V3+1*V4+1*V5+1*V6
                  #correlation between factors

          F2 ~ F1      #the regression
fit2c <- sem(mod2fc,data=x.df,meanstructure=TRUE)
summary(fit2c,fit.measures=TRUE)

```

Modeling change using the moments matrix

- 1 McArdle (2009) Latent variable modeling of differences and changes with longitudinal data. Annual Review of Psychology, 60, 577-605
 - Use moments rather than covariances
- 2 Probably can be done in lavaan, but I don't know how. Can be done in sem package

Create the model to be fit in sem

```

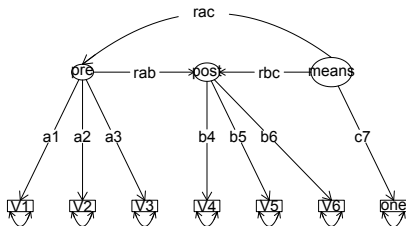
fxg
  pre post means
V1 "a1" "0" "0"
V2 "a2" "0" "0"
V3 "a3" "0" "0"
V4 "0" "b4" "0"
V5 "0" "b5" "0"
V6 "0" "b6" "0"
one "0" "0" "c7"
> phi
  F1 F2 F3
F1 "1" "0" "rac"
F2 "rab" "1" "rbc"
F3 "0" "0" "1"

mod.mom1 <- structure.diagram(fog,phi,errors=TRUE)

```

Modeling the means in a moments matrix

Structural model



the basic path model, with some editing

```
mod.mom1
      Path                Parameter Value
[1,] "pre->V1"           "a1"         NA
[2,] "pre->V2"           "a2"         NA
[3,] "pre->V3"           "a3"         NA
[4,] "post->V4"          "b4"         NA
[5,] "post->V5"          "b5"         NA
[6,] "post->V6"          "b6"         NA
[7,] "means->one"        "c7"         NA
[8,] "V1<->V1"          "x1e"         NA
[9,] "V2<->V2"          "x2e"         NA
[10,] "V3<->V3"          "x3e"         NA
[11,] "V4<->V4"          "x4e"         NA
[12,] "V5<->V5"          "x5e"         NA
[13,] "V6<->V6"          "x6e"         NA
[14,] "one<->one"        NA          "1"         <-- edited
[15,] "pre ->post"       "rF1F2"        NA
[16,] "means->pre"       "rF3F1"        NA      <- edited
[17,] "means->post"      "rF3F2"        NA      <- edited
[18,] "pre<->pre"        NA          "1"
[19,] "post<->post"      NA          "1"
[20,] "means<->means"    NA          "1"
attr(,"class")
[1] " "
```

sem output

```

                                Parameter Estimates
> sem.mom1 <- sem(mod.mom,MomMat,N=250,raw=TRUE)  Estimate Std Error z value Pr(>|z|)
> summary(sem.mom1)
                                a1  0.830111 0.069823 11.8888 1.3536e-32 V1 <--- pre
                                a2  0.881776 0.076506 11.5256 9.7982e-31 V2 <--- pre
                                a3  0.698963 0.074824  9.3415 9.5005e-21 V3 <--- pre
Model fit to raw moment matrix.  b4  0.664838 0.062395 10.6553 1.6468e-26 V4 <--- post
                                b5  0.554498 0.053510 10.3626 3.6687e-25 V5 <--- post
                                b6  0.510270 0.051499  9.9084 3.8265e-23 V6 <--- post
Model Chisquare = 12.077 Df = 12  b7  1.118034 0.050000 22.3607 9.5054e-111 one <--- means
                                c1e 0.525613 0.078258  6.7164 1.8623e-11 V1 <--> V1
                                x2e 0.673405 0.093381  7.2114 5.5387e-13 V2 <--> V2
                                x3e 0.836504 0.090362  9.2572 2.0983e-20 V3 <--> V3
                                x4e 0.567286 0.081353  6.9732 3.0990e-12 V4 <--> V4
                                x5e 0.628041 0.073463  8.5490 1.2412e-17 V5 <--> V5
                                x6e 0.750522 0.080300  9.3465 9.0592e-21 V6 <--> V6
                                x7e 0.893184 0.142998  6.2461 4.2076e-10 post <--- pre
AIC = 44.077  MaxF1F2 0.086583 0.073172 1.1833 2.3669e-01 pre <--- means
AICc = 14.411  rF3F1 1.375097 0.159247 8.6350 5.8723e-18 post <--- means
BIC = 100.42
CAIC = -66.181

Normalized Residuals
  Min. 1st Qu.  Median    Mean 3rd Qu.  Max
-1.2500 -0.1150  0.0000 -0.0103  0.0972  0.9743

Iterations = 21
  
```

Traits and States and time

- ① With just two time points, traits and states are confounded
 - Is the correlation a trait like stability
 - or does the state dissipate slowly?
- ② With > 2 time points we can distinguish states and traits
 - States should have an autocorrelation component
 - Traits should be consistent across time
- ③ Consider the simplex structure of 4 time points
 - Clean within time factor structure
 - Simplex across time points

A factor simplex

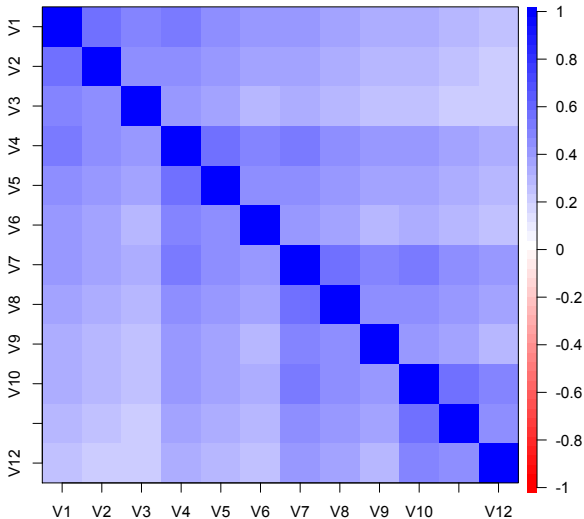
```
simp <- sim()
```

```
$model (Population correlation matrix)
```

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
V1	1.00	0.56	0.48	0.51	0.45	0.38	0.41	0.36	0.31	0.33	0.29	0.25
V2	0.56	1.00	0.42	0.45	0.39	0.34	0.36	0.31	0.27	0.29	0.25	0.22
V3	0.48	0.42	1.00	0.38	0.34	0.29	0.31	0.27	0.23	0.25	0.22	0.18
V4	0.51	0.45	0.38	1.00	0.56	0.48	0.51	0.45	0.38	0.41	0.36	0.31
V5	0.45	0.39	0.34	0.56	1.00	0.42	0.45	0.39	0.34	0.36	0.31	0.27
V6	0.38	0.34	0.29	0.48	0.42	1.00	0.38	0.34	0.29	0.31	0.27	0.23
V7	0.41	0.36	0.31	0.51	0.45	0.38	1.00	0.56	0.48	0.51	0.45	0.38
V8	0.36	0.31	0.27	0.45	0.39	0.34	0.56	1.00	0.42	0.45	0.39	0.34
V9	0.31	0.27	0.23	0.38	0.34	0.29	0.48	0.42	1.00	0.38	0.34	0.29
V10	0.33	0.29	0.25	0.41	0.36	0.31	0.51	0.45	0.38	1.00	0.56	0.48
V11	0.29	0.25	0.22	0.36	0.31	0.27	0.45	0.39	0.34	0.56	1.00	0.42
V12	0.25	0.22	0.18	0.31	0.27	0.23	0.38	0.34	0.29	0.48	0.42	1.00

A simplex

Correlation plot



Factor structure of a simplex

```
> fsimp <- fa(simp$model)
> fsimp
```

Factor Analysis using method = minres

Call: fa(r = simp\$model)

Standardized loadings (pattern matrix) based upon correlation matrix

	MR1	h2	u2
V1	0.64	0.41	0.59
V2	0.57	0.33	0.67
V3	0.49	0.24	0.76
V4	0.73	0.54	0.46
V5	0.65	0.42	0.58
V6	0.56	0.31	0.69
V7	0.73	0.54	0.46
V8	0.65	0.42	0.58
V9	0.56	0.31	0.69
V10	0.64	0.41	0.59
V11	0.57	0.33	0.67
V12	0.49	0.24	0.76

	MR1
SS loadings	4.50
Proportion Var	0.38

Factors over time

```
> fsimp4 <- fa(simp$model,4)
> fsimp4
```

```
Factor Analysis using method = minres
Call: fa(r = simp$model, nfactors = 4)
Standardized loadings (pattern matrix)
      based upon correlation matrix
```

	MR3	MR1	MR2	MR4	h2	u2
V1	0.8	0.0	0.0	0.0	0.64	0.36
V2	0.7	0.0	0.0	0.0	0.49	0.51
V3	0.6	0.0	0.0	0.0	0.36	0.64
V4	0.0	0.0	0.0	0.8	0.64	0.36
V5	0.0	0.0	0.0	0.7	0.49	0.51
V6	0.0	0.0	0.0	0.6	0.36	0.64
V7	0.0	0.8	0.0	0.0	0.64	0.36
V8	0.0	0.7	0.0	0.0	0.49	0.51
V9	0.0	0.6	0.0	0.0	0.36	0.64
V10	0.0	0.0	0.8	0.0	0.64	0.36
V11	0.0	0.0	0.7	0.0	0.49	0.51
V12	0.0	0.0	0.6	0.0	0.36	0.64

	MR3	MR1	MR2	MR4
SS loadings	1.49	1.49	1.49	1.49
Proportion Var	0.12	0.12	0.12	0.12
Cumulative Var	0.12	0.25	0.37	0.50
Proportion Explained	0.25	0.25	0.25	0.25
Cumulative Proportion	0.25	0.50	0.75	1.00

With factor correlations of

	MR3	MR1	MR2	MR4
MR3	1.00	0.64	0.51	0.80
MR1	0.64	1.00	0.80	0.80
MR2	0.51	0.80	1.00	0.64
MR4	0.80	0.80	0.64	1.00