

The semexamples: R point of view

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Outline

- 1 Overview
- 2 1. EFA
- 3 2. CFA
- 4 3. Multi-Group CFA
 - Configural
 - Metric Invariance
 - Scalar Invariance
- 5 4. Regression
- 6 5. SEM
- 7 6. Latent Growth
- 8 Conclusion

The Repository

- CRMDA created an archive of SEM working examples.
- To the extent possible, the same models are estimated with
 - Mplus
 - R
 - Stata
- The repository can be browsed online:
<https://gitlab.crmda.ku.edu/crmda/semexample>
 - And a snapshot can also be obtained with Git.
- The data folder includes the information that is imported into each of the 3 programs.

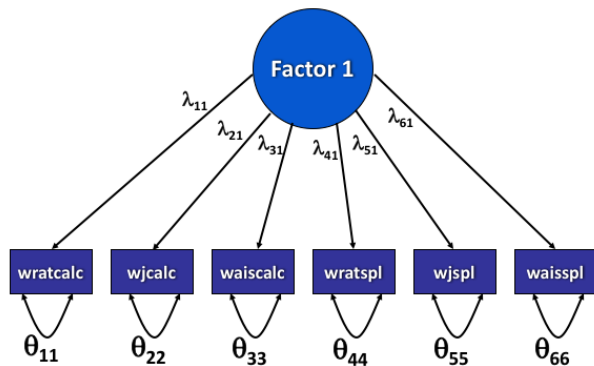
Runnable examples

- 1 Exploratory Factor Analysis (EFA)
- 2 Confirmatory Factor Analysis (CFA)
- 3 Measurement Invariance (Multi-group CFA)
- 4 Multiple Regression
- 5 Structural Equation Model (SEM)
- 6 Latent Growth Curve (LGC)
- 7 Modeling strategy changes for Ordinal Data

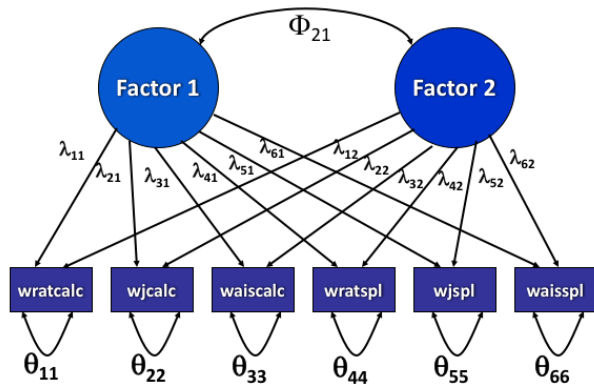
Exploratory Factor Analysis

- The Excelsior Springs data. How many latent variables underlie subtest scores (6 items)?
- R's function `factanal` is delivered with the R base package set
- We run EFAs for one and two possible latent factors.

One Factor



Two Factors



R code and results

```
head(scalescores)
```

	wjcalc	wjspl	wratspl	wratcalc	waiscalc	waisspl
1	29	51	47	49	12	45
2	31	54	57	49	21	47
3	23	45	38	40	9	36
4	31	34	38	48	14	38
5	31	31	30	52	15	38
6	27	42	40	42	12	41

```
output1 <- factanal(scalescores, 1, rotation =  
  "varimax")  
output1
```


R code and results ...

```
Call:
factanal(x = scalescores, factors = 1, rotation = "varimax")
```

Uniquenesses:

wjcalc	wjspl	wratspl	wratcalc	waiscalc	waisspl
0.728	0.093	0.108	0.695	0.749	0.116

Loadings:

	Factor1
wjcalc	0.522
wjspl	0.953
wratspl	0.945
wratcalc	0.552
waiscalc	0.501
waisspl	0.940

	Factor1
SS loadings	3.511
Proportion Var	0.585

Test of the hypothesis that 1 factor is sufficient.
The chi square statistic is 461.38 on 9 degrees of freedom.
The p-value is 1.06e-93

R code and results ...

```
output2 <- factanal(scalescores , 2, rotation =
  "varimax")
output2
```

Call:

```
factanal(x = scalescores , factors = 2, rotation = "varimax")
```

Uniquenesses:

wjcalc	wjspl	wratspl	wratcalc	waiscalc	waisspl
0.184	0.089	0.107	0.096	0.477	0.112

Loadings:

	Factor1	Factor2
wjcalc	0.230	0.873
wjspl	0.907	0.298
wratspl	0.894	0.306
wratcalc	0.248	0.918
waiscalc	0.281	0.667
waisspl	0.896	0.293

	Factor1	Factor2
SS loadings	2.617	2.318
Proportion Var	0.436	0.386

R code and results ...

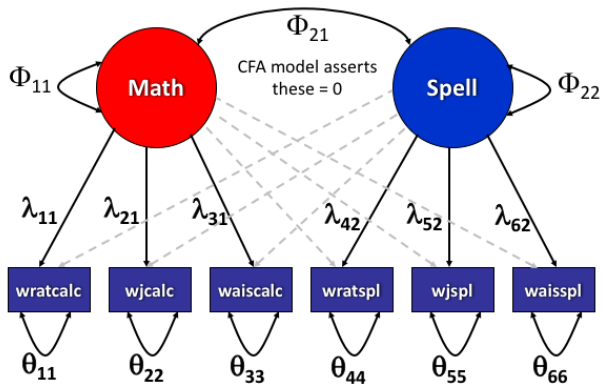
```
Cumulative Var    0.436    0.823
```

```
Test of the hypothesis that 2 factors are sufficient.  
The chi square statistic is 3.8 on 4 degrees of freedom.  
The p-value is 0.434
```

Confirmatory Factor Analysis

- EFA allowed connections between each factor and each indicator
- In CFA, we restrict—for theoretical reasons—linkages between factors and indicators
- Math is indicated by:
 - wratcalc, wjcalc, waiscalc
- Spelling is indicated by:
 - wratspl, wjspl, waisspl

Two Factor CFA



R code and results

```
library(lavaan)
CFModel <- "
  MATH ≈ wratcalc + wjcalc + waiscalc
  SPELL ≈ wratspl + wjspl + waisspl
"

testOutput <- cfa(model = CFModel, data = dat,
  std.lv = TRUE, missing = "fiml")
summary(testOutput, fit.measures = TRUE)
```

lavaan (0.5-22) converged normally after 73 iterations

Number of observations	322
Number of missing patterns	4
Estimator	ML
Minimum Function Test Statistic	9.540
Degrees of freedom	8
P-value (Chi-square)	0.299

R code and results ...

Model test baseline model:

Minimum Function Test Statistic	1882.335
Degrees of freedom	15
P-value	0.000

User model versus baseline model:

Comparative Fit Index (CFI)	0.999
Tucker–Lewis Index (TLI)	0.998

Loglikelihood and Information Criteria:

Loglikelihood user model (H0)	−5127.830
Loglikelihood unrestricted model (H1)	−5123.060
Number of free parameters	19
Akaike (AIC)	10293.661
Bayesian (BIC)	10365.377
Sample-size adjusted Bayesian (BIC)	10305.112

Root Mean Square Error of Approximation:

RMSEA	0.024
90 Percent Confidence Interval	0.000 0.073

R code and results ...

P-value RMSEA \leq 0.05

0.761

Standardized Root Mean Square Residual:

SRMR

0.024

Parameter Estimates:

Information
Standard Errors

Observed
Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
MATH \approx				
wratcalc	6.041	0.276	21.921	0.000
wjcalc	4.144	0.203	20.370	0.000
waiscalc	2.410	0.165	14.636	0.000
SPELL \approx				
wratspl	6.532	0.288	22.645	0.000
wjspl	6.809	0.296	23.025	0.000
waisspl	6.354	0.283	22.463	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
MATH \sim				

R code and results ...

```
SPELL                0.553      0.042    13.191      0.000
```

Intercepts :

	Estimate	Std.Err	z-value	P(> z)
.wratcalc	38.922	0.355	109.514	0.000
.wjcalc	23.812	0.255	93.297	0.000
.waiscalc	11.022	0.186	59.230	0.000
.wratspl	36.484	0.385	94.751	0.000
.wjspl	41.674	0.398	104.808	0.000
.waisspl	37.163	0.376	98.788	0.000
MATH	0.000			
SPELL	0.000			

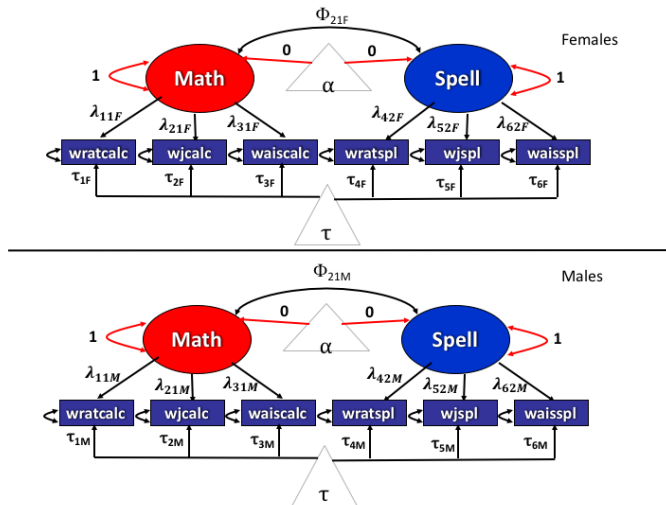
Variances :

	Estimate	Std.Err	z-value	P(> z)
.wratcalc	4.179	1.014	4.122	0.000
.wjcalc	3.769	0.537	7.017	0.000
.waiscalc	5.304	0.457	11.596	0.000
.wratspl	5.053	0.612	8.256	0.000
.wjspl	4.541	0.616	7.369	0.000
.waisspl	5.156	0.599	8.605	0.000
MATH	1.000			
SPELL	1.000			

Multiple Group CFA

- Compare males and females on Math and Spelling

Two group model



Goal: Simplify separate parameter sets

- If the two genders are given completely separate models, there is not much hope of achieving an analytical purpose, which is to compare differences in the latent variable across genders.

Model comparison process

- 1 Fit the model with all measurement parameters free to vary between groups
- 2 Fit a model in which measurement parameters are assumed to be the same
- 3 Conduct a " $\Delta\chi^2$ " test to find out if restricting some parameters to be equal between groups caused the model to fit the data poorly.

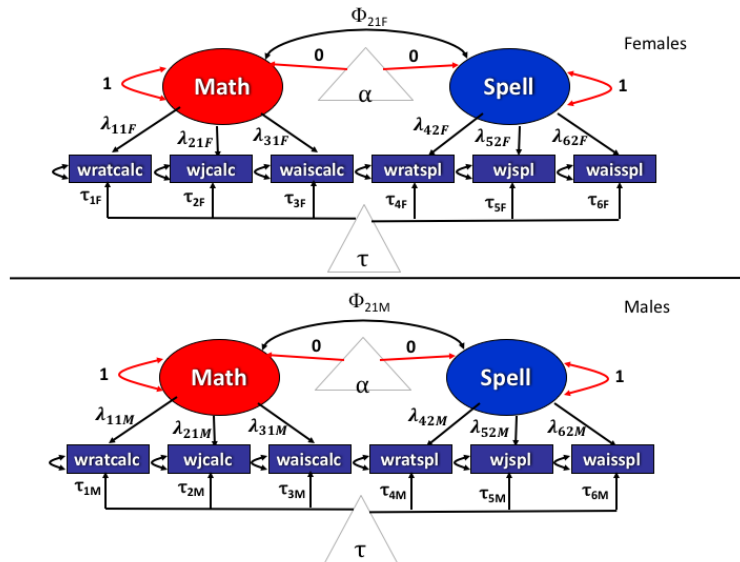
Configural, Metric, Scalar

- Three stages of comparison (models successively drop coefficient differences for the 2 genders)
 - 1 Configural invariance (same model)
 - 2 Metric invariance (factor loadings same for both genders)
 - 3 Scalar invariance (item intercepts are also the same)

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Configural Invariance Model



subscript "g" indicates that the parameters estimated for each group

R code and results

```
configModel <- "  
  MATH ≈ wratcalc + wjcalc + waiscalc  
  SPELL ≈ wratspl + wjspl + waisspl  
"  
configOutput <- cfa(model = configModel, data =  
  dat, group = "female", std.lv = TRUE, missing  
  = "fiml")  
summary(configOutput)
```

lavaan (0.5-22) converged normally after 118 iterations

Number of observations per group

1	101
0	221

Number of missing patterns per group

1	4
0	2

Estimator

ML

R code and results ...

```

Minimum Function Test Statistic      19.215
Degrees of freedom                    16
P-value (Chi-square)                 0.258

```

Chi-square for each group:

```

1      11.555
0      7.660

```

Parameter Estimates:

```

Information      Observed
Standard Errors  Standard

```

Group 1 [1]:

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
MATH ≈				
wratcalc	6.545	0.496	13.187	0.000
wjcalc	4.215	0.366	11.530	0.000
waiscalc	2.290	0.276	8.306	0.000
SPELL ≈				
wratspl	7.010	0.547	12.817	0.000

R code and results ...

wjspl	6.833	0.518	13.182	0.000
waisspl	6.638	0.520	12.763	0.000
Covariances :				
	Estimate	Std.Err	z-value	P(> z)
MATH ~				
SPELL	0.634	0.064	9.914	0.000
Intercepts :				
	Estimate	Std.Err	z-value	P(> z)
.wratcalc	38.267	0.666	57.464	0.000
.wjcalc	23.603	0.465	50.781	0.000
.waiscalc	10.266	0.316	32.528	0.000
.wratspl	37.171	0.735	50.590	0.000
.wjspl	42.337	0.705	60.073	0.000
.waisspl	38.030	0.697	54.579	0.000
MATH	0.000			
SPELL	0.000			
Variances :				
	Estimate	Std.Err	z-value	P(> z)
.wratcalc	1.957	1.621	1.208	0.227
.wjcalc	3.960	0.848	4.671	0.000
.waiscalc	4.765	0.714	6.678	0.000
.wratspl	5.307	1.105	4.804	0.000

R code and results ...

```
.wjspl      3.474    0.910    3.818    0.000
.waisspl    4.900    1.007    4.865    0.000
MATH        1.000
SPELL       1.000
```

Group 2 [0]:

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
MATH \Rightarrow				
wratcalc	5.764	0.330	17.492	0.000
wjcalc	4.123	0.244	16.926	0.000
waiscalc	2.446	0.200	12.212	0.000
SPELL \Rightarrow				
wratspl	6.278	0.337	18.646	0.000
wjspl	6.788	0.359	18.929	0.000
waisspl	6.177	0.335	18.441	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
MATH \sim				
SPELL	0.520	0.053	9.762	0.000

Intercepts:

R code and results ...

	Estimate	Std.Err	z-value	P(> z)
.wratcalc	39.222	0.417	93.962	0.000
.wjcalc	23.910	0.305	78.420	0.000
.waiscalc	11.367	0.226	50.320	0.000
.wratspl	36.172	0.448	80.762	0.000
.wjspl	41.371	0.480	86.157	0.000
.waisspl	36.767	0.444	82.899	0.000
MATH	0.000			
SPELL	0.000			

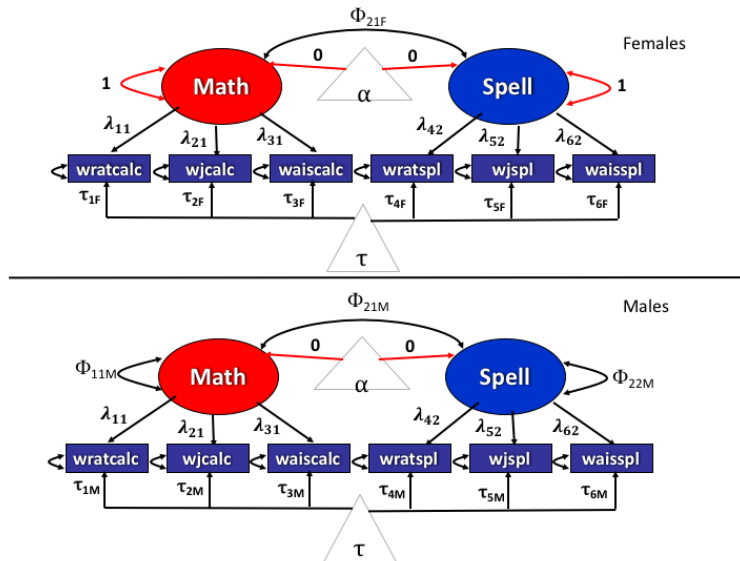
Variances :

	Estimate	Std.Err	z-value	P(> z)
.wratcalc	5.280	1.232	4.285	0.000
.wjcalc	3.549	0.664	5.342	0.000
.waiscalc	5.269	0.557	9.463	0.000
.wratspl	4.915	0.726	6.772	0.000
.wjspl	4.881	0.795	6.138	0.000
.waisspl	5.285	0.736	7.176	0.000
MATH	1.000			
SPELL	1.000			

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Metric Invariance Model



R code and results

```
metricModel <- "  
  MATH =~ wratcalc + wjcalc + waiscalc  
  SPELL =~ wratspl + wjspl + waisspl  
  MATH ~ c(1, NA)*MATH  
  SPELL ~ c(1, NA)*SPELL  
  "  
metricOutput <- cfa(model = metricModel, data =  
  dat, std.lv = TRUE,  
                    group = "female",  
                    group.equal = "loadings",  
                    missing = "fiml")  
summary(metricOutput)
```


R code and results ...

```
lavaan (0.5–22) converged normally after 94 iterations
```

```
Number of observations per group
```

1	101
0	221

```
Number of missing patterns per group
```

1	4
0	2

```
Estimator
```

```
ML
```

```
Minimum Function Test Statistic
```

```
25.871
```

```
Degrees of freedom
```

```
20
```

```
P-value (Chi-square)
```

```
0.170
```

```
Chi-square for each group:
```

1	15.581
0	10.290

```
Parameter Estimates:
```

```
Information
```

```
Observed
```

```
Standard Errors
```

```
Standard
```

R code and results ...

Group 1 [1]:

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
MATH \approx				
wratclc (.p1.)	6.359	0.490	12.972	0.000
wjcalc (.p2.)	4.354	0.342	12.729	0.000
waiscalc (.p3.)	2.502	0.229	10.909	0.000
SPELL \approx				
wratspl (.p4.)	6.751	0.508	13.295	0.000
wjspl (.p5.)	7.020	0.516	13.592	0.000
waisspl (.p6.)	6.568	0.493	13.326	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
MATH \sim SPELL	0.641	0.063	10.164	0.000

Intercepts:

	Estimate	Std.Err	z-value	P(> z)
.wratcalc	38.267	0.656	58.319	0.000
.wjcalc	23.602	0.474	49.832	0.000
.waiscalc	10.263	0.330	31.085	0.000

R code and results ...

```
.wratspl      37.172    0.713    52.136    0.000
.wjspl        42.337    0.721    58.719    0.000
.waisspl      38.031    0.691    55.052    0.000
MATH          0.000
SPELL         0.000
```

Variances :

	Estimate	Std.Err	z-value	P(> z)
MATH	1.000			
SPELL	1.000			
.wratcalc	3.047	1.413	2.157	0.031
.wjcalc	3.603	0.778	4.632	0.000
.waiscalc	4.700	0.714	6.586	0.000
.wratspl	5.686	1.123	5.061	0.000
.wjspl	3.230	0.929	3.478	0.001
.waisspl	4.995	1.023	4.883	0.000

Group 2 [0]:

Latent Variables :

	Estimate	Std.Err	z-value	P(> z)
MATH \approx				
wratclc (.p1.)	6.359	0.490	12.972	0.000
wjcalc (.p2.)	4.354	0.342	12.729	0.000

R code and results ...

```

      waisclac (.p3.)      2.502      0.229      10.909      0.000
SPELL ~
      wratspl (.p4.)      6.751      0.508      13.295      0.000
      wjspl   (.p5.)      7.020      0.516      13.592      0.000
      waisspl (.p6.)      6.568      0.493      13.326      0.000

Covariances:
              Estimate Std.Err  z-value  P(>|z|)
MATH ~
SPELL              0.456    0.089    5.103    0.000

Intercepts:
              Estimate Std.Err  z-value  P(>|z|)
.wratcalc      39.222    0.422   92.880    0.000
.wjcalc        23.910    0.302   79.192    0.000
.waiscalc      11.367    0.221   51.462    0.000
.wratspl       36.172    0.454   79.673    0.000
.wjspl         41.371    0.472   87.637    0.000
.waisspl       36.767    0.446   82.522    0.000
MATH            0.000
SPELL            0.000

Variances:
              Estimate Std.Err  z-value  P(>|z|)
MATH            0.860    0.156    5.501    0.000

```

R code and results ...

SPELL	0.895	0.158	5.676	0.000
.wratcalc	4.619	1.205	3.834	0.000
.wjcalc	3.835	0.654	5.864	0.000
.waiscalc	5.370	0.564	9.525	0.000
.wratspl	4.764	0.721	6.607	0.000
.wjspl	5.154	0.790	6.526	0.000
.waisspl	5.233	0.732	7.153	0.000

```
anova(configOutput , metricOutput)
```

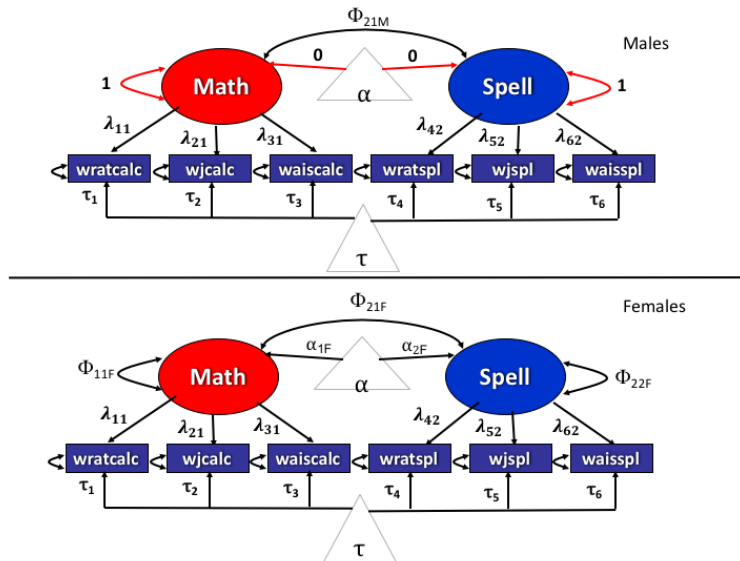
Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
configOutput	16	10301	10444	19.215			
metricOutput	20	10300	10428	25.871	6.6558	4	0.1552

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Scalar Invariance Model



R code and results

```
scalarModel <- "  
  MATH =~ wratcalc + wjcalc + waiscalc  
  SPELL =~ wratspl + wjspl + waisspl  
  MATH =~ c(1, NA)*MATH  
  SPELL =~ c(1, NA)*SPELL  
  MATH ~ c(0, NA)*1  
  SPELL ~ c(0, NA)*1  
"  
scalarOutput <- cfa(model = scalarModel, data =  
  dat, std.lv = TRUE,  
                    group = "female",  
                    group.equal = c("loadings",  
                                     "intercepts"),  
                    missing = "fiml")  
summary(scalarOutput)
```


R code and results ...

```
lavaan (0.5-22) converged normally after 95 iterations
```

```
Number of observations per group
```

1	101
0	221

```
Number of missing patterns per group
```

1	4
0	2

```
Estimator
```

```
ML
```

```
Minimum Function Test Statistic
```

```
36.362
```

```
Degrees of freedom
```

```
24
```

```
P-value (Chi-square)
```

```
0.051
```

```
Chi-square for each group:
```

1	22.546
0	13.815

```
Parameter Estimates:
```

```
Information
```

```
Observed
```

```
Standard Errors
```

```
Standard
```

R code and results ...

Group 1 [1]:

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
MATH \approx				
wratclc (.p1.)	6.381	0.491	12.994	0.000
wjcalc (.p2.)	4.340	0.342	12.699	0.000
waiscalc (.p3.)	2.529	0.232	10.895	0.000
SPELL \approx				
wratspl (.p4.)	6.751	0.508	13.299	0.000
wjspl (.p5.)	7.015	0.516	13.592	0.000
waisspl (.p6.)	6.578	0.494	13.329	0.000

Covariances:

	Estimate	Std.Err	z-value	P(> z)
MATH \sim SPELL	0.640	0.063	10.128	0.000

Intercepts:

	Estimate	Std.Err	z-value	P(> z)
MATH	0.000			
SPELL	0.000			
.wratclc (.18.)	38.273	0.653	58.628	0.000

R code and results ...

```
.wjcalc (.19.)    23.374    0.454    51.465    0.000
.waisclc (.20.)    10.751    0.289    37.239    0.000
.wratspl (.21.)    37.211    0.692    53.771    0.000
.wjspl   (.22.)    42.411    0.713    59.443    0.000
.waisspl (.23.)    37.869    0.675    56.144    0.000
```

Variances :

	Estimate	Std.Err	z-value	P(> z)
MATH	1.000			
SPELL	1.000			
.wratcalc	2.841	1.424	1.995	0.046
.wjcalc	3.743	0.793	4.723	0.000
.waiscalc	4.977	0.766	6.496	0.000
.wratspl	5.681	1.123	5.056	0.000
.wjspl	3.237	0.930	3.481	0.000
.waisspl	5.035	1.032	4.880	0.000

Group 2 [0]:

Latent Variables :

	Estimate	Std.Err	z-value	P(> z)
MATH \approx				
wratclc (.p1.)	6.381	0.491	12.994	0.000
wjcalc (.p2.)	4.340	0.342	12.699	0.000

R code and results ...

```

      waisclac (.p3.)      2.529      0.232      10.895      0.000
SPELL ~
      wratspl (.p4.)      6.751      0.508      13.299      0.000
      wjspl   (.p5.)      7.015      0.516      13.592      0.000
      waisspl (.p6.)      6.578      0.494      13.329      0.000

```

Covariances:

	Estimate	Std.Err	z-value	P(> z)
MATH ~ SPELL	0.454	0.089	5.104	0.000

Intercepts:

	Estimate	Std.Err	z-value	P(> z)
MATH	0.148	0.121	1.220	0.222
SPELL	-0.156	0.121	-1.293	0.196
.wratclac (.18.)	38.273	0.653	58.628	0.000
.wjcalac (.19.)	23.374	0.454	51.465	0.000
.waisclac (.20.)	10.751	0.289	37.239	0.000
.wratspl (.21.)	37.211	0.692	53.771	0.000
.wjspl (.22.)	42.411	0.713	59.443	0.000
.waisspl (.23.)	37.869	0.675	56.144	0.000

Variances:

	Estimate	Std.Err	z-value	P(> z)
MATH	0.857	0.156	5.502	0.000

R code and results ...

SPELL	0.894	0.158	5.676	0.000
.wratcalc	4.518	1.204	3.753	0.000
.wjcalc	3.911	0.655	5.970	0.000
.waiscalc	5.431	0.576	9.435	0.000
.wratspl	4.762	0.721	6.603	0.000
.wjspl	5.173	0.791	6.541	0.000
.waisspl	5.235	0.734	7.134	0.000

```
anova(metricOutput , scalarOutput)
```

Chi Square Difference Test

	Df	AIC	BIC	Chisq	Chisq diff	Df diff	Pr(>Chisq)
metricOutput	20	10300	10428	25.871			
scalarOutput	24	10302	10415	36.361	10.491	4	0.03293

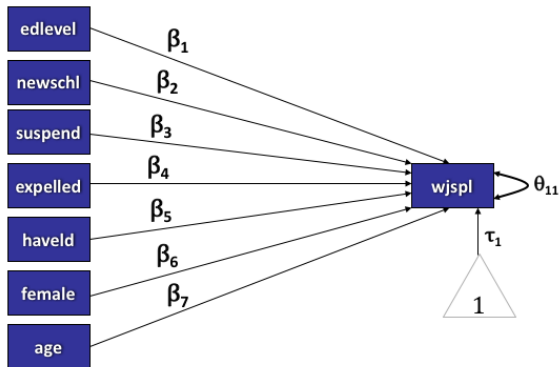
```
metricOutput
scalarOutput *
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Regression

- The SEM framework includes the ordinary linear regression on observed variables as a special case
- SEM can fit several linear regressions at once
 - possibly allowing correlation between the error terms in the 2 regressions (Seemingly Unrelated Regressions, SUR).

Multiple predictors



R code and results

```
MLRModel <- "  
  wjspl ~ edlevel + newschl + suspend + expelled +  
    haveld + female + age  
  wjspl ~ 1  
"  
  
output <- sem(model = MLRModel, data = dat)  
summary(output)
```

lavaan (0.5-22) converged normally after 58 iterations

	Used	Total
Number of observations	313	322
Estimator	ML	
Minimum Function Test Statistic	0.000	
Degrees of freedom	0	

Parameter Estimates:

Information	Expected
-------------	----------

R code and results ...

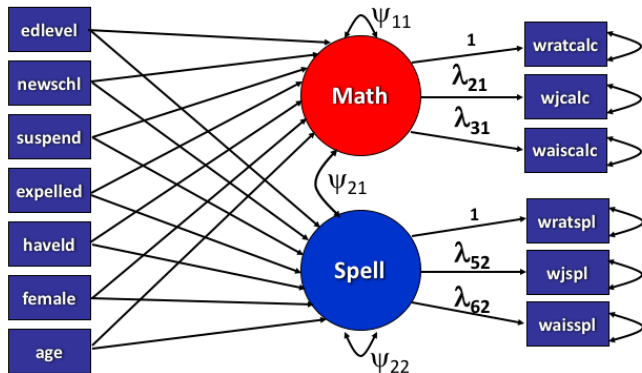
Standard Errors		Standard		
Regressions :				
	Estimate	Std.Err	z-value	P(> z)
wjspl ~				
edlevel	1.162	0.324	3.584	0.000
newschl	0.063	0.747	0.085	0.932
suspend	-0.052	0.773	-0.067	0.947
expelled	-2.758	1.098	-2.510	0.012
haveld	-6.974	0.987	-7.063	0.000
female	0.720	0.792	0.909	0.363
age	0.412	0.207	1.994	0.046
Intercepts :				
	Estimate	Std.Err	z-value	P(> z)
.wjspl	21.953	4.414	4.974	0.000
Variances :				
	Estimate	Std.Err	z-value	P(> z)
.wjspl	39.904	3.190	12.510	0.000

Regression

- Estimate regression coefficients that link together latent (unmeasured) variables.
- This is an example of a LISREL model (measurement and structural component)

Math and Spelling

- Continues with previous data
- Research question: are variations in the latent factors “Math” and “Spell” predictable using the variables
 - edlevel
 - newschl
 - suspend
 - expelled
 - haveld
 - female
 - age



R code and results

```
SEMMModel <- "  
  MATH =~ wratcalc + wjcalc + waiscalc  
  SPELL =~ wratspl + wjspl + waisspl  
  MATH ~ edlevel + newschl + suspend + expelled  
         + haveld + female + age  
  SPELL ~ edlevel + newschl + suspend + expelled  
         + haveld + female + age  
  MATH ~ SPELL  
"  
output <- sem(model = SEMModel, data = dat,  
  missing = "fiml")  
summary(output)
```

R code and results ...

```
lavaan (0.5-22) converged normally after 196 iterations
```

Number of observations	322
Number of missing patterns	9
Estimator	ML
Minimum Function Test Statistic	53.744
Degrees of freedom	36
P-value (Chi-square)	0.029

Parameter Estimates:

Information	Observed
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
MATH \approx				
wratcalc	1.000			
wjcalc	0.683	0.027	25.075	0.000
waiscalc	0.395	0.024	16.229	0.000
SPELL \approx				
wratspl	1.000			

R code and results ...

```
wjspl      1.044    0.029   36.398    0.000
waisspl    0.974    0.028   34.537    0.000
```

Regressions :

	Estimate	Std.Err	z-value	P(> z)
MATH ~				
edlevel	1.555	0.265	5.870	0.000
newschl	0.504	0.640	0.787	0.431
suspend	-1.767	0.666	-2.652	0.008
expelled	-0.533	0.943	-0.565	0.572
haveld	-1.436	0.844	-1.701	0.089
female	-0.847	0.677	-1.250	0.211
age	0.634	0.176	3.601	0.000
SPELL ~				
edlevel	1.143	0.285	4.016	0.000
newschl	-0.258	0.688	-0.375	0.707
suspend	-0.008	0.711	-0.012	0.991
expelled	-2.510	1.016	-2.470	0.014
haveld	-6.369	0.909	-7.004	0.000
female	0.970	0.724	1.340	0.180
age	0.351	0.189	1.860	0.063

Covariances :

	Estimate	Std.Err	z-value	P(> z)
.MATH ~				

R code and results ...

```
.SPELL          14.951      1.993      7.504      0.000
```

Intercepts :

	Estimate	Std.Err	z-value	P(> z)
.wratcalc	10.349	3.676	2.815	0.005
.wjcalc	4.288	2.585	1.659	0.097
.waiscalc	-0.278	1.585	-0.175	0.861
.wratspl	18.069	3.941	4.585	0.000
.wjspl	22.455	4.110	5.463	0.000
.waisspl	19.219	3.840	5.004	0.000
.MATH	0.000			
.SPELL	0.000			

Variances :

	Estimate	Std.Err	z-value	P(> z)
.wratcalc	3.963	0.971	4.083	0.000
.wjcalc	3.814	0.526	7.246	0.000
.waiscalc	5.372	0.460	11.678	0.000
.wratspl	5.131	0.609	8.426	0.000
.wjspl	4.526	0.609	7.430	0.000
.waisspl	5.095	0.595	8.570	0.000
.MATH	27.269	2.540	10.736	0.000
.SPELL	32.493	2.908	11.174	0.000

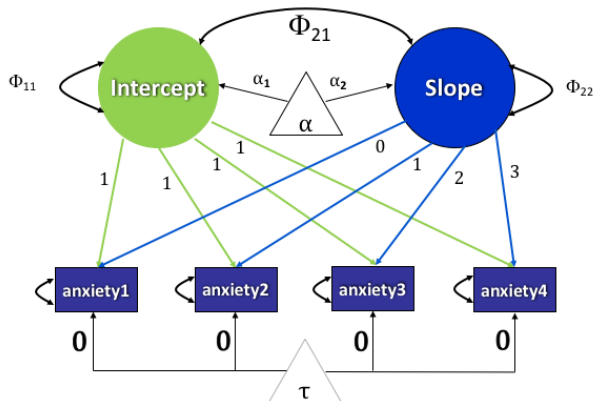
Latent Growth Curve Modeling

- Repeated measurements allow us to think about change in a latent variable over time
- If we can predictably measure the latent variable, then we can assess its linkage to other outcomes (both observed and latent).
- However, in this example we are mostly interested in the possibility that
 - some people are more anxious than others at the outset of the study, and they remain more (or less) anxious across time
 - as time passes, some people become progressively more and more (or less and less) anxious

Measurements

- The data set is named “anxiety.dat”
- participants anxiety level at four different time points were measured
- Do anxiety levels change over time?
- Initial anxiety (intercept) and change in anxiety (slope) can be modeled as latent variables.

Latent Growth Curve Graph



R code and results

```
dat <- read.table("../data/anxiety.dat", header =  
  F)  
names(dat) <- c("a1", "a2", "a3", "a4")  
model <- "  
  intercept =~ 1*a1 + 1*a2 + 1*a3 + 1*a4  
  slope =~ 0*a1 + 1*a2 + 2*a3 + 3*a4  
  a1 ~ 0*1  
  a2 ~ 0*1  
  a3 ~ 0*1  
  a4 ~ 0*1  
  intercept ~ 1  
  slope ~ 1  
"  
output <- sem(model, data = dat)  
summary(output)
```

R code and results ...

```
lavaan (0.5-22) converged normally after 45 iterations
```

Number of observations	485
Estimator	ML
Minimum Function Test Statistic	27.288
Degrees of freedom	5
P-value (Chi-square)	0.000

Parameter Estimates:

Information	Expected
Standard Errors	Standard

Latent Variables:

	Estimate	Std.Err	z-value	P(> z)
intercept \approx				
a1	1.000			
a2	1.000			
a3	1.000			
a4	1.000			
slope \approx				
a1	0.000			
a2	1.000			

R code and results ...

```

      a3          2.000
      a4          3.000

Covariances:
      Estimate Std.Err z-value P(>|z|)
intercept ~ slope      -0.011    0.003   -3.472    0.001

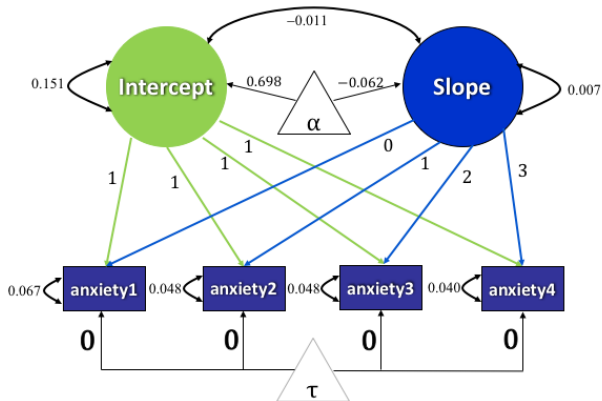
Intercepts:
      Estimate Std.Err z-value P(>|z|)
.a1          0.000
.a2          0.000
.a3          0.000
.a4          0.000
intercept    0.698    0.020   35.050    0.000
slope      -0.062    0.006  -10.513    0.000

Variances:
      Estimate Std.Err z-value P(>|z|)
.a1          0.067    0.007    8.910    0.000
.a2          0.048    0.004   11.119    0.000
.a3          0.048    0.004   11.383    0.000
.a4          0.040    0.006    6.658    0.000
intercept    0.151    0.013   11.871    0.000
slope        0.007    0.001    4.790    0.000

```

R code and results ...

Latent Growth Results



SEM Examples

- More examples will be created in future

Session

sessionInfo()

```
R version 3.3.3 (2017-03-06)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 17.04

locale:
 [1] LC_CTYPE=en_US.UTF-8      LC_NUMERIC=C
 [3] LC_TIME=en_US.UTF-8      LC_COLLATE=en_US.UTF-8
 [5] LC_MONETARY=en_US.UTF-8  LC_MESSAGES=en_US.UTF-8
 [7] LC_PAPER=en_US.UTF-8     LC_NAME=C
 [9] LC_ADDRESS=C             LC_TELEPHONE=C
[11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C

attached base packages:
[1] stats      graphics  grDevices  utils      datasets   base

other attached packages:
[1] lavaan_0.5-22

loaded via a namespace (and not attached):
[1] MASS_7.3-45      tools_3.3.3      mnormt_1.5-5     pbivnorm_0.6.0
[5] methods_3.3.3    stats4_3.3.3     quadprog_1.5-5
```