

# Latent Variable Modeling using R

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# R Exercise: Data Entry

# Talk Outline

## Data Entry Exercises

Exercise 1

Exercise 2

Exercise 3

Exercise 4

# Talk Outline

## Data Entry Exercises

Exercise 1

Exercise 2

Exercise 3

Exercise 4

# Data Entry Exercises

## Exercise 1

- In **R**, create a dataset called `prac1` with the following data

10 25 63 54 78 41 33

```
prac1 <- c(10,25, 63, 54, 78, 41, 33)
```

```
prac1
```

```
## [1] 10 25 63 54 78 41 33
```

# Data Entry Exercises

## Exercise 1

- In `prac1`, change the 4th observation from 54 to 45

```
prac1[4] <- 45
```

```
prac1
```

```
## [1] 10 25 63 45 78 41 33
```

# Talk Outline

## Data Entry Exercises

Exercise 1

**Exercise 2**

Exercise 3

Exercise 4

# Data Entry Exercises

## Exercise 2

- In **R**, create a data frame called `prac2` with the following data

Last Name	Salary (in \$10,000)
Franklin	8.0
Kahn	6.0
Redding	7.8
Cooke	4.1
Pickett	6.3



# Data Entry Exercises

## Exercise 2

```
lname <- c("Franklin", "Kahn", "Redding", "Cooke", "Pickett")
salary <- c(8.0, 6.0, 7.8, 4.1, 6.3)
prac2 <- data.frame(lname, salary)
prac2
```

```
##      lname salary
## 1 Franklin   8.0
## 2     Kahn    6.0
## 3  Redding   7.8
## 4     Cooke   4.1
## 5  Pickett   6.3
```

# Data Entry Exercises

## Exercise 2

- Convert *Salary* to \$1 units (e.g. 3.2  $\rightarrow$  32000)

```
# remember to save the transformed variable in the dataset
```

```
prac2$salary10 <- prac2$salary*10000
```

```
prac2
```

```
##      lname salary salary10
```

```
## 1 Franklin   8.0   80000
```

```
## 2     Kahn   6.0   60000
```

```
## 3 Redding   7.8   78000
```

```
## 4     Cooke  4.1   41000
```

```
## 5 Pickett   6.3   63000
```

# Talk Outline

## Data Entry Exercises

Exercise 1

Exercise 2

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Exercise 4

# Data Entry Exercises

## Exercise 3

- On website, there is a dataset named SampleData.txt.  
(<http://blogs.baylor.edu/rlatentvariable/sample-page/courses/>)
  - Download the file to your computer
- Import the data into **R** and print out the first 2 observation values on the console

```
x <- read.table(file="SampleData.txt",header=TRUE)
head(x, 2)
```

```
##   Age  IQ Height Sex
## 1  18 100     65   F
## 2  21 110     68   M
```

# Talk Outline

## Data Entry Exercises

Exercise 1

Exercise 2

Exercise 3

Exercise 4

# Data Entry Exercises

## Exercise 4

- The psych package for **R** has a dataset named *peas*, which has the diameter of parent and child for 700 sweet peas

```
##      parent child
## 4         21    15
## 150        20    18
## 300        19    22
```

1. Download the psych package (if it is not already downloaded)
2. Load the psych package
3. Load the peas dataset

```
install.packages("psych", dependencies=TRUE)
library(psych)
data(peas)
```

# Data Entry Exercises

## Exercise 4

- In the *peas* dataset
  1. Find mean parent diameter

```
mean(peas$parent)
```

```
## [1] 18
```

2. Find the correlation (`cor()`) between parent and child diameter

```
cor(peas$parent, peas$child)
```

```
## [1] 0.35
```

# R Exercise: Path Models



# Talk Outline

## Path Model Example

## Path Model Example

- From Page and Keith (1981)
- $n = 18,058$  from *High School and Beyond* 1980 data
- Question of Interest: Relationship between school type and school academic achievement

## Path Model Example

	Race	SES	CogAbil	PrivSch	AcadAch	Homework
Race	1.00	0.18	0.23	0.11	0.20	-0.00
SES	0.18	1.00	0.33	0.24	0.36	0.23
CogAbil	0.23	0.33	1.00	0.18	0.72	0.28
PrivSch	0.11	0.24	0.18	1.00	0.18	0.21
AcadAch	0.20	0.36	0.72	0.18	1.00	0.30
Homework	-0.00	0.23	0.28	0.21	0.30	1.00

Race: White/Hispanic=1, Black=0

CogAbil: composite of verbal and nonverbal subtests

PrivSch: Private School=1, Public=0

AcadAch: composite of Reading Math subtests

Homework: Time spent on homework (not used)

## Path Model Example

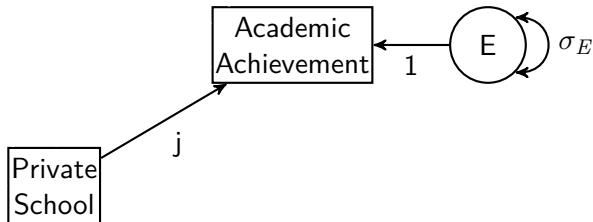
	Race	SES	CogAbil	PrivSch	AcadAch	Homework
Race	1.00	0.18	0.23	0.11	0.20	-0.00
SES	0.18	1.00	0.33	0.24	0.36	0.23
CogAbil	0.23	0.33	1.00	0.18	0.72	0.28
PrivSch	0.11	0.24	0.18	1.00	0.18	0.21
AcadAch	0.20	0.36	0.72	0.18	1.00	0.30
Homework	-0.00	0.23	0.28	0.21	0.30	1.00

- Enter data into **R**
- Name variables

# Path Model Example

```
# load lavaan
library(lavaan)
# enter upper matrix of correlation values
privSchool.cor <- c(1.000, .178, .230, .106, .195, -.001, 1.000, .327, .245, .356,
                  .229, 1.000, .183, .721, .278, 1.000, .178, .211, 1.000, .304, 1.000)
# make full matrix
privSchool.cor <- lav_matrix_upper2full(privSchool.cor)
# name variables
dimnames(privSchool.cor) <- list(c("Race", "SES", "CogAbil", "PrivSch", "AcadAch",
"Homework"),c("Race", "SES", "CogAbil", "PrivSch", "AcadAch", "Homework"))
```

# Path Model Example



Initial Path Model

- Specify simple regression in **R**
- Fit model to data

# Path Model Example

```
initial.model <- '  
AcadAch ~ j*PrivSch  
'
```

# Path Model Example

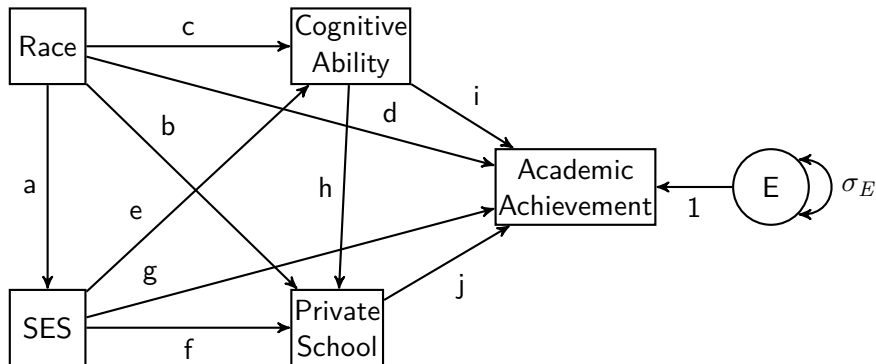
```
initial.fit <- sem(initial.model, sample.cov=privSchool.cor, sample.nobs=18058)  
parameterEstimates(initial.fit)
```

##	lhs	op	rhs	label	est	se	z	pvalue	ci.lower	ci.upper
## 1	AcadAch	~	PrivSch	j	0.18	0.007	24	0	0.16	0.19
## 2	AcadAch	~~	AcadAch		0.97	0.010	95	0	0.95	0.99
## 3	PrivSch	~~	PrivSch		1.00	0.000	NA	NA	1.00	1.00

- parameterEstimates() is an alternative to using summary()
  - Returns path estimates, standard errors, and 95% confidence intervals



## Path Model Example



Full Path Model

- Specify and fit full model in **R**

# Path Model Example

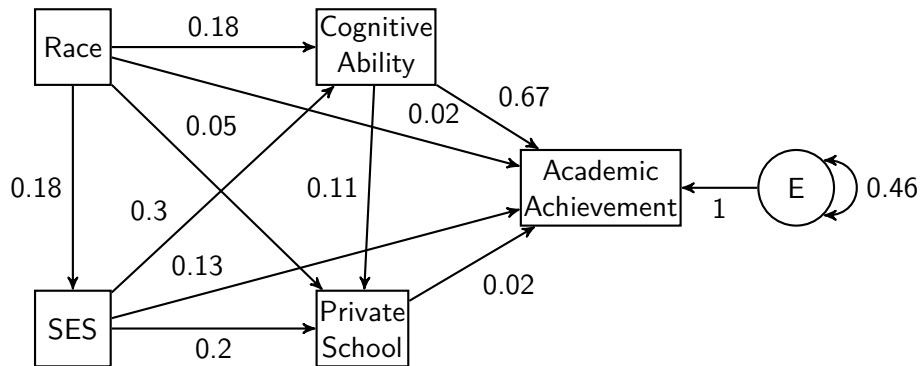
```
full.model <- '  
AcadAch ~ j*PrivSch + g*SES + d*Race + i*CogAbil  
PrivSch ~ f*SES + b*Race + h*CogAbil  
CogAbil ~ e*SES + c*Race  
SES ~ a*Race  
  
# error variance  
AcadAch~~ev*AcadAch  
'  
full.fit <- sem(full.model, sample.cov=privSchool.cor, sample.nobs=18058)
```

# Path Model Example

```
parameterEstimates(full.fit)
```

##	lhs	op	rhs	label	est	se	z	pvalue	ci.lower	ci.upper
## 1	AcadAch	~	PrivSch	j	0.022	0.005	4.2	0.000	0.012	0.032
## 2	AcadAch	~	SES	g	0.128	0.005	23.3	0.000	0.118	0.139
## 3	AcadAch	~	Race	d	0.015	0.005	2.9	0.003	0.005	0.026
## 4	AcadAch	~	CogAbil	i	0.671	0.005	122.5	0.000	0.661	0.682
## 5	PrivSch	~	SES	f	0.202	0.008	26.5	0.000	0.187	0.217
## 6	PrivSch	~	Race	b	0.046	0.007	6.2	0.000	0.031	0.060
## 7	PrivSch	~	CogAbil	h	0.106	0.008	13.8	0.000	0.091	0.122
## 8	CogAbil	~	SES	e	0.295	0.007	42.1	0.000	0.282	0.309
## 9	CogAbil	~	Race	c	0.177	0.007	25.3	0.000	0.164	0.191
## 10	SES	~	Race	a	0.178	0.007	24.3	0.000	0.164	0.192
## 11	AcadAch	~~	AcadAch	ev	0.463	0.005	95.0	0.000	0.454	0.473
## 12	PrivSch	~~	PrivSch		0.926	0.010	95.0	0.000	0.907	0.945
## 13	CogAbil	~~	CogAbil		0.863	0.009	95.0	0.000	0.845	0.880
## 14	SES	~~	SES		0.968	0.010	95.0	0.000	0.948	0.988
## 15	Race	~~	Race		1.000	0.000	NA	NA	1.000	1.000

## Path Model Example



Full Path Model

# R Exercise: Simple Latent Variable Models

# Talk Outline

Simple Latent Variable Model Example

## Simple Latent Variable Model Example

- Example from Little, Slegers, and Card (2006)
- Enter the correlations and standard deviations ( $n= 380$ )
- Fit the path model using the standardized LV and marker variable methods to scale the the LV
  - For the marker variable method, use indicators 1 and 5 as the marker variables

## Simple Latent Variable Model Example

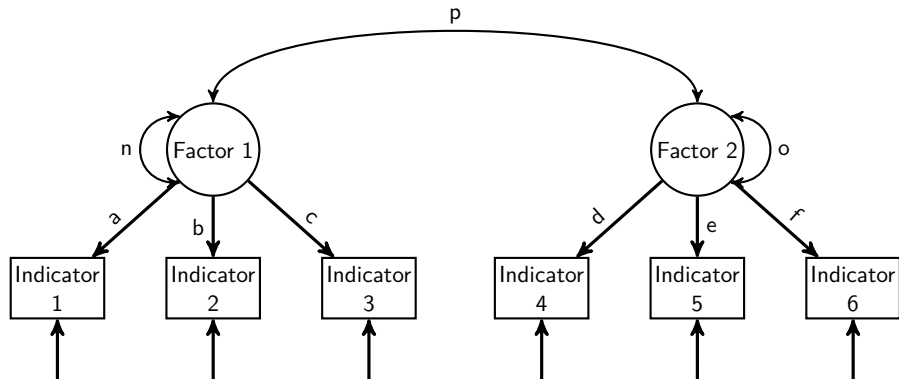
	I1	I2	I3	I4	I5	I6
Indicator 1	1.000					
Indicator 2	0.759	1.000				
Indicator 3	0.762	0.787	1.000			
Indicator 4	0.028	0.010	-0.058	1.000		
Indicator 5	-0.061	-0.061	-0.141	0.785	1.000	
Indicator 6	-0.022	-0.052	-0.102	0.816	0.816	1.000
SD	0.668	0.685	0.707	0.714	0.663	0.653



# Simple Latent Variable Model Example

```
library(lavaan)
# Little et al correlations
little.cor <- c(1.00000, 0.759, 1.000, 0.762, 0.787, 1.000, 0.0278, 0.010, -0.058,
               1.000, -0.061, -0.061, -0.141, 0.785, 1.000, -0.022, -0.052, -0.102, 0.816,
               0.816, 1.000)
# make full matrix
little.cor <- lav_matrix_lower2full(little.cor)
# name columns and rows in correlation matrix
rownames(little.cor) <- colnames(little.cor) <- paste("I", seq(1,6), sep="")
# SDs
little.sd <- c(0.6678, 0.685, 0.707, 0.714, 0.663, 0.653)
# create covariance matrix
little.cov <- cor2cov(little.cor, little.sd)
```

# Simple Latent Variable Model Example



# Simple Latent Variable Model Example

```
# marker variable
little.marker.model <- '
# factor model
F1 =~ a*I1 + b*I2 + c*I3
F2 =~ e*I5 + d*I4 + f*I6

# label latent (co)variances
F1~~n*F1
F2~~o*F2
F1~~p*F2
'

## fit model
little.marker.fit <- cfa(little.marker.model, sample.cov=little.cov, sample.nobs=380)
```

```
summary(little.marker.fit)
```

```
## lavaan (0.5-18) converged normally after 31 iterations
```

```
##
```

```
##   Number of observations                    380
```

```
##
```

```
##   Estimator                                ML
```

```
##   Minimum Function Test Statistic         17.330
```

```
##   Degrees of freedom                       8
```

```
##   P-value (Chi-square)                    0.027
```

```
##
```

```
## Parameter estimates:
```

```
##
```

```
##   Information                                Expected
```

```
##   Standard Errors                          Standard
```

```
##
```

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

```
## Latent variables:
```

```
##   F1 =~
```

```
##     I1      (a)      1.000
```

```
##     I2      (b)      1.059    0.049    21.688    0.000
```

```
##     I3      (c)      1.100    0.050    21.817    0.000
```

```
##   F2 =~
```

```
##     I5      (e)      1.000
```

```
##     I4      (d)      1.076    0.044    24.252    0.000
```

```
##     I6      (f)      1.023    0.040    25.698    0.000
```

```
##
```

## Covariances:

## F1 ~~

##	F2	(p)	-0.024	0.019	-1.252	0.211
----	----	-----	--------	-------	--------	-------

##

## Variances:

##	F1	(n)	0.326	0.032
----	----	-----	-------	-------

##	F2	(o)	0.344	0.032
----	----	-----	-------	-------

##	I1		0.118	0.012
----	----	--	-------	-------

##	I2		0.102	0.012
----	----	--	-------	-------

##	I3		0.104	0.013
----	----	--	-------	-------

##	I5		0.094	0.010
----	----	--	-------	-------

##	I4		0.110	0.012
----	----	--	-------	-------

##	I6		0.064	0.009
----	----	--	-------	-------

# Simple Latent Variable Model Example

```
# standardized LV
little.standardized.model <- '
# factor model
F1 =~ NA*I1 + a*I1 + b*I2 + c*I3
F2 =~ NA*I4 + d*I4 + e*I5 + f*I6

# fix latent variances
F1~~1*F1
F2~~1*F2

# label latent covariance
F1~~p*F2
'

## fit model
little.standardized.fit <- cfa(little.standardized.model, sample.cov=little.cov,
                               sample.nobs=380)
```

```
summary(little.standardized.fit)
```

```
## lavaan (0.5-18) converged normally after 34 iterations
```

```
##
```

```
##   Number of observations                        380
```

```
##
```

```
##   Estimator                                     ML
```

```
##   Minimum Function Test Statistic              17.330
```

```
##   Degrees of freedom                           8
```

```
##   P-value (Chi-square)                         0.027
```

```
##
```

```
## Parameter estimates:
```

```
##
```

```
##   Information                                     Expected
```

```
##   Standard Errors                               Standard
```

```
##
```

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

```
## Latent variables:
```

```
##   F1 =~
```

```
##     I1      (a)    0.571    0.028    20.216    0.000
```

```
##     I2      (b)    0.605    0.029    21.213    0.000
```

```
##     I3      (c)    0.628    0.029    21.403    0.000
```

```
##   F2 =~
```

```
##     I4      (d)    0.631    0.029    21.542    0.000
```

```
##     I5      (e)    0.587    0.027    21.582    0.000
```

```
##     I6      (f)    0.601    0.026    22.945    0.000
```

```
##
```

## Covariances:

## F1 ~~

##	F2	(p)	-0.070	0.056	-1.262	0.207
----	----	-----	--------	-------	--------	-------

##

## Variances:

##	F1	1.000
----	----	-------

##	F2	1.000
----	----	-------

##	I1	0.118	0.012
----	----	-------	-------

##	I2	0.102	0.012
----	----	-------	-------

##	I3	0.104	0.013
----	----	-------	-------

##	I4	0.110	0.012
----	----	-------	-------

##	I5	0.094	0.010
----	----	-------	-------

##	I6	0.064	0.009
----	----	-------	-------



# R Exercise: Latent Variable Models with Multiple Groups in R

# Talk Outline

## Multiple Groups Example

## Multiple Groups Example

- Example from Little et al. (2006), now with data from two groups
  - Group 1  $n = 380$ ; Group 2  $n = 379$
- Enter the correlations and standard deviations
- Examine configural, metric, and scalar invariance using the marker variable method to scale the the LV
  - For the marker variable method, use indicators 1 and 5 as the marker variables

## Multiple Groups Example

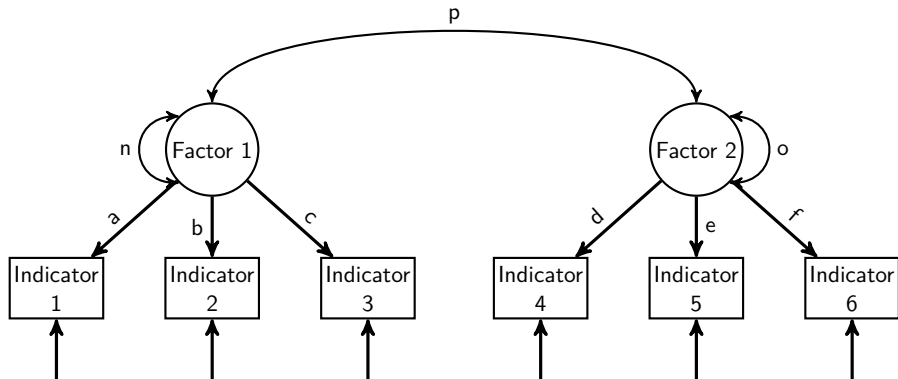
	I1	I2	I3	I4	I5	I6
Indicator 1	1.000	0.813	0.850	-0.188	-0.289	-0.293
Indicator 2	0.759	1.000	0.835	-0.155	-0.250	-0.210
Indicator 3	0.762	0.787	1.000	-0.215	-0.338	-0.306
Indicator 4	0.028	0.010	-0.058	1.000	0.784	0.800
Indicator 5	-0.061	-0.061	-0.141	0.785	1.000	0.832
Indicator 6	-0.022	-0.052	-0.102	0.816	0.816	1.000
Group One SD	0.668	0.685	0.707	0.714	0.663	0.653
Group One Mean	3.135	2.991	3.069	1.701	1.527	1.545
Group Two SD	0.703	0.718	0.762	0.650	0.602	0.614
Group Two Mean	3.073	2.847	2.979	1.717	1.580	1.550

Correlations for group one are given in the lower diagonal, and those for group two are given in the upper diagonal.

# Multiple Groups Example

```
library(lavaan)
# group 1
group1.cor <- c(1.00000, 0.759, 1.000, 0.762, 0.787, 1.000, 0.0278, 0.010, -0.058,
               1.000, -0.061, -0.061, -0.141, 0.785, 1.000, -0.022, -0.052, -0.102, 0.816,
               0.816, 1.000)
group1.cor <- lav_matrix_lower2full(group1.cor)
rownames(group1.cor) <- colnames(group1.cor) <- paste("I", seq(1,6), sep="")
group1.sd <- c(0.6678, 0.685, 0.707, 0.714, 0.663, 0.653)
group1.cov <- cor2cov(group1.cor, group1.sd)
group1.mean <- c(3.135, 2.991, 3.069, 1.701, 1.527, 1.545)
# group 2
group2.cor <- c(1.000, 0.813, 1.000, 0.850, 0.835, 1.000, -0.188, -0.155, -0.215,
               1.000, -0.289, -0.250, -0.338, 0.784, 1.000, -0.293, -0.210, -0.306, 0.800,
               0.832, 1.000)
group2.cor <- lav_matrix_lower2full(group2.cor)
rownames(group2.cor) <- colnames(group2.cor) <- paste("I", seq(1,6), sep="")
group2.sd <- c(0.703, 0.718, 0.762, 0.650, 0.602, 0.614)
group2.cov <- cor2cov(group2.cor, group2.sd)
group2.mean <- c(3.073, 2.847, 2.979, 1.717, 1.580, 1.550)
# combine the data
little.cov <- list(group1=group1.cov, group2=group2.cov)
little.mean <- list(group1=group1.mean, group2=group2.mean)
little.n <- list(group1=380, group2=379)
```

## Multiple Groups Example



# Multiple Groups Example

```
# marker variable
little.marker.model <- '
# factor model
F1 =~ a*I1 + b*I2 + c*I3
F2 =~ e*I5 + d*I4 + f*I6
'

## configural
little.configural.fit <- cfa(little.marker.model, sample.cov=little.cov,
                             sample.mean=little.mean, sample.nobs=little.n)

## metric
little.metric.fit <- cfa(little.marker.model, sample.cov=little.cov,
                         sample.mean=little.mean, sample.nobs=little.n, group.equal=c("loadings"))

## scalar
little.scalar.fit <- cfa(little.marker.model, sample.cov=little.cov,
                         sample.mean=little.mean, sample.nobs=little.n,
                         group.equal=c("loadings", "intercepts"))
```

# Multiple Groups Example

```
# examine model fit
# selected fit measures
fit.indices <- c("chisq", "df", "cfi", "rmsea", "srmr", "mfi")
```

```
fitMeasures(little.configural.fit, fit.indices)
```

```
##  chisq      df      cfi  rmsea   srmr    mfi
## 46.224 16.000  0.992  0.071  0.033  0.980
```

```
fitMeasures(little.metric.fit, fit.indices)
```

```
##  chisq      df      cfi  rmsea   srmr    mfi
## 49.014 20.000  0.992  0.062  0.036  0.981
```

```
fitMeasures(little.scalar.fit, fit.indices)
```

```
##  chisq      df      cfi  rmsea   srmr    mfi
## 58.786 24.000  0.990  0.062  0.033  0.977
```



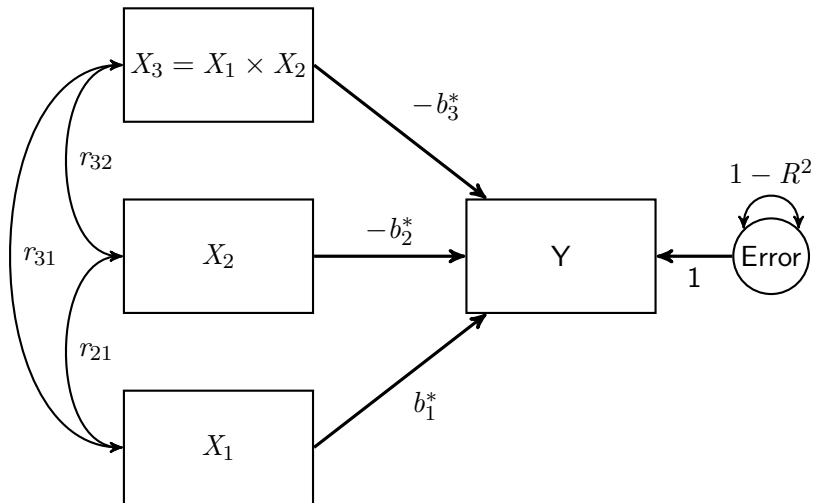
# R Exercise: Sample Size Determination

## Sample Size Determination Example

## Sample Size Determination Example

- Is there an interaction between the antisocial behavior and hyperactivity in predicting academic achievement?

## Sample Size Determination Example



# Sample Size Determination Example

- Review the literature and determine that:
  - The main effects should be approximately twice the size of the interaction
  - The correlation between antisocial behavior and hyperactivity is  $\approx 0.3$
  - After controlling for hyperactivity
    - Antisocial behavior is positively related to academic achievement
    - Hyperactivity is negatively related to academic achievement
  - The interaction has a negative relationship to academic achievement

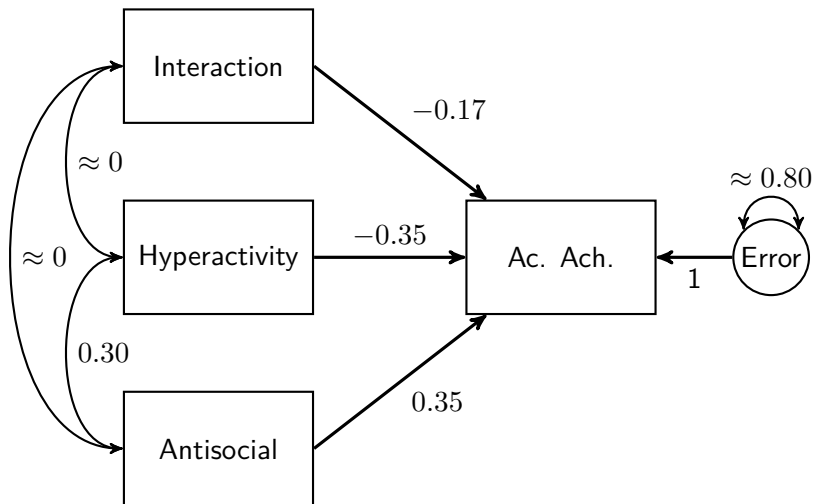
## Sample Size Determination Example

- Say we have the following data

$$b_{YX} = \begin{matrix} \text{anti} = \\ \text{hyper} = \\ \text{int} = \end{matrix} \begin{bmatrix} 0.35 \\ -0.35 \\ -0.17 \end{bmatrix} \text{ and } R_{YX} = V_{YX} = \begin{bmatrix} 1.00 & 0.30 & 0.00 \\ 0.30 & 1.00 & 0.00 \\ 0.00 & 0.00 & 1.00 \end{bmatrix}$$

$$R^2 = 0.2$$

## Sample Size Determination Example



- Specify population and analysis models using *lavaan* syntax

# Sample Size Determination Example

```
# population model
antiPop.model<- '
academ ~ 0.35*anti + -0.35*hyp + -0.17*int
anti~~0.3*hyp
int ~~ 0*anti + 0*hyp
academ~~0.80*academ
'

# analysis model
antiReg.model <- '
academ ~ anti + hyp + int
int ~~ 0*anti + 0*hyp
'
```



# Sample Size Determination Example

- Double check your model
  - “Fit” population model in *lavaan*
    - Hint: Use the `fixed.x=FALSE` argument in the `sem()` function
  - Calculate implied correlations
  - Compare implied correlations to hypothesized values

```

library(lavaan)
# fit model with population moments
antiPop.fit <- sem(antiPop.model, fixed.x=FALSE)
summary(antiPop.fit, std=TRUE, rsquare=TRUE)

## ** WARNING ** lavaan (0.5-18) model has NOT been fitted
## ** WARNING ** Estimates below are simply the starting values
##
##   Number of observations                0
##
##   Estimator                            ML
##
## Parameter estimates:
##
##   Information                          Expected
##   Standard Errors                      None
##
##               Estimate  Std.err  Z-value  P(>|z|)   Std.lv  Std.noxx
## Regressions:
##   academ ~
##     anti      0.350                0.350    0.350
##     hyp      -0.350               -0.350   -0.350
##     int      -0.170               -0.170   -0.170
##
## Covariances:
##   anti ~~
##     hyp      0.300                0.300    0.300

```

```
##      int      0.000      0.000      0.000
##    hyp ~~
##      int      0.000      0.000      0.000
##
## Variances:
##    academ    0.800      0.800      0.800
##    anti      1.000      1.000      1.000
##    hyp       1.000      1.000      1.000
##    int       1.000      1.000      1.000
##
## R-Square:
##
##    academ    0.200
```

```
# implied correlations
```

```
fitted(antiPop.fit)
```

```
## $cov
```

```
##      academ anti  hyp   int
```

```
## academ  1.00
```

```
## anti    0.24  1.00
```

```
## hyp     -0.24  0.30  1.00
```

```
## int     -0.17  0.00  0.00  1.00
```

```
##
```

```
## $mean
```

```
## academ  anti    hyp    int
```

```
##      0      0      0      0
```

## Sample Size Determination Example

- Determine if a sample size of 200 is sufficient to find an interaction effect.

# Sample Size Determination Example

```
library(simsem)
intReg.sim.n200 <- sim(nRep=1000, model=antiReg.model, n=200,
  generate=antiPop.model, lavaanfun = "sem", multicore=TRUE)
antiPop.pwr.n200 <- summaryParam(intReg.sim.n200)
antiPop.pwr.n200["academ~int",]
```

##	Estimate.Average	Estimate.SD	Average.SE	Power..Not.equal.0.	Std.Est	
## academ~int	-0.17	0.065	0.063		0.78 -0.17	
##	Std.Est.SD	Average.Param	Average.Bias	Coverage	Rel.Bias	Std.Bias
## academ~int	0.062	-0.17	-0.0035	0.94	0.021	-0.055
##	Rel.SE.Bias	Not.Cover.Below	Not.Cover.Above	Average.CI.Width		
## academ~int	-0.031	0.023	0.039	0.25		
##	SD.CI.Width					
## academ~int	0.018					

- Will a sample size of 200 be sufficient to find an interaction effect?
  - From a power perspective, it will not
  - From an AIPE perspective, it might

# Sample Size Determination Example

- Determine the sample size for a power of .80
  - Simulate  $m = 10$  data sets from  $n = 200$  to  $n = 300$  increasing by units of 20

# Sample Size Determination Example

```
# simulate data
antiPop.n <- sim(nRep = NULL, model=antiReg.model, n = rep(seq(200,300,20), 10),
generate=antiPop.model, lavaanfun = "sem", multicore=TRUE)

# find sample size for desire power
antiPop.pwr.n <- getPower(antiPop.n)
findPower(antiPop.pwr.n, "N", 0.8)

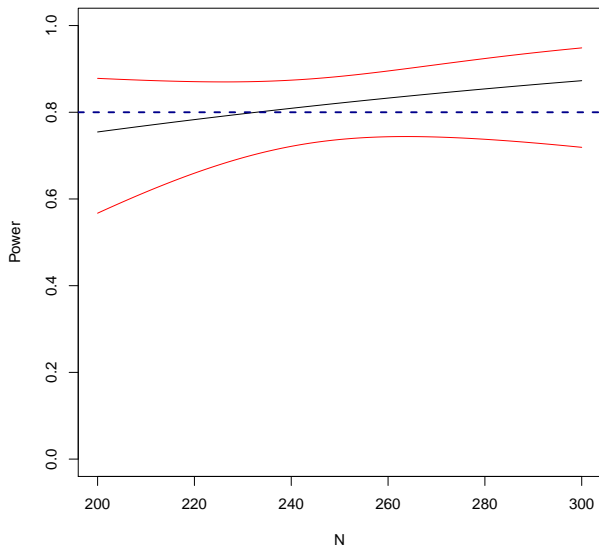
##      academ~anti      academ~hyp      academ~int      academ~~academ      anti~~anti
##              Inf              Inf              233              Inf              Inf
##      hyp~~hyp      int~~int
##              Inf              Inf

# plot power curve
plotPower(antiPop.n, powerParam="academ~int")
# line at power = 0.80
abline(h=.8, lwd=2, lty=2, col="blue4")
```



# Sample Size Determination Example

academ-int



# Sample Size Determination Example

## Advanced

- Equation 1 can estimate  $R^2$

$$R^2 = \rho'_{YX} R_{XX}^{-1} \rho_{YX} = \frac{b'_{YX} V_{XX} b_{YX}}{\sigma_Y^2} \quad (1)$$

where

- $\rho_{YX}$  is the population  $k \times 1$  column vector of correlations of each of the  $k$  predictors with the outcome
- $b_{YX}$  is the population  $k \times 1$  column vector of regression coefficients of each of the  $k$  predictors with the outcome
- $R_{XX}$  and  $V_{XX}$  are the  $k \times k$  population correlation and covariance matrixes, respectively, of the predictor variables,
- $\sigma_Y^2$  is the variance of the outcome, and
- ' is the transpose

## References

- Little, T. D., Slegers, D. W., & Card, N. A. (2006). A non-arbitrary method of identifying and scaling latent variables in SEM and MACS models. *Structural Equation Modeling: A Multidisciplinary Journal*, 13, 59-72. doi: 10.1207/s15328007sem1301\_3
- Page, E. B., & Keith, T. Z. (1981). Effects of U.S. private schools: A technical analysis of two recent claims. *Educational Researcher*, 10, 7-17. doi: 10.2307/1174256