ADVANCED DATA ANALYSIS FOR PSYCHOLOGICAL SCIENCE

Part 2. Introduction to multivariate modeling

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Outline of Part 2

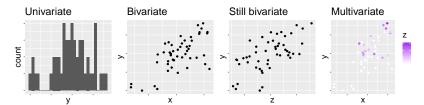
- sem() intro: Gentle introduction to the world of structural equation modeling (SEM)
- Path analysis: Introduction to path analysis (aka SEM with observed variables) and focus on mediation models
- Data structure: How to approach a multivariate data structure, how to manipulate and pre-process multivariate data \mathbf{Q}
- Model fit & evaluation: How to fit a path analysis in R, to evaluate model fit, compare multiple models, and interpret model results •
- cfa(): How to conduct a confirmatory factor analysis (CFA) and to interpret its results \mathbf{Q}
- Related topics: In-depth topics related to multivariate modeling (e.g., cross-lagged panel models, multilevel and Bayesian SEM)

_b = not for the exam

R = exercises with R (bring your laptop!)

sem() intro

Multivariate analyses for a multivariate reality



- In psychology, we mainly inspect empirical data focusing on **univariate** (y)or **bivariate** relationships (either y by x or y by z)
- But reality (particularly psychosocial reality) is complex, it is **multivariate** i.e., more than two variables covarying at the same time
- It is reductionist to separately analyze our variables without considering their overall interactions \rightarrow biased effect estimates
- Structural equation modeling (SEM) allow to analyze the relationships of interest by accounting for the multivariate reality of psychosocial phenomena (e.g., y by x covarying with z; x affects y through z)

Observed indicators & latent variables







- In psychology, we are mainly interested in latent variables = phenomena that
 we cannot directly observe, but we can estimate from 1+ observed indicators
 (e.g., 10-item scale measuring anxiety)
- Are we allowed to do that? Yes (let's say yes), provided that we trust the
 indicator construct validity = their relationship with the latent variable they
 claim to measure
- SEM allow to evaluate that by quantifying the latent variables and their relationships with observed indicators

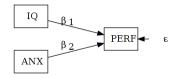
Structural what!?

Structural equation modeling (SEM)

sem() intro

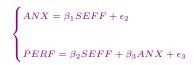
= multivariate *linear* models formalized by systems of equations

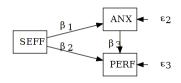
Linear models (LM): determining the link between a dependent and 1+ independent variables through a single equation like: $PERF = \beta_1 IQ + \beta_2 ANX + \epsilon$



LM can only predict one dependent variable at a time, being either univariate (without predictors, i.e., intercept-only) or bivariate (with predictors).

SEM allow to simultaneously model multiple dependent endogenous variables with a system of equations like:



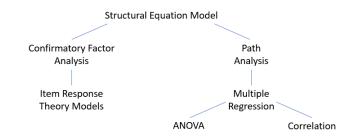


The SEM family

SEM = broad family of statistical models within which LM, ANOVA, and even correlation can be included.

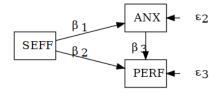
Particularly, 2 main sub-families can be distinguished based on whether **latent variables** are included in the model or not:

- Path analysis: multivariate linear models with observed variables only
- Confirmatory factor analysis (CFA): multivariate linear models with both observed and latent variables



Path models & path analysis

Path models/diagrams = multivariate models with observed variables only = pictorial representations (diagrams) of a theory of variable relationships

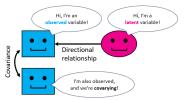


Paths = arrows (edges) linking the variables (nodes) in a model

Path analysis = analysis of multivariate relationships between observed variables ('quantification of the paths accounting for all other paths and errors')

Latent factors & CFA

- Observed/Manifest variable (OV) variable that is directly observable (e.g., height, heart rate, item responses)
- Latent variable/factor (LV) variable that is not directly observable (e.g., anxiety, intelligence), but can be indexed by one or more observed variables
- In SEM, OVs are represented by squares/rectangles and indexed with lower case letters (e.g., x), whereas LVs are represented by circles/ellipses and indexed by the Greek letter η

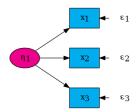


sem() intro 000000000000

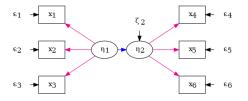
Confirmatory factor analysis (CFA)

= analysis of the relationships (factor loadings) between a set of OVs and one or more LVs

CFA uses latent variable models to form or quantify LVs and their relationships with OVs (evaluation of construct validity)



To properly talk about 'full SEM' (or just SEM), we need both OVs and LVs



A SEM consists of two parts:

- Structural model: Regression-like relationships among the variables, working similar to path analysis
- Measurement model (or latent variable model): Relationships between OVs and LVs, working a little differently

Notes:

sem() intro

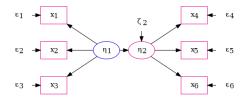
In this sense, we may say that a CFA model is a 'full SEM' whereas a path model is not

A CFA is a SEM with just the measurement part (without the structural model)

sem() intro

A new classification: From in/dependent to exo/endogenous variables

In both SEM (e.g., CFA) and path models, the classic independent vs. dependent classification is replaced with a more meaningful one:



- Exogenous variables: variables (both OVs and LVs) without a direct 'cause' from inside the model (predictors), without error estimate
- Endogenous variables: variables (both OVs and LVs) directly 'caused' from inside the model (predictors & outcomes), with error estimate ϵ (OV) or ζ (LV)

A new starting point: From dataset columns to covariance matrices

The starting point of LM(ER) is a vector (or a set of vectors) of variable values. usually corresponding to one or more columns from a dataset.

head(df,4)

MAT QI WM STM 1 57 21 15 18 77 22 19 17 51 13 13 16 58 24 6 21 The starting point of SEM and path models is the covariance matrix of the observed variables.

MAT MAT 100.70 24.89 17.21 7.99 24.89 19.43 6.69 4.04 17.21 6.69 17.33 2.23 7.99 4.04 2.23 5.34

SEM estimate a number of parameters θ so that the **implied covariance matrix** $\hat{\sum}(\theta)$ (i.e., the covariance matrix predicted by the model based on the parameter estimates) is as close as possible to the sample covariance matrix S





Covariance & correlation

• Variance = Expected value of the squared deviation from the mean of a random variable, or degree to which it deviates from its expected value

Covariance = Measure of the joint variability of two random variables, or
Degree to which they tend to deviate from their expected values in similar ways,
either directly (positive cov) or inversely (negative cov), whose value depends on
the variable scales of measurement (from −∞ to +∞)

• Correlation = standardized covariance of two random variables Correlation ranges from -1 (perfectly negative) to +1 (perfectly positive)











Covariance matrix (S)

Given a set of p variables, we can define the covariance matrix:

sem() intro 000000000000

$$S = \begin{bmatrix} s_{11} & \dots, & s_{1j} & \dots & s_{1p} \\ \dots & \dots & \dots & \dots \\ s_{i1} & \dots & s_{ij} & \dots & s_{ip} \\ \dots & \dots & \dots & \dots & \dots \\ s_{p1} & \dots & s_{pj} & \dots & s_{pp} \end{bmatrix}$$

```
cov(df[,c("MAT","QI","WM","STM")])
```

```
MAT 100.70 24.89 17.21 7.99
     24.89 19.43 6.69 4.04
     17.21 6.69 17.33 2.23
      7 99 4 04 2 23 5 34
STM
```

Properties of the covariance matrix:

- 1. Symmetrical: $s_{ij} = s_{ji}$
- 2. The main diagonal shows the variances (= covariance between each variable and itself)

SEM estimate a number of parameters θ so that the **implied covariance matrix** $\sum_{i=1}^{n} (\theta)$ (i.e., the covariance matrix predicted by the model based on the parameter estimates) is as close as possible to the sample covariance matrix S

Questions?

sem() intro

Homework (optional):

- read the slides presented today and write in the Moodle forum if you have any doubts
- exe Cises 12-13 from exeRcises.pdf

For each exercise, the solution (or one of the possible solutions) can be found in dedicated chunk of commented code within the exercises.Rmd file

In the last episode...

The problem

Psychosocial reality is complex: it's multivariate (3+ variables interacting at the same time) and involves latent variables (not directly measurable)

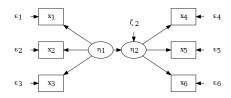
The solution

SEM allows to analyze the multivariate relationships among observed and latent variables through systems of equations:

$$\begin{cases} ANX = \beta_{21}SEFF + \epsilon_2 \\ \\ PERF = \beta_{31}SEFF + \beta_{32}ANX + \epsilon_3 \end{cases}$$

SEM basics

- Observed (x) vs latent variables (η) depending on whether can be directly measured or not
- Exogenous vs endogenous variables depending on whether directly caused inside the model or not
- Structural vs measurement model depending on whether focusing on structural relationships or construct validity of the observed indicators
- Path model: SEM with observed variables only
- CFA = SEM with measurement model only
- Starting point of any SEM = covariance matrix



Path models: SEM with observed variables

A path model is a pictorial representation (diagram) of a theory of variable relationships. Path analysis is widely used to model complex multivariate relationships (e.g., mediation models).

- Path analysis tests models of causal relationships* among observed variables
- All variables in path analysis are observed
- Path analysis uses systems of regression equations

^{*}Note: Within path analysis (and SEM) we assume that the relationships are *causal*, but this is not necessarily true (e.g., observational studies) → causation requires experimental manipulation, control group, etc.

Case study: Early mathematical abilities





A sample of 120 first-grade children (58) females: mean age: 6 years, 3 months) was assessed over the following variables:

The contribution of general cognitive abilities and approximate number system to early mathematics

Maria Chiara Passolunghi 1x1, Elisa Cargnelutti and Massimiliano Pastore²

Department of Life Sciences, University of Trieste, Italy ²Department of Developmental and Social Psychology, University of Padua, Italy

- MAT: early mathematical abilities (e.g., comparison, classification) measured with the Early Numeracy Test
- QI: intelligence level measured with the Wechsler Intelligence Scale for Children (WISC-III)
- WM: working memory capacity measured with the Backward word recall task
- STM: short-term memory capacity measured with the Forward word recall task
- ANS: approximate number system = innate system for approximate quantity manipulation (e.g., approximate computations, comparing 2+ sets of elements without counting), measured with several tasks

RQ: How much can MAT abilities be attributed to memory & ANS?

Data exploration

First, let's explore the data:

```
library(devtools); install github("https://github.com/masspastore/ADati") # install ADati pkg
data( earlymath, package = "ADati" ) # loading earlymath dataset from ADati pkg
head(earlymath,3) # showing first 3 rows
    gender MAT QI WM STM ANS
147
         m 57 21 15 18
         m 77 22 19 17 76
144
155
        f 51 13 13 16 79
summary(earlymath[,c(2,4:ncol(earlymath))]) # summarizing variables (not showing QI due to space limits)
      MAT
                                       STM
                                                       ANS
        .36.00
                        : 1.00
                                 Min.
                                        :13.00
                                                  Min
                                                         .45.00
 Min
                 Min.
 1st Qu.:61.75 1st Qu.:12.00
                                 1st Qu.:17.00
                                                  1st Qu.:74.00
 Median :68.00
               Median :14.50
                                 Median :18.00
                                                  Median :80.00
        :68.56
                 Mean
                        :14.55
                                         :18.43
                                                  Mean
                                                         :79.34
 Mean
                                 Mean
 3rd Qu.:75.00
                 3rd Qu.:17.00
                                 3rd Qu.:20.00
                                                  3rd Qu.:85.00
        :91.00
                        :28.00
                                        :26.00
                                                         :94.00
 Max.
                 Max.
                                 Max.
                                                  Max.
round( cor(earlymath[,2:ncol(earlymath)]), 2) # correlations
                WM STM ANS
MAT 1.00 0.56 0.41 0.34 0.26
  0.56 1.00 0.36 0.40 0.23
WM 0.41 0.36 1.00 0.23 0.12
STM 0.34 0.40 0.23 1.00 0.19
ANS 0.26 0.23 0.12 0.19 1.00
```

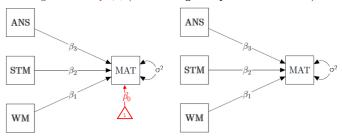
Linear model as a path diagram

Let's fit a multiple linear model: $MAT = \beta_0 + \beta_1 WM + \beta_2 STM + \beta_3 ASN + \epsilon$

```
lm.fit <- lm(MAT ~ WM + STM + ANS, data = earlymath) # fitting LM</pre>
```

summary(lm.	fit)\$coeffi	cients #	LM rear	ession table	Residual variance σ^2 :
•	Estimate Sto		3		<pre>summary(lm.fit)\$sigma^2</pre>
(Intercept) WM	20.03 0.81	9.61 0.20	2.09 4.10	0.04	[1] 75.94542
STM ANS	1.01	0.36 0.11	2.81	0.01	

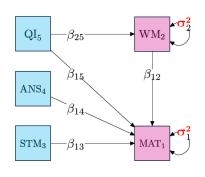
This model can be graphically represented as a path diagram and further simplified by removing the intercept β_0 (note: triangles represent constants)



How many parameters? Five: Intercept, 3 slopes, residual variance

Multivariate path models

In the previous example, we only considered **bivariate relationships** (i.e., 2 variables at a time, controlling for other variables). But what if we include IQ as a common predictor of both WM and MAT? We would have 3 variables interacting at the same time.



Both MAT and WM are endogenous variables because they receive 1+ arrow(s) and have error variance σ^2 . In contrast, STM, ANS, and QI are exogenous variables because they do not

A single LM equation is insufficient to describe this model. We need 2 separated equations: one for each variable that depends upon another variable

receive any arrow and have no errors.

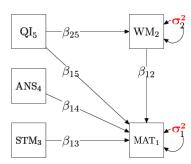
Path analysis (and SEM) uses one equation per endogenous variable:

$$\begin{cases} MAT_1 = \beta_{12}WM_2 + \beta_{13}STM_3 + \beta_{14}ANS_4 + \beta_{15}QI_5 + \epsilon_1 \\ WM_2 = \beta_{25}QI_5 + \epsilon_2 \end{cases}$$

Graphical notation (1/3): Error terms

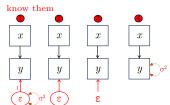
$$\begin{cases} MAT_{1} = \beta_{12}WM_{2} + \beta_{13}STM_{3} + \beta_{14}ANS_{4} + \beta_{15}QI_{5} + \epsilon_{1} \\ WM_{2} = \beta_{25}QI_{5} + \epsilon_{2} \end{cases}$$

Errors = residuals or disturbances = discrepancy between observed and predicted values (as in LM!), they represent something unexplained = exogenousand not directly observable = latent



= variance of a variable error (residual var.)

Alternative ways to represent errors: some highlight their latent nature (#1 and #2), some highlight their variance (#1 and #4), and some highlight both (#1). You need to

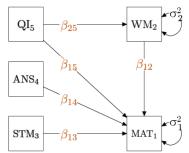


In this course, we will mainly use notation #4.

Graphical notation (2/3): Arrows & coefficients

$$\begin{cases} MAT_{1} = \beta_{12}WM_{2} + \beta_{13}STM_{3} + \beta_{14}ANS_{4} + \beta_{15}QI_{5} + \epsilon_{1} \\ WM_{2} = \beta_{25}QI_{5} + \epsilon_{2} \end{cases}$$

Arrows = relationships between 2 variables (paths or slopes) or between a variable and itself (residual variance), such that we do not include an arrow when a relationship is not expected (e.g., between QI and ASN) \rightarrow path models are complete



How to index variables and paths:

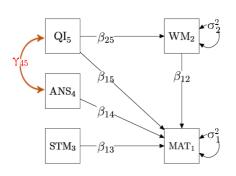
- Variables are indexed from the one receiving most arrows (MAT_1) to the last exogenous variable (QI_5)
- Path coefficients β are indexed by firstly reporting the index of the endogenous variable and then that of the exogenous variable

From plot to equations: endogenous v. ~ sum of all linked exogenous v. + error

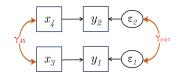
Graphical notation (3/3): Covariances

$$\begin{cases} MAT_1 = \beta_{12}WM_2 + \beta_{13}STM_3 + \beta_{14}ANS_4 + \beta_{15}QI_5 + \epsilon_1 \\ WM_2 = \beta_{25}QI_5 + \epsilon_2 \\ Cov(ANS_4, QI_5) = \gamma_{ANS_4, QI_5} \end{cases}$$

Covariances = non-directional (symmetric) relationships between 2 exogenous v.



- Covariances are usually not reported in the system of equations, but they can be graphically represented with (rounded) double-headed arrows
- Endogenous variables cannot covary but their errors ϵ can



□ Clarification on covariance terms in SEM

Covariances γ are intrinsic relationships between observed variables (we saw that SEM are fitted on the covariance matrix of observed variables).

In slide #22, we saw that path models are assumed to be *complete* models (i.e., we don't include an arrow when a relationship is not expected).

However, this rule only applies to single-headed arrows (path coefficients β), whereas it does not applies to the covariances γ .

Covariances γ are always there, whether you estimate them or not. In contrast, if we don't specify a path coefficient β between two variables, the two variables can only covariate but they are not in a symmetric relationship.

 \rightarrow the explicit inclusion of covariances γ does not affect the estimation of the path coefficients β , it only means that the models estimate the covariance parameter and its standard error, but we will see this later...

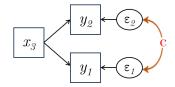
For the exam, you only need to know that double-headed arrows between two variables represent covariances, and that endogenous variables cannot covary but their errors can

Regression, partial correlation, and path coefficients

Path coefficients (single-headed arrows) are partial regression coefficients (slopes): as in LM, they index the effect of x on y by controlling for (i.e., after removing the effect of) other predictors, which are fixed to zero

Covariances between two exogenous variables (double-headed arrows), or between the errors of two endogenous variables, are **partial correlation coefficients**: they express the relationship between two variables by controlling for (i.e., after removing the effect of) all other correlated variables, which are fixed to zero

For instance, the figure below (source: Beaujeau, 2014) shows a path model of a partial correlation. Variables y_1 and y_2 are not allowed to covary since they are endogenous, but their errors are allowed to do so. Thus, the c coefficient is the relationship between y_1 and y_2 after removing the effect of x_1 from both variables.



Graphical notation: Recap



Directional (asymmetric) relationship



Non-directional (symmetric) relationship (covariance/correlation)



Endogenous observed variable with associated variance σ^2 of errors ε



Exogenous observed variable without associated error



Covarying exogenous variables



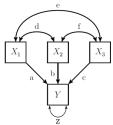
Endogenous variable with covarying errors



Constant (intercept)

Tracing rules & path coefficients





Sewall Wright (1889–1988): US geneticist that firstly developed rules for how to estimate values for a path model's coefficients by tracing the paths within it (i.e., path analysis).

Tracing rules = rules to estimate the covariance between 2 variables by summing the appropriate connecting paths:

- Trace all paths between 2 variables multiplying all coefficients
- 2. Start by going backwards along single-headed arrows, no loops
- Once you start going forward, you cannot no longer go back
- 4. Each path can only include one double-headed arrow

Starting from observed covariances (or correlations), we can compute the value of path coefficients. For instance, to compute path a starting from the observed correlations between X_1 and Y (e.g., r = .70), between X_1 and X_2 (e.g., d = .24), and between X_1 and X_3 (e.g., e = .20):

$$r_{X_1,Y} = a + db + ec \rightarrow .70 = a + .24c + .20b \rightarrow a = .70 - .24c - .20b$$

Standardized vs. *Unstandardized* solution

Path coefficients are partial regression coefficients (relationship between an exogenous x and an endogenous variable y, controlling for all other exogenous variable affecting y). Similar to LM, they can be either unstandardized or standardized:

- Unstandardized coefficients are obtained when the model is fitted on the variables expressed in their natural metrics (raw score units of measurement) → useful when raw score units are meaningful (e.g., age, meters, bpm) and when comparing the same variable relationship across samples
- Standardized coefficients (ranging from -1 to 1) are obtained when the model is fitted on standardized variables (i.e., variables transformed into **z-scores**: $z_{x_i} = (x_i - \overline{x})/s_x$ \rightarrow useful to compare coefficients within the same model and/or the same sample
- **b** To standardize an unstandardized coefficient: $b^* = b \times (s_Y/s_X)$
- **b** To unstandardize a standardized coefficient: $b = b^* \times (s_X/s_Y)$

That's all for now!

Questions?

Homework (optional):

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- exe cises 14-15 from exeRcises.pdf

For each exercise, the solution (or one of the possible solutions) can be found in dedicated chunk of commented code within the exeRcises.Rmd file

In the last episodes...

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RQ: How much can MAT abilities be attributed to memory & ANS?

Data structure in multivariate analyses

Model fit 00000000000

In SEM (including path analysis and CFA), data analyses are usually based on wide-form datasets with one row per participant:

head(earlymath) # showing first 6 rows

```
gender MAT QI WM STM ANS
147
                    18
                        80
        m 77 22 19
144
                    17
                        76
          51 13 13
155
                   16
                        79
55
        f 58 24 6 21
                        86
          64 28 15
                        75
6
                   19
13
        m 68 27 14 19
                        86
```

Provided that we have **no missing data** (but there are ways to deal with that), such wide-form dataset is used by the model to automatically compute the **covariance** matrix of observed variables, which is the starting points to fit the models.

cov(earlymath[,2:ncol(earlymath)])

```
MAT
                     QI
                               WM
                                       STM
                                                 ANS
MAT 100.702451 24.889286 17.211345 7.991317 20.261415
QΙ
    24.889286 19.427941 6.692017 4.039496 7.844328
    17.211345 6.692017 17.325210 2.230252
WM
                                            3.902941
STM
     7.991317 4.039496 2.230252 5.340056 3.413725
    20.261415 7.844328 3.902941 3.413725 59.924300
```

▶ Note: since the covariance matrix is the starting point, many software (including R) can fit

Fitting a (bivariate) path model with R

We will use the lavaan ($latent\ variable\ analysis$) package (Rosseel, 2012), which uses the sem() function to fit SEM with observed (path analysis) and/or latent variables.

```
library(lavaan)
```

Let's start with a bivariate model (with only one endogenous variable) to highlight the differences between path analysis and LM in the model specification:

Linear model (LM)

[1] 75.95

```
# fitting model
fit.lm <- lm(MAT ~ WM + STM + ANS.
              data = earlymath)
# parameter estimates
summary(fit.lm)$coefficients
     Estimate Std. Error t value Pr(>|t|)
                           2.09
(Int)
        20.03
                   9.61
                                   0.04
WM
         0.81
                   0.20
                           4.10
                                   0.00
                           2.81
                                   0.01
STM
         1.01
                   0.36
ANS
         0.23
                           2.16
                                   0.03
                   0.11
# residual variance siama2
summary(fit.lm)$sigma^2
```

Path model (PM)

```
# specifying model
mvmodel <- 'MAT ~ WM + STM + ANS'
# fitting model to the data
fit.sem <- sem(model = mymodel, data = earlymath)
parameterestimates(fit.sem) # par. estimates
  lhs op rhs
                           z pvalue ci.lower ci.upper
       ~ WM
              0.81 0.19 4.17
                              0.00
  MAT
                                       0.43
                                                1.19
  MAT
       ~ STM 1.01 0.35 2.85
                              0.00
                                       0.32
                                                1.71
  MAT
      ~ ANS 0.23 0.10 2.19
                              0.03
                                       0.02
                                               0.43
  MAT ~~ MAT 73.41 9.48 7.75
                              0.00
                                      54.84
                                               91.99
                                      17.18
                                               17.18
          WM 17.18 0.00
                         NA
                                NA
   WM ~~ STM 2.21 0.00
                         NA
                                NA
                                       2.21
                                                2.21
   WM ~~ ANS 3.87 0.00
                         NA
                                NA
                                       3.87
                                               3.87
  STM ~~ STM 5.30 0.00
                         NA
                                NA
                                       5.30
                                               5.30
  STM ~~ ANS 3.39 0.00
                                       3.39
                                                3.39
                         NΑ
                                NA
10 ANS ~~ ANS 59 42 0 00
                         NΑ
                                NΑ
                                      59 42
                                               59.42
```

Path model summary

summary(fit.sem)

lavaan 0.6.16 ended normally after 1 iteration

Estimator	ML
Optimization method	NLMINB
Number of model parameters	4
Number of observations	120

Model Test User Model:

Test statistic 0.000
Degrees of freedom 0

Parameter Estimates:

Standard errors		Standard
Information		Expected
Information saturated	(h1) model	Structured

Regressions:

	Estimate	Std.Err	z-value	P(> z)
MAT ~				
WM	0.812	0.195	4.172	0.000
STM	1.012	0.354	2.855	0.004
ANS	0.228	0.104	2.195	0.028

Variances:

	Estimate	Std.Err	z-value	P(> z)
.MAT	73.414	9.478	7.746	0.000

Here is the model summary:

- First lines: info on convergence, parameter estimation method (ML), optimization (...), and number of estimated parameters (3 path coeff. + 1 residual variance)
- Model test User Model: info on model fit (we will see this later)
- Parameter Estimates: other info on parameter estimation method
- Regressions: path coefficients estimated by the structural model, with their standard error, z-value, and p-value
- Variances: estimated residual variance of any endogenous variable

Path model vs. linear model estimates

We can see that the coefficients estimated by the path model are very similar to those estimated with LM:

```
coef( fit.sem ) # path model estimates
 MAT~WM
         MAT~STM MAT~ANS MAT~~MAT
           1.012
                   0.228
                           73.414
  0.812
round(c( coef(fit.lm), sigma2 = summary(fit.lm)$sigma^2 ) ,3) # LM estimates
(Intercept)
                   WM
                              STM
                                         ANS
                                                 sigma2
    20.035
                0.812
                            1.012
                                       0.228
                                                 75.945
```

But where is the intercept?

In SEM, intercepts are usually not considered as 'direct' model parameters. To estimate them, we need to set meanstructure = TRUE

```
fit.sem <- sem(model = mymodel, data = earlymath, meanstructure= TRUE)

coef(fit.sem) # Here's the intercept!

MAT-WM MAT-STM MAT-ANS MAT--MAT MAT-1
0.812 1.012 0.228 73.414 20.035
```

Note: Path analysis coefficients can be interpreted identically to LM coefficients

Hands on \mathbf{Q} (part 1)

1. Open the earlymath dataset from the ADati package

```
# how to install the ADati package:
library(devtools) # install and open the devtools package
install github("https://github.com/masspastore/ADati") # install the ADati pkq
data(earlymath, package = "ADati") # load earlymath dataset from ADati pkg
```

- 2. Fit a LM 1m1 predicting MAT by WM, STM, ANS, and QI
- 3. Fit a path model pm1 with the same outcome and 'predictors'
- 4. Print, interpret, and compare the parameters estimated by both models
- 5. Inspect the predicted covariance matrix by running inspect(fit.sem, "estimates") \$psi[2:4, 2:4] and compare it with the covariance matrix of observed variables S
- 6. Now standardize all variables, re-fit model pm1, and print the estimated parameters
- 7. Now refit model pm1 on the original variables by setting std.lv = TRUE and compare the estimated parameters to those estimated from the standardized variables

Fitting a (multivariate) path model with R

Hands on \mathbf{Q} (part 2)

Hands on \mathbf{Q} (part 3)

Credits

The present slides are partially based on:

- Altoè, G. (2023) Corso Modelli lineari generalizzati ad effetti misti 2023. https://osf.io/b7tkp/
- Beaujean, A. A. (2014) Latent Variable Modeling Using R. A Step-by-Step Guide. New York: Routledge
- Finch, W. H., Bolin, J. E., Kelley, K. (2014). Multilevel Modeling Using R (2nd edition). Boca Raton: CRC Press
- Pastore, M. (2015). Analisi dei dati in psicologia (e applicazioni in R). Il Mulino.
- Pastore, M. (2021). Analisi dei dati in ambito di comunità

Achronyms & Greek letters

- CFA: confirmatory factor analysis
- LM: linear models/modeling
- LV: latent variable
- OV: observed variable
- SEM: structural equation models/modeling
- SS: sum of squares

- $\beta = beta$, indexing path coefficients (or regression coefficients)
- $\epsilon = epsilon$, indexing the error of an observed variable
- $\sigma = sigma$, indexing the variance σ^2 of the errors ϵ
- $\eta = eta$, indexing latent variables
- $\theta = theta$, indexing overall model parameters

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- ciao