

CORRELATION

PARTIAL CORRELATION

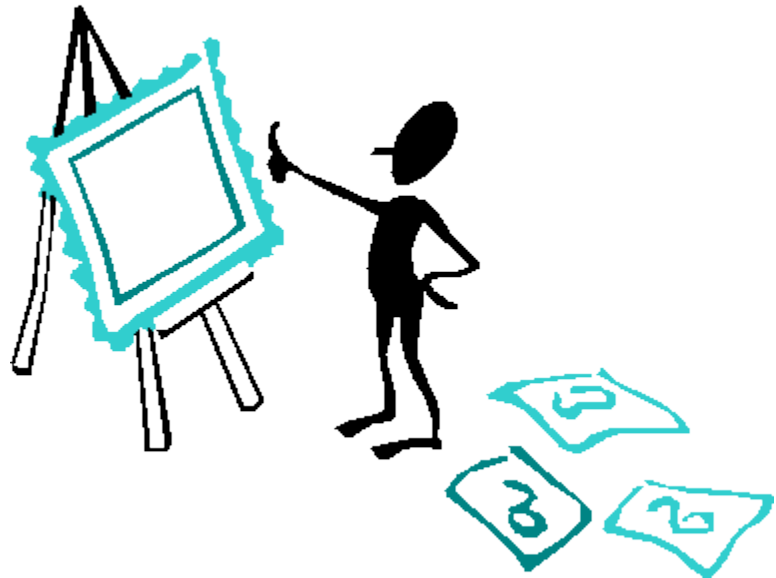
MULTIPLE REGRESSION

Modeling latent variables

Outline

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- 1. Introduction
- 2. Correlation
- 3. Partial correlation
- 4. Multiple Regression



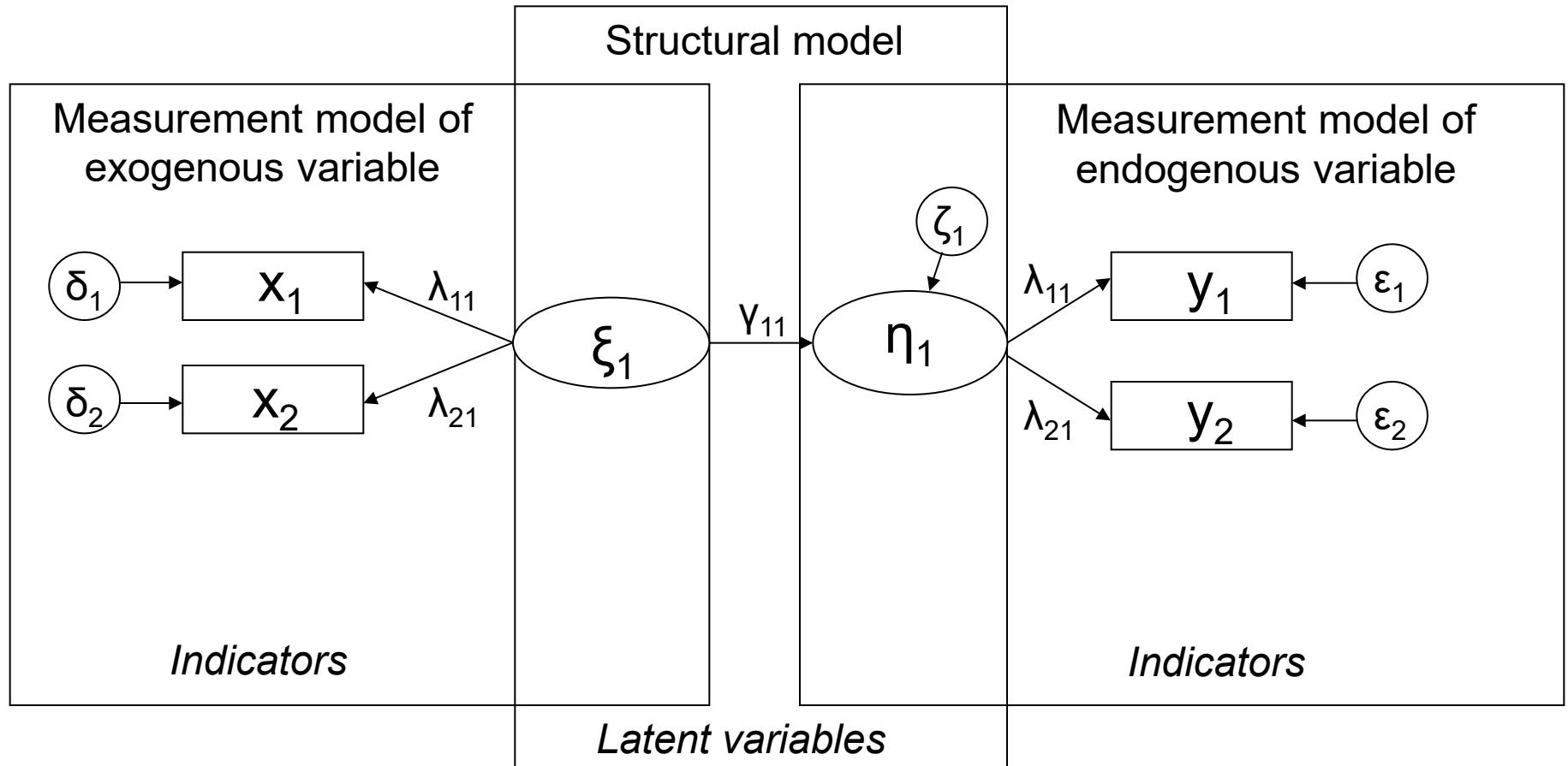
1. Introduction

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- This course unit prepares for the modeling of the relationships between latent variables at the latent level.

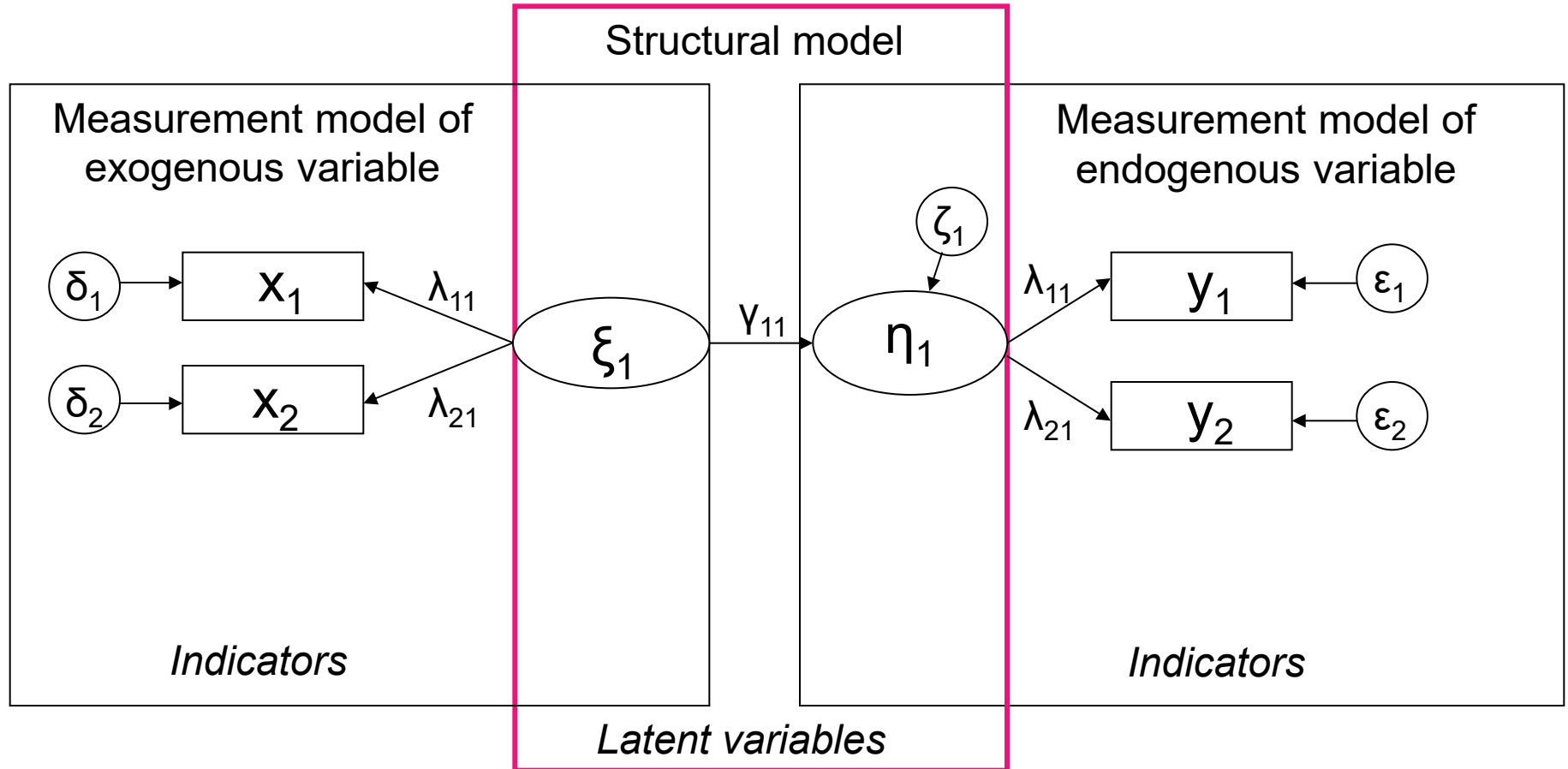
1. Introduction

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1. Introduction

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2. Correlation

2. The correlation

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- The correlation serves the description of relationships between random variables



- It provides information on the degree of the relationship
- It provides **no** information on the direction of the relationship (same direction vs contrary)

2. The correlation

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□ There are different types of correlation:

□ Pearson correlation / PM correlation

Data scales:

interval – interval

□ tetrachoric correlation

binary – binary

□ polychoric correlation

ordered cat. – ord. cat.

□ biserial correlation

binary – ordinal

□ Phi coefficient

dichotomous – dich.

□ rank correlation

ordinal – ordinal

□ point-biserial correlation

binary - interval

2. The correlation

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□ There are different types of correlation:

... of importance:

□ Pearson correlation / PM correlation

□ tetrachoric correlation

□ polychoric correlation

□ biserial correlation

□ Phi coefficient

□ rank correlation

□ point-biserial correlation

2. The correlation

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- An example: the correlation of „logical thinking“ and „creativity“:

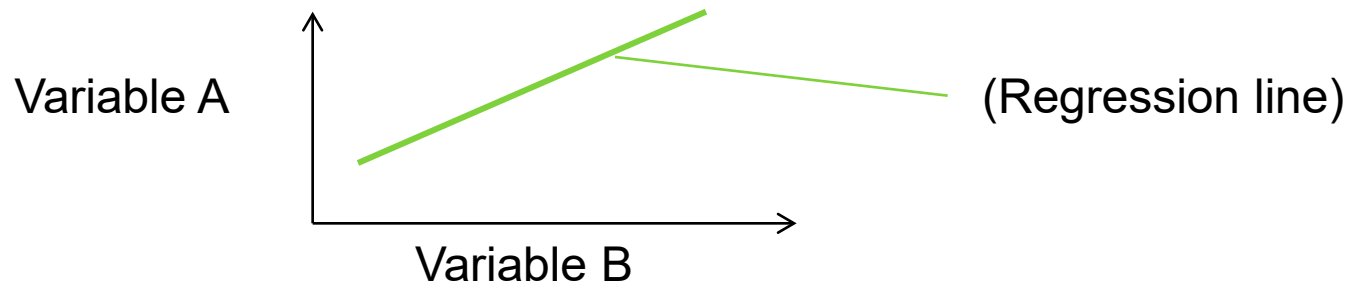


- There is information on the size of the correlation but not on the direction of an influence

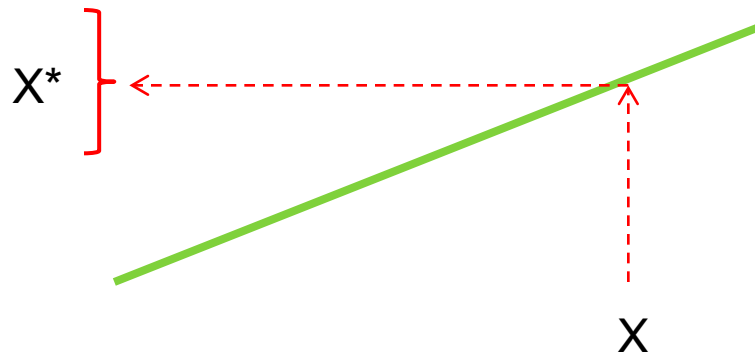
2. The correlation

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- Note. Correlation coefficients typically assume that there is a linear relationship



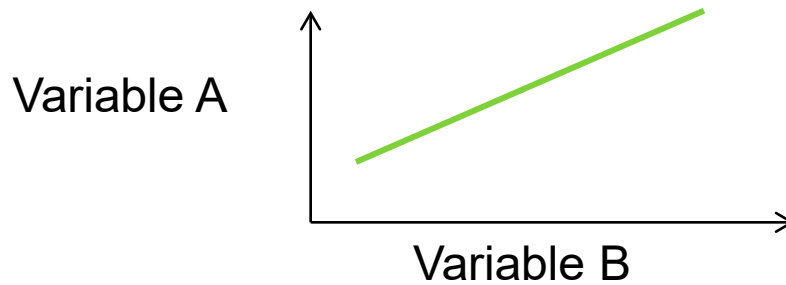
... in a model it can enables basic prediction:



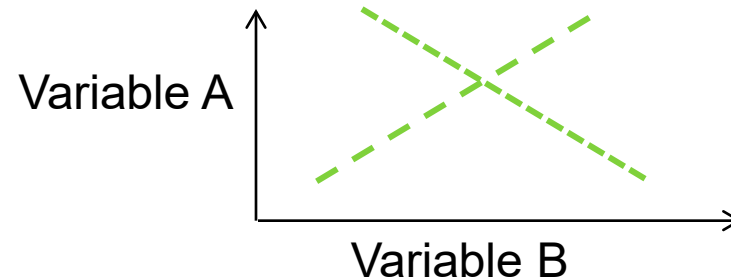
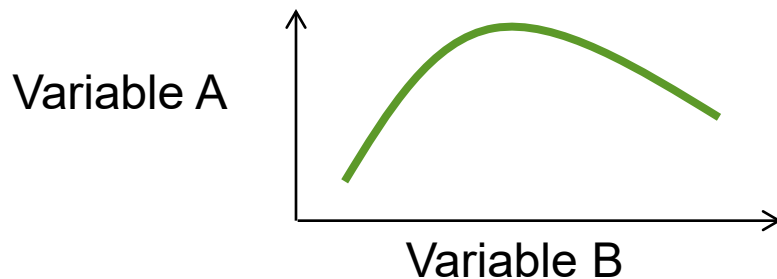
2. The correlation

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- Note. Correlation coefficients typically assume that there is a linear relationship



- But there may be a non-linear relationship or different relationships in sub-groups

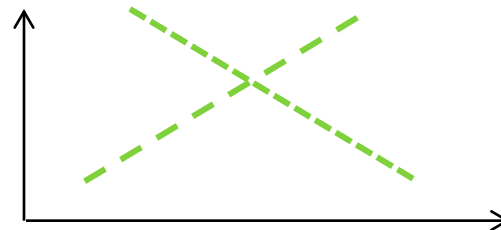
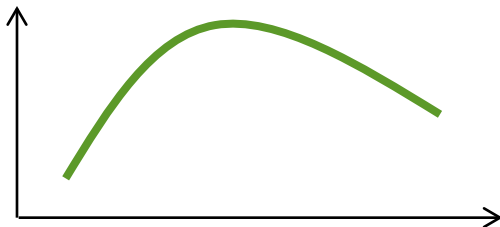


2. The correlation

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- Note. Correlation coefficients typically assume that there is a linear relationship
- But there may be a non-linear relationship or different relationships in sub-groups

... such cases should be avoided; search for reasons.



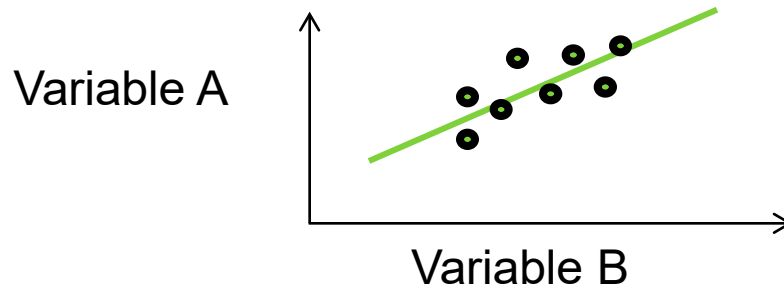
2. The correlation

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- Note. Correlation coefficients typically assume that there is a linear relationship

How to find out?

Use the scatterplot

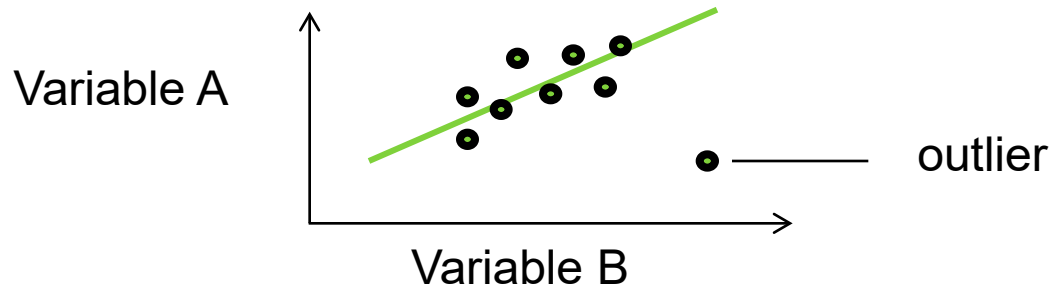


2. The correlation

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- Note. Correlation coefficients typically assume that there is a linear relationship

It also helps to detect outliers!



2. The correlation

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- The correlation is important because it can provide the basis for investigating **hypotheses**



- ... it can be assumed to include **effects**
- ... it can provide the basis for **estimating effects**

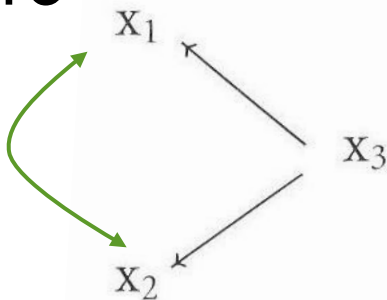


3. Partial correlation

3. Partial correlation: aspects

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- *Idea:* an observed correlation may not reflect the assumed structure



- Possibility: x_1 and x_2 are influenced by x_3 // x_3 brings about the correlation between x_1 and x_2
- A high correlation between x_1 and x_2 may be a **fake correlation**

3. Partial correlation: aspects

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□ „**fake correlation**“ = correlation between two variables that is actually due to another variable

■ **an example** from southern Sweden

... allegedly the return of storks from their Winter journey coincides with an increase of house burns

(... are storks responsible for the house burns?)

... the presumably true reason is **spring** with all kinds of spring activities including festivities!

3. Partial correlation: aspects

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- „fake correlation“ = correlation between two variables that is actually due to another variable
- Basic idea of partial correlation:
 - There is a correlation between x_1 and x_2 that is due to x_3
 - Variables x_1 and x_2 must be „cleaned“ from the influence of x_3 → the influence of x_3 must be eliminated
 - Correlation „cleaned“ of influence of x_3 on x_1 and x_2 → **partial correlation**

3. Partial correlation: definition

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□ Formula:

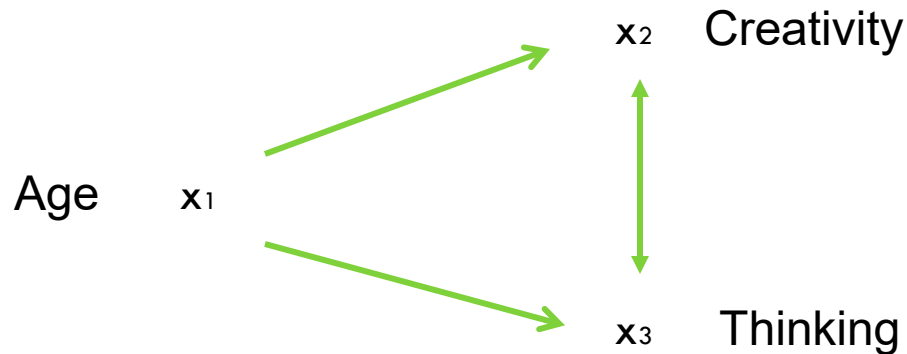
$$r_{x_1 x_2 \cdot x_3} = \frac{r_{x_1 x_2} - r_{x_1 x_3} * r_{x_2 x_3}}{\sqrt{1 - r_{x_1 x_3}^2} * \sqrt{1 - r_{x_2 x_3}^2}}$$

- computation requires 3 *product-moment correlations* between x_1 , x_2 and x_3
- partial correlation is zero? → Indication that the correlation is actually a fake correlation

3. Partial correlation: example

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- Example: 2 traits (x_2 , x_3) plus age (x_1) are correlated ($r_{12}=.8$; $r_{13}=.7$; $r_{23}=.6$)



- Research question: is the relationship of creativity and thinking a „fake correlation“?

3. Partial correlation: example

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- Preparation for the application of the formula:
 - re-assignment of subscripts

age – creativity (r_{12}) \longrightarrow [r_{23}]

age – thinking (r_{13}) \longrightarrow [r_{13}]

creativity – thinking (r_{23}) \longrightarrow [r_{12}]

What it should be!



3. Partial correlation: example

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□ Result:

(using original assignment)

$$r_{23 \cdot 1} = \frac{r_{23} - r_{12} \cdot r_{13}}{\sqrt{1 - r_{12}^2} \cdot \sqrt{1 - r_{13}^2}} = \frac{0.6 - 0.8 \times 0.7}{\sqrt{1 - 0.8^2} \times \sqrt{1 - 0.7^2}} = 0.09$$

- Is the influence of the variable age eliminated from the variables creativity and thinking by **partialling out**, the remaining partial correlation is virtually zero!
- In sum: the relationship of x2 and x3 is almost completely due to the influence of x1

3. Partial correlation: *practice*

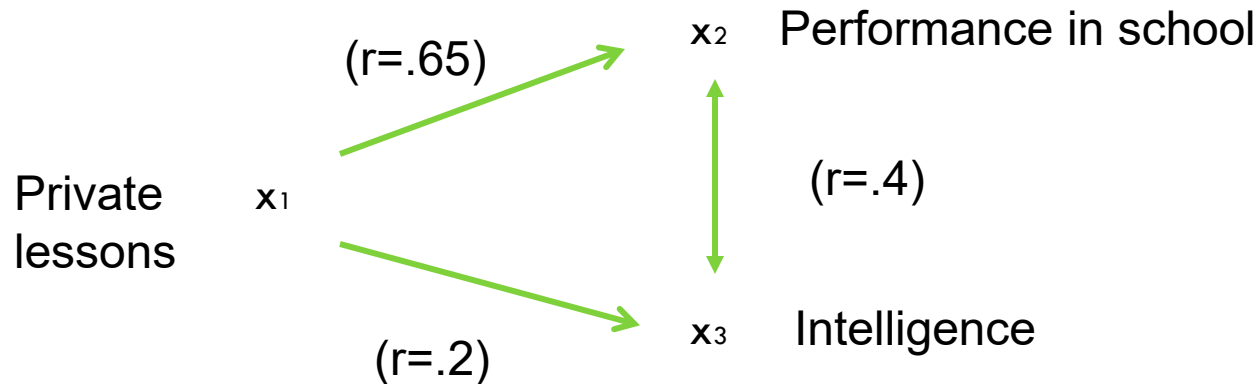
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- Find out whether the positive correlation between performance in school and intelligence (.4) is due private lessens

3. Partial correlation: *practice*

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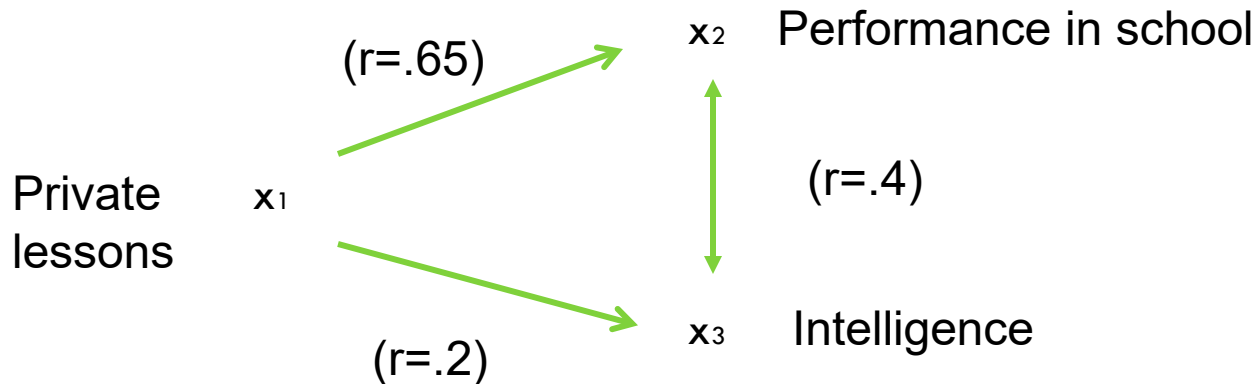
- Find out whether the positive correlation between performance in school and intelligence (.4) is due private lessons



3. Partial correlation: *practice*

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Is the correlation of „Performance in school“ and „Intelligence“ a fake correlation?



$$r_{x_1 x_2 \cdot x_3} = \frac{r_{x_1 x_2} - r_{x_1 x_3} \cdot r_{x_2 x_3}}{\sqrt{1 - r_{x_1 x_3}^2} \cdot \sqrt{1 - r_{x_2 x_3}^2}}$$

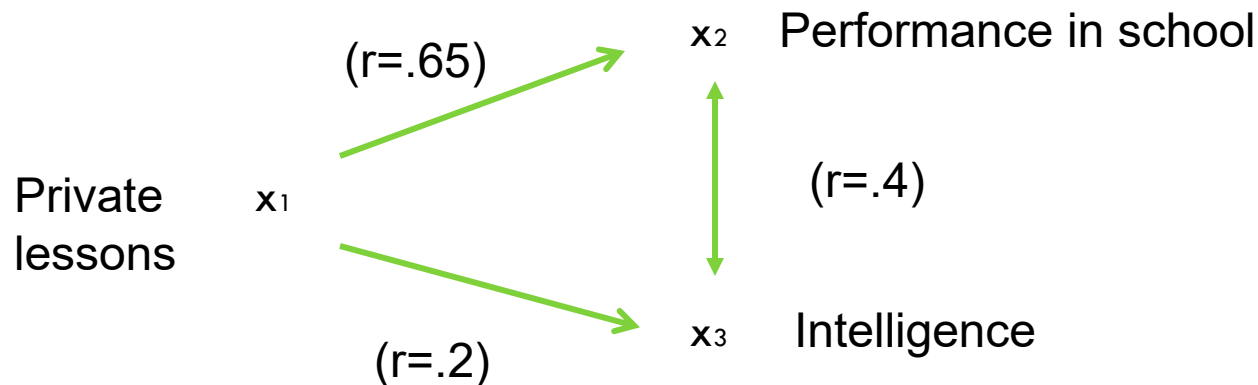
$$r_{23 \cdot 1} = \frac{r_{23} - r_{12} \cdot r_{13}}{\sqrt{1 - r_{12}^2} \cdot \sqrt{1 - r_{13}^2}}$$

(using original assignment)

3. Partial correlation: *practice*

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- Find out whether the positive correlation between performance in school and intelligence (.4) is due private lessons



Possible Results:

.09 / .21 / .28 / **.36** / .41

3. Partial correlation

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A comment: the partial correlation

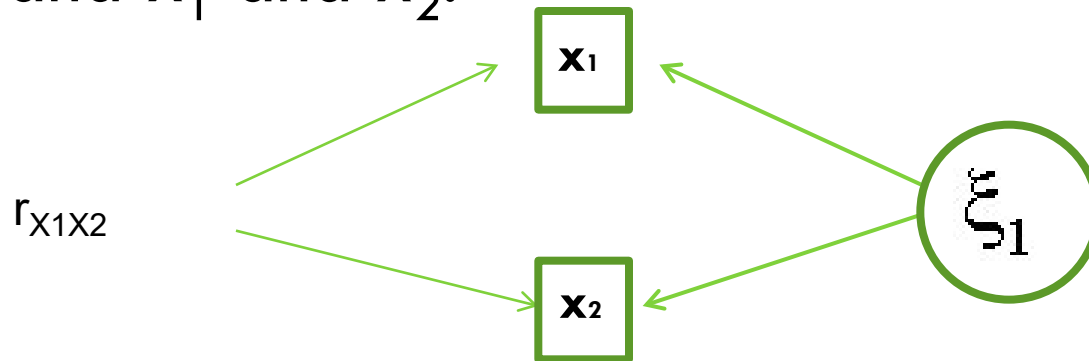
- ... made apparent – probably for the first time – that a correlation can originate from different sources
- ... is a coefficient for evaluating a hypothesis
(e.g., the hypothesis is that an external variable is the true source)

3. Partial correlation

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- The idea of the partial correlation is related to the idea of the *models of measurement* with one latent variable:

... it is variable ξ_1 that establishes the relation of x_1 and x_2 :

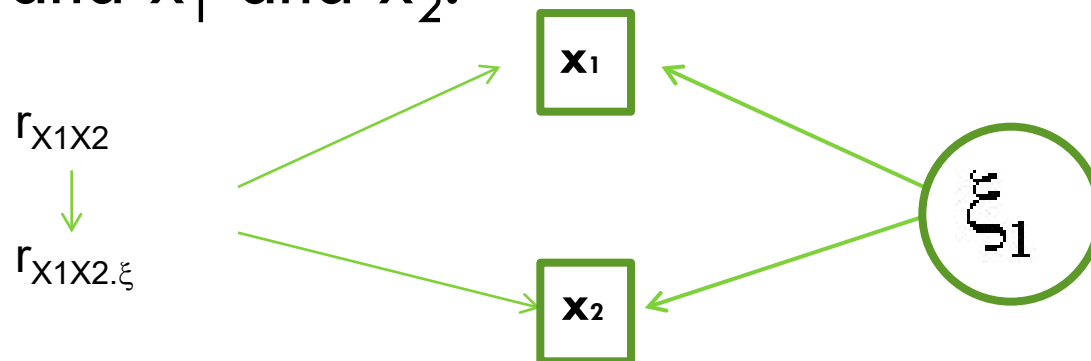


3. Partial correlation

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- The idea of the partial correlation is related to the idea of the *models of measurement* with one latent variable:

... it is variable ξ_1 that establishes the relation of x_1 and x_2 :





4. Multiple regression

4. Multiple regression: introduction

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- multiple regression = prediction of a **criterion variable** (y) using a linear equation model including **several predictors** (x)

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p + \varepsilon$$

criterion predictor error component

4. Multiple regression: introduction

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- multiple regression = prediction of a **criterion variable** (y) using a linear equation model including **several predictors** (x)

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p + \varepsilon$$

The diagram shows the equation $y = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p + \varepsilon$ with labels below it: 'criterion' for y , 'predictor' for x_1 , 'regression weight' for β_1 , and 'error component' for ε . Solid black lines connect each label to its corresponding term. A dashed red line connects the 'regression weight' label to the β_0 term.

criterion predictor regression weight error component

4. Multiple regression: introduction

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- multiple regression = prediction of a **criterion variable** (y) using a linear equation model including **several predictors**
- one aim of multiple regression: estimation of β weights (or b)
- β (instead of b) weights are also addressed as **standard partial regression coefficients**

4. Multiple regression: introduction

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- ... serves the estimation of the effects of **several** predictors on the criterion
- ... estimation of β respectively **b** is conducted according to the ordinary least-square (OLS) criterion:

$$\min = \varepsilon' \varepsilon$$

... the estimation method (OLS) :

$$\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{y}$$

4. Multiple regression: introduction

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- An example regarding OLS

$$\min = \varepsilon' \varepsilon$$

... the estimation method:

$$\mathbf{b} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{y}$$

$$\mathbf{x} = \begin{pmatrix} 1 \\ 2 \\ 4 \end{pmatrix}, \quad \mathbf{y} = \begin{pmatrix} 2 \\ 5 \\ 6 \end{pmatrix}$$

4. Multiple regression: introduction

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□ An example regarding OLS

$$\min = \varepsilon' \varepsilon$$

... the estimation method for one predictor:

$$\mathbf{b} = (\mathbf{x}'\mathbf{x})^{-1} \mathbf{x}'\mathbf{y}$$

$$\mathbf{x} = \begin{pmatrix} 1 \\ 2 \\ 4 \end{pmatrix}, \quad \mathbf{y} = \begin{pmatrix} 2 \\ 5 \\ 6 \end{pmatrix}$$

$$\mathbf{x}'\mathbf{x} = 21 \quad (\mathbf{x}'\mathbf{x})^{-1} = 1/21 \quad \mathbf{x}'\mathbf{y} = 36$$

$$b = (1/21) \times 36 = 1.71$$

4. Multiple regression: introduction

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- ... serves the estimation of the effects of **several** predictors on the criterion

Problem:

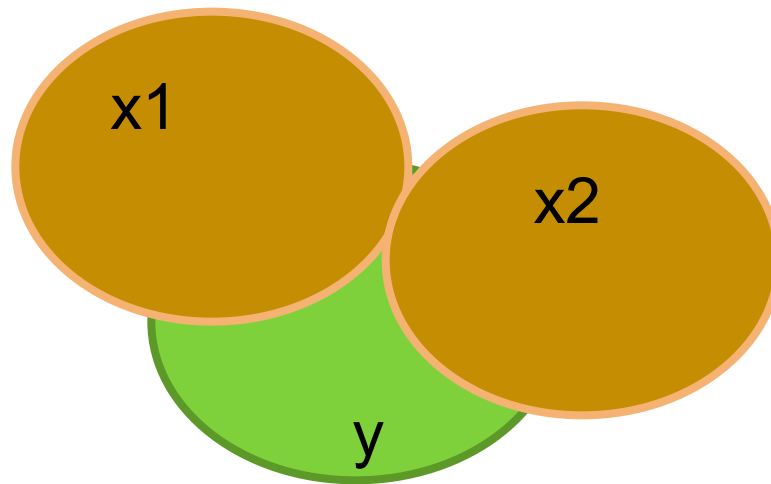
- ... the method must take the correlations among the predictors into consideration because ...
- ... **overlapping predictions** are a *major problem*:

4. Multiple regression: introduction

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- ... two predictor variables (x_1 , x_2) predict a criterion variable (y)

... no overlap!

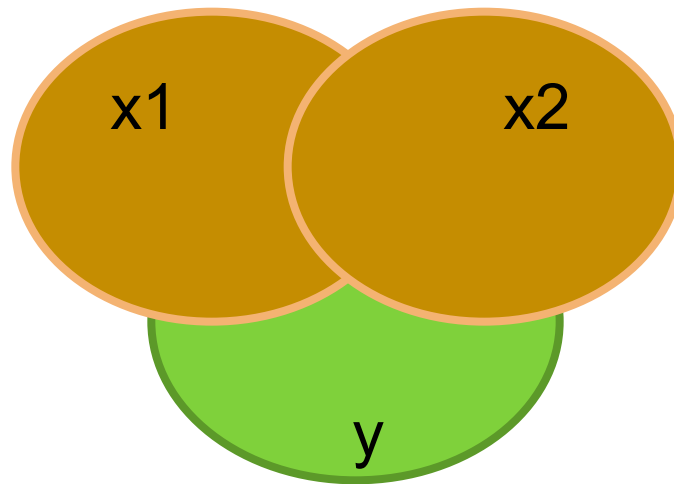


The ellipses represent variance of variables

4. Multiple regression: introduction

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- ... two predictor variables (x_1 , x_2) predict a criterion variable (y)

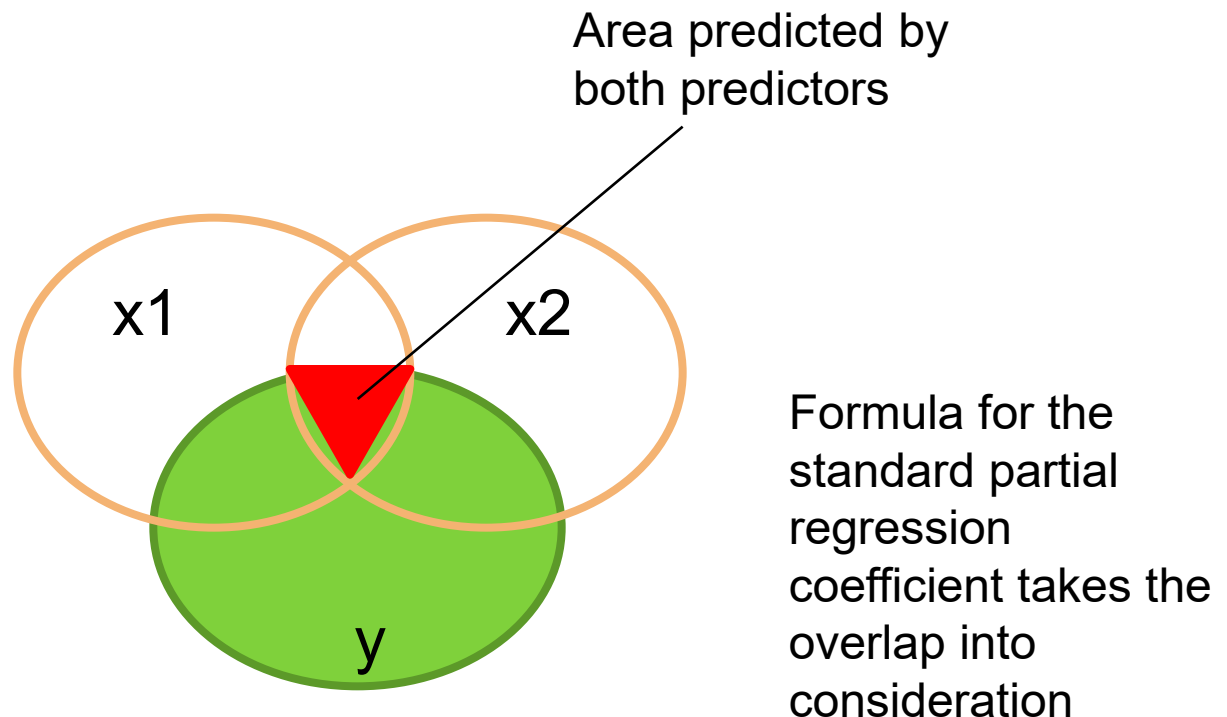


The ellipses represent variance of variables

4. Multiple regression: introduction

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- ... two predictor variables (x_1 , x_2) predict a criterion variable (y)



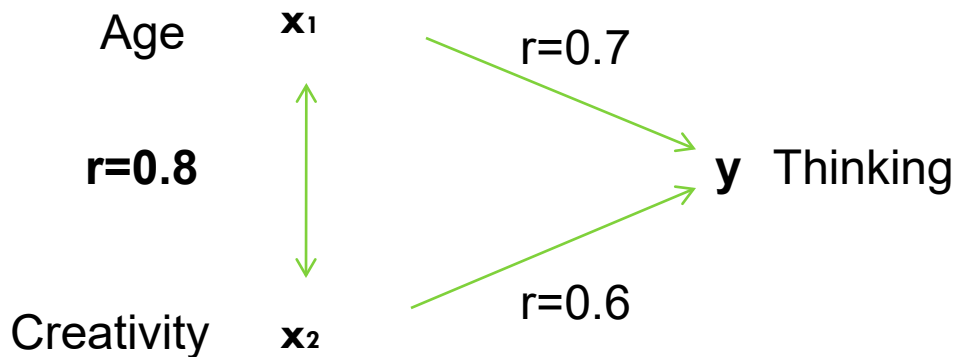
4. Multiple regression: example

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□ an example: overlapping predictors

Predictors

Criterion



$$r_{x_1, x_2} = .8$$

$$r_{x_1, y} = .7$$

$$r_{x_2, y} = .6$$

Question: do the correlations reflect the influences of the predictors correctly?

4. The alternative: partial regression

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There is an alternative way of estimating regressions weights

... if correlations are available

.. the **partial regression coefficient**

4. Partial regression

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The formula for the computation of the standard partial regression coefficient β is ...

$$\beta_{Y1,X1,X2} = \frac{r_{Y1,X1} - r_{Y1,X2} \cdot r_{X1,X2}}{1 - r_{X1,X2}^2}$$

Diagram illustrating the components of the partial regression coefficient formula:

- $\beta_{Y1,X1,X2}$: Partial regression coefficient
- $r_{Y1,X1}$: Correlation between Criterion variable and Predictor 1
- $r_{Y1,X2}$: Correlation between Criterion variable and Predictor 2 (= additionally considered predictor)
- $r_{X1,X2}$: Correlation between Predictor 1 and Predictor 2 (= additionally considered predictor)

4. Partial regression

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The formula for the computation of the standard partial regression coefficient β is ...

$$\beta_{Y1,X1 \cdot X2} = \frac{r_{Y1,X1} - r_{Y1,X2} \cdot r_{X1,X2}}{1 - r_{X1,X2}^2}$$

... compare denominator of partial correlation:

$$\sqrt{1 - r_{X1,X3}^2} \sqrt{1 - r_{X2,X3}^2}$$

4. Partial regression: example

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Formulas:

Criterion: thinking
Predictor: age

$$\beta_{Y1,X1 \cdot X2} = \frac{r_{Y1,X1} - r_{Y1,X2} \cdot r_{X1,X2}}{1 - r_{X1,X2}^2}$$

Criterion: thinking
Predictor: creativity

$$\beta_{Y1,X2 \cdot X1} = \frac{r_{Y1,X2} - r_{Y1,X1} \cdot r_{X1,X2}}{1 - r_{X1,X2}^2}$$

4. Partial regression: example

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□ Equations:

$$\beta_{Y1,X1 \cdot X2} = \frac{r_{Y1,X1} - r_{Y1,X2} \cdot r_{X1,X2}}{1 - r_{X1,X2}^2}$$

Predictor: age

$$\beta_{Y1,X2 \cdot X1} = \frac{r_{Y1,X2} - r_{Y1,X1} \cdot r_{X1,X2}}{1 - r_{X1,X2}^2}$$

Predictor:
creativity

□ Results:

$$\beta_{Y1,X1 \cdot X2} = \frac{0.70 - 0.60 \cdot 0.80}{1 - 0.80^2} = \frac{0.22}{0.36} = 0.61$$

Age →
Thinking

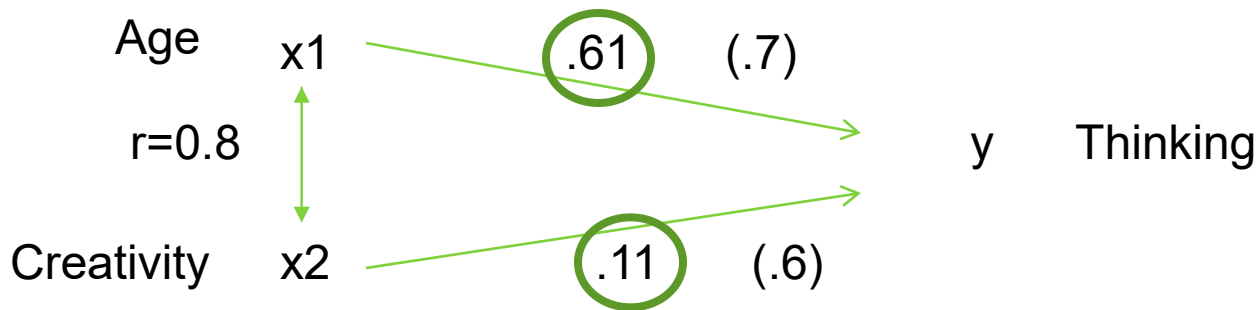
$$\beta_{Y1,X2 \cdot X1} = \frac{0.60 - 0.70 \cdot 0.80}{1 - 0.80^2} = \frac{0.04}{0.36} = 0.11$$

Creativity →
Thinking

4. Partial regression: example

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- partial regression coefficients:



- the criterion *thinking* is influenced to a higher degree by *age* than by *creativity*
- the correlation of creativity & thinking: it appears to be to a high degree due to the correlation of the predictors that means due to an ***indirect effect***.

4. Partial regression: *practice*

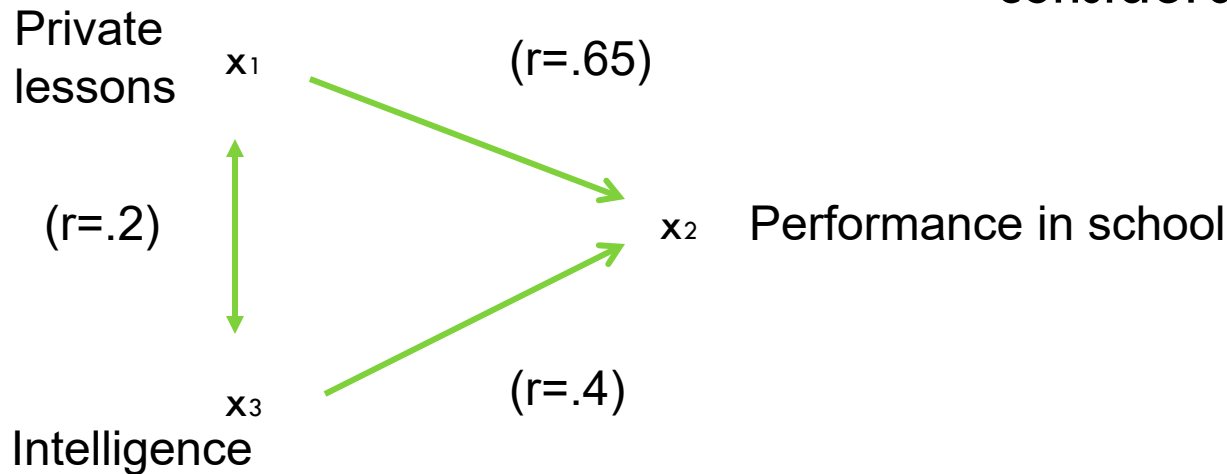
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- Find out how strong the effect of private lessons is on performance in school when taking *intelligence* into consideration!

4. Partial regression: *practice*

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- Find out how strong the effect of private lessons is on performance in school when taking *intelligence* into consideration!

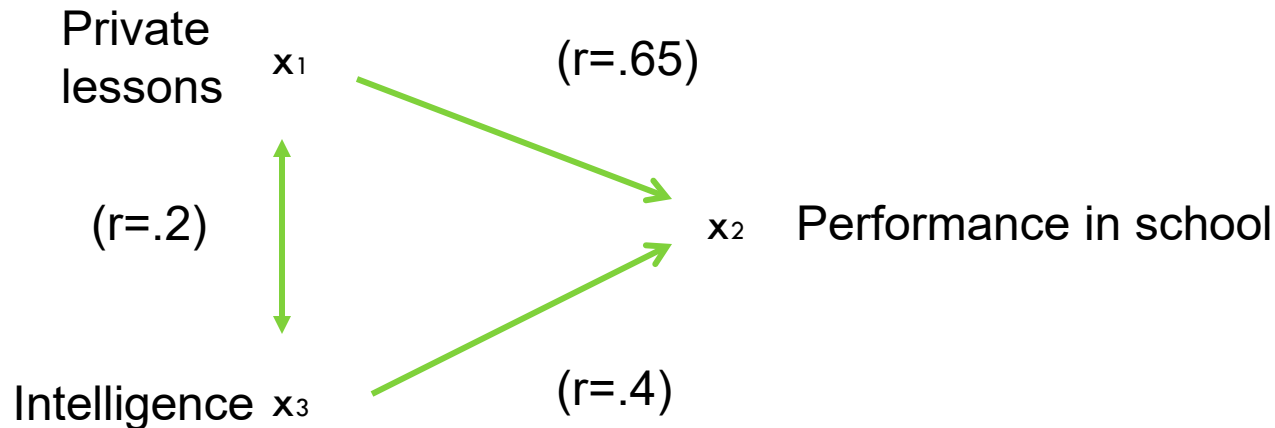


$$\beta_{Y1,X1-X2} = \frac{r_{Y1,X1} - r_{Y1,X2} \cdot r_{X1,X2}}{1 - r_{X1,X2}^2}$$

4. Partial regression: *practice*

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- Find out how strong

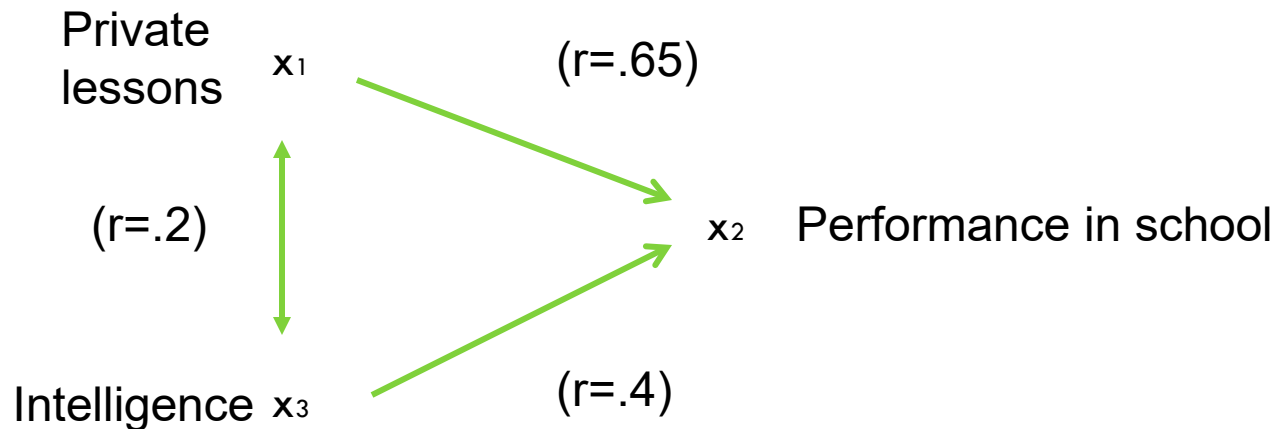


Possible results: $\beta_{\text{Private lessons}} = .51$ **.59** $.61 / .64$

4. Partial regression: *practice*

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- Find out how strong the effect of intelligence on performance in school is in taking *private lessons* into consideration!

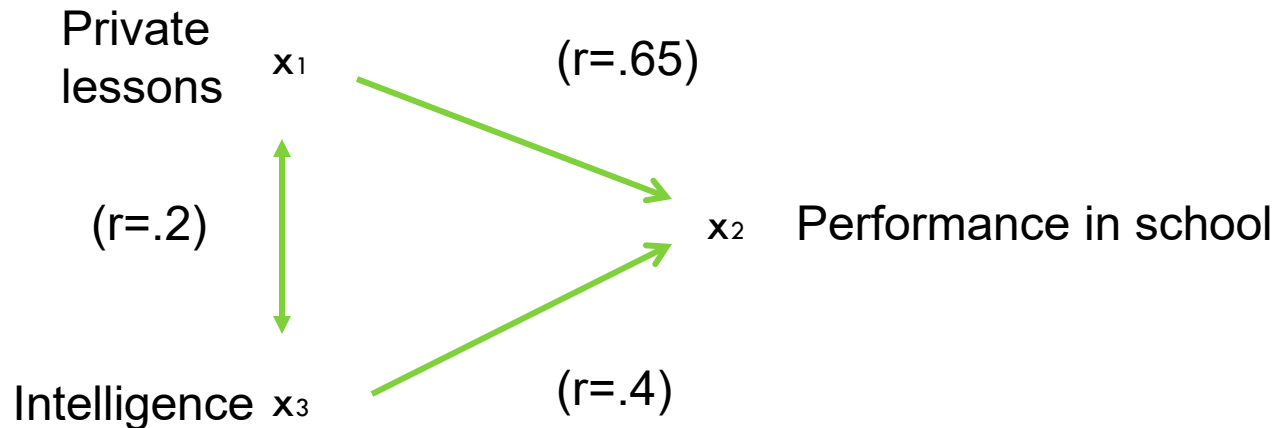


$$\beta_{Y1,X1-X2} = \frac{r_{Y1,X1} - r_{Y1,X2} \cdot r_{X1,X2}}{1 - r_{X1,X2}^2}$$

4. Partial regression: *practice*

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□ Find out ...



Possible results: $\beta_{\text{Intelligence}} = .00 / .13 / .19 / .28$

4. Partial regression: a note

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- in multiple regression the regression weights are computed on the basis of *raw data* and the computation is conducted according to another principle.

4. Partial regression: a note

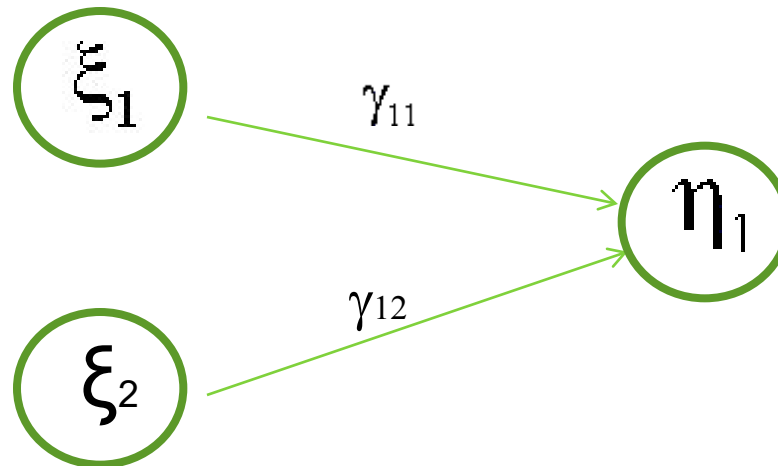
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- in multiple regression the regression weights are computed on the basis of *raw data* and the computation is conducted according to another principle.
- There are two way of determing regression coefficients:
 - computation using formulas
 - estimation using estimation methods
 - ordinary least square estimation (OLS)
 - maximum likelihood estimation (ML)

4. Multiple regression: *an analogy*

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- Given the **correlations** between the latent variables ξ_1 , ξ_2 and η , it is possible to compute the standardized partial regression coefficient for the following structural model:



- ... with γ_{11} as β_1 and γ_{12} as β_2

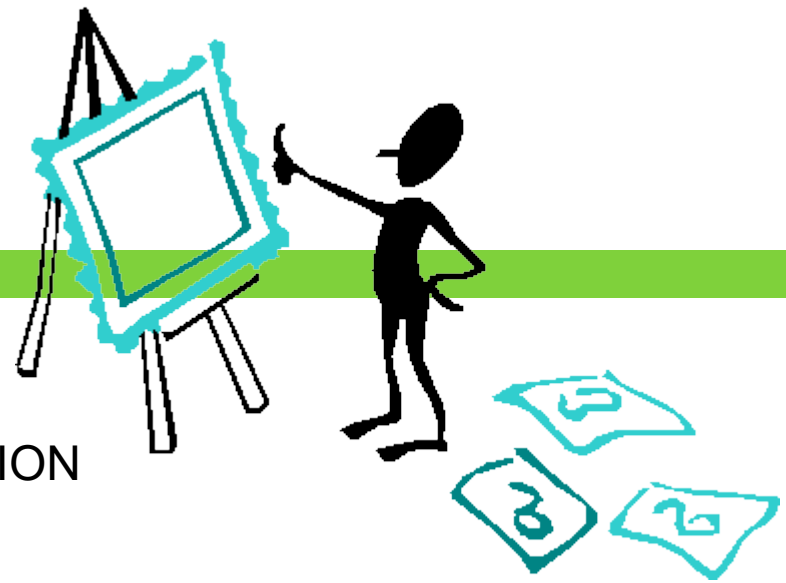
4. Multiple regression: in sum

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- multiple regression can be used for investigating effects of *several predictors* on a criterion
- under *appropriate preconditions* the standard partial regression coefficient can be used for estimating the influences of predictors in *the structural model*
- it can be conducted **on the basis of correlations**

Summary and brush up:

CORRELATION
PARTIAL CORRELATION
MULTIPLE REGRESSION



- 1. **Concern with structure**
- 2. Correlation ... measure of the closeness of the relationship / but there may be a linearity problem
- 3. Partial correlation ... signifies what remains after removing the effect of another variable from the correlation
- 4. Multiple Regression ... prediction of criterion variable by means of several predictor variables

QUESTIONS REGARDING COURSE UNIT 7

- What is a fake correlation?
- What is a standardized partial regression coefficient?
- What is an indirect effect?
- Which correlations are suitable for CFA, SEM?

Literature

- Kline, R. B. (2011). *Principles and practices of structural equation modeling* (3rd edition) (Chapter 2: Basic statistical concepts: correlations and regression, Chapter 5: Introduction to path analysis). New York, NJ: The Guilford Press.
- Cohen, J., Cohen, P., West, S. G. & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (Partial regression, partial correlation, direct and indirect effects: S. 64-79). Mahwah, N.J.: Lawrence Erlbaum.