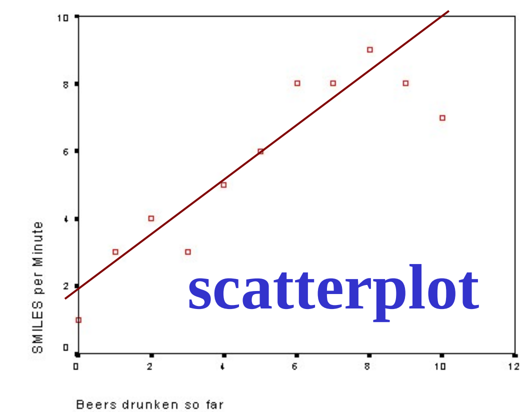
A moderated view of regression

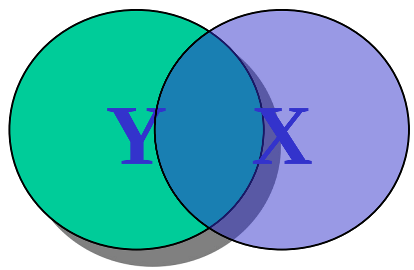
General Linear Model and its applications

Marcello Gallucci
University of Milano-Bicocca

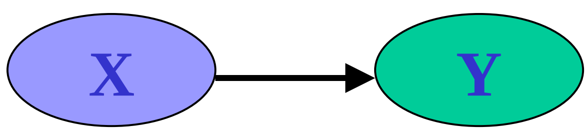
Introduction

A simple **statistical model** is an efficient and concise representation of the data describing an empirical phenomenon

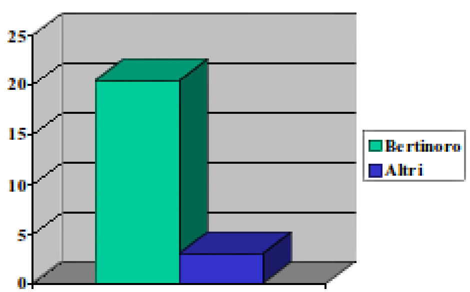




Path Diagram



Difference in mean

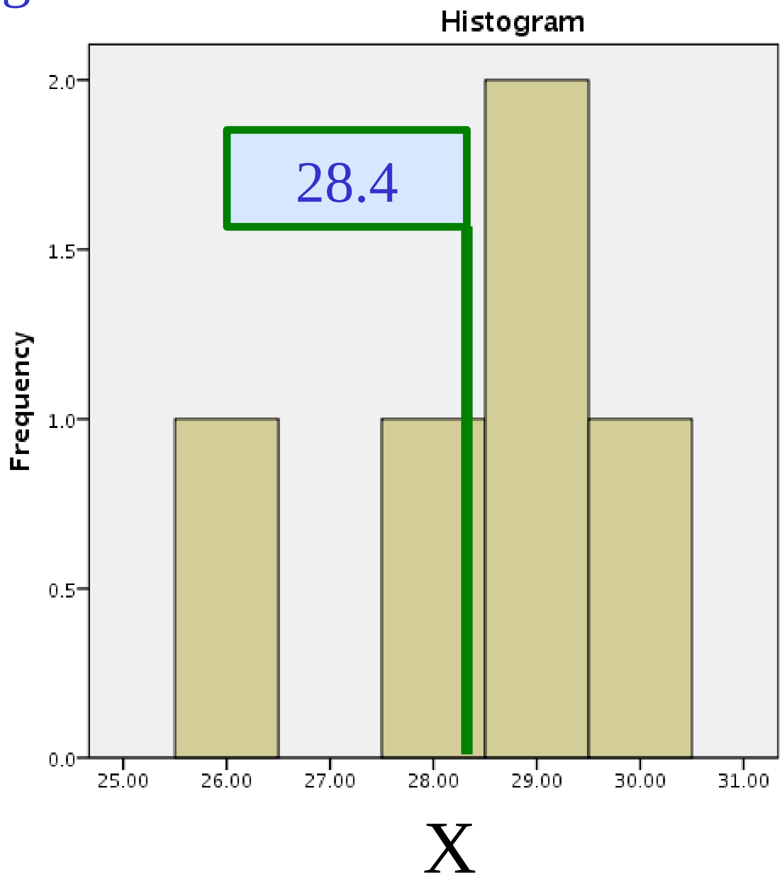


Example: the mean

Q: “How do my participants score on variable X?”

R: “They score 28.4 on average”

$$\frac{\sum_i X_i}{N} = \bar{X}$$

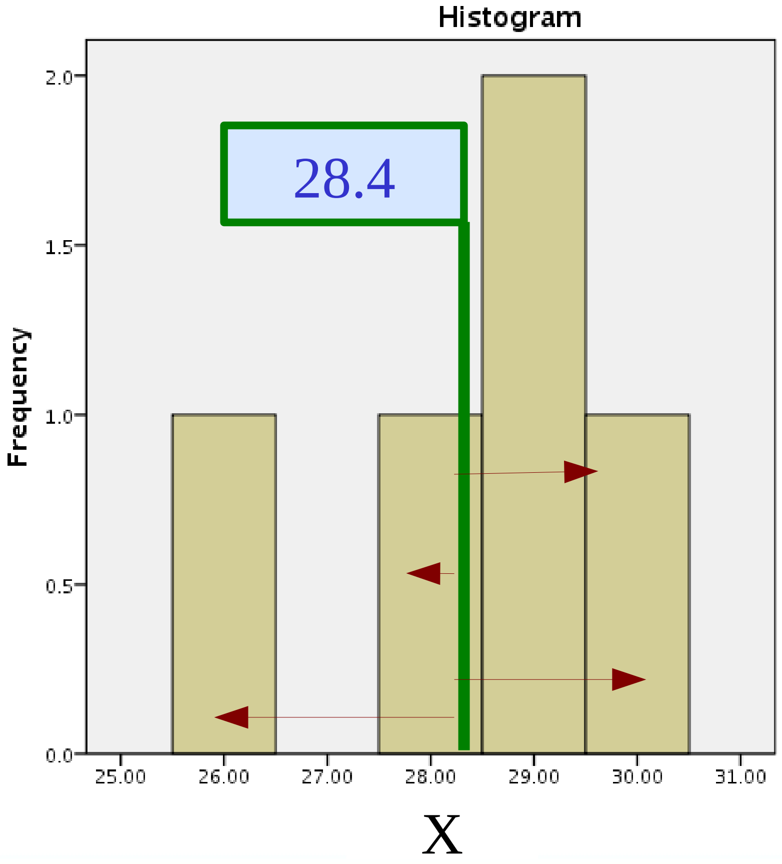


Approximation error

As any other representation, e model only approximates the data, and thus is associated with an error

When we say the score is 28.4, we misrepresent many of the observed scores, even if on average we represent them well

Residuals



- The statistical techniques we review today belong to one single **general model**

General Linear Model

$$y_i = a + b_1 \cdot x_{1i} + b_2 \cdot x_{2i} + \ldots b_k \cdot x_{ki} + e_i$$

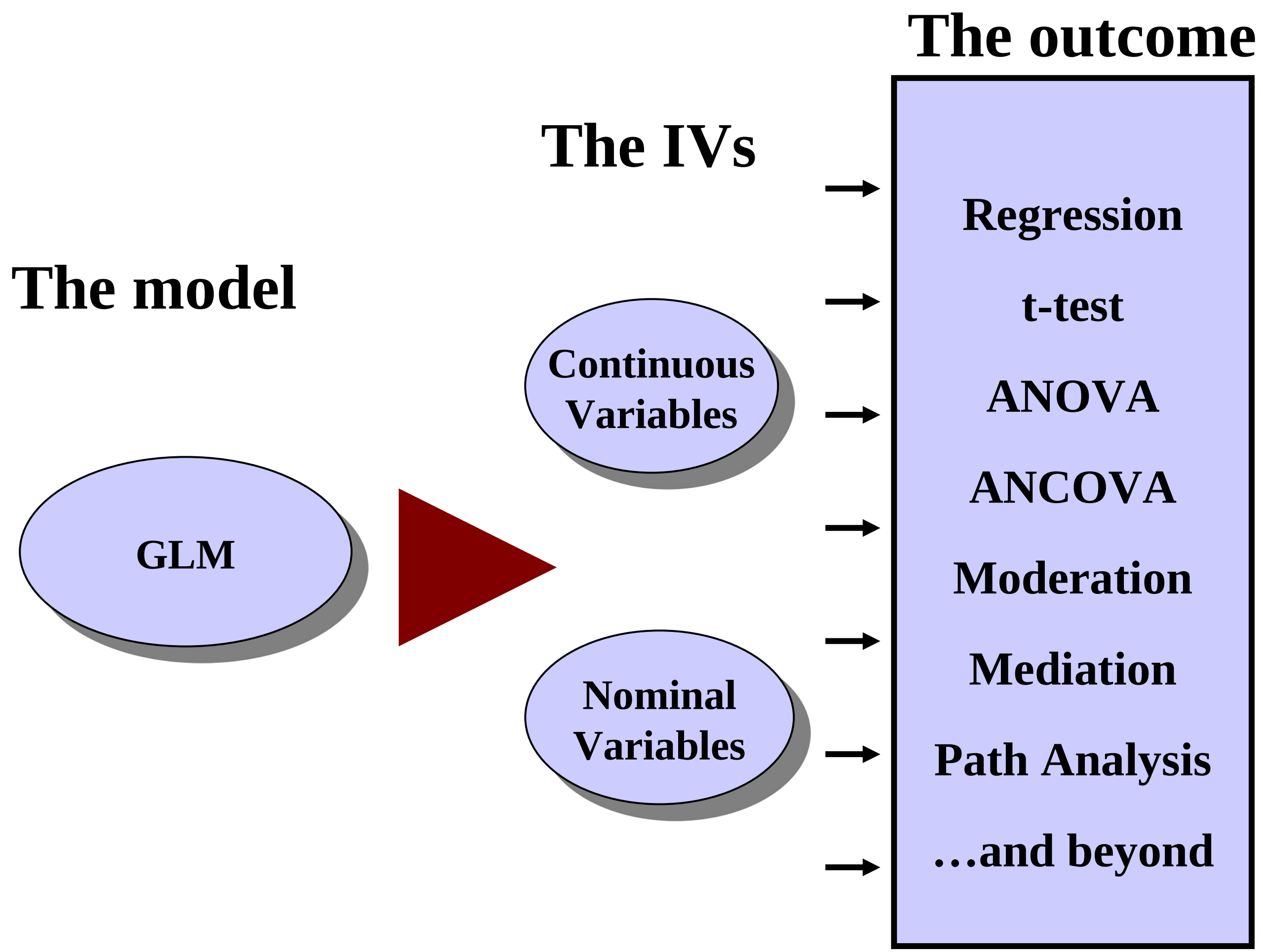
Dependent variable

Independent variables

Errors

GLM

When the assumptions are met, we can use the GLM for..



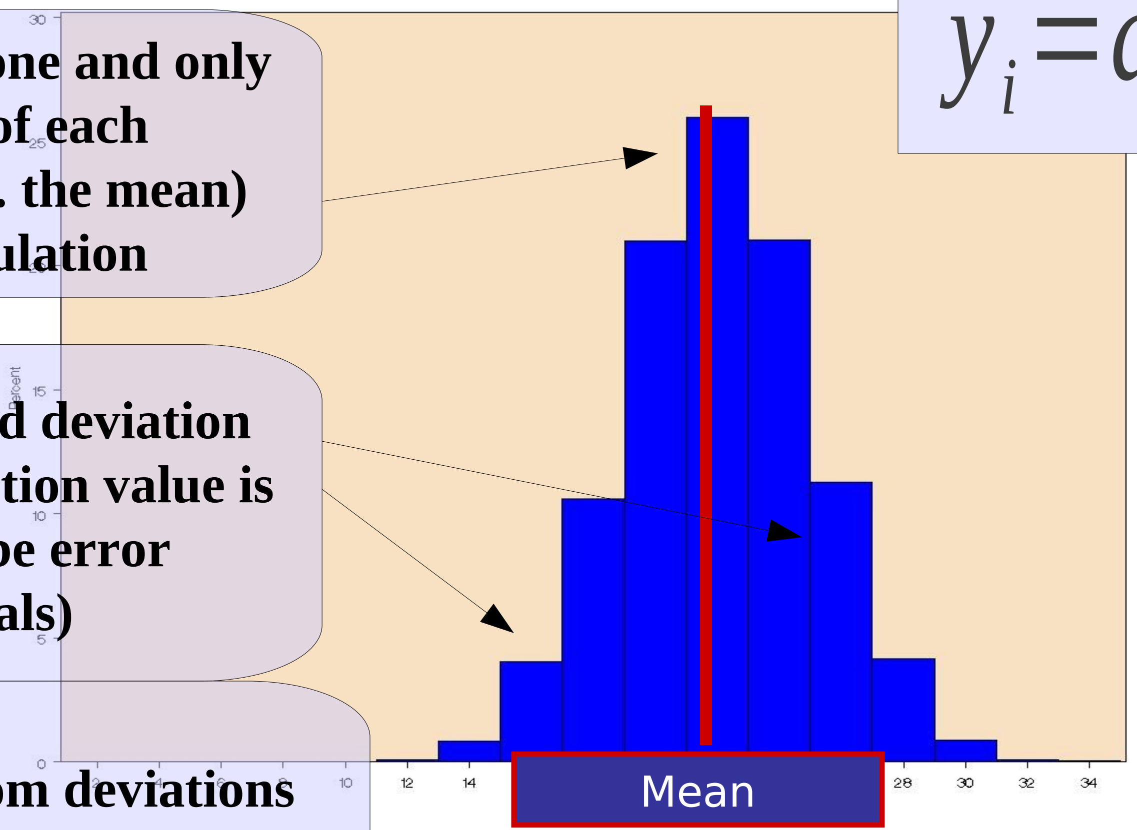
Some GLM Assumptions

$$y_i = a + e_i$$

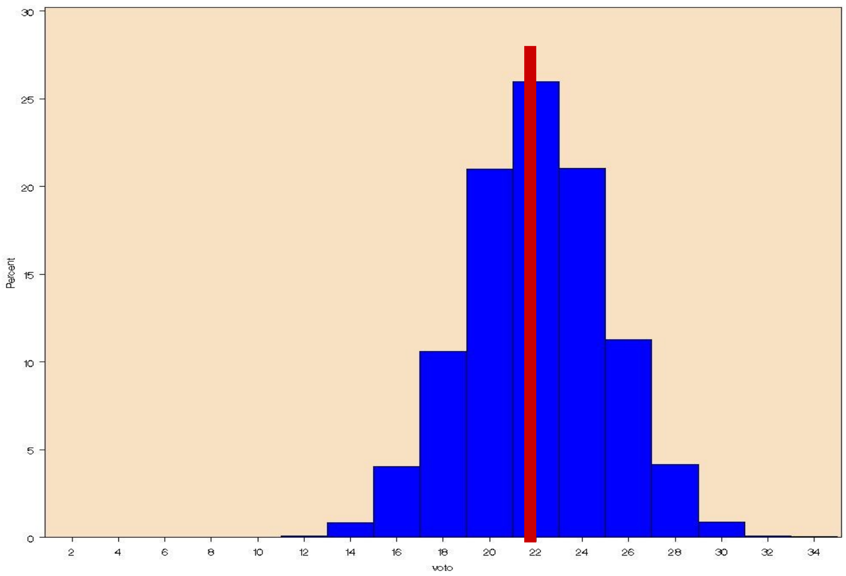
1) There exists one and only one value of each parameter (e.g. the mean) in the population

2) Any observed deviation from the population value is deemed to be error (residuals)

3) The random deviations from the model are normally distributed



GLM Assumptions



The estimated value is a fixed parameter

$$y_i = a + e_i$$

$$corr(e_i, e_j) = 0$$

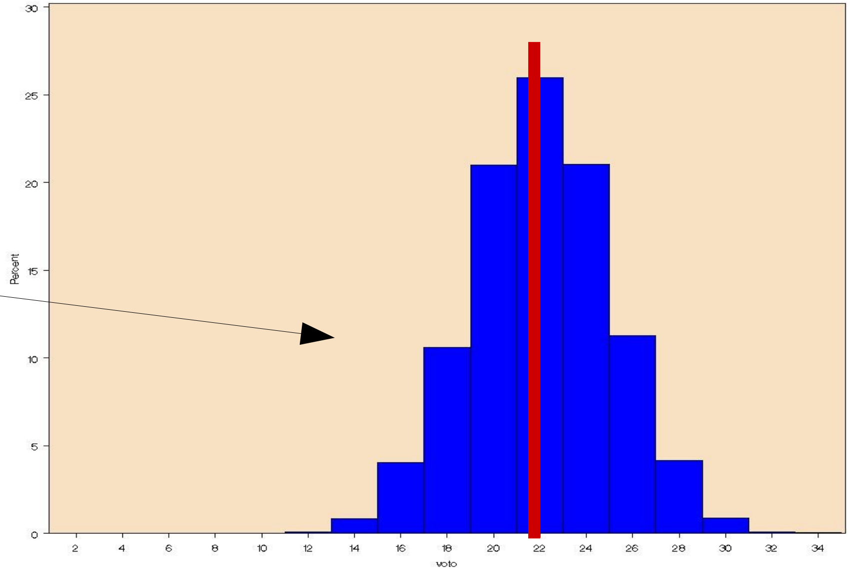
Random variations are uncorrelated

GLM Assumptions

$$y_i = a + e_i$$

$$corr(e_i, e_j) = 0$$

3) Random variations are normally distributed



$$e_i \sim N(0, \sigma)$$

GLM

When the assumptions are NOT met because the data, and thus the residuals, **have more complex structures**, we generalize the GLM to the **Linear Mixed Model**

Linear Mixed Model

GLM

Regression

T-test

ANOVA

ANCOVA

Moderation

Mediation

Path Analysis

LMM

Random coefficients models

Random intercept regression models

One-way ANOVA with random effects

One-way ANCOVA with random effects

Intercepts-and-slopes-as-outcomes models

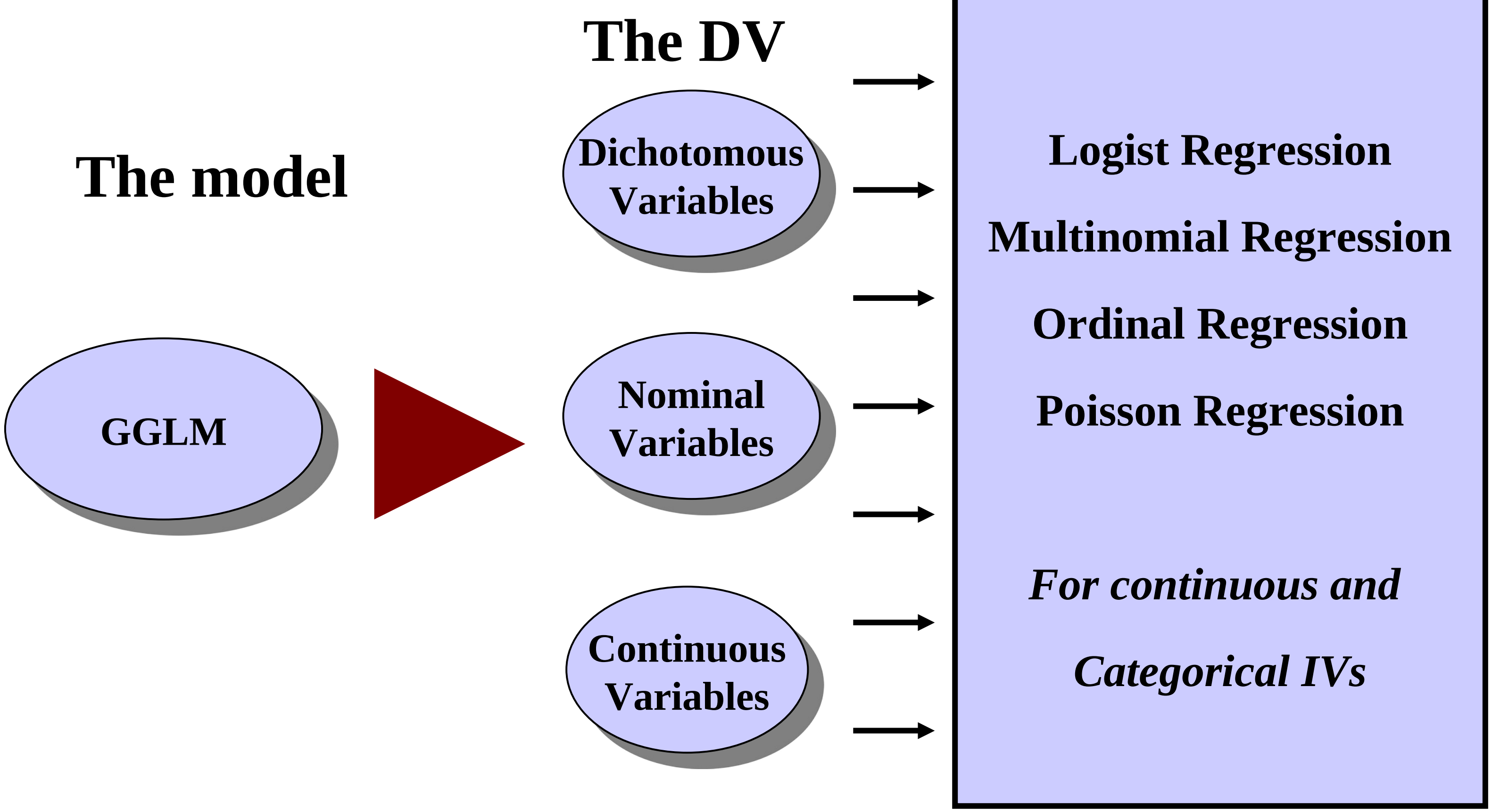
Multi-level models

GLM

When the assumptions are NOT met because the dependent variable is **not normally distributed** (dichotomous, frequencies, categorical etc), we generalize the GLM to the

Generalized Linear Model

Generalized Linear Model



The linear models

- We will (try) to cover the models that can be applied to a great number of research designs, in different fields of psychology

	Dependent Variable	
	Normal and Continuous	**Non-normal or categorical**
Independent cases	General Linear Model	Generalized Linear Models
Clustered cases	Mixed Model	Generalized Mixed Models

Software

SPSS

jamovi

jamovi

Point and click approach

Read data from SPSS and others

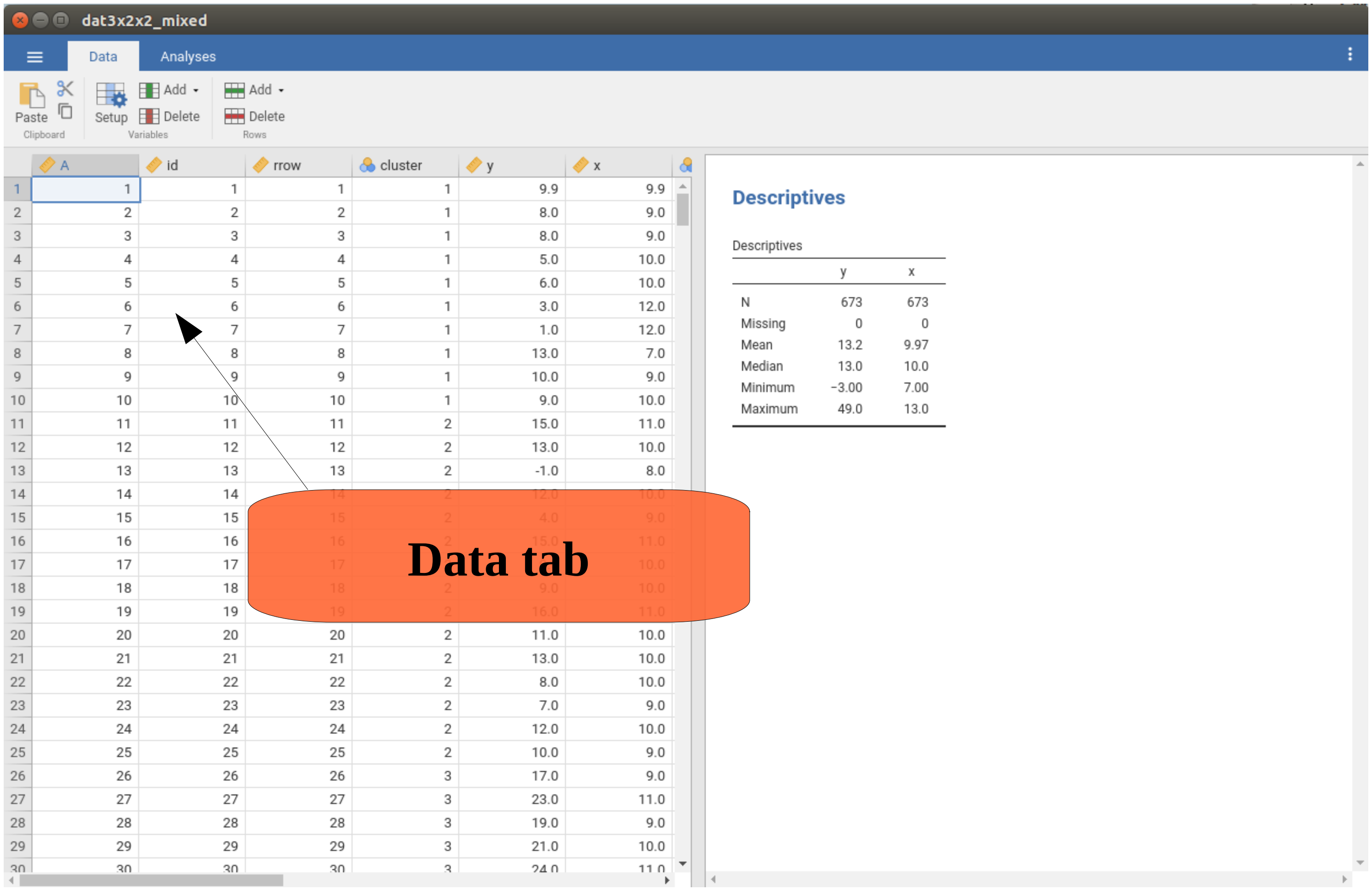
Does all major analyses you can need

Interface with R syntax

It’s free as in free beer

https://www.jamovi.org/

jamovi has a very intuitive interface



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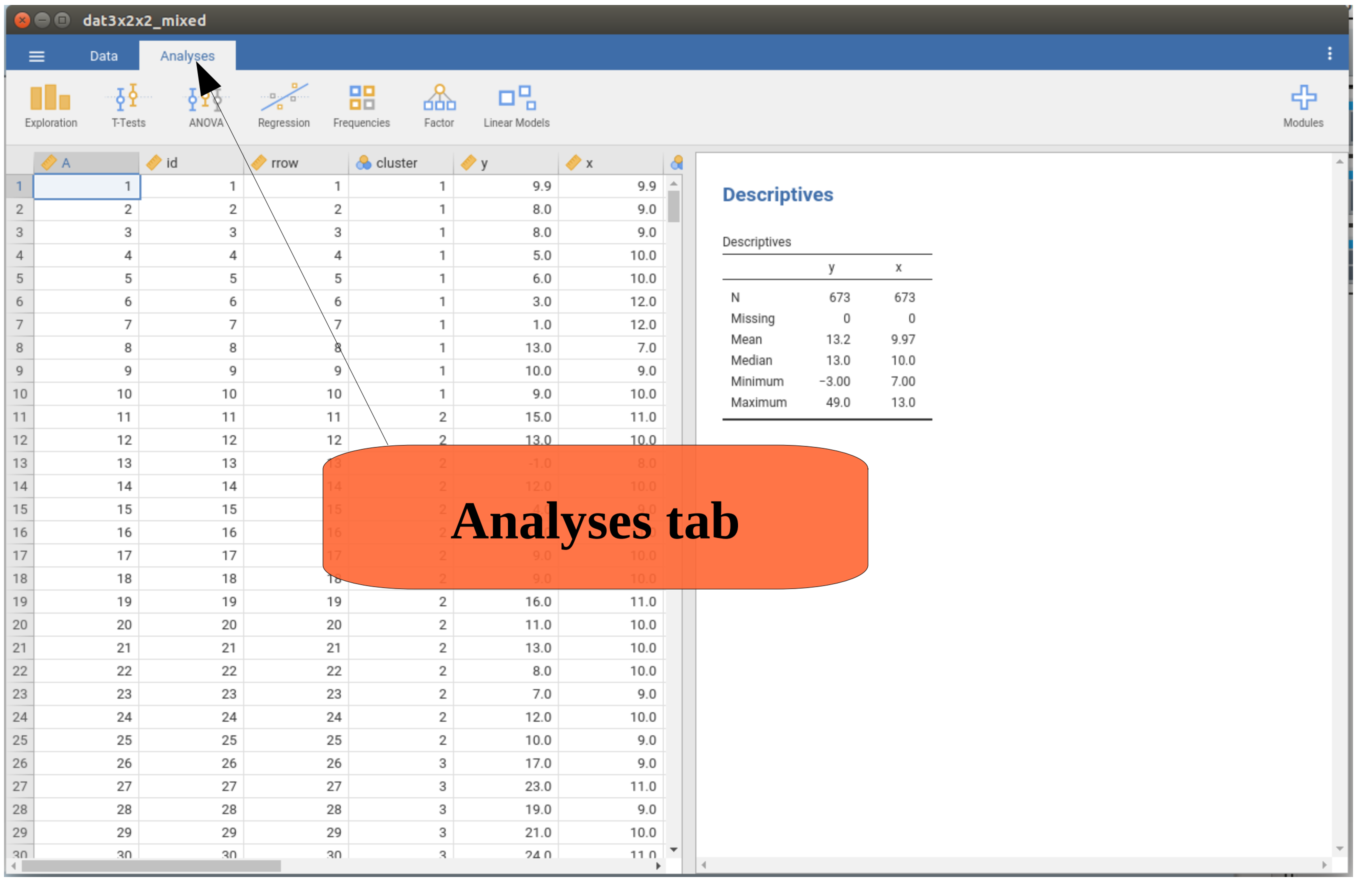
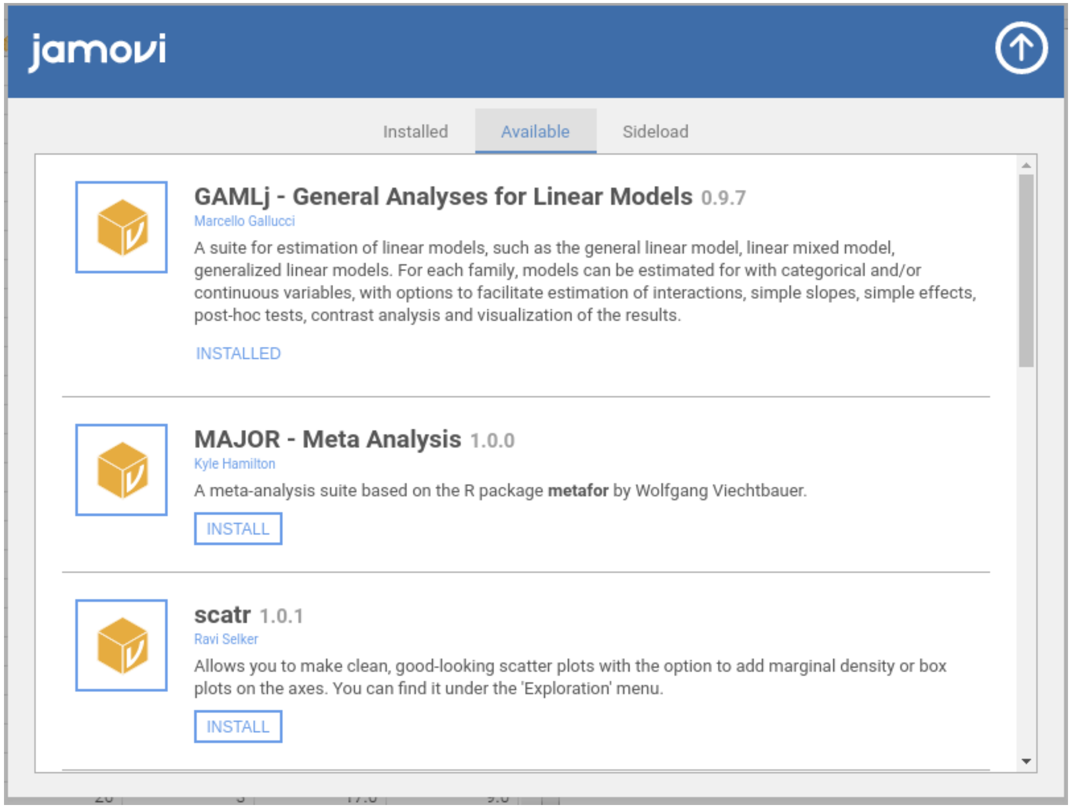


jamovi

It has a core of analyses plus modules (add-ons you install only if you need them)



jamovi GLM: GAMLj module

- One module we can use in this course is GAMLj:
  - GLM with simple effects, effects size and many other things
  - Mixed models (Multilevel models)
  - Generalized linear model
  - Generalized Mixed Models

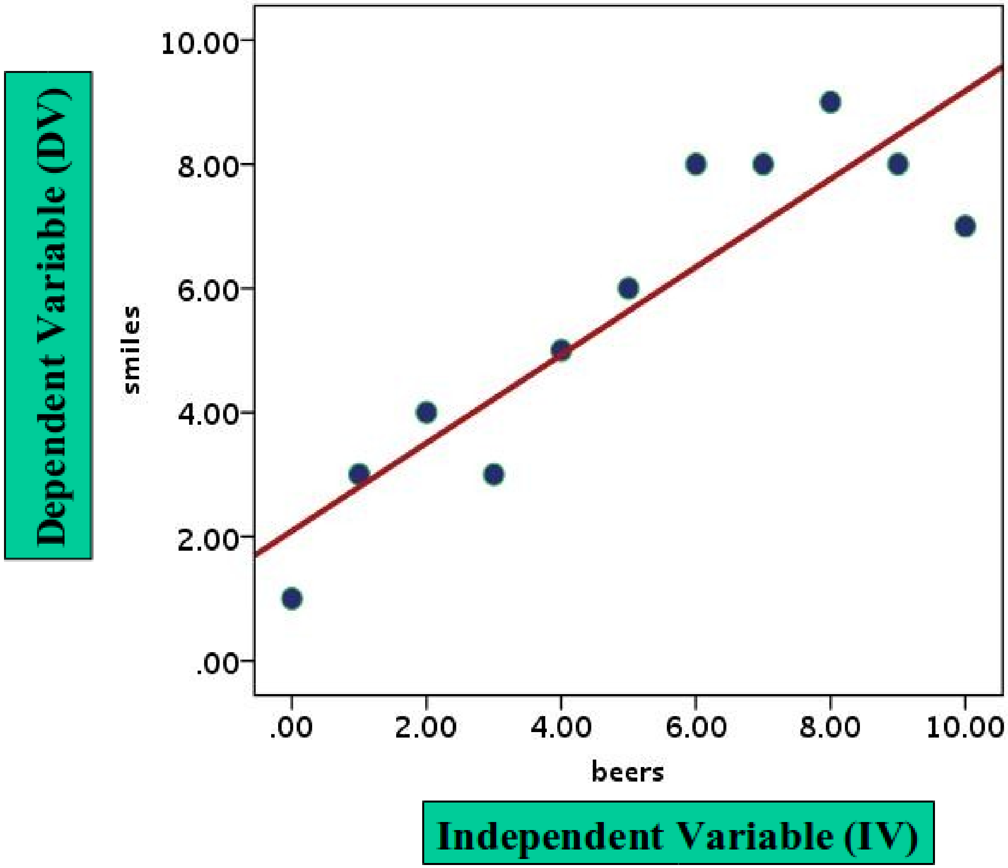
The latest version of the module is called **GAMLj3**

General Linear Model:

Regression

Regression Basics

The aim of regression analysis is to fit the data using a linear function



For most applications, we just need a linear function: straight line

$$y_i = a + b \cdot x_i + e_i$$

$$\hat{y}_i = a + b \cdot x_i$$

Regression Coefficients

The regression line can be described with two coefficients:

Unstandardized Coefficient B and the intercept term

$$\hat{y}_i = a + b \cdot x_i$$

Parameter Estimates

Dependent Variable: smiles

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	2.091	.684	3.057	.014	.543	3.638
beers	.709	.116	6.132	.000	.448	.971

The intercept term (or constant)

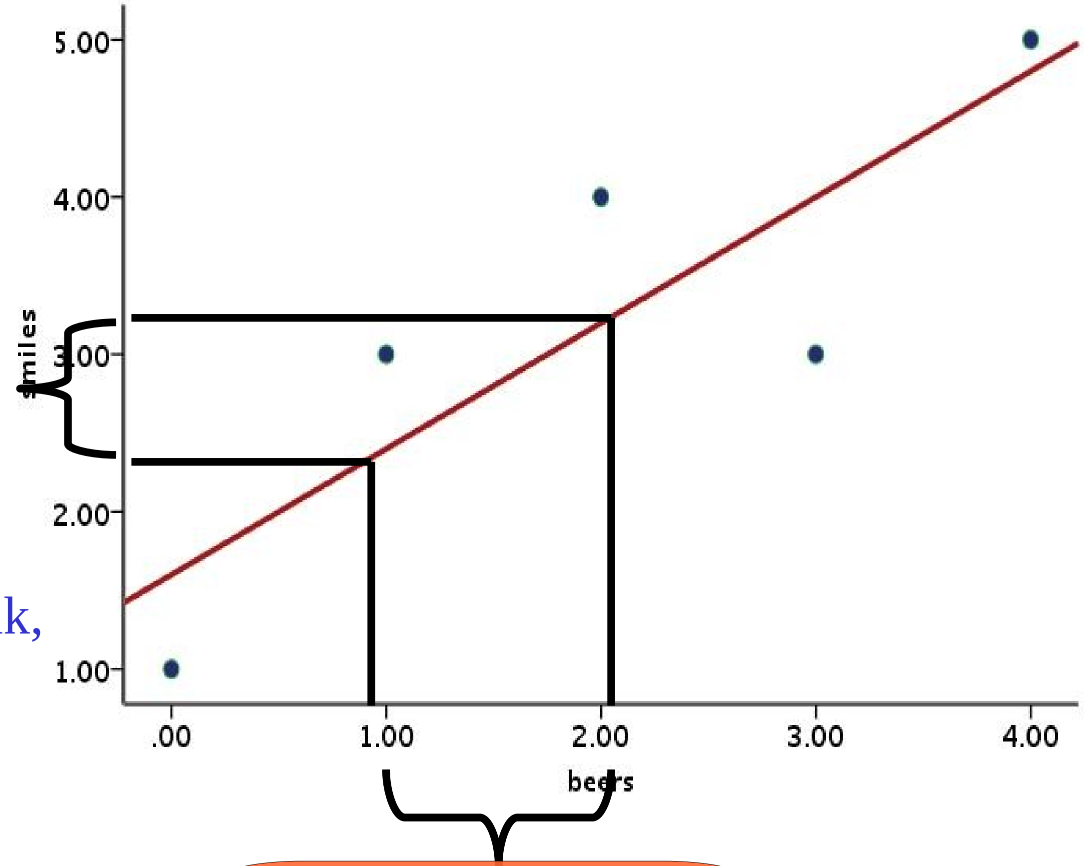
The regression coefficient (the slope)

Slope coefficient

b is the **slope** of the line: It tells us the amount of change in DV for 1 unit of chang
in IV

b smiles more

For each beer the participants drink, they increase their smiling of .709 smiles per minute

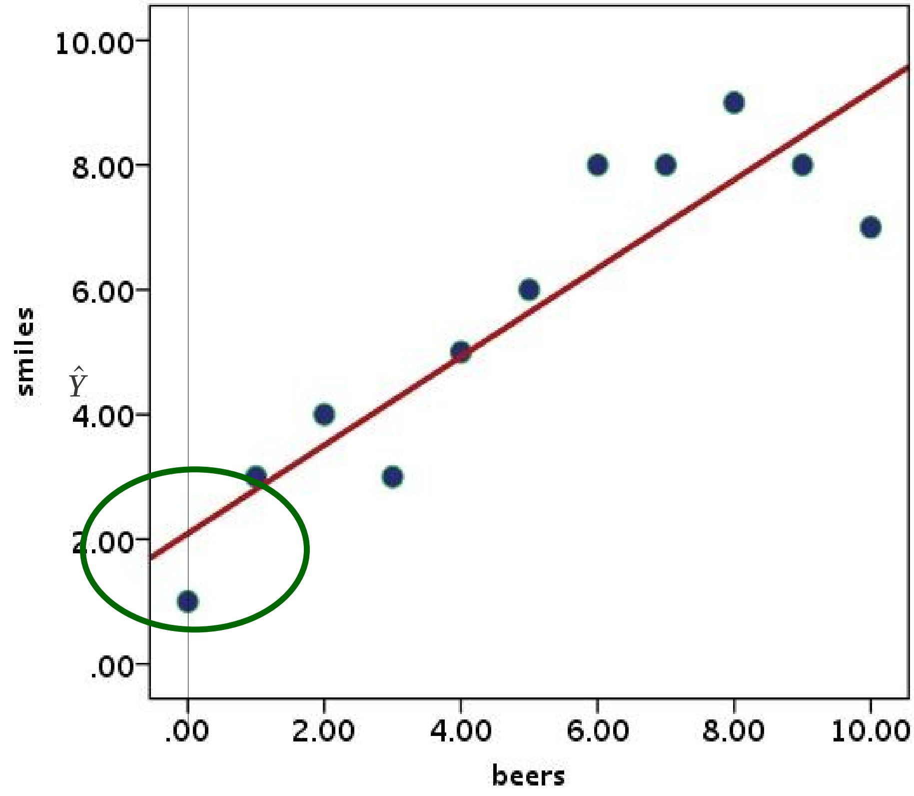


For 1 unit change in IV: one beer more

Constant coefficient

a is the **intercept** of the line: It tells us the expected value of the DV when the IV=

$$\hat{y}_i = a + b \cdot 0$$



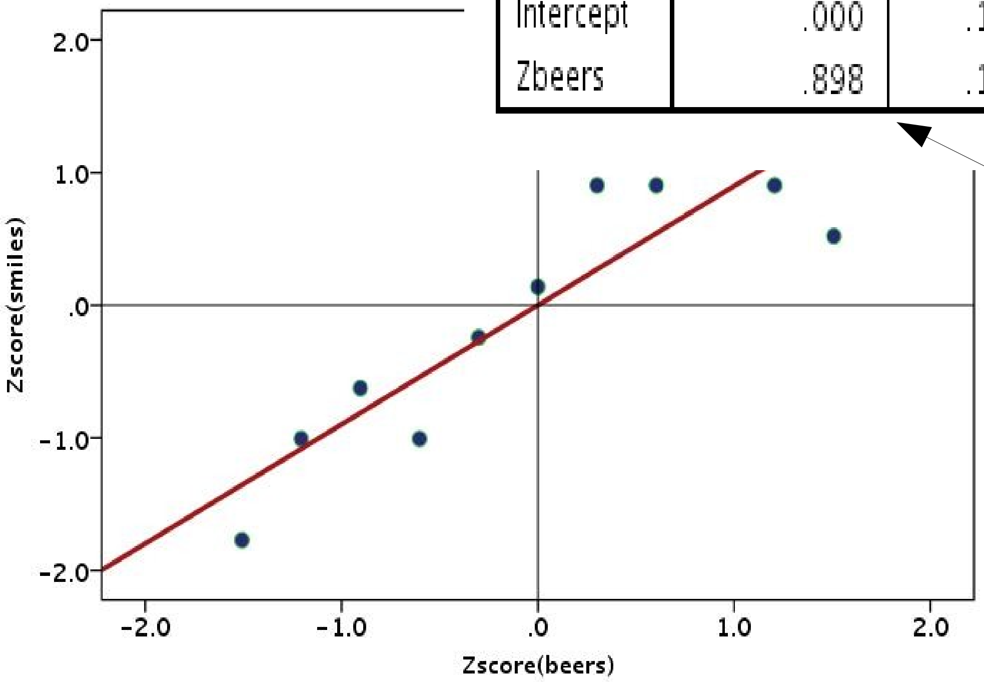
When participants drink 0 beers, they smile on average 2.09 times

Standardized Regression Coefficient

The **beta coefficient** is the **b** coefficient obtained in a regression after standardizing all variables. It is the **Pearson correlation**

Dependent Variable: Zscore(smiles)

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	.000	.140	.000	1.000	-.316	.316
Zbeers	.898	.146	6.132	.000	.567	1.230



beta=r

Significance Testing

The coefficients are tested if they are zero or not, using simple **t test**

Parameter Estimates

Dependent Variable: smiles

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					Lower Bound	Upper Bound
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beers	.709	.116	6.132	.000	.448	.971

If Sig. < 0.05, we say that **b** is significantly different from zero

Precision of estimates

One can focus on the precision of the estimates by reporting the confidence intervals of the parameter

Parameter Estimates

Dependent Variable: smiles

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	2.091	.684	3.057	.014	.543	3.638
beers	.709	.116	6.132	.000	.448	.971

If t-test is significant, the confidence interval does not contain zero

R: Regression Coefficients

Code

```
# run the model
model<-lm(smiles~beers,data=mydata)
# look at the results
summary(model)
```

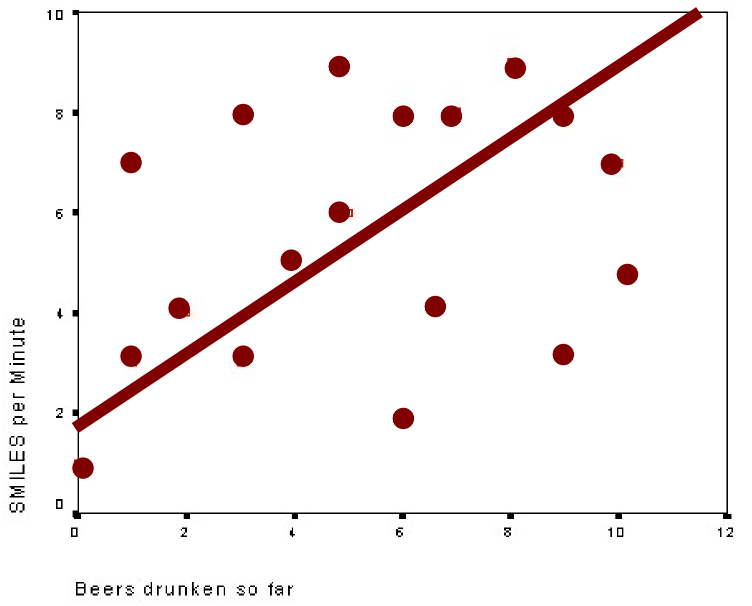
Results

```
##
## Call:
## lm(formula = smiles ~ beers, data = mydata)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.1818 -0.7818  0.2000  0.7182  1.6545
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.0909     0.6841   3.057 0.013647 *
## beers         0.7091     0.1156   6.132 0.000172 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

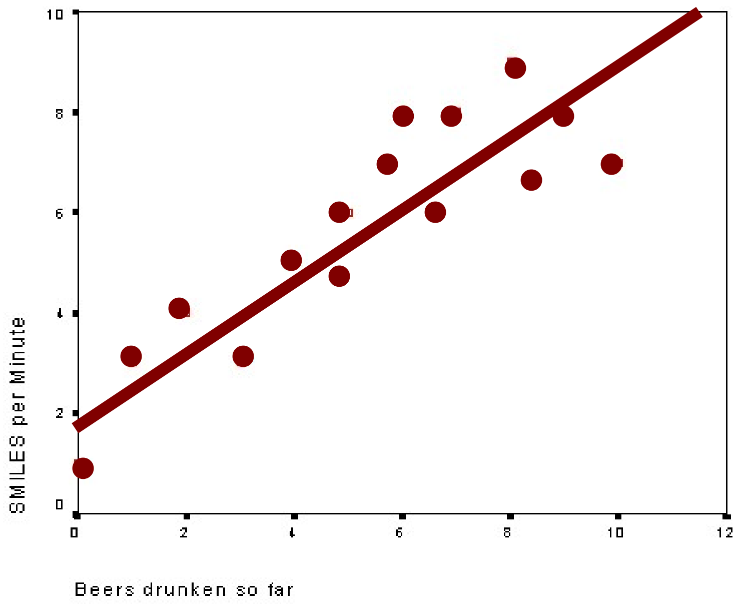
Goodness of Fit

Obviously, not all lines are created equal!

Poor Fit



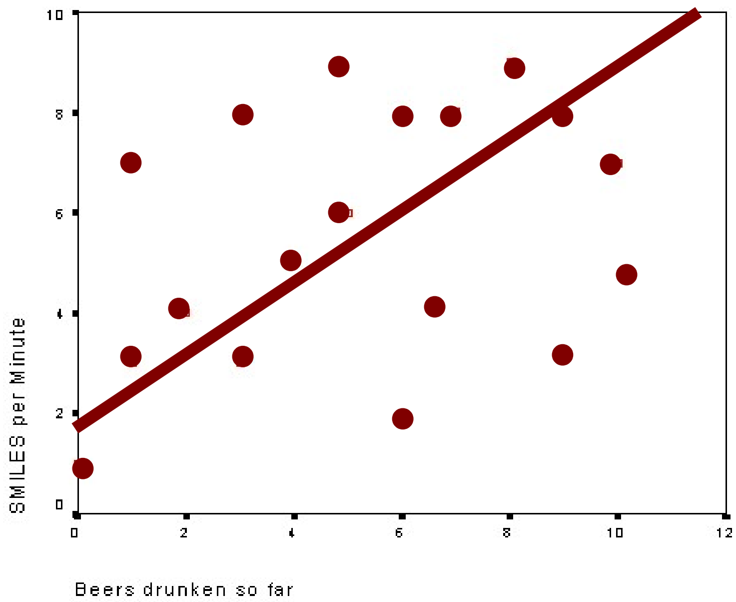
Good Fit



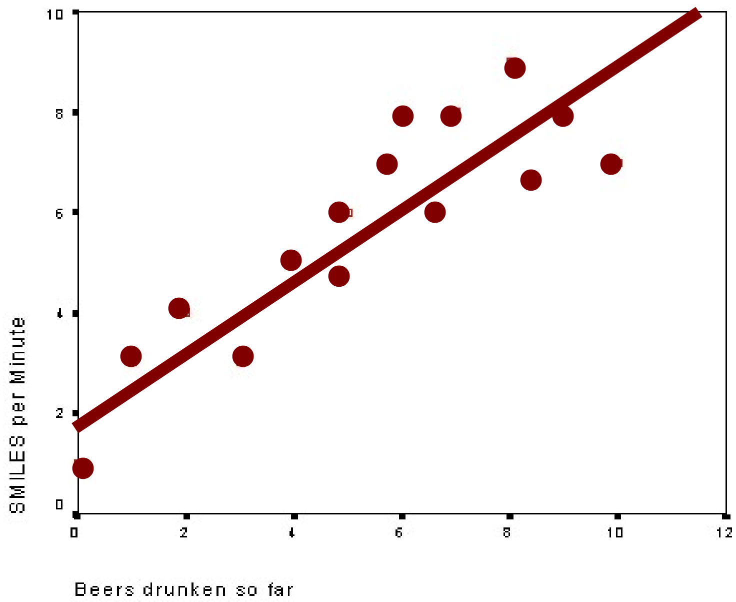
Goodness of Fit

We establish the goodness of fit of our regression line by computing **R^2**, which is the index of explained variance of IV by the DV

Low R^2



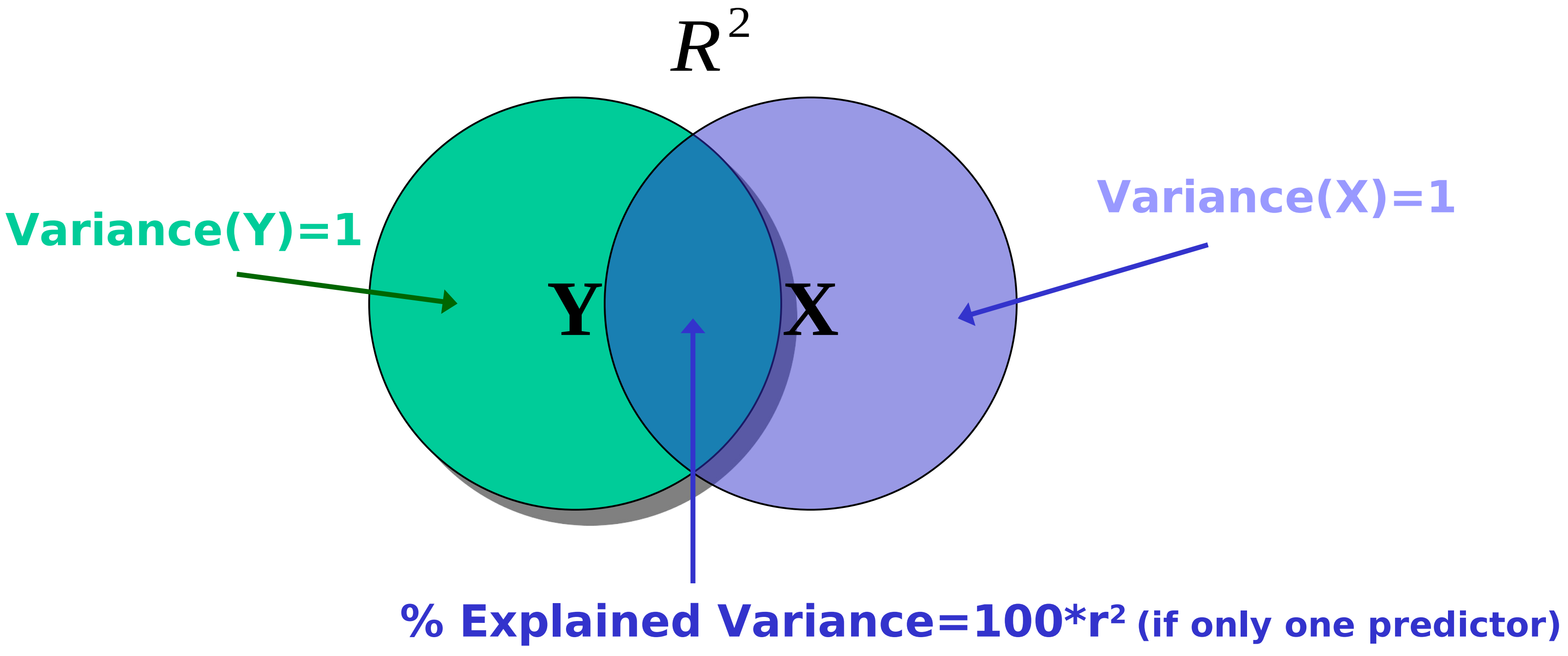
High R^2



Explained Variance

The R^2 coefficient can be interpreted as the variance of DV explained by the IV. It tells us how well we can predict DV from IV

Residuals variance=$1-R^2$



Significance of R^2

We test if the percentage of explained variance R^2 is significantly different from zero using the **F-test**. This can be found what is called the ANOVA Table

Test for the R-squared

Tests of Between-Subjects Effects

Dependent Variable: smiles

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	55.309[a]	1	55.309	37.607	.000
Intercept	13.740	1	13.740	9.343	.014
beers	55.309	1	55.309	37.607	.000
Error	13.236	9	1.471		
Total	418.000	11			
Corrected Total	68.545	10			

a. R Squared = .807 (Adjusted R Squared = .785)

R-squared

F-test for the effect

Even though we estimated a regression, we do have the F-test for the effect of beers. The F-test tests the variance explained by the effect of beer.

Test for Beers

Tests of Between-Subjects Effects

Dependent Variable: smiles

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Error	13.236	9	1.471		
Total	418.000	11			
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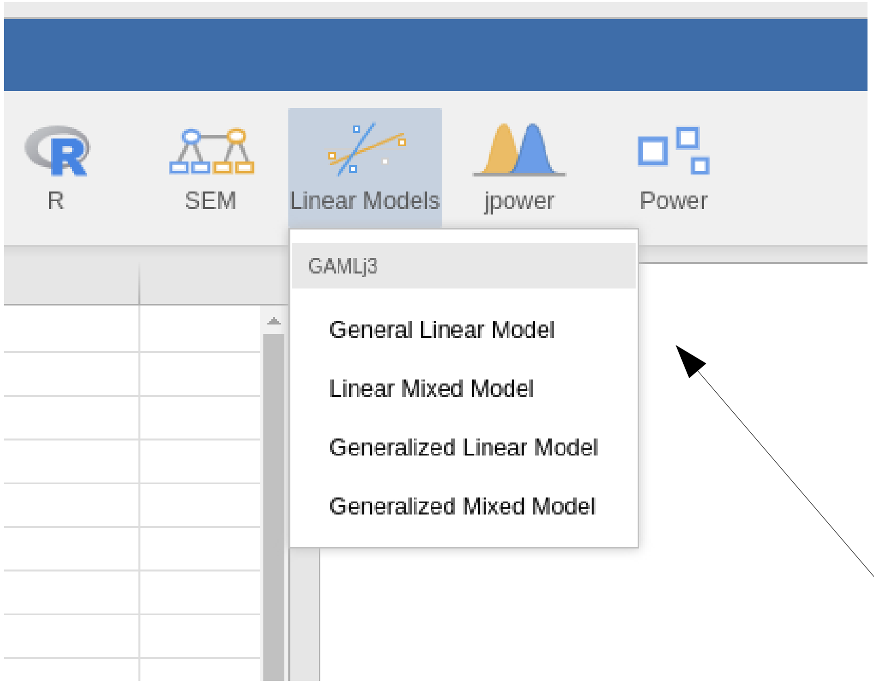
In simple regression (on IV) this test is equal to the test of the R-squared. When the model is more complex, more IVs, the two tests are different

jamovi

- jamovi has a built-in “regression module” (full of options), but we can used GAMLj module for introducing it (for later on)



GLM

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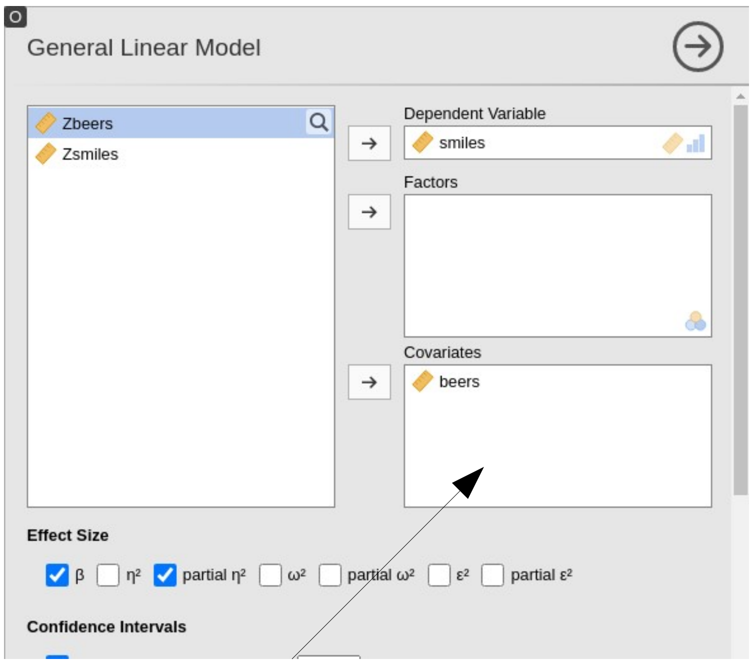

Variables definitions

Model Results

ANOVA Omnibus tests

	SS	df	F	p	$\eta^2 p$
Model	55.3	1	37.6	< .001	0.807
beers	55.3	1	37.6	< .001	0.807
Residuals	13.2	9			
Total	68.5	10			

Fixed Effects Parameter Estimates

			95% Confidence Interval				
Names	Estimate	SE	Lower	Upper	β	df	t
(Intercept)	5.636	0.366	4.809	6.464	0.000	9	15.41
beers	0.709	0.116	0.448	0.971	0.898	9	6.13

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Standardized B: the beta

- The beta coefficient is the regression coefficient one obtains from a regression **run on all standardized variables**

- **It is equal to the Pearson correlation**

Model Results

ANOVA Omnibus tests

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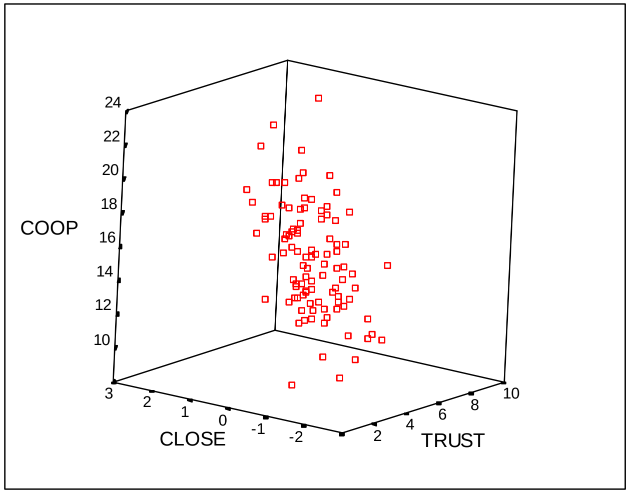
Results

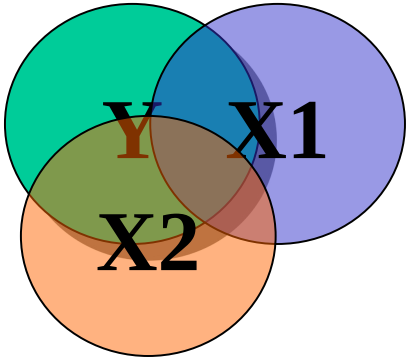
Multiple regression

When we have more than one IV, we talk about multiple regression

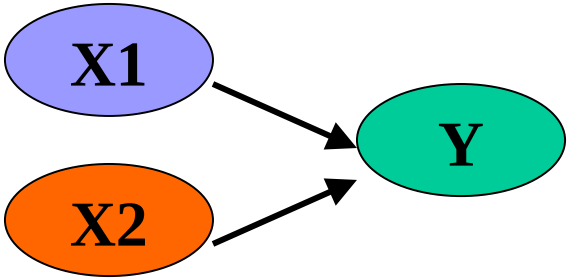
Geometrical



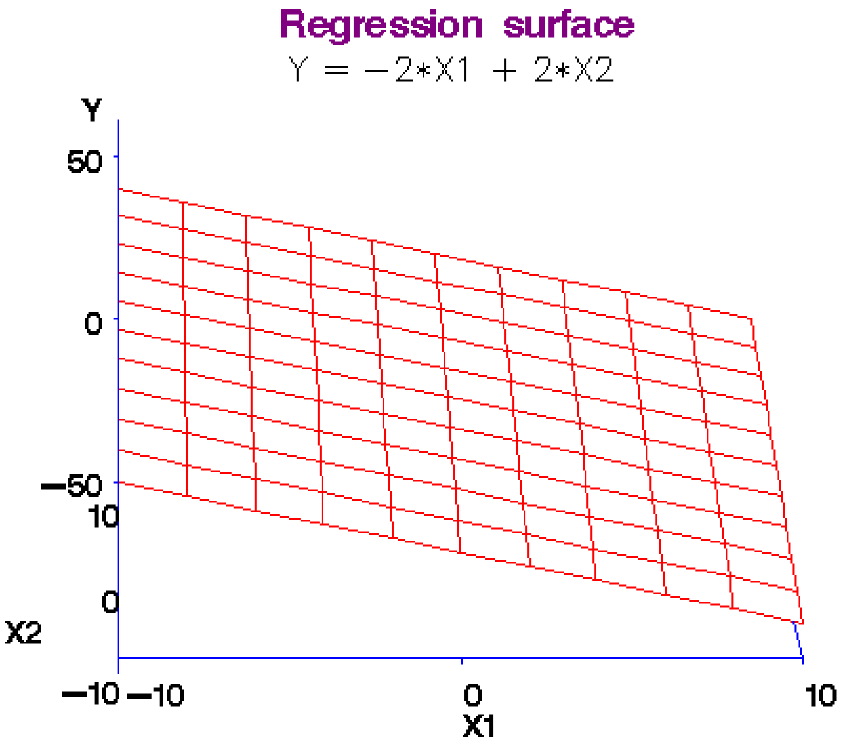
Variance Partitioning



Path Model



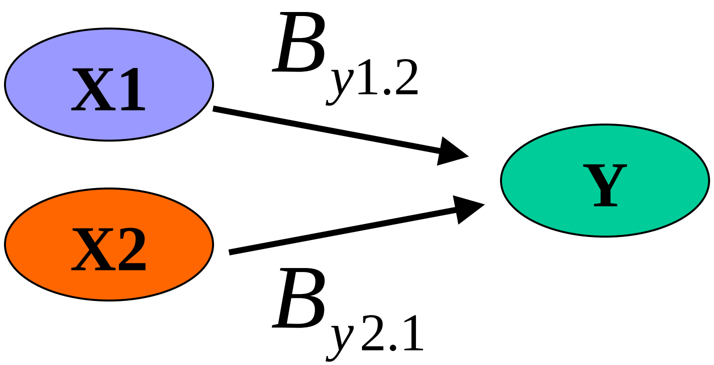
Geometrical Representation



$$\hat{y} = a + b_{y1.2}\, x_1 + b_{y2.1}\, x_2$$

Coefficients

The B_{y1} coefficient represents the expected change in Y for each change in X_1, ***holding constant all the other IVs***



$$\hat{y}_i = a + b_{y1.2} x_{1i} + b_{y2.1} 1$$

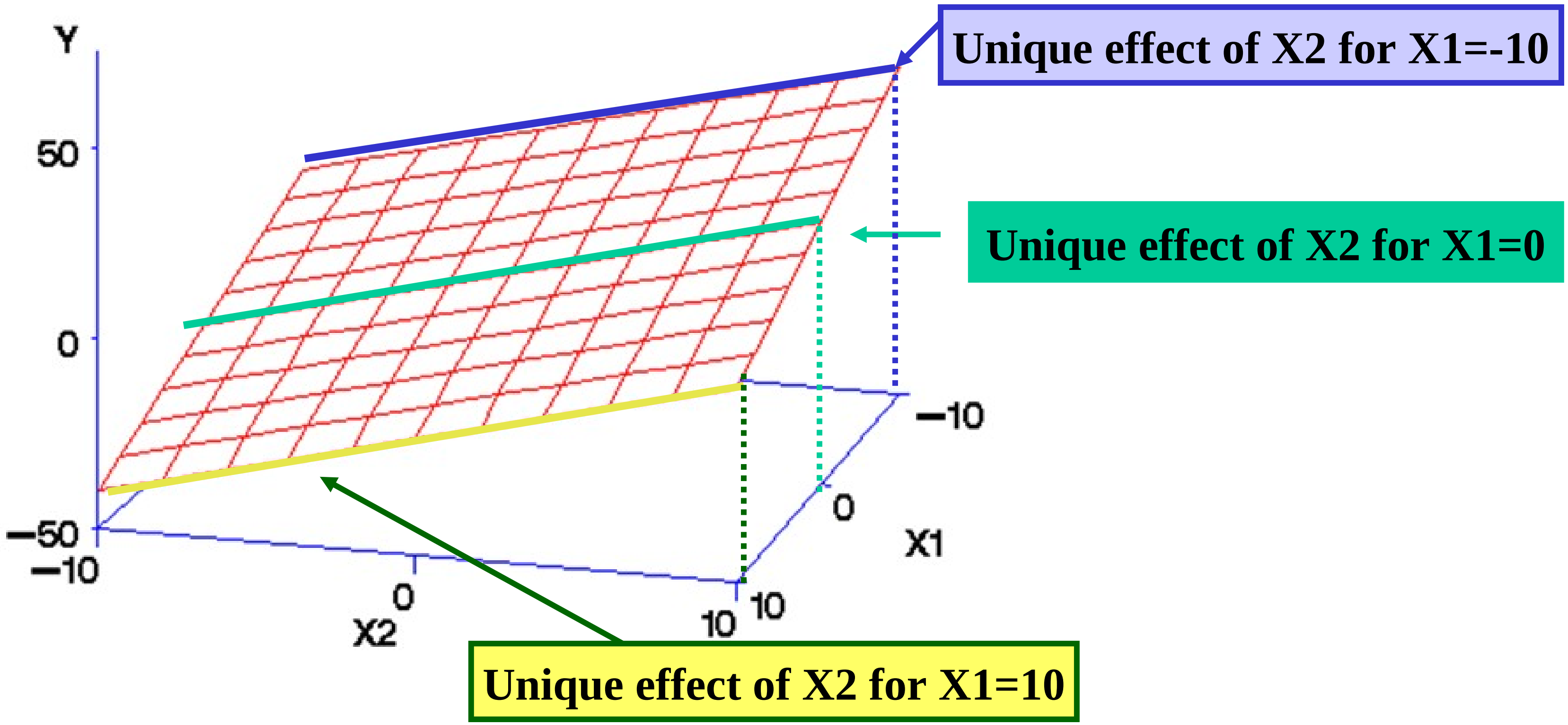
Unique effect of X1

When this is constant

Coefficients

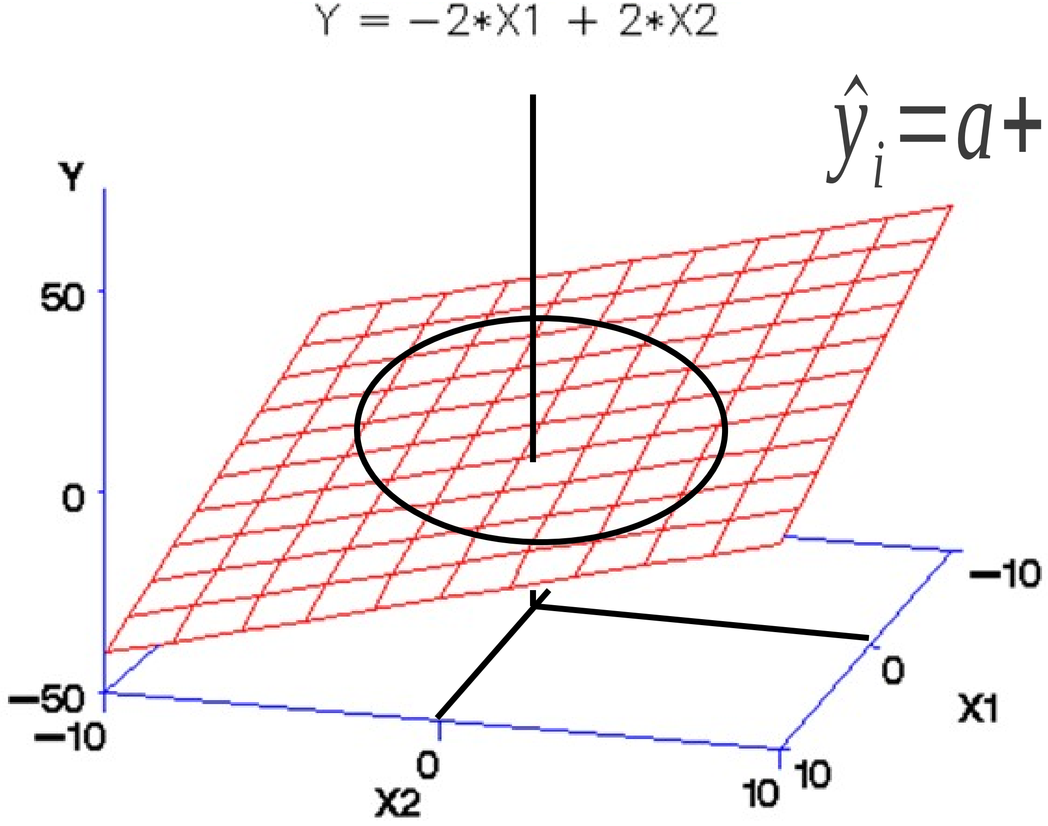
The effect of one IV is computed as constant across all the values of the other IV

$$Y = -2*X1 + 2*X2$$



Intercept

The intercept is the expected value when all IVs are 0



$$\hat{y}_i = a + b_{y1.2}0 + b_{y2.1}0$$

$$\hat{y}_i = a$$

Variance Explained

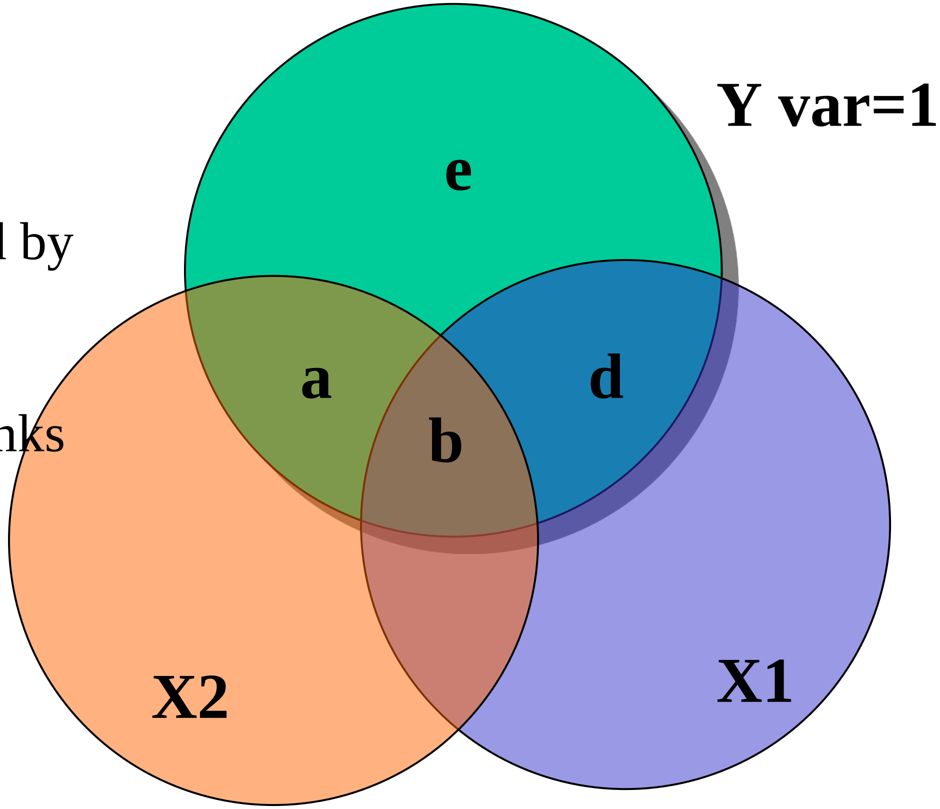
The overall ability of our IVs to predict the DV is

R^2

The amount of variance explained by the regression (all IVs)

The % of error we can reduce thanks to the IVs used as predictors

$$R^2 = a + b + d$$



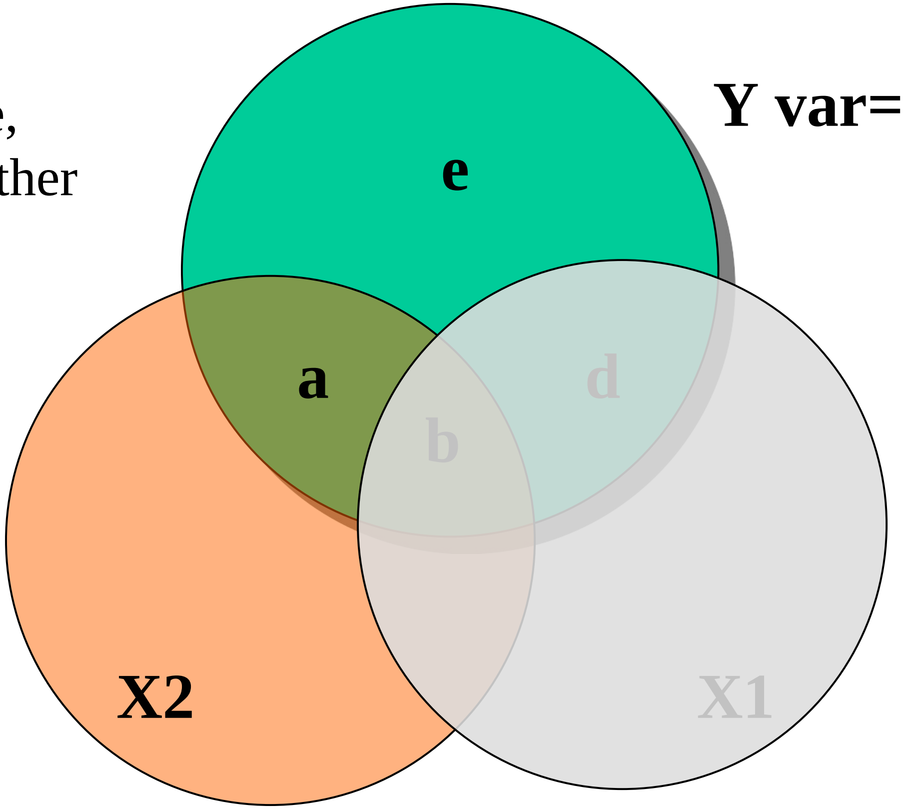
Contribution of Variables

A similar information is given by the partial correlation

Eta squared (partial)

The unique effect of each variable, removing all the variance of the other IVs

$$\eta^2_{y2.1} = \frac{a}{a+e}$$



Example

Anti-smoke campaign results: The ability to remember the ads (memory), the perception of smoke-related risks (risk perception) were measured to predict smoke aversion

Tests of Between-Subjects Effects

Dependent Variable: aversion

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	86819.693[a]	2	43409.847	156.250	.000	.763
Intercept	34849.839	1	34849.839	125.439	.000	.564
memory	298.474	1	298.474	1.074	.303	.011
riskperception	78779.171	1	78779.171	283.558	.000	.745
Error	26948.865	97	277.823			
Total	115981.320	100				
Corrected Total	113768.558	99				

a. R Squared = .763 (Adjusted R Squared = .758)

Tests of variances

Coefficients estimates

Parameter Estimates

Dependent Variable: aversion

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Partial Eta Squared
Intercept	-73.668	6.577	-11.200	.000	-86.722	-60.613	.564
memory	1.975	1.906	1.036	.303	-1.807	5.758	.011
riskperception	1.441	.086	16.839	.000	1.271	1.611	.745

GLM Example

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Tests of significance for the R-squared

GLM Example

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riskperception	78779.171	1	78779.171	283.558	.000	.745
Error	26948.865	97	277.823			
Total	115981.320	100				
Corrected Total	113768.558	99				

a. R Squared = .763 (Adjusted R Squared = .758)

F-Tests of for the effects

GLM Example

Anti-smoke campaign results: The ability to remember the ads (memory), the perception of smoke-related risks (risk perception) were measured to predict smoke aversion

Parameter Estimates

Dependent Variable: aversion

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared
					Lower Bound	Upper Bound	
Intercept	-73.668	6.577	-11.200	.000	-86.722	-60.613	.564
memory	1.975	1.906	1.036	.303	-1.807	5.758	.011
riskperception	1.441	.086	16.839	.000	1.271	1.611	.745

B coefficients and tests and effect size indexes

Recap

- Multiple regression is a simple generalization of simple regression
- Test of significance of the coefficients is performed as for the simple case
- The coefficients are interpreted as the effect of a IV holding the others constant
- R^2 is simply the cumulative ability of all the IVs to explain the DV

Applications

- Partitioning the effects
- Complex effects
- Nominal Variables

- Mediation Analysis
- Path analysis
- Interactions
- Analysis of Covariance
- Analysis of Variance
- Contrast Analysis

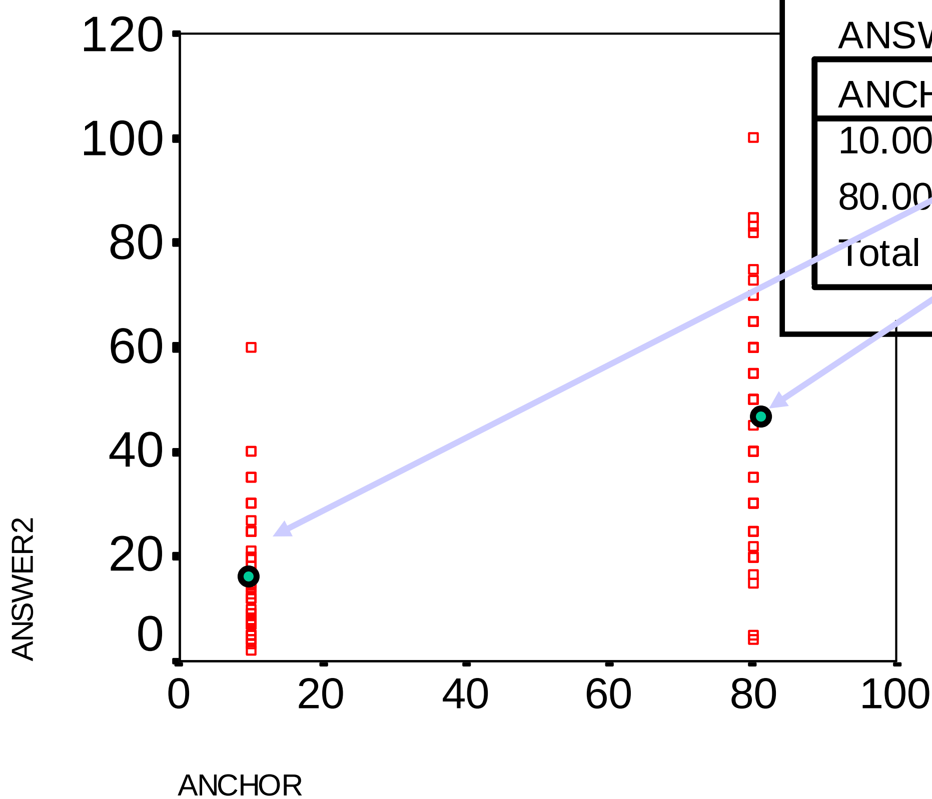
GLM with Categorical Independent Variables

(ANOVA)

Scatter Plot

- Example with two categories (Dichotomous)

Experiment: participants' numerical estimates after they receive a numerical anchor?



Report

ANSWER2

ANCHOR	Mean	N	Std. Deviation
10.00	17.0447	85	10.08970
80.00	44.8288	85	19.68864
Total	30.9368	170	20.91424

Is there a significant effect?

What is the effect size?

Coefficients for dichotomies

- X= Anchor. Low=0 High=1

$$y_i = a + b \cdot x_i$$

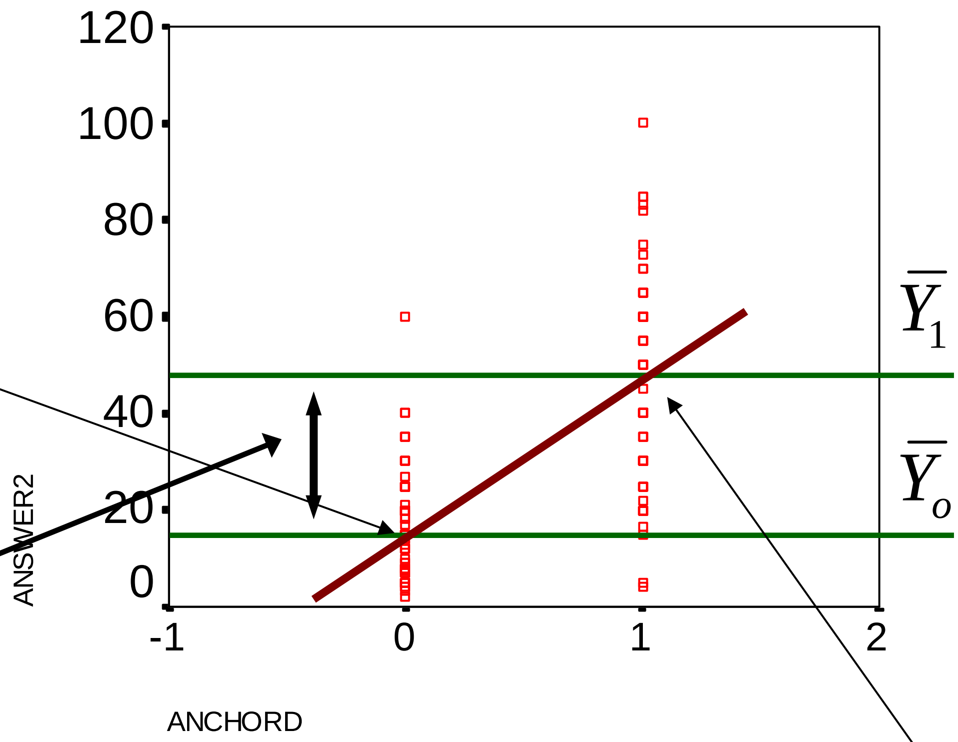
Constant term, X=0=Low

$$y_i = a + b \cdot 0 = a = \bar{y}_o$$

b coefficient, moving X from 0 to 1

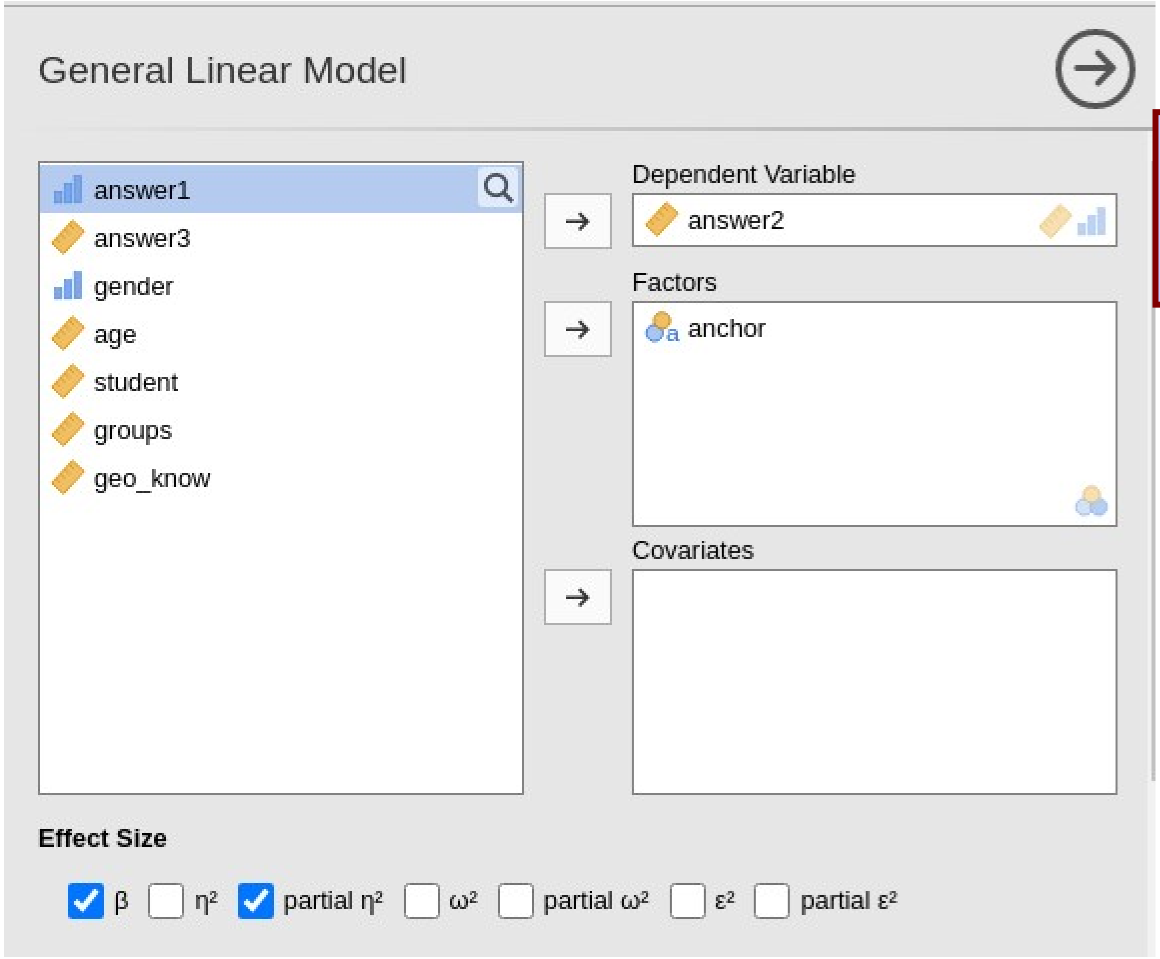
$$b = \bar{y}_1 - \bar{y}_o$$

Represents the difference between group means



$$y_i = \bar{y}_0 + b \cdot 1 = \bar{y}_1$$

ANOVA: GLM for dichotomies



We set “anchor” in Factors to say that it is a categorical variable

ANOVA: GLM for dichotomies

Model Results

Tests on variances

ANOVA Omnibus tests

	SS	df	F	p	η^2p
Model	32808	1	134	< .001	0.444
anchor	32808	1	134	< .001	0.444
Residuals	41113	168			
Total	73922	169			

B coefficents and effect sizes

Fixed Effects Parameter Estimates

				95% Confidence Interval					
Names	Effect	Estimate	SE	Lower	Upper	β	df	t	p
(Intercept)	(Intercept)	30.9	1.20	28.6	33.3	0.00	168	25.8	< .001
anchor1	80 - 10	27.8	2.40	23.0	32.5	1.33	168	11.6	< .001

Effect sizes

Model Results

Tests on variances

ANOVA Omnibus tests

	SS	df	F	p	$\eta^2 p$
Model	32808	1	134	< .001	0.444
anchor	32808	1	134	< .001	$\boxed{0.444}$
Residuals	41113	168			
Total	73922	169			

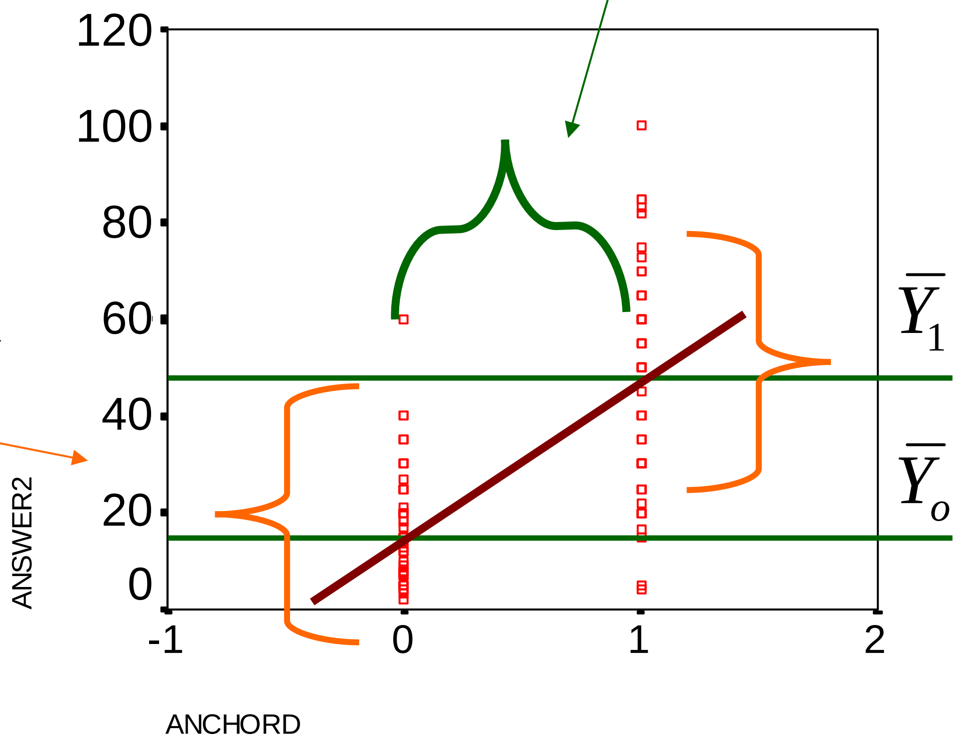
- In case of dichotomous IV one can use the **eta^2**, **Cohen's d** or its variations.

- The partial **eta^2** indicates the amount of variance of the DV explained by the specific comparison: Variance of the means over total variance

eta^2 for dichotomies

- The **eta^2** is the variance explained by the difference between groups

- The residual variance 1-eta^2 is the variance not explained by groups, that is the variance within groups

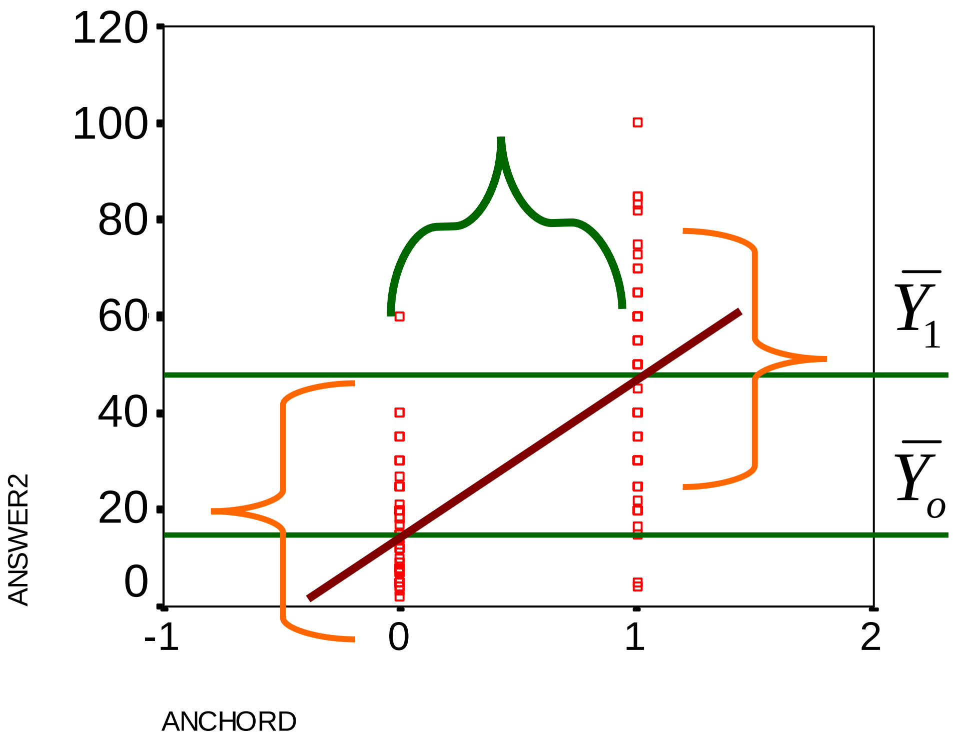


Statistical test for dichotomies

- The test for significance is done with the F-test

$$F = \frac{\eta^2}{1-\eta^2} \frac{df_{within}}{df_{between}}$$

$$F = \frac{\text{variance between}}{\text{variance within}} \frac{df_{within}}{df_{between}}$$



Cohen's d

Model Results

Tests on variances

ANOVA Omnibus tests

	SS	df	F	p	η²p
Model	32808	1	134	< .001	0.444
anchor	32808	1	134	< .001	$\boxed{0.444}$
Residuals	41113	168			
Total	73922	169			

- In case of dichotomous IV with equal N, **Cohen's d** can be computed from eta^2

$$d = 2\sqrt{\frac{\eta^2}{1-\eta^2}} \qquad d = 2\sqrt{\frac{.44}{1-.44}} = 1.78$$

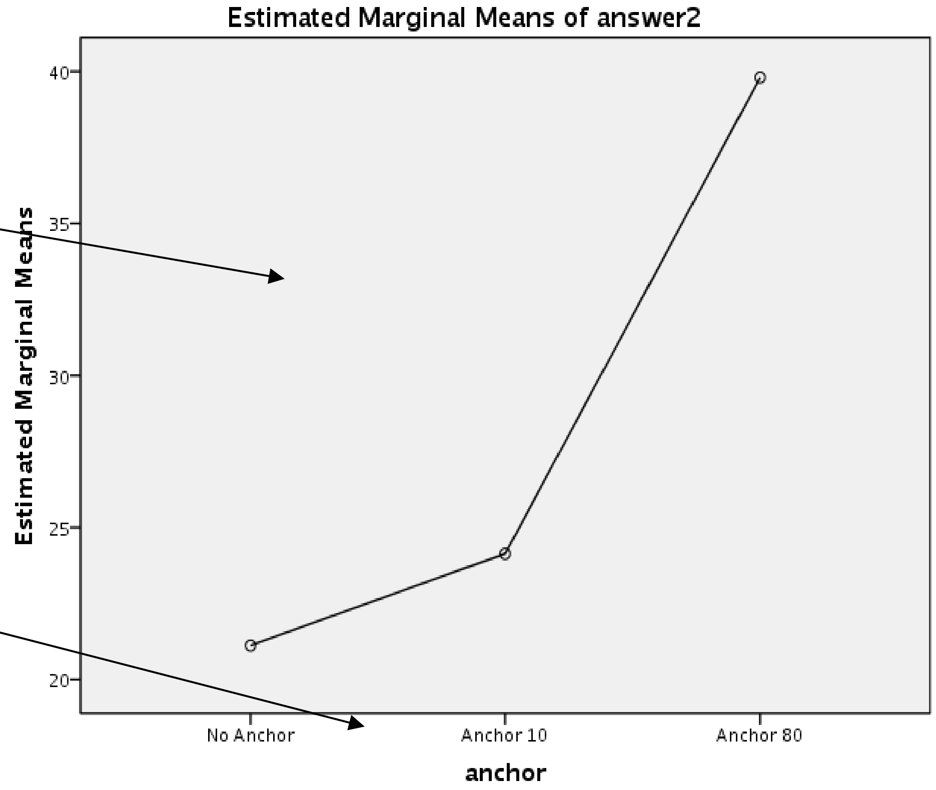
- The Cohen's d represents the standardized difference between the DV means of the two groups: the two groups means are **d** S.D. apart

What about three groups

- ANOVA is generally applicable when the IV has many categories
- If we estimated regression with a IV with K groups, it would not make sense

The differences cannot be represented by one straight line

The order of the groups is arbitrary



An example with three anchors, in three groups

Categorical IV

- When we have more then two groups, we should represent the information contained in the categorical IV by means of different dichotomous variables

- The categorical variable informs us that there are K groups and who is in each group

If we use one dichotomous variable we loose information

Categorial	Category	var
	None	1
Anchor	10	0
	80	0

Anchor 10 and anchor 80 are pooled.

Dummy variables

- The categorical variable informs us that there are K groups and who is in each group
- If we create K-1 new variables (called **Dummy variables**), we can represent the same information

We call these variables dummy variables

If we use two dichotomous variables, we do not loose information

Categorial	Category	var1	var2
	No anchor	1	0
Nationality	Anchor 10	0	1
	Anchor 80	0	0

3 groups, 2 variables represent all the differences in the IV

Coefficients for dummies

- What if we put the two dummies in a regression predicting a DV

$$\begin{array}{cccccl} & & \text{var1} & & \text{var2} & \\ \hat{Y}=a+B_1 & & \begin{bmatrix}1\\0\\0\end{bmatrix} & +B_2 & \begin{bmatrix}0\\1\\0\end{bmatrix} & \begin{array}{l}\text{No anchor}\\ \text{Anchor 10}\\ \text{Anchor 80}\end{array}\end{array}$$

What is the constant term a?

Coefficients for dummies

- What if we put the two dummies in a regression predicting a DV

$$\hat{Y} = a + B_1 \begin{array}{c} \text{var1} \\ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \end{array} + B_2 \begin{array}{c} \text{var2} \\ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \end{array}$$

No anchor

Anchor 10

Anchor 80

What is the constant term a?

The mean value of the DV when the IVs are all equal to zero

$$\hat{Y}_i = a + B_1 \cdot 0 + B_2 \cdot 0 = a = \bar{Y}_{80}$$

Coefficients for dummies

- What is the B associated with var1?

$$
\hat{Y} = a + B_1 \begin{array}{c} \text{var1} \\ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \end{array} + B_2 \begin{array}{c} \text{var2} \\ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \end{array}
\quad
\begin{array}{l} \text{No anchor} \\ \text{Anchor 10} \\ \text{Anchor 80} \end{array}
$$

The change in the DV when moving var1 from 0 to 1, holding constant var2

$$
\hat{Y}_i = \bar{Y}_{80} + B_1 \cdot 1 + B_2 \cdot 0 = \bar{Y}_{no}
$$

The difference between no anchor group and anchor 80 group

$$
B_1 = \bar{Y}_{no} - \bar{Y}_{80}
$$

Coefficients for dummies

- What is the B associated with var2?

$$\hat{Y} = a + B_1 \begin{array}{c} \text{var1} \\ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \end{array} + B_2 \begin{array}{c} \text{var2} \\ \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \end{array} \quad \begin{array}{l} \text{No anchor} \\ \text{Anchor 10} \\ \text{Anchor 80} \end{array}$$

The change in the DV when moving var2 from 0 to 1, holding constant var1

$$\hat{Y}_i = \bar{Y}_{80} + B_1 \cdot 0 + B_2 \cdot 1 = \bar{Y}_{1o}$$

The difference between anchor 10 group and anchor 80 group

$$B_2 = \bar{Y}_{10} - \bar{Y}_{80}$$

Categorical IV

- We can represent a categorical IV with K groups by means of K-1 dummies
- We call the group with zeros in all dummies (no anchor) the reference group
- The constant term of the regression is the average of the DV for the reference group
- The B of each dummy represents the difference between the group with 1 in that dummy and the reference group
- Test of significance of each B tests the difference between the group with 1 in the dummy and the reference group

Categorical IV

- The variance explained by all the dummies if the **main effect** of the categorical independent variable

Between-Subjects Factors

		Value Label	N
xanchor	1	No Anchor	50
	2	Anchor 10	50
	3	Anchor 80	50

Tests of Between-Subjects Effects

Dependent Variable: answer2

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	10054.973[a]	2	5027.487	42.441	.000	.366
Intercept	120586.727	1	120586.727	1017.972	.000	.874
xanchor	10054.973	2	5027.487	42.441	.000	.366
Error	17413.300	147	118.458			
Total	148055.000	150				
Corrected Total	27468.273	149				

a. R Squared = .366 (Adjusted R Squared = .357)

Effect sizes

- In general, the **eta**^{2} can be used as effect size index: The amount of variance of the DV explained by the effect

Tests of Between-Subjects Effects

Dependent Variable: answer2

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	10054.973[a]	2	5027.487	42.441	.000	.366
Intercept	120586.727	1	120586.727	1017.972	.000	.874
xanchor	10054.973	2	5027.487	42.441	.000	$\boxed{.366}$
Error	17413.300	147	118.458			
Total	148055.000	150				
Corrected Total	27468.273	149				

a. R Squared = .366 (Adjusted R Squared = .357)

Categorical IV

- So when we run a "ANOVA" we are actually running a regression with dummy variables

Between-Subjects Factors

		Value Label	N
xanchor	1	No Anchor	50
	2	Anchor 10	50
	3	Anchor 80	50

Parameter Estimates

Dependent Variable: answer2

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Partial Eta Squared
Intercept	39.800	1.539	25.857	.000	36.758	42.842	.820
[xanchor=1,00]	-18.680	2.177	-8.582	.000	-22.982	-14.378	.334
[xanchor=2,00]	-15.660	2.177	-7.194	.000	-19.962	-11.358	.260
[xanchor=3,00]	0[a]	.	.	.	.	.	.

a. This parameter is set to zero because it is redundant.

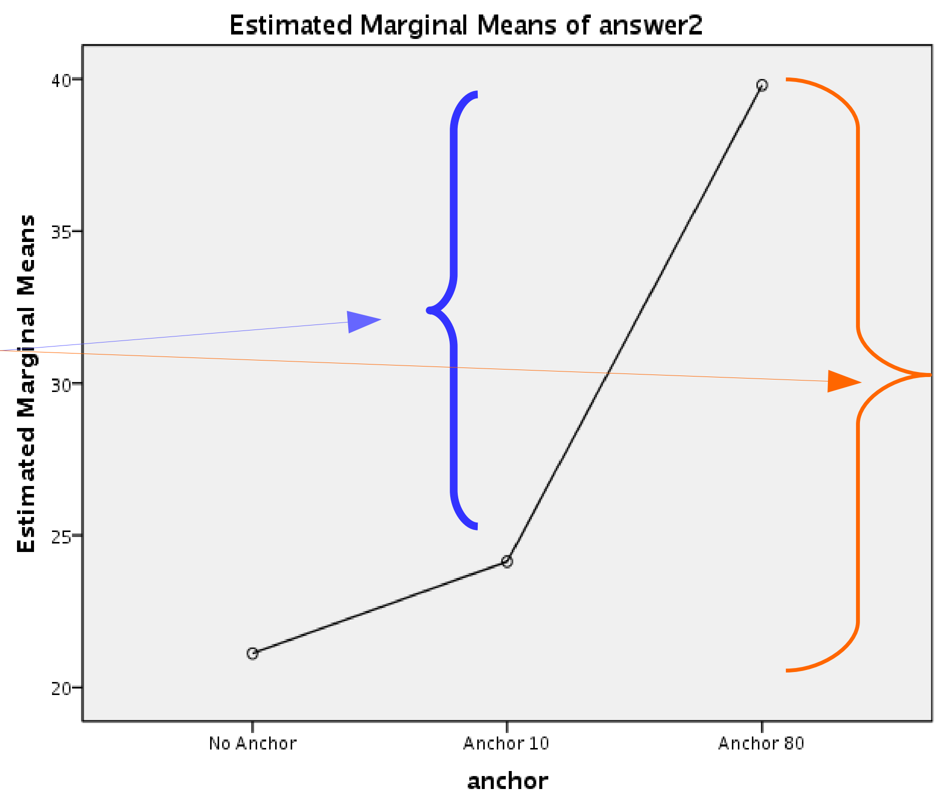
Check the means

Parameter E

Dependent Variable: answer2

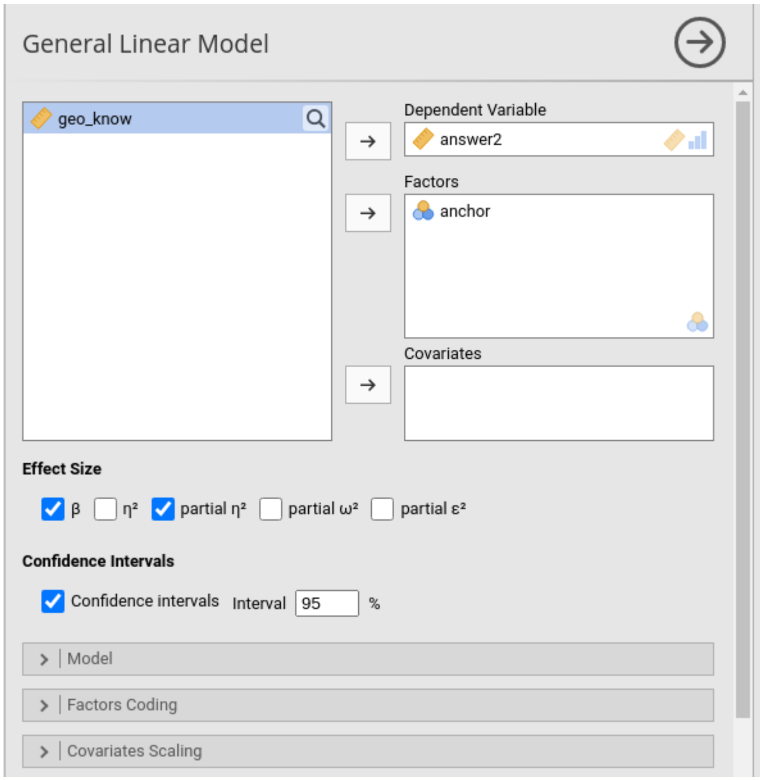
Parameter	B	Std. Error	t
Intercept	39.800	1.539	25.857
[xanchor=1,00]	-18.680	2.177	-8.582
[xanchor=2,00]	-15.660	2.177	-7.194
[xanchor=3,00]	0[a]	.	.

a. This parameter is set to zero because it is redundar



jamovi

- In SPSS dummies are always (0 vs 1)
- JAMOVI allows for different comparisons. The default is comparing each mean with the average of the sample



General Linear Model

Model Info

Info	
Estimate	Linear model fit by OLS
Call	answer2 ~ 1 + anchor
R-squared	0.366
Adj. R-squa	

Model setup

Model Results

ANOVA Omnibus tests

	SS	df	F	p	η²p
Model	10054.973	2	42.441	< .001	0.366
anchor	10054.973	2	42.441	< .001	0.366
Residuals	17413.300	147			
Total	148055.000	150			

Fixed Effects Parameter Estimates

				95% Confidence Interval		
Names	Effect	Estimate	SE	Lower	Upper	β
(Intercept)	(Intercept)	28.353	0.889	26.597	30.110	0.000
anchor1	1 - 0	3.020	2.177	-1.282	7.322	0.222
anchor2	2 - 0	18.680	2.177	14.378	22.982	1.376

jamovi

Model Results

ANOVA Omnibus tests

	SS	df	F	p	η²p
Model	10054.973	2	42.441	< .001	0.366
anchor	10054.973	2	42.441	< .001	0.366
Residuals	17413.300	147			
Total	148055.000	150			

The F are equal to SPSS

The estimates are different than SPSS because dummies are coded differently

Fixed Effects Parameter Estimates

				95% Confidence Interval					
Names	Effect	Estimate	SE	Lower	Upper	β	df	t	p
(Intercept)	(Intercept)	28.353	0.889	26.597	30.110	0.000	147	31.906	< .001
anchor1	1 - 0	3.020	2.177	−1.282	7.322	0.222	147	1.387	0.167
anchor2	2 - 0	18.680	2.177	14.378	22.982	1.376	147	8.582	< .001

jamovi

- The **simple contrast** coding compares each group with a reference group (like dummy coding) but the contrast is centered (useful when we have interactions)

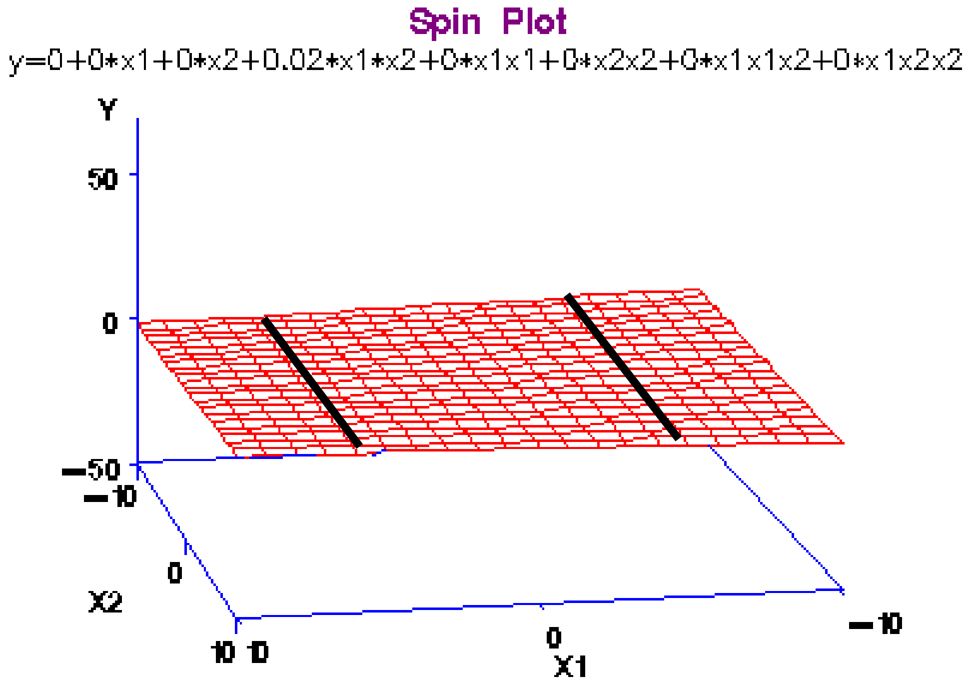
Fixed Effects Parameter Estimates

				95% Confidence Interval					
Names	Effect	Estimate	SE	Lower	Upper	β	df	t	p
(Intercept)	(Intercept)	28.353	0.889	26.597	30.110	0.000	147	31.906	< .001
anchor1	1 - 0	3.020	2.177	−1.282	7.322	0.222	147	1.387	0.167
anchor2	2 - 0	18.680	2.177	14.378	22.982	1.376	147	8.582	< .001

Interactions

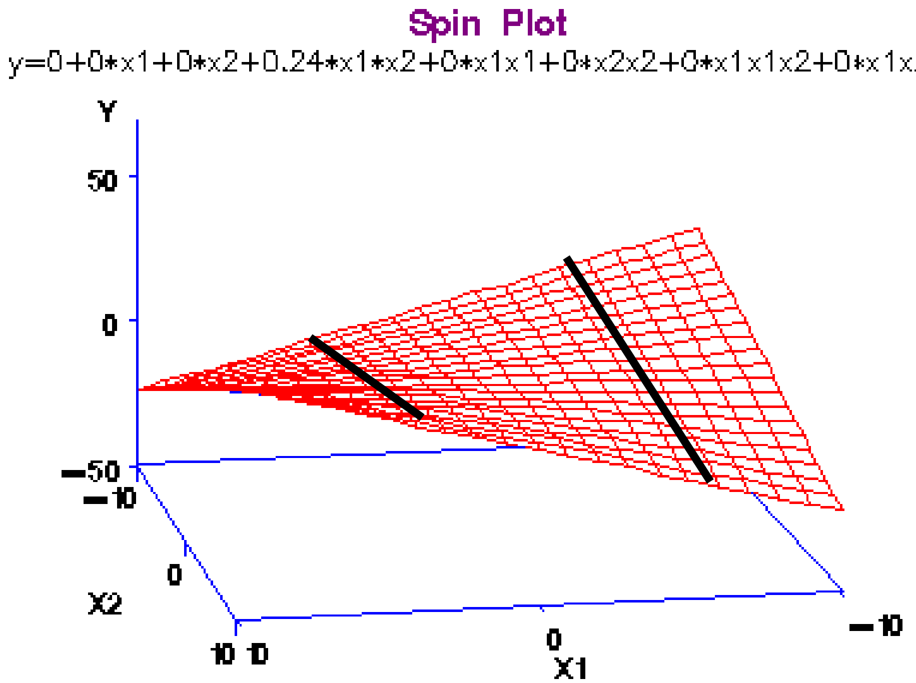
Two continuous variables

- In the multiple regression we have seen, lines are parallels, making a flat surface
- The effect of one IV is constant (the same) for each level of the other IV



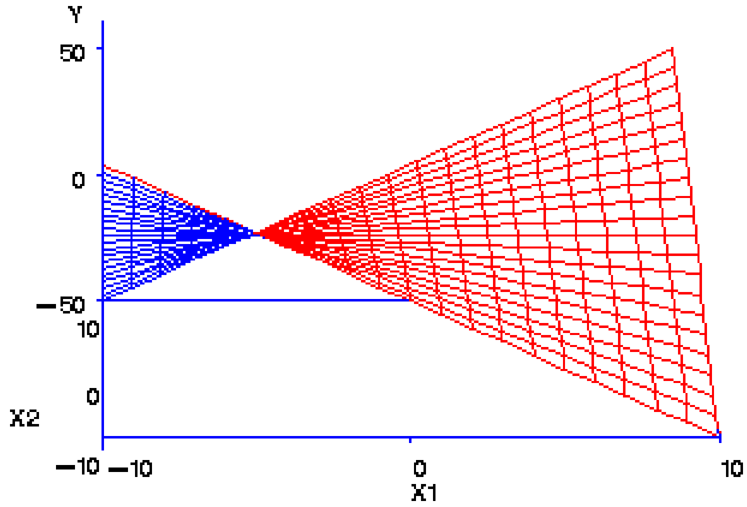
Interaction lines

- We say we have an interaction between the IVs when:
- **The effect of one IV is different for each level of the other IV**



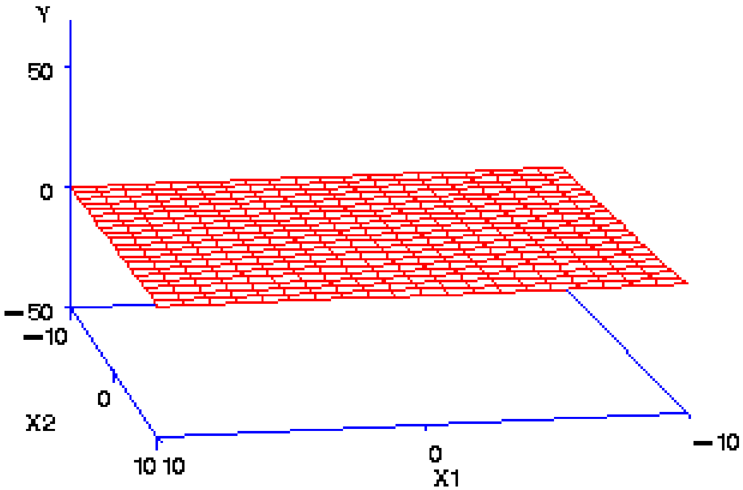
Interactions lines

- Interaction: Lines are **not** parallel
- The effect of one IV is different for each level of the other IV



Interactions line

- The bigger the interaction, the less parallel the lines: Bigger difference in the slopes



Multiplicative effect

- The interaction effect is captured in the regression by a multiplicative term

The product of the two independent variables

$$\hat{y}_i = a + b_1 \cdot x_1 + b_2 \cdot x_2 + b_{\text{int}} x_1 x_2$$

The coefficient of x_1 is changing as x_2 changes

$$\hat{y}_i = a + \overbrace{\left(b_1 + b_{\text{int}} x_2 \right)} \cdot x_1 + b_2 \cdot x_2$$

The effect of one IV changes at different levels of the other IV

Conditional effect

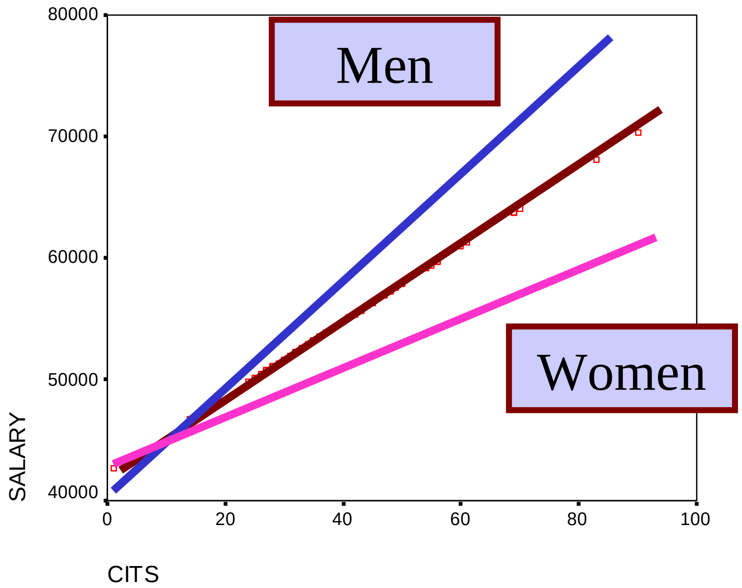
- We say that the effect of one IV is conditional to the level of the other IV

For Women (0) the slope is different

$$\hat{y}_i = a + \left(b_2 + b_{\text{int}} 0\right) \cdot x_2 + b_1 \cdot 0$$

…than for Men (1)

$$\hat{y}_i = a + \left(b_2 + b_{\text{int}} 1\right) \cdot x_2 + b_1 \cdot 1$$



Conditional vs linear effect

- A linear effect (when no interaction is present) tells you how much change there is in the DV when you change the IV

$$\hat{y}_i = a + b_1 \cdot x_1 + b_2 \cdot x_2 + b_{int}\, x_1 x_2$$

Change in the DV

- An interaction effect (the B of the product term) tells you how much change there is **in the effect** of one IV on the DV when you change the other IV

$$\hat{y}_i = a + \left(b_1 + b_{int}\, x_2\right) \cdot x_1 + b_2 \cdot x_2$$

Change in the effect

Change in the DV

Terminology

- When there is an interaction term in the equation, one refers to the linear effect (the ones that are not interactions) as the first-order effect

$$\hat{y}_i = a + b_1 \cdot x_1 + b_2 \cdot x_2 + b_{\text{int}} x_1 x_2$$

First order effects

Estimating Interactions

- To estimate the interaction we simply tell our software that we want to have a product term in the model

Example

- We have measured *physical endurance* in a sample of adults, and we record their *age* and *years of exercising*.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
xage	245	20	82	49.18	10.107
zexer	245	0	26	10.67	4.775
yendu	245	0	55	26.53	10.819
Valid N (listwise)	245				

Estimating Interactions

- To estimate the interaction we simply tell our software that we want to have a product term in the model

Example

```
GLM yendu WITH xage zexer
  /METHOD=SSTYPE(3)
  /INTERCEPT=INCLUDE
  /CRITERIA=ALPHA(0.05)
 /PRINT PARAMETER
  /DESIGN=xage zexer xage*zexer.
```

This can be done with the menus as well

Estimating Interactions

- The B (betas, sr, t-test and p.) associated with the product term gives us all the information regarding the interaction between IVs

First-order effects

Second-order effects

Parameter Estimates

Dependent Variable: yendu

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared
					Lower Bound	Upper Bound	
Intercept	53.179	7.527	7.065	.000	38.353	68.005	.172
xage	-.766	.160	-4.793	.000	-1.081	-.451	.087
zexer	-1.351	.666	-2.028	.044	-2.663	-.039	.017
xage * zexer	.047	.014	3.476	.001	.020	.074	.048

We reject the null B=0. We say that we there is a difference in slopes (B=.04) of **age** for different levels of **exercising**

The slopes can be considered as not parallel

First-order effects with interaction

- When the interaction is in the regression, the first order effects become conditional to the values of the other IVs

$$\hat{y}_i = a + b_1 \cdot x_1 + b_2 \cdot x_2 + b_{int} x_1 x_2$$

What is B_1?

Is not the effect of X_1 while keeping constant X_2!

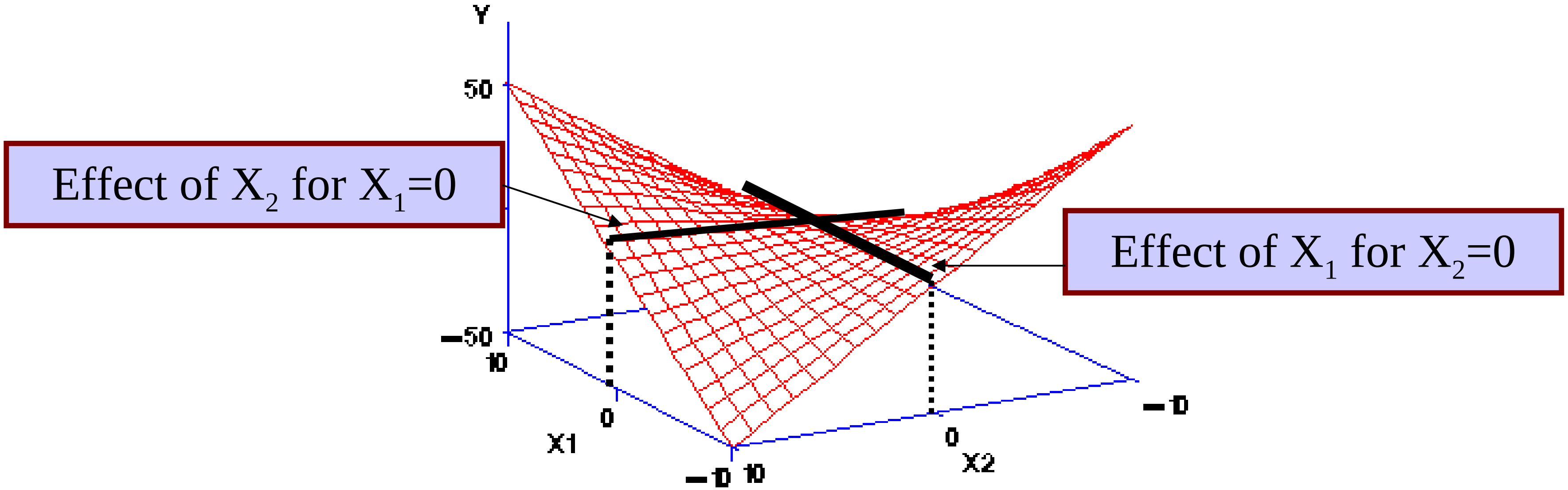
B_1 is the effect of X_1 while the other IV X_2 is kept constant at zero

$$\hat{y}_i = a + b_1 \cdot x_1 + b_2 \cdot 0 + b_{int} x_1 0 = a + b_1 \cdot x_1$$

First-order effects with interaction

- When the interaction is in the regression, the first order effects become the effect of the IV while keeping the other IV's constant to zero

$$\hat{y}_i = a + b_1 \cdot x_1 + b_2 \cdot 0 + b_{\text{int}} x_1 0 = a + b_1 \cdot x_1$$



Meaningless zeros

- In many applications, zero does not mean anything:
- Physical endurance is predicted by age, years of exercise and their interaction

Parameter Estimates

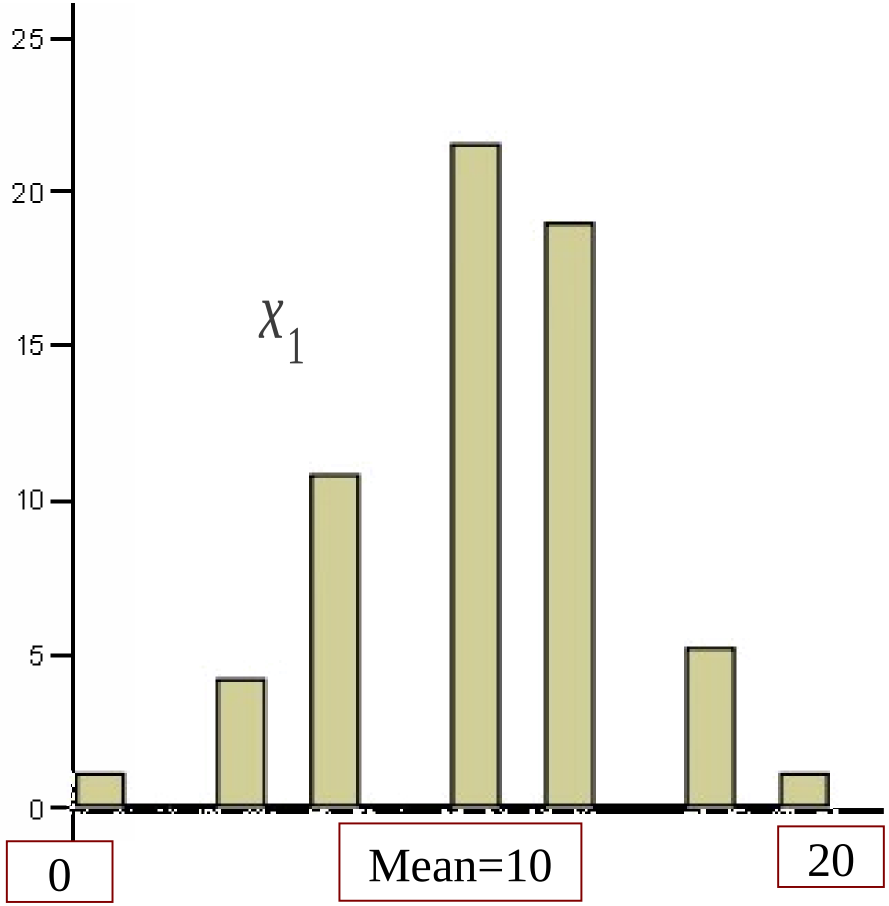
Dependent Variable: yendu

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared
					Lower Bound	Upper Bound	
Intercept	53.179	7.527	7.065	.000	38.353	68.005	.172
xage	-.766	.160	-4.793	.000	-1.081	-.451	.087
zexer	-1.351	.666	-2.028	.044	-2.663	-.039	.017
xage * zexer	.047	.014	3.476	.001	.020	.074	.048

This is the effect of years of exercise when the participant is 0 year old (a baby)
This cannot be interpreted, and so are the other coefficients (beta, sr).

Making zero meaningful

- We can always make zero a meaningful value by centering the variables before computing the product term:



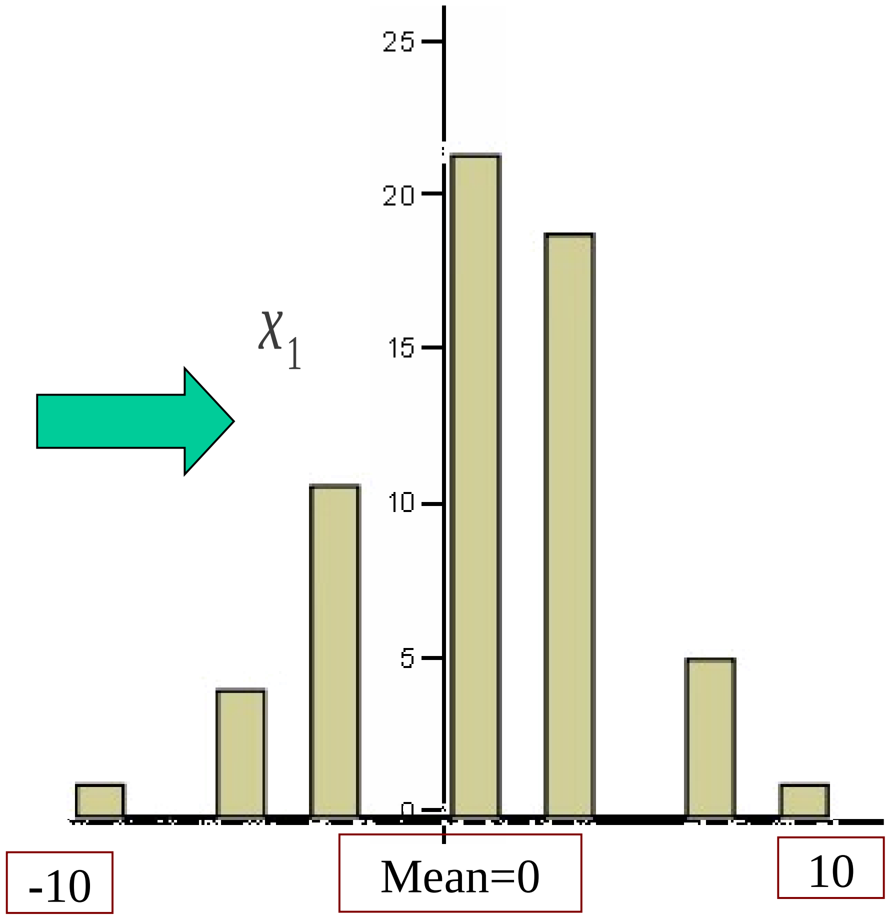
For each participant, compute a new variable as the old minus the average

$$c = x_1 - \bar{x}_1$$

The new variable has mean=0

Making zero meaningful

- By subtracting the mean, we create a new variable centered around 0



For each participant, compute a new variable as the old minus the average

$$c = x_1 - \bar{x}_1$$

The new variable has mean=0

After you centered the variable, you should compute the product again

Making zero meaningful

- We can always make zero a meaningful value by centering the variables before computing the product term:

$$c = x_1 - mean(x_1)$$

For each participant, compute a new variable as the old variable minus the average

The new variable has mean=0

Parameter Estimates

Dependent Variable: yendu

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	15.509	1.614	9.609	.000	12.330	18.689
cage	-.766	.160	-4.793	.000	-1.081	-.451
zexer	.973	.137	7.123	.000	.704	1.241
cage * zexer	.047	.014	3.476	.001	.020	.074

This is the effect of years of exercise for the average value of years of exercise: this can be interpreted

Centered vs no centered

Age not centered

Parameter Estimates

Dependent Variable: yendu

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared
					Lower Bound	Upper Bound	
Intercept	53.179	7.527	7.065	.000	38.353	68.005	.172
xage	-.766	.160	-4.793	.000	-1.081	-.451	.087
zexer	-1.351	.666	-2.028	.044	-2.663	-.039	.017
xage * zexer	.047	.014	3.476	.001	.020	.074	.048

Interaction does not change

First-order effects change

Parameter Estimates

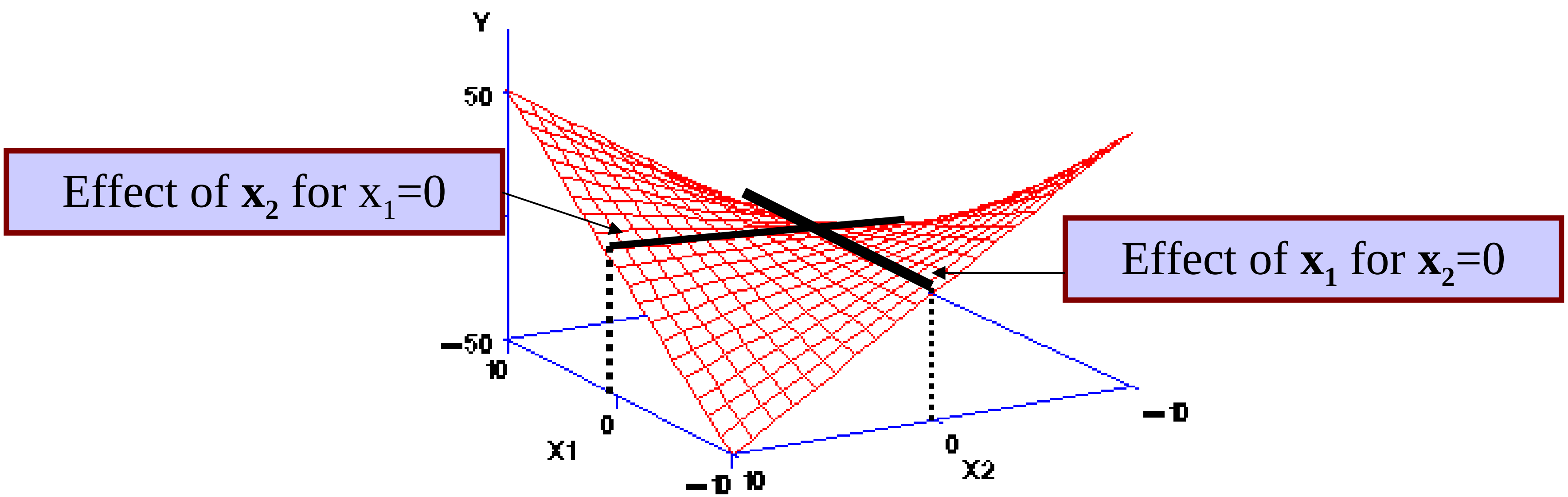
Dependent Variable: yendu

Age centered

Parameter	B	Std. Error	t	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Intercept	15.509	1.614	9.609	.000	12.330	18.689
cage	-.766	.160	-4.793	.000	-1.081	-.451
zexer	.973	.137	7.123	.000	.704	1.241
cage * zexer	.047	.014	3.476	.001	.020	.074

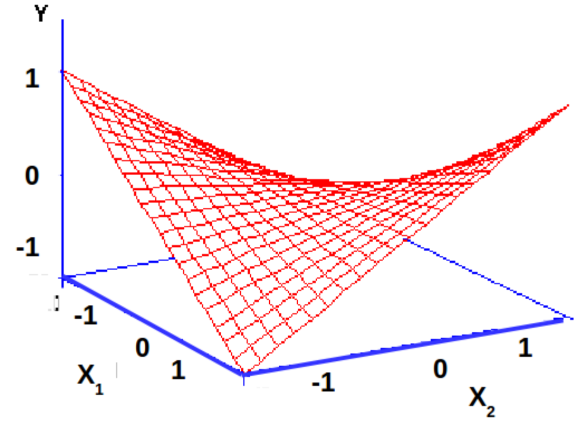
Centering

- The first-order effects computed on centered variables represent the average effect (the one in the middle) of the IV, across all levels of the other IV



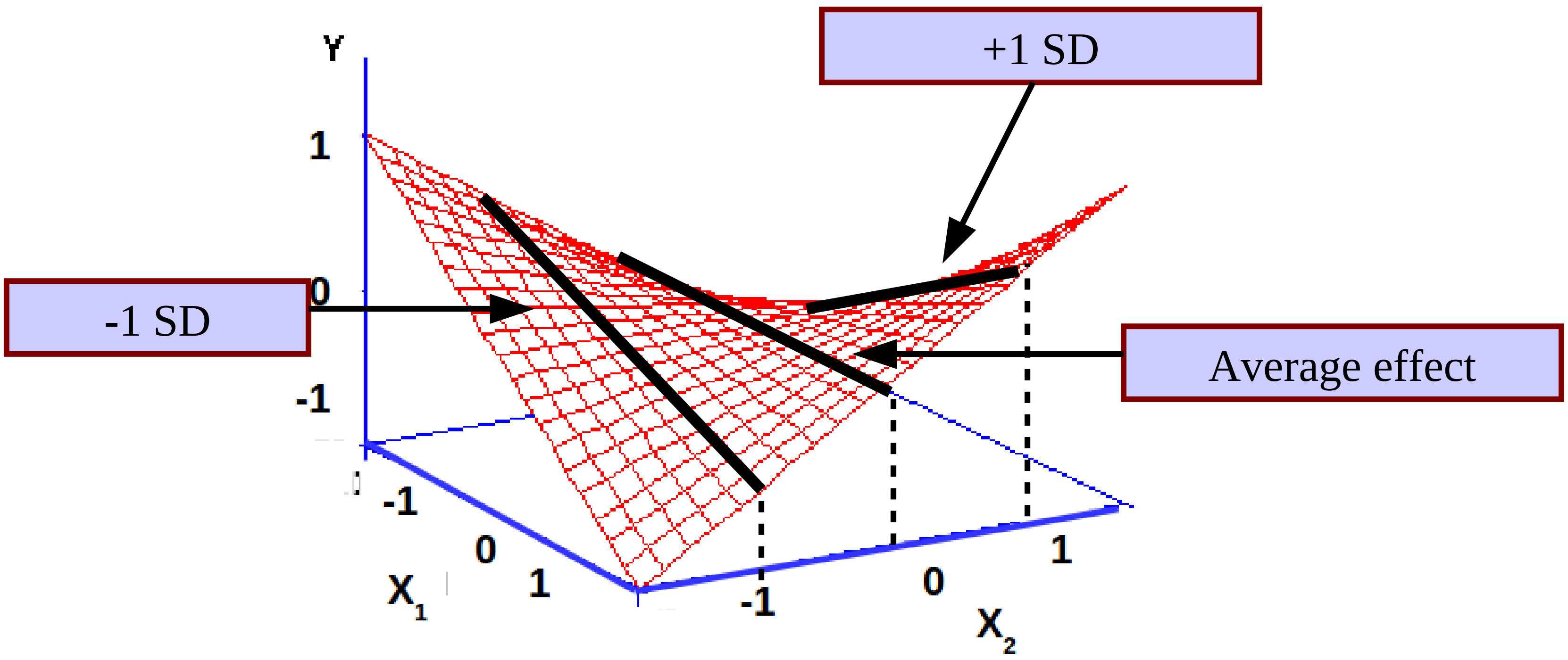
Standardizing the variables

- Even better than centering is standardizing the variables:
  1. Z-scores are centered
  2. One unit means one standard deviation
  3. Coefficient are in the correlation scale (-1 to 1)



Standardizing the variables

- Effects for standardized variables



Recap

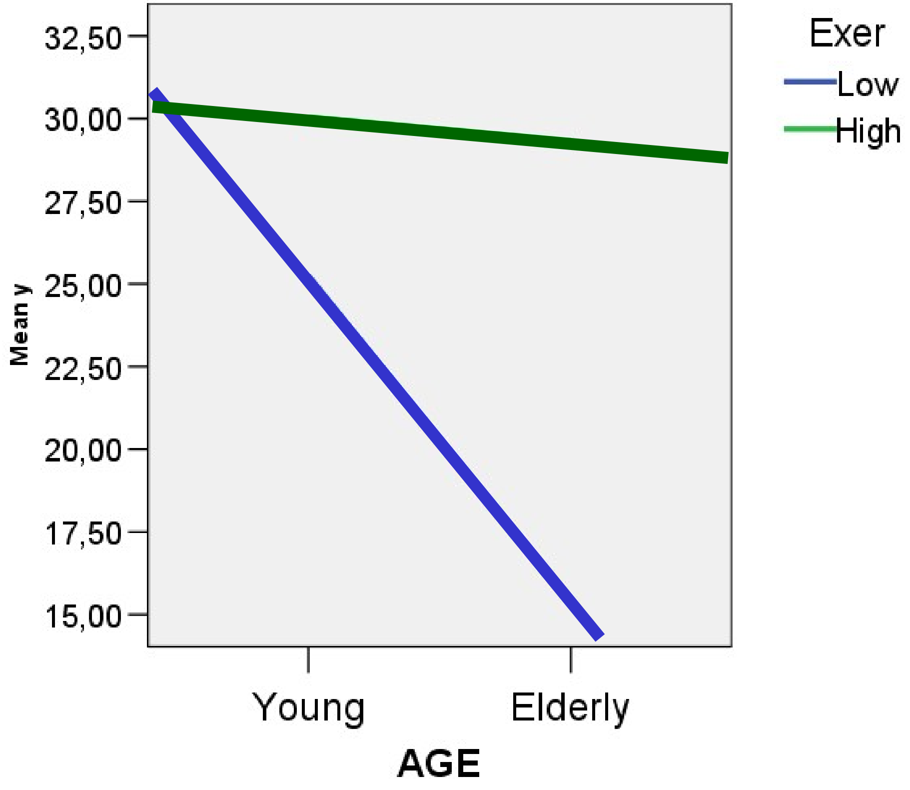
- An interaction occurs when the effect of one IV is different for different levels of the other independent variable
- To estimate the interaction, we compute the product of the IVs and put the product in the regression
- If the product is significant, the effects of are not constant, but conditional to the other variable values
- The first-order effect is interpreted as the effect of the IV while the other variable is 0
- When zero is not meaningless, we center or standardize the variables (so their mean=0) **before** computing the product, so we can interpret the first order effect as the effect of one IV for the average value of the other
- The product term B (and rest) is not changed by the centering of the variables
- The R^2 is not affected by centering.

Issues with interactions

- How to interpret the interaction beyond the mere definition of conditional effect: How to picture what is going on
- How to test if single regression lines are significant different from zero

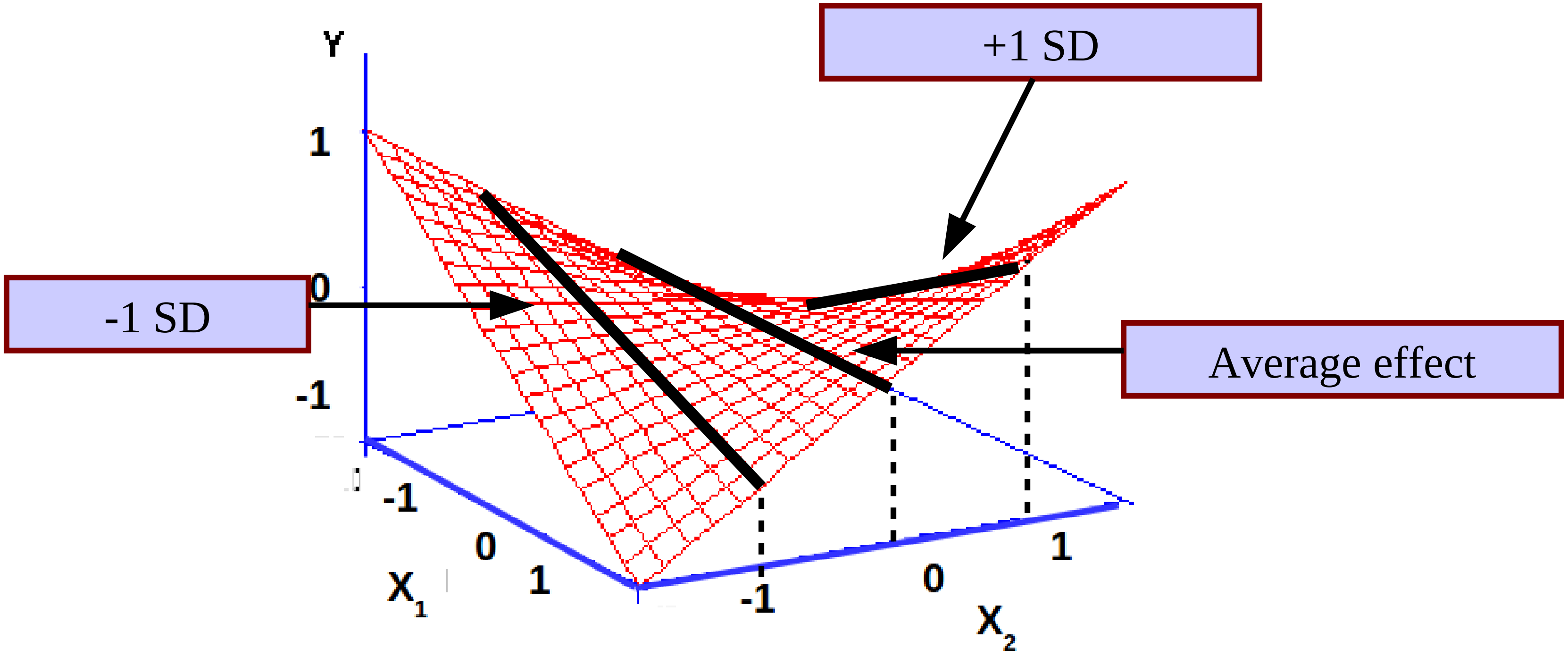
Simple slope analysis

- Simple slope analysis entails to compute the regression line for one IV at some meaningful levels of the other independent variable



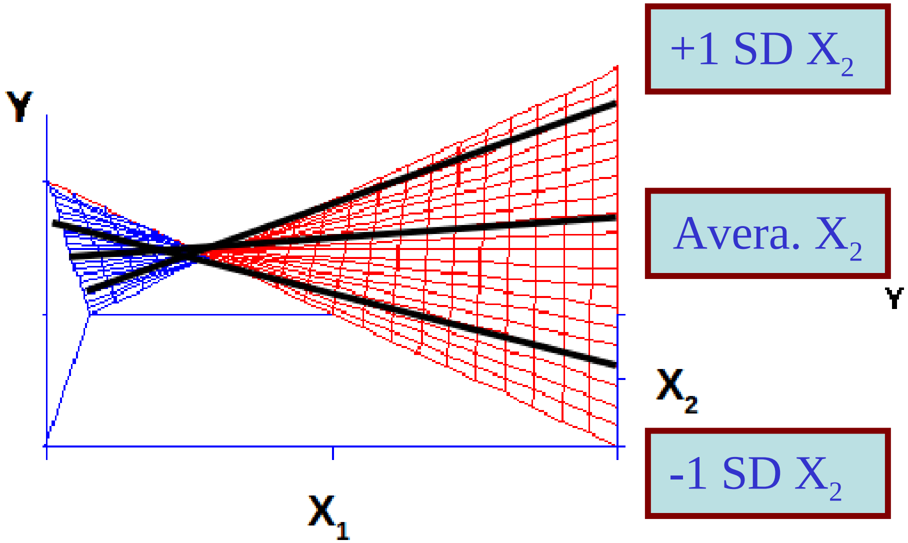
Simple slope analysis

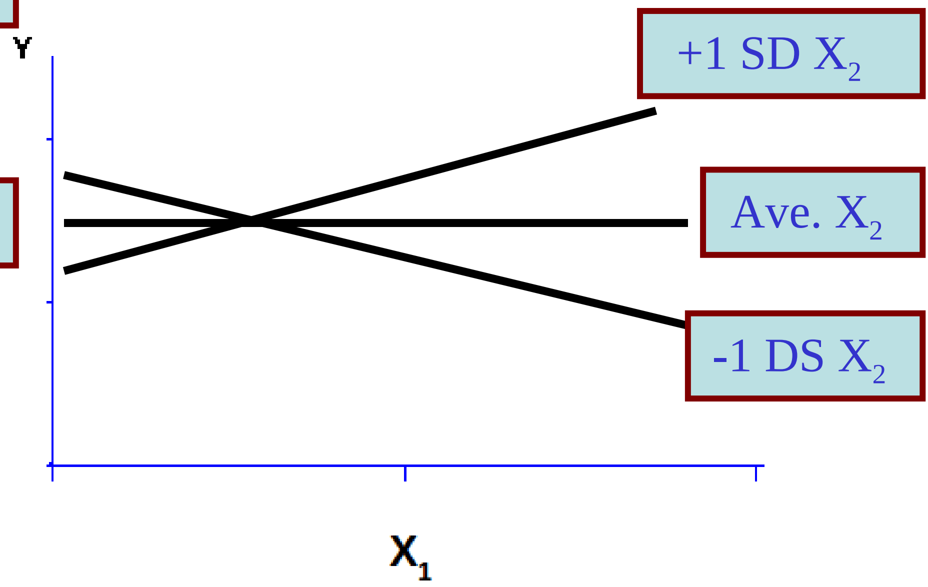
- We use the standardized variables (for simplicity)
- We pick three lines out of many in the regression plane



Simple slope analysis

- We represent them in two dimensions



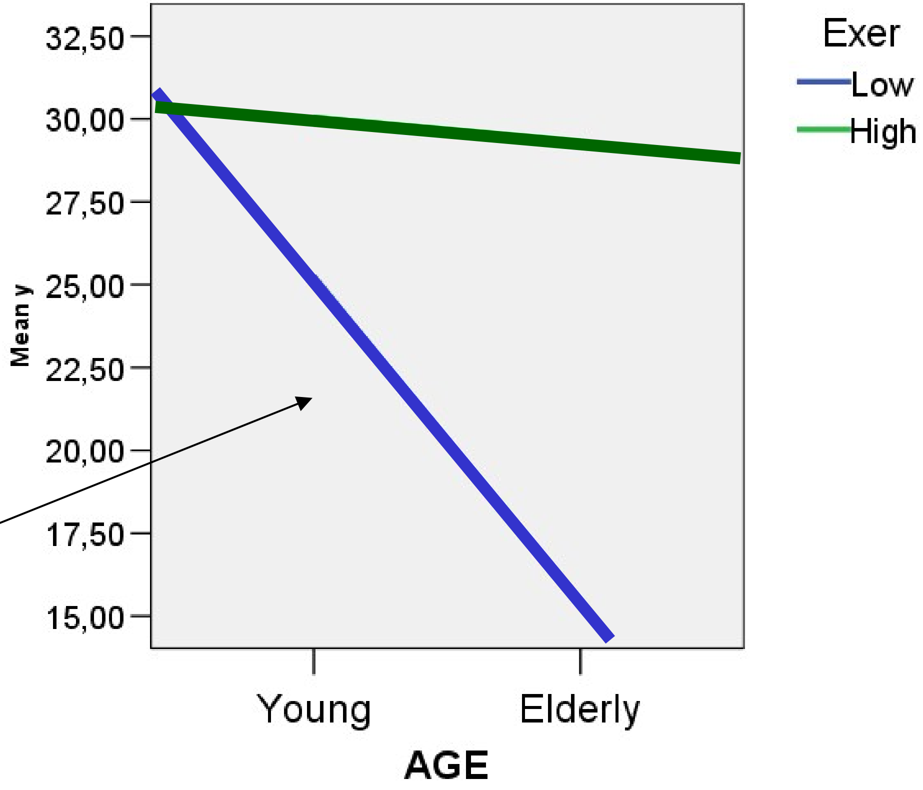


Simple slopes

- We want to test of the mull hypothesis that the simple slopes are different from zero

Is the effect of Age on Endurance significant for people who exercise a lot

Is the effect of Age on Endurance significant for people who exercise a little



Practical things

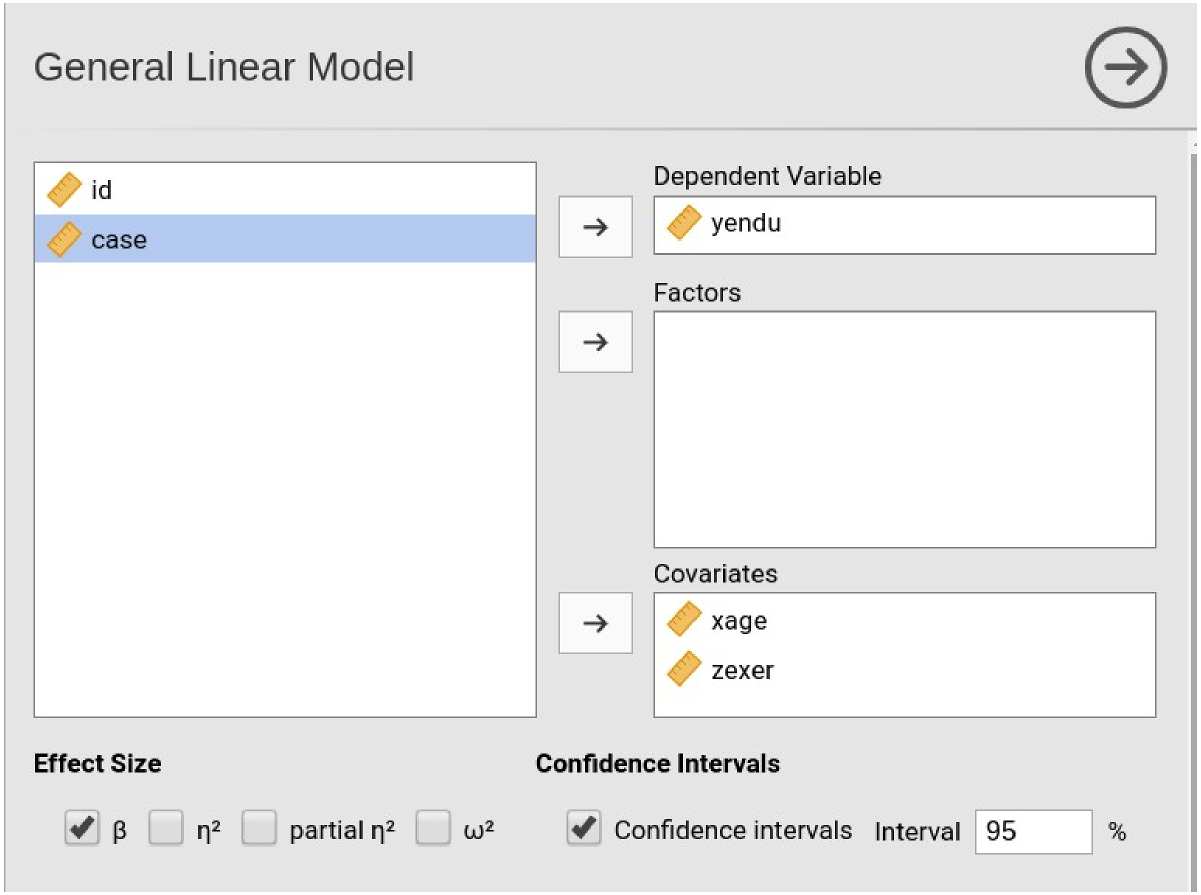
- You can find on Internet different SPSS macros or add-ons to make the computation automatic (e.g **Process**).

- I generally discourage that, because they do not generalize at any linear model and you loose control of what you do

- We can use **jamovi** with simplifies a lot of things.

jamovi: Estimating Interactions

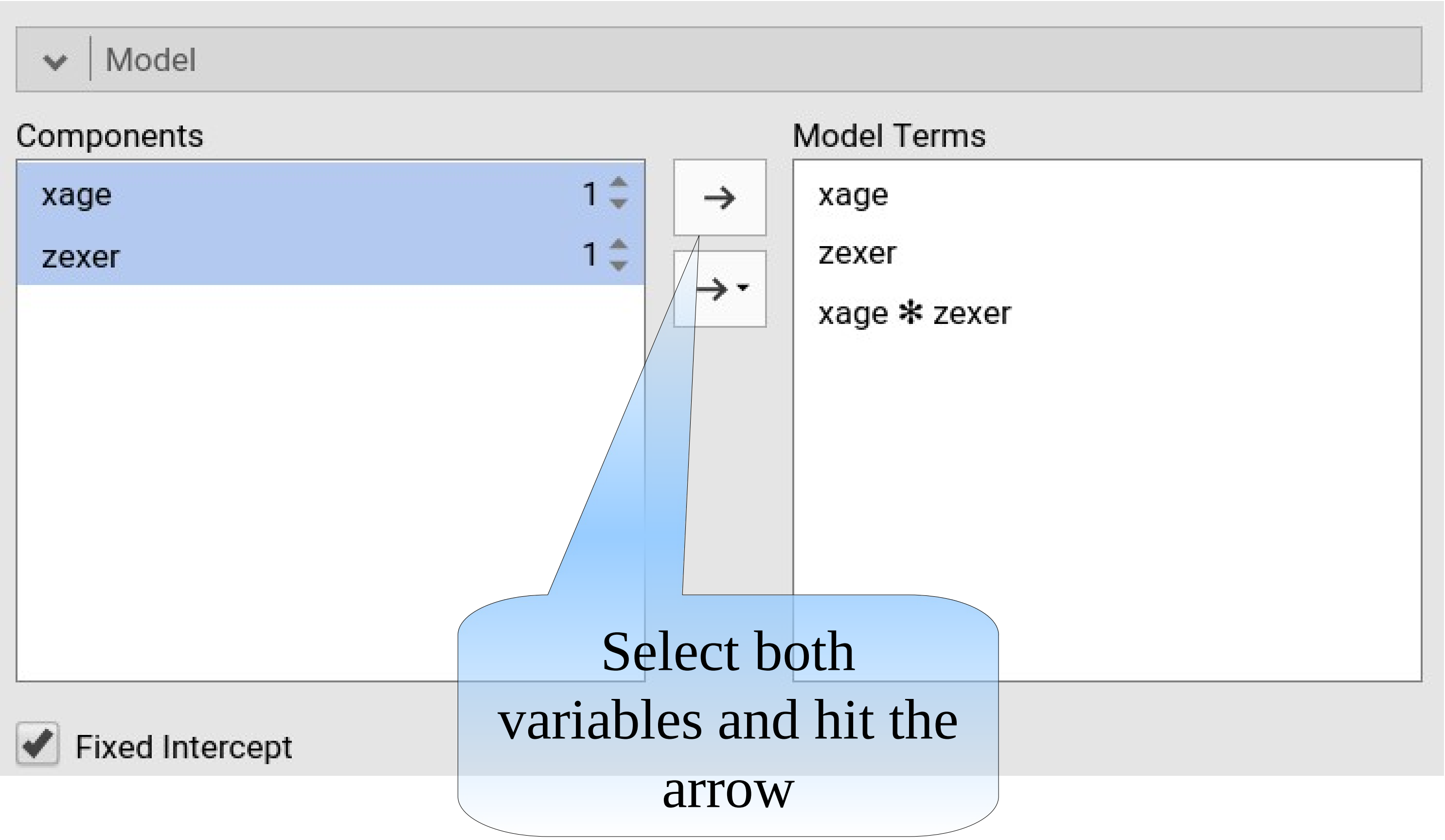
- To estimate the interaction we simply tell jamovi that we want to have a product term in the model



Select variables role

jamovi: Estimating Interactions

- To estimate the interaction we go to "model" panel and insert a product term



jamovi: Estimating Interactions

- As for the others GLM models, we can look at the coefficients (estimates)

Fixed Effects Parameter Estimates

				95% Confidence Interval					
Names	Effect	Estimate	SE	Lower	Upper	β	df	t	p
(Intercept)	(Intercept)	25.8887	0.6466	24.6150	27.1625	0.000	241	40.04	< .001
xage	xage	−0.2617	0.0641	−0.3879	−0.1355	−0.244	241	−4.08	< .001
zexer	zexer	0.9727	0.1365	0.7038	1.2417	0.429	241	7.12	< .001
xage ✻ zexer	xage ✻ zexer	0.0472	0.0136	0.0205	0.0740	0.211	241	3.48	< .001

Interaction term. It seems significant, so the effect of age depends on how much one exercises

jamovi: Estimating Interactions

- As for the others GLM models, we can look at the coefficients (estimates)

Fixed Effects Parameter Estimates

				95% Confidence Interval					
Names	Effect	Estimate	SE	Lower	Upper	β	df	t	p
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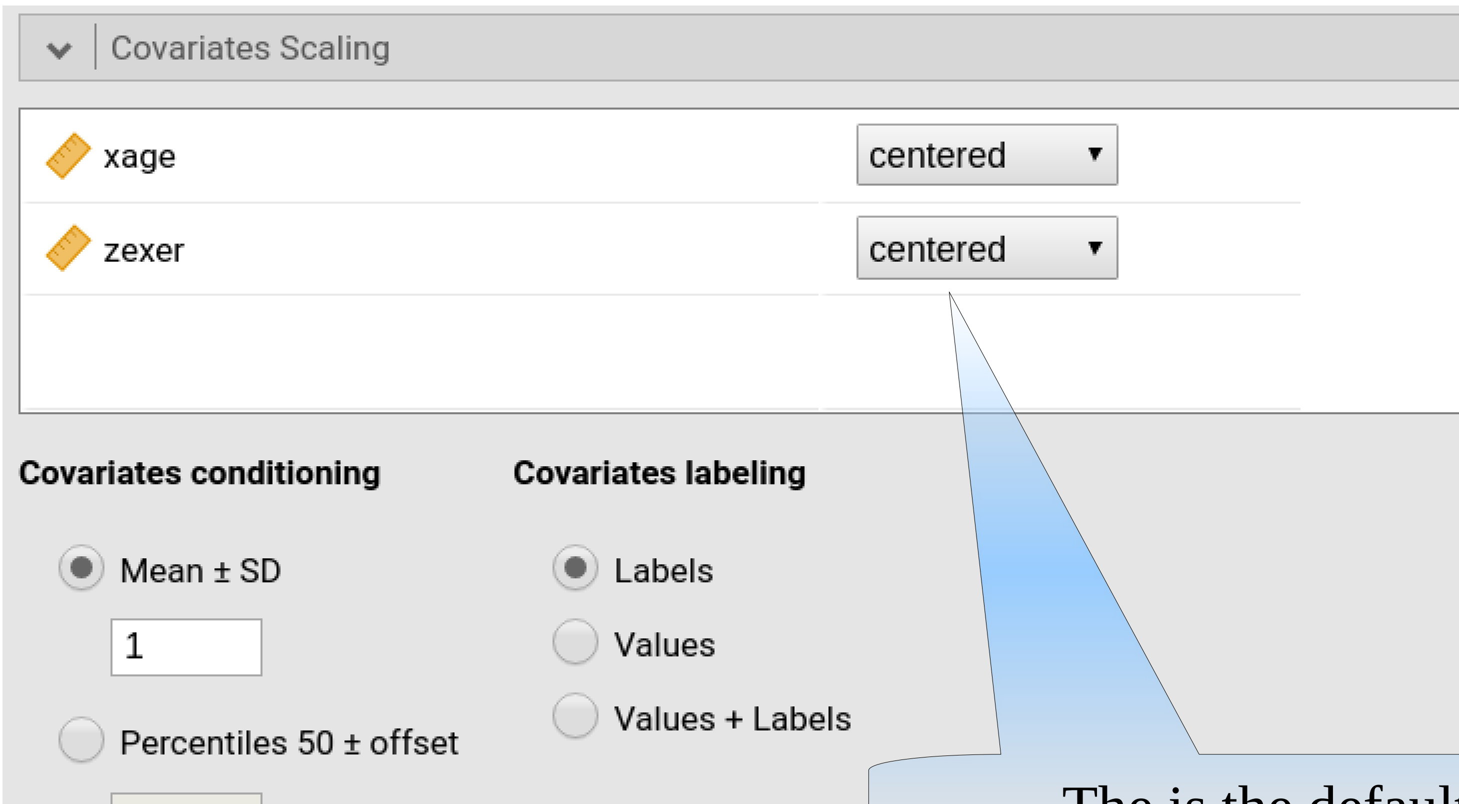
xage ✻ zexer	xage ✻ zexer	0.0472	0.0136	0.0205	0.0740	0.211	241	3.48	< .001

What about the first-order effects?

jamovi: Estimating Interactions

- The reason jamovi GAMLh gives correct results is because **jamovi by default centers** the variables in the model



The is the default

jamovi: Estimating Interactions

- As for the others GLM models, we can look at the coefficients (estimates)

Fixed Effects Parameter Estimates

Names	Effect	Estimate	SE	95% Confidence Interval Lower	95% Confidence Interval Upper	β	df	t	p
(Intercept)	(Intercept)	25.8887	0.6466	24.6150	27.1625	0.000	241	40.04	< .001
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zexer	zexer	0.9727	0.1365	0.7038	1.2417	0.429	241	7.12	< .001
xage ✻ zexer	xage ✻ zexer	0.0472	0.0136	0.0205	0.0740	0.211	241	3.48	< .001

The effect of age for average years of exercise

jamovi: Estimating Interactions

- As for the others GLM models, we can look at the coefficients (estimates)

Fixed Effects Parameter Estimates

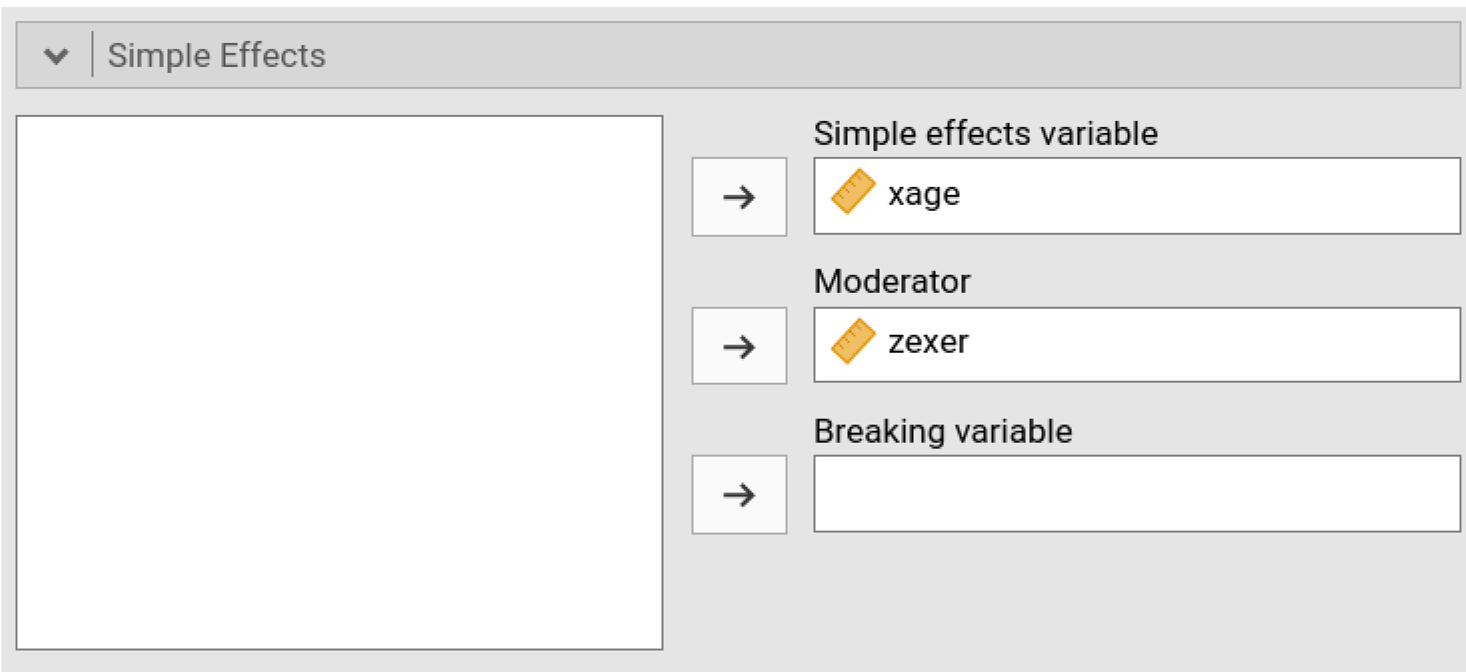
				95% Confidence Interval					
Names	Effect	Estimate	SE	Lower	Upper	β	df	t	p
(Intercept)	(Intercept)	25.8887	0.6466	24.6150	27.1625	0.000	241	40.04	< .001
xage	xage	−0.2617	0.0641	−0.3879	−0.1355	−0.244	241	−4.08	< .001
zexer	zexer	0.9727	0.1365	0.7038	1.2417	0.429	241	7.12	< .001
xage ✻ zexer	xage ✻ zexer	0.0472	0.0136	0.0205	0.0740	0.211	241	3.48	< .001

The effect of exercise for average age

jamovi simple slopes

- jamovi GAMLj provides a simple interface for simple effects (slopes) tests and graphs

Simple effects setup



jamovi simple slopes

- jamovi GAMLj provides a simple interface for simple effects (slopes) tests and graphs

Simple Effects

Variances

Simple effects of xage : Omnibus Tests

Moderator levels zexer	F	Num df	Den df	p
Mean-1·SD=-4.775	27.972	1.00	241	< .001
Mean=0	16.686	1.00	241	< .001
Mean+1·SD=4.775	0.160	1.00	241	0.690

Coefficients

Simple effects of xage : Parameter estimates

Moderator levels			95% Confidence Interval			
zexer	Estimate	SE	Lower	Upper	t	p
Mean-1·SD=-4.775	−0.4873	0.0921	−0.669	−0.306	−5.289	< .001
Mean=0	−0.2617	0.0641	−0.388	−0.135	−4.085	< .001
Mean+1·SD=4.775	−0.0361	0.0903	−0.214	0.142	−0.400	0.690

jamovi simple slope

- jamovi GAMLj provides a simple interface for simple effects (slopes) tests and graphs

Coefficients

Simple effects of xage : Parameter estimates

Moderator levels			95% Confidence Interval			
zexer	Estimate	SE	Lower	Upper	t	p
Mean-1·SD=-4.775	−0.4873	0.0921	−0.669	−0.306	-5.289	< .001
Mean=0	−0.2617	0.0641	−0.388	−0.135	-4.085	< .001
Mean+1·SD=4.775	−0.0361	0.0903	−0.214	0.142	-0.400	0.690

Those are the effects of age computed at different levels of exercising

jamovi simple slope

- jamovi GAMLj: one can use the standardized variables as well

Simple effects setup

jamovi simple slope

- jamovi GAMLj: one can use the standardized variables as well

Simple effects

Simple Effects ANOVA

Simple effects of xage

Effect	Moderator Levels	Sum of Squares	df	F	p
xage	zexer at -1	22.483	1	27.972	< .001
xage	zexer at 0	13.411	1	16.686	< .001
xage	zexer at 1	0.128	1	0.160	0.690

Simple Effects Parameters

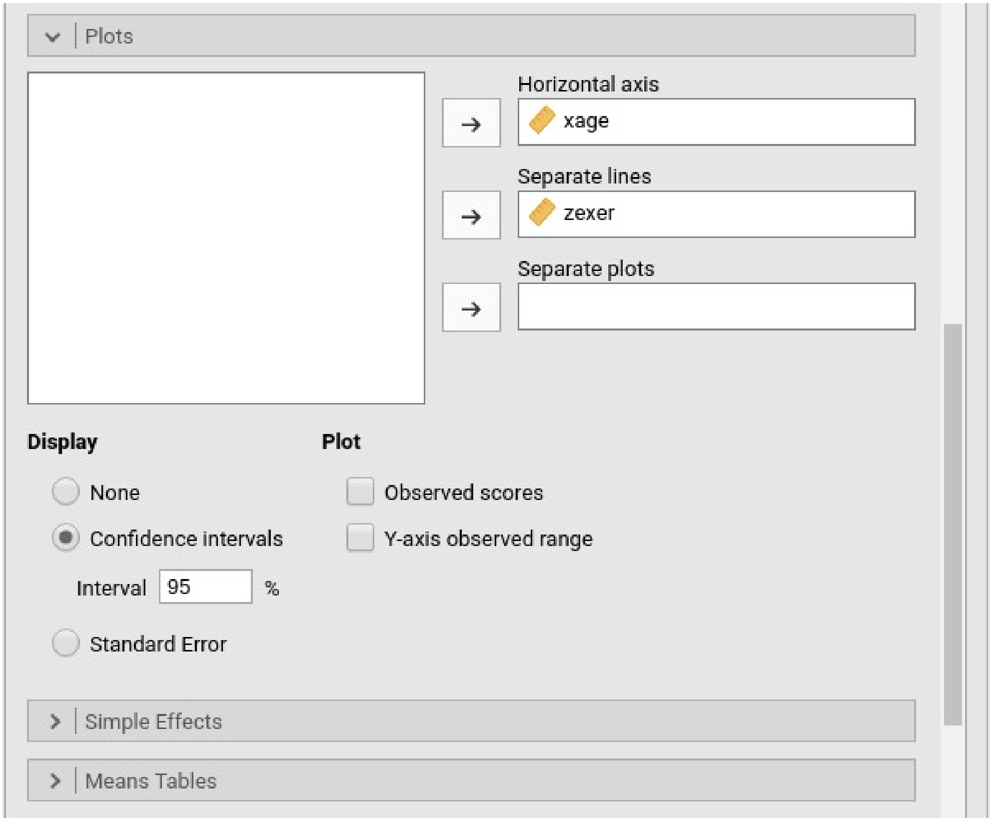
Simple effects of xage

Effect	Moderator Levels	Estimate	SE	t	p
xage	zexer at -1	−0.4552	0.0861	−5.289	< .001
xage	zexer at 0	−0.2445	0.0598	−4.085	< .001
xage	zexer at 1	−0.0337	0.0843	−0.400	0.690

Simple slopes plot

- jamovi GAMLj provides a simple interface for simple effects (slopes) tests and graphs

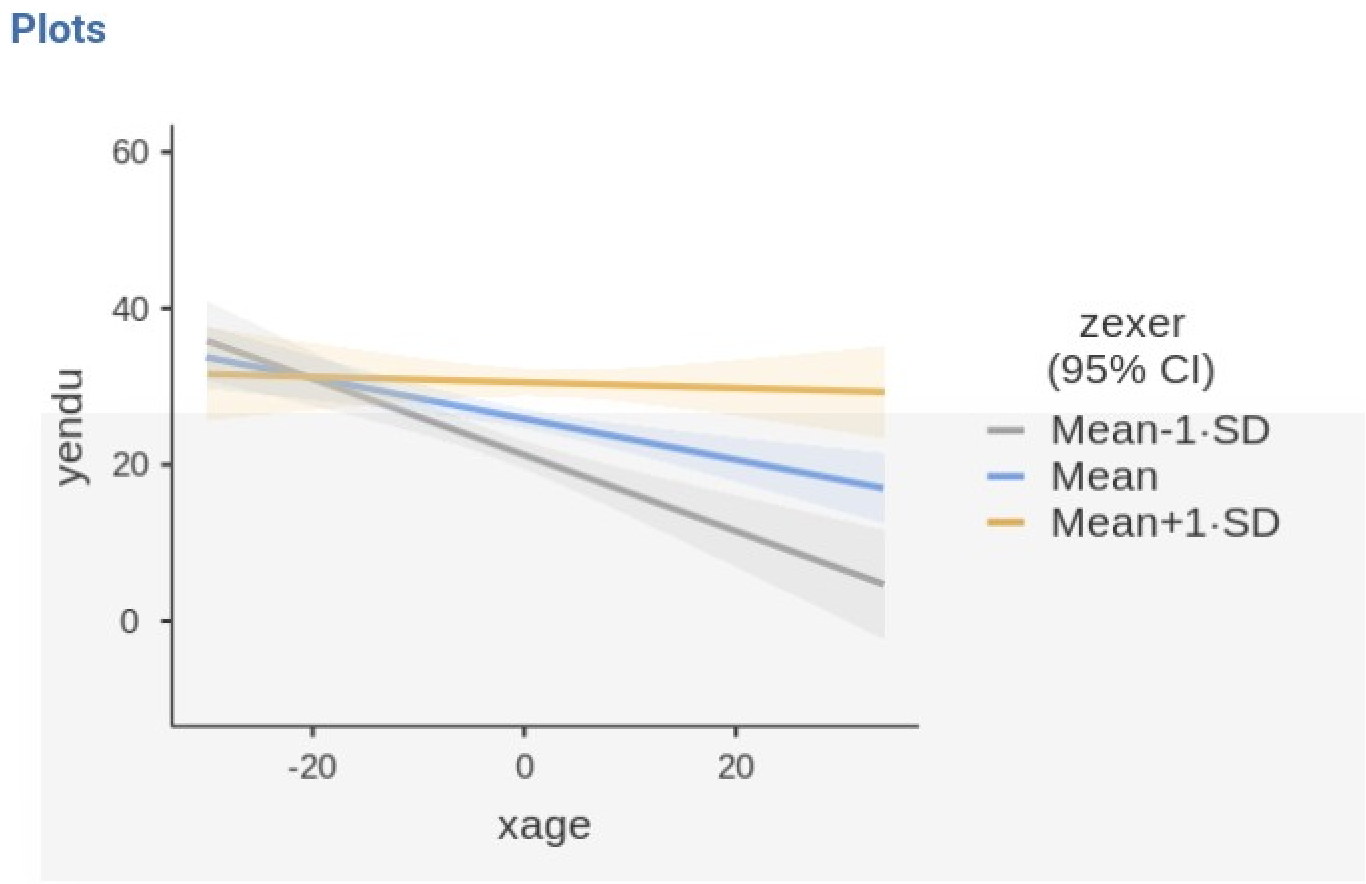
Simple effects graph



Simple slopes plot

- jamovi GAMLj provides a simple interface for simple effects (slopes) tests and graphs

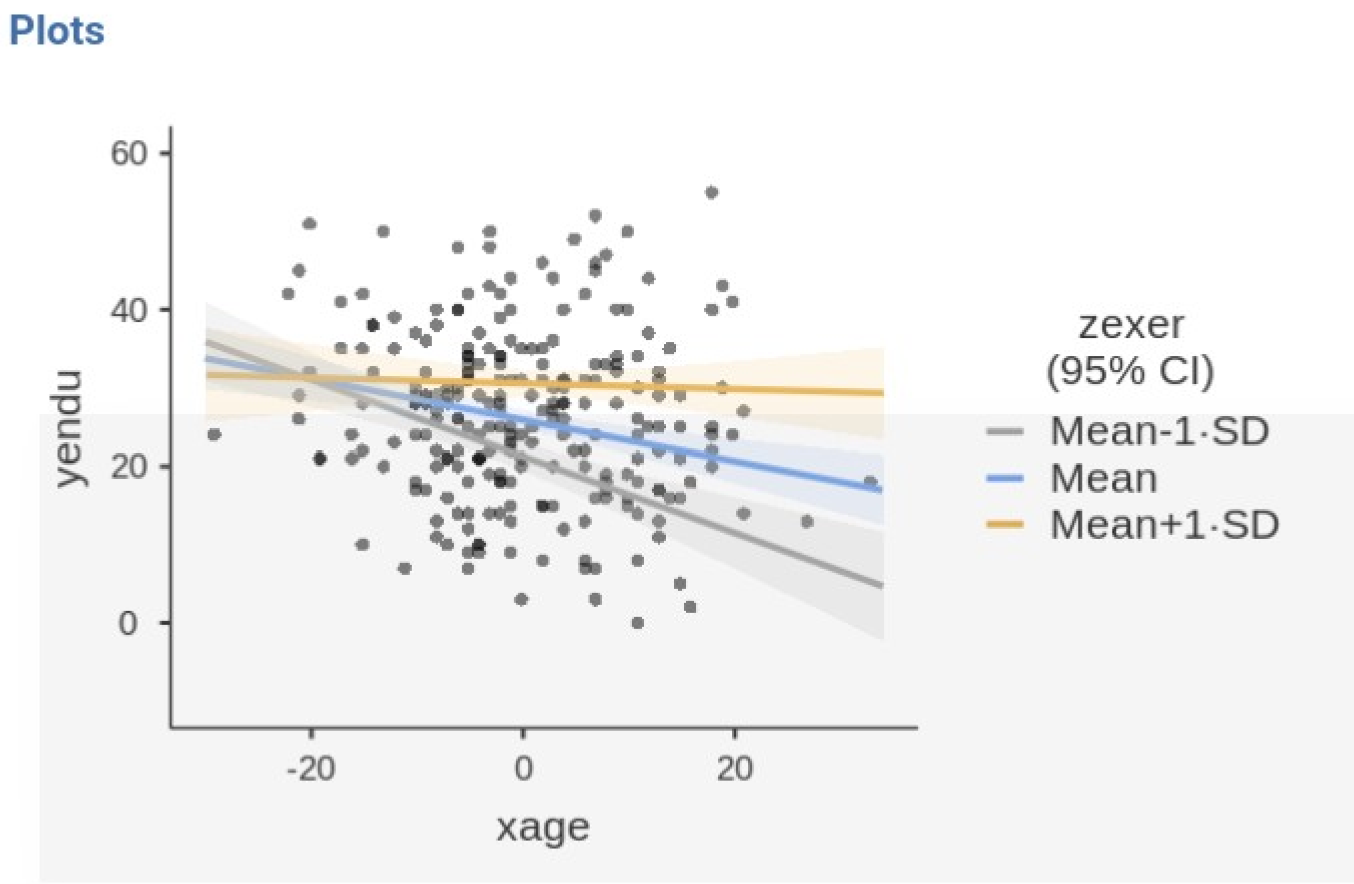
Simple effects graph



Simple slopes plot

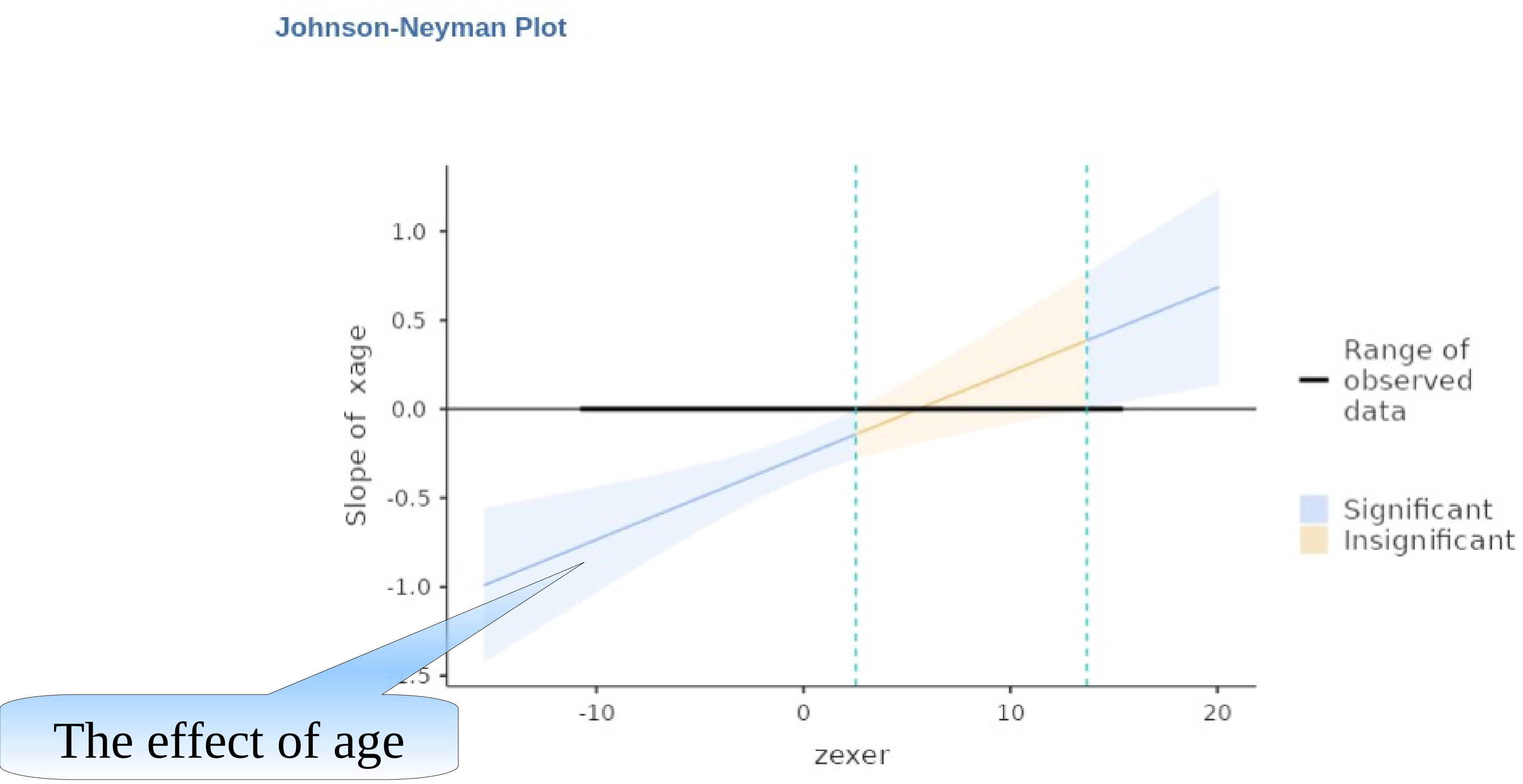
- jamovi GAMLj provides a simple interface for simple effects (slopes) tests and graphs

Simple effects graph with actual data



Johnson-Newman Plot

- The JN plot shows for which levels of the moderator the effect of the IV is significant



Interactions with Categorical IVs

jamovi factorial ANOVA

- Everything simplifies for categorical IV!

- Consider a design were people evaluated a stimulus (on some property) featuring Gender (male vs female) and nationality (French, German, Italian)

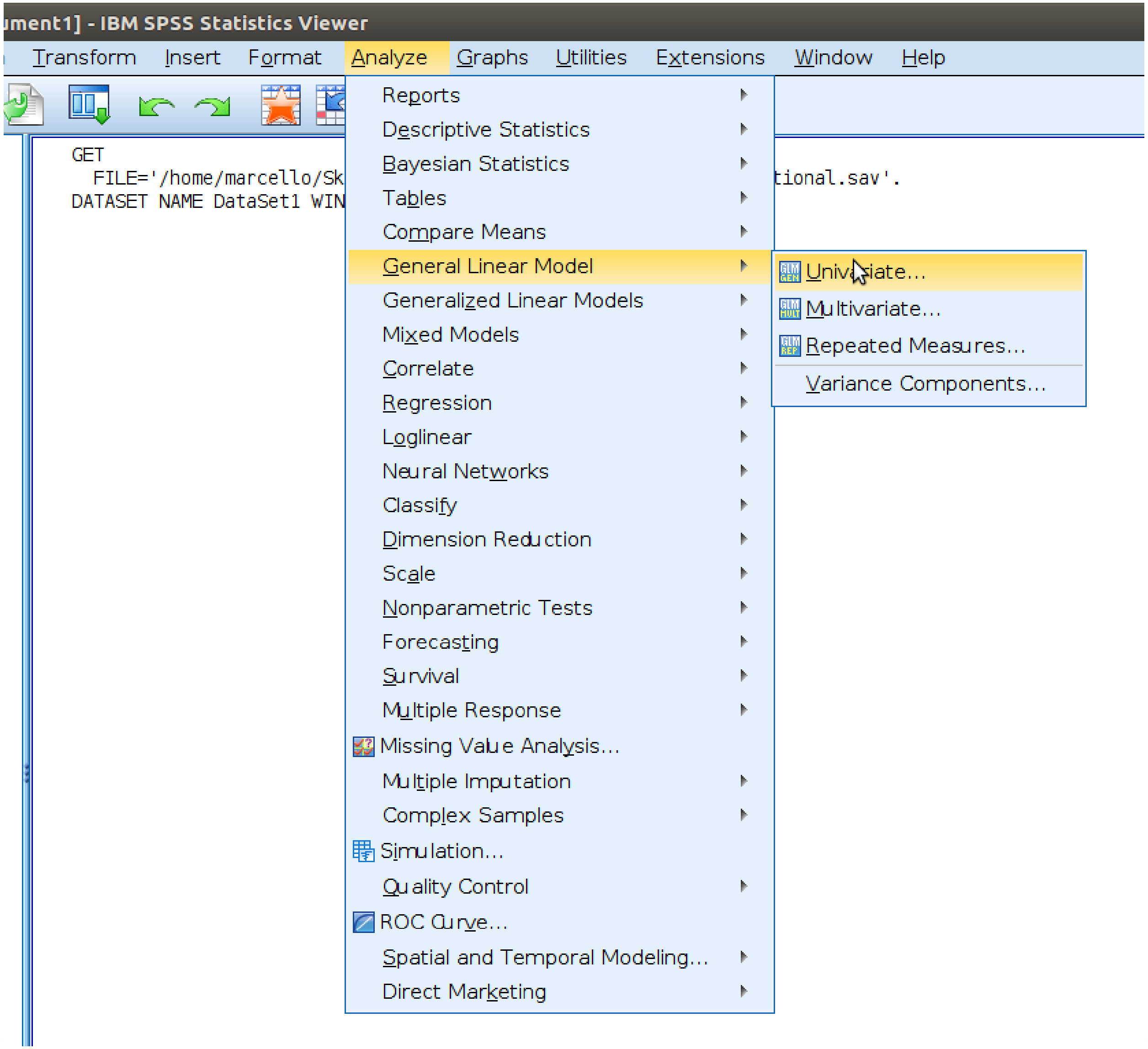
- *We have a factorial design: 3 (Nation) X 2 (Gender)*

gender * nation Crosstabulation

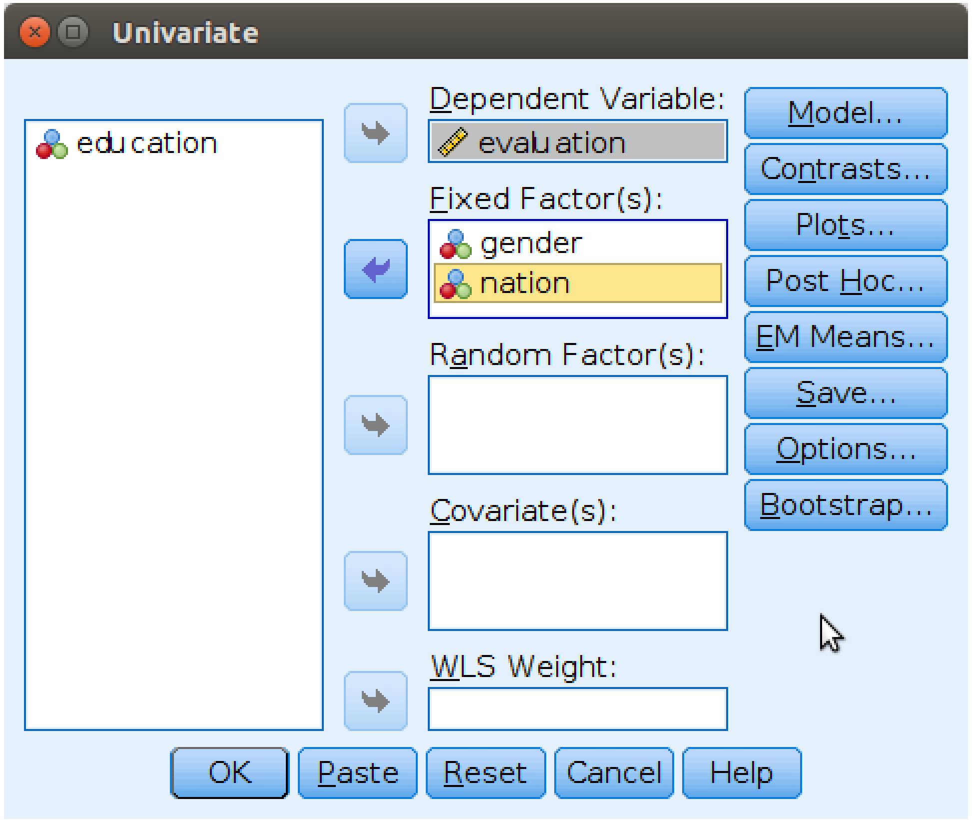
Count

		nation			Total
		France	Germany	Italy	
gender	Men	24	24	24	72
	Women	24	24	24	72
Total		48	48	48	144

Let’s do it: SPSS



Let’s do it: SPSS



Overall effects and significance

- The test for significance is done with the F-test

Tests of Between-Subjects Effects

First-order (main) effects

Variance uniquely explained

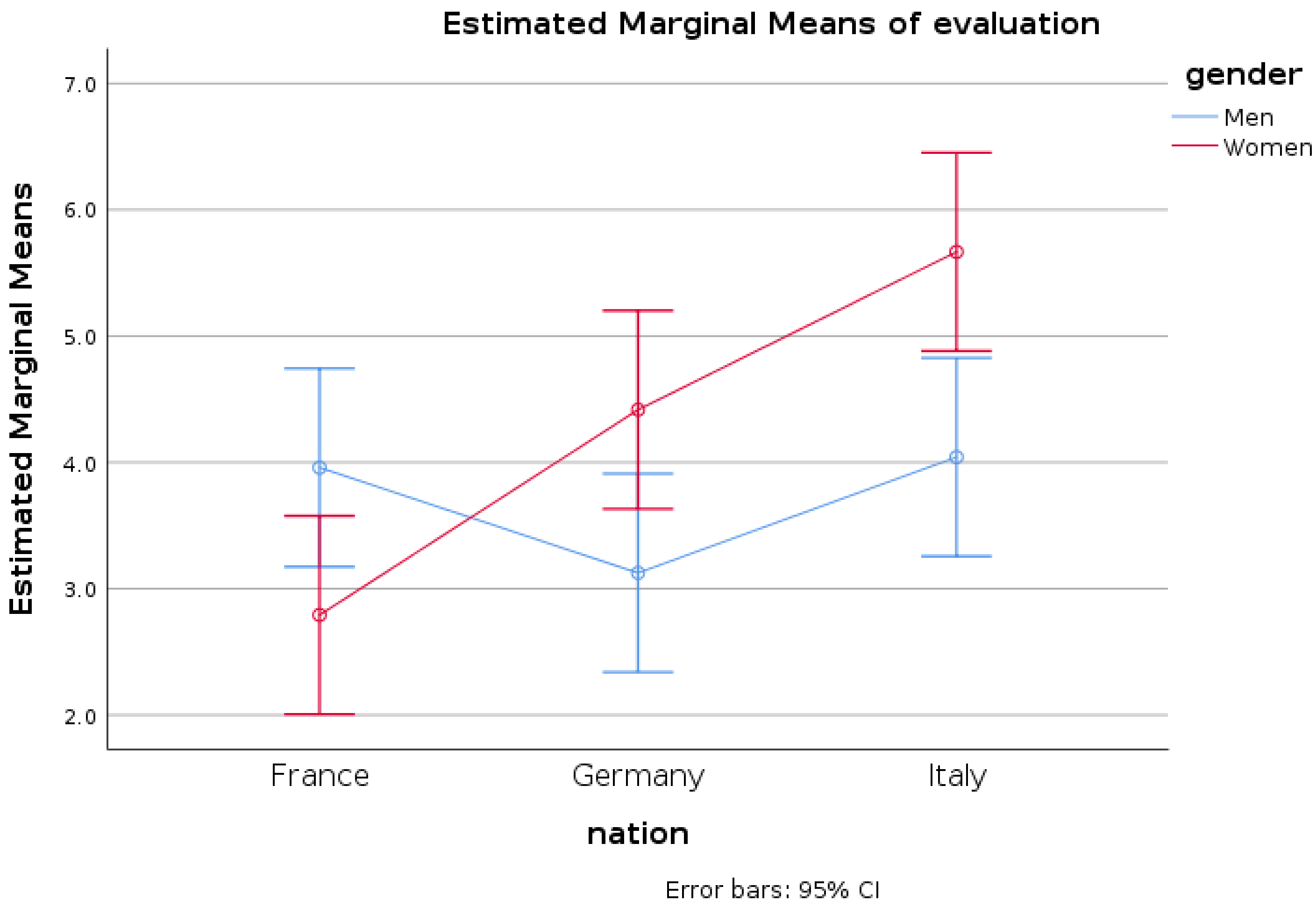
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	124.333[a]	5	24.867	6.566	.000	.192
Intercept	2304.000	1	2304.000	608.327	.000	.815
gender	12.250	1	12.250	3.234	.074	.023
nation	56.292	2	28.146	7.431	.001	.097
gender * nation	55.792	2	27.896	7.365	.001	.096
Error	522.667	138	3.787			
Total	2951.000	144				
Corrected Total	647.000	143				

a. R Squared = .192 (Adjusted R Squared = .163)

R^2

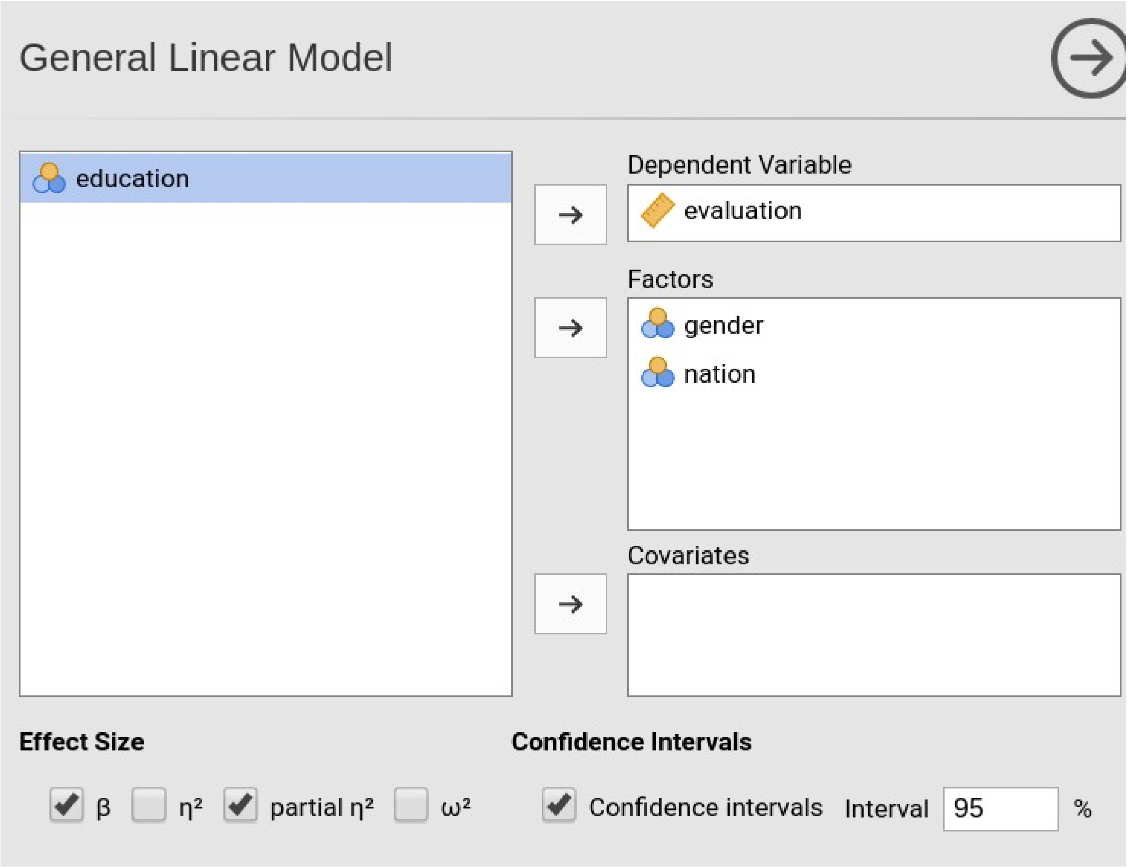
Interaction

Looking at the interaction



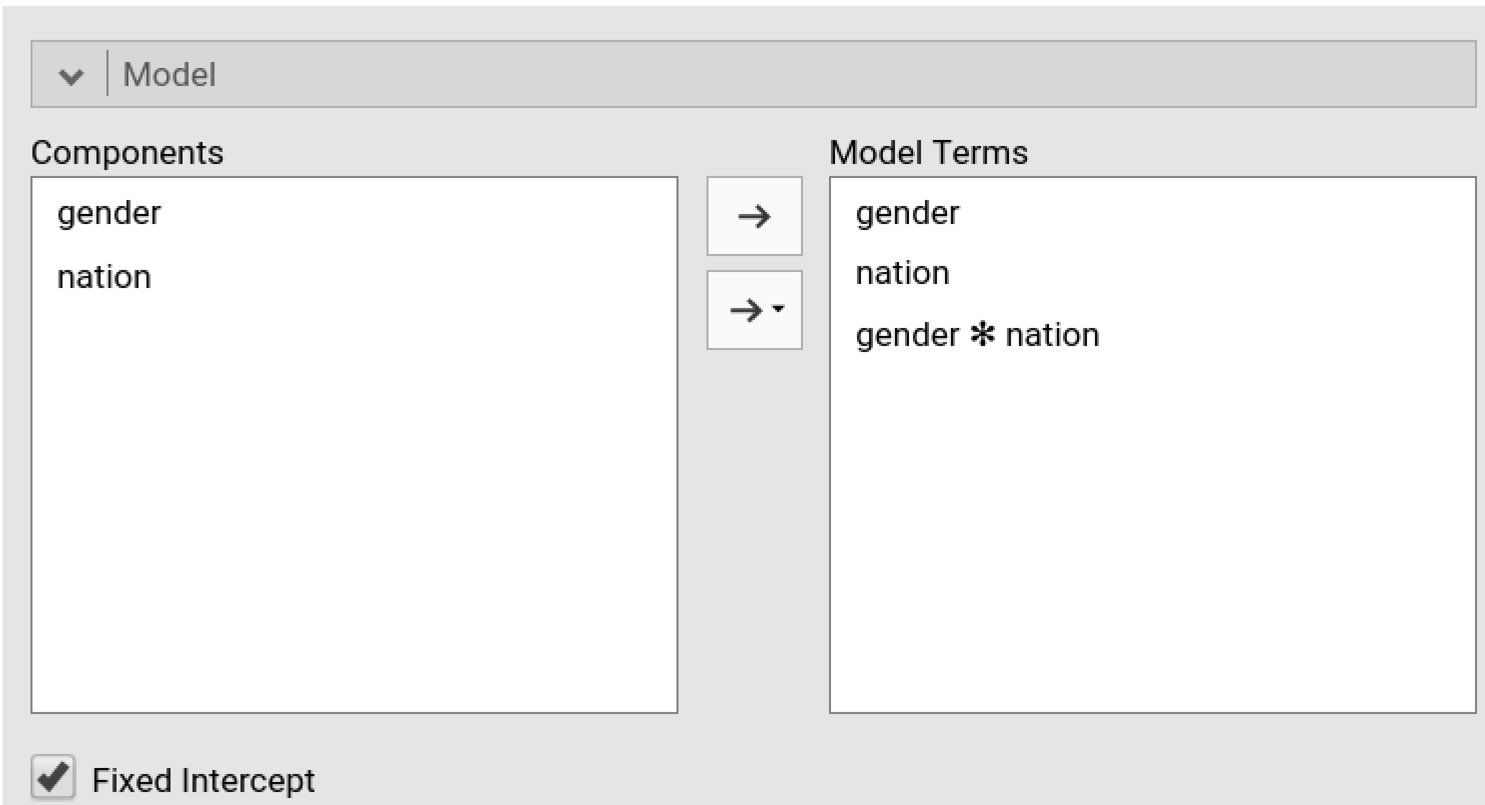
jamovi

- We can use GAMLj in jamovi



jamovi

- We do not need to change the “model” panel. With factors the interaction is included by default



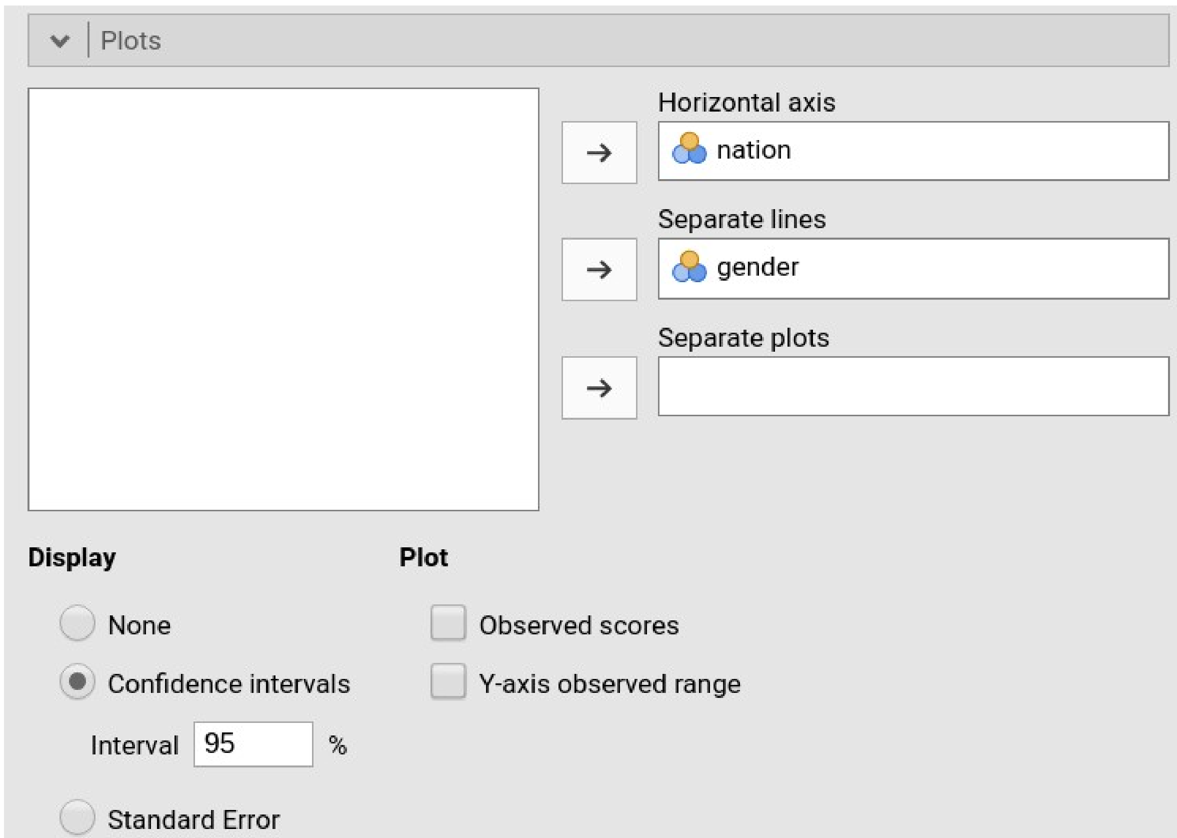
Interpretation: Interaction

- We have a main effect of nation and an interaction of nation and gender

ANOVA Omnibus tests

	SS	df	F	p	η^2p
Model	124.3	5	6.57	< .001	0.192
gender	12.3	1	3.23	0.074	0.023
nation	56.3	2	7.43	< .001	0.097
gender ✻ nation	55.8	2	7.37	< .001	0.096
Residuals	522.7	138			

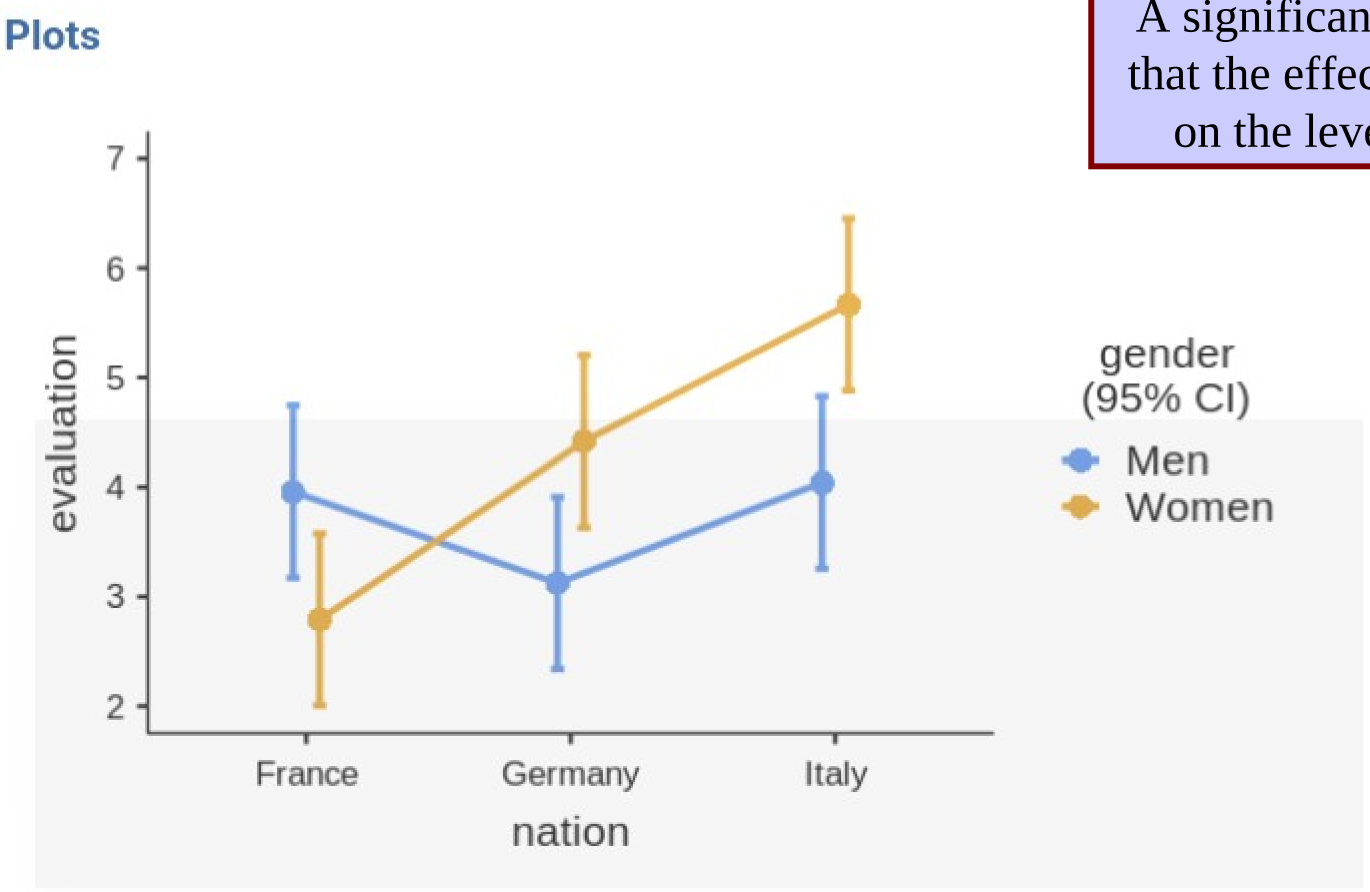
Interpretation: plot



Example: Looking at the interaction

- In the cross-national example: Is the effect of gender the same in each country?

A significant interaction tells us that the effects of one IV depend on the levels of the other IV

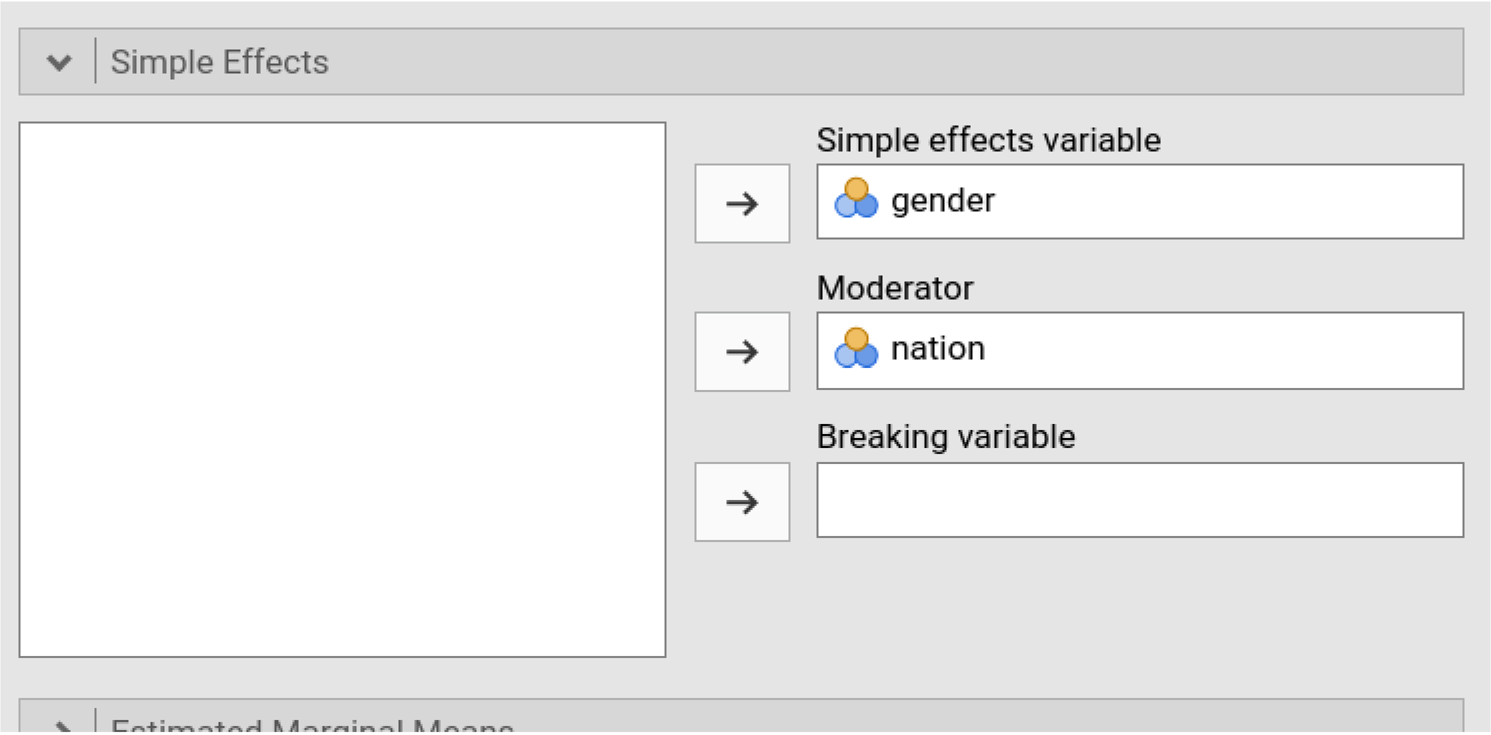


Factorial designs

- Estimate GLM with factors as independent variables
- Look at the variances (ANOVA) main effects and interactions
- Look at the graphs of means and interpret the interaction
- Probe effects:
  - Simple effects (like simple slopes)
  - Post-hoc tests

Simple effects

- Simple effects are exactly like simple slopes: the effect of one variable is tested at each level of the other variable (the moderator)



Simple effects

- Simple effects are exactly like simple slopes: the effect of one variable is tested at each level of the other variable (the moderator)

Simple Effects

variances

Simple effects of gender : Omnibus Tests

Moderator levels				
nation	F	Num df	Den df	p
France	4.31	1.00	138	0.040
Germany	5.29	1.00	138	0.023
Italy	8.37	1.00	138	0.004

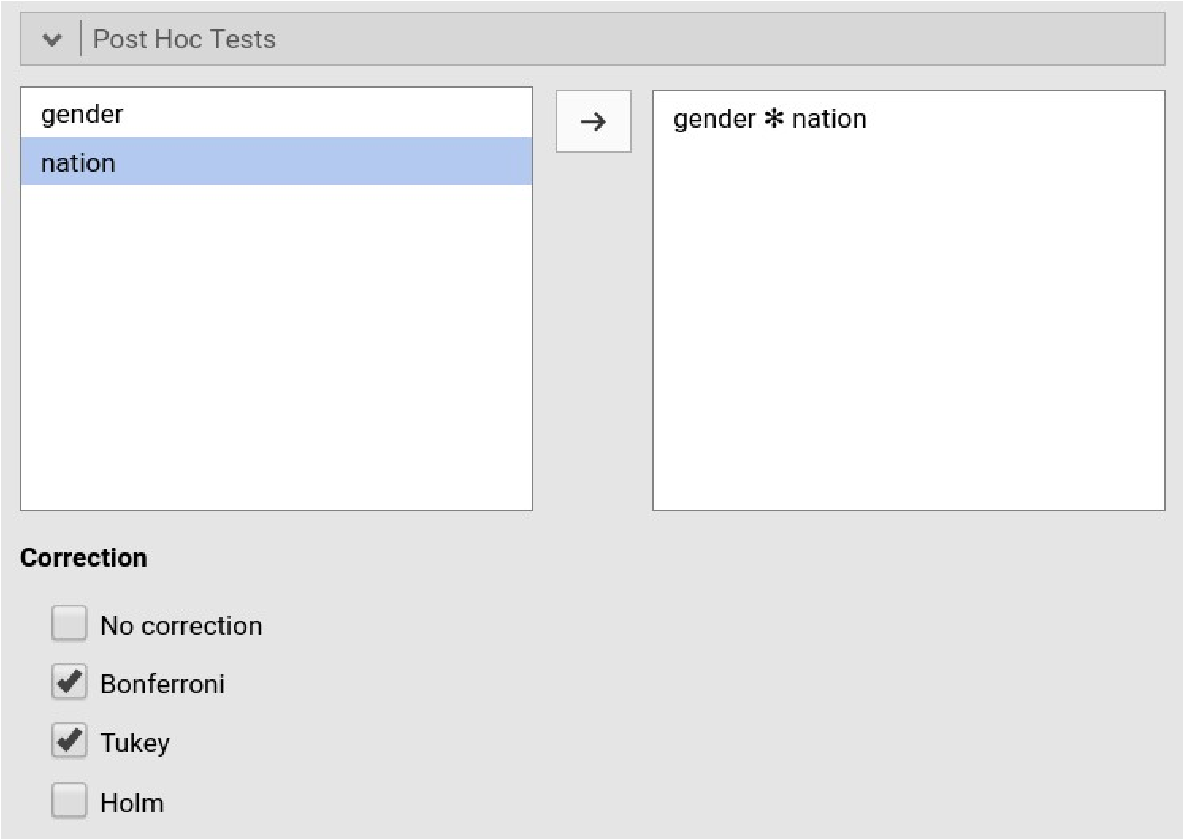
coefficients

Simple effects of gender : Parameter estimates

Moderator levels				95% Confidence Interval			
nation	contrast	Estimate	SE	Lower	Upper	t	p
France	Women - Men	−1.17	0.562	−2.278	−0.0558	−2.08	0.040
Germany	Women - Men	1.29	0.562	0.181	2.4025	2.30	0.023
Italy	Women - Men	1.62	0.562	0.514	2.7359	2.89	0.004

Post-hoc tests

- Post-hoc tests compare each group mean against any other group mean and adjust the p-value to keep the Type I error to a reasonable level



Post-hoc tests

- Post-hoc tests compare each group mean against any other group mean and adjust the p-value to keep the Type I error to a reasonable level

Post Hoc Tests

Post Hoc Comparisons - gender ✻ nation

Comparison										
gender	nation		gender	nation	Difference	SE	test	df	$p_{bonferroni}$	p_{tukey}
Men	Germany	-	Men	Italy	−0.9167	0.562	−1.632	138	1.000	0.579
Men	Germany	-	Women	Germany	−1.2917	0.562	−2.299	138	0.345	0.201
Men	Germany	-	Women	Italy	−2.5417	0.562	−4.524	138	< .001	< .001
Men	France	-	Men	Germany	0.8333	0.562	1.483	138	1.000	0.675
Men	France	-	Men	Italy	−0.0833	0.562	−0.148	138	1.000	1.000
Men	France	-	Women	Germany	−0.4583	0.562	−0.816	138	1.000	0.964
Men	France	-	Women	France	1.1667	0.562	2.077	138	0.595	0.306
Men	France	-	Women	Italy	−1.7083	0.562	−3.041	138	0.042	0.033
Men	Italy	-	Women	Italy	−1.6250	0.562	−2.892	138	0.067	0.050
Women	Germany	-	Men	Italy	0.3750	0.562	0.667	138	1.000	0.985
Women	Germany	-	Women	Italy	−1.2500	0.562	−2.225	138	0.416	0.233
Women	France	-	Men	Germany	−0.3333	0.562	−0.593	138	1.000	0.991
Women	France	-	Men	Italy	−1.2500	0.562	−2.225	138	0.416	0.233
Women	France	-	Women	Germany	−1.6250	0.562	−2.892	138	0.067	0.050
Women	France	-	Women	Italy	−2.8750	0.562	−5.117	138	< .001	< .001

Thank you for your attention!