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- 03/08/2020

Module Title: Introduction to Statistics

Session Title: Simple Linear Regression

Topic title: Correlation and Linear Regression

Learning Outcomes

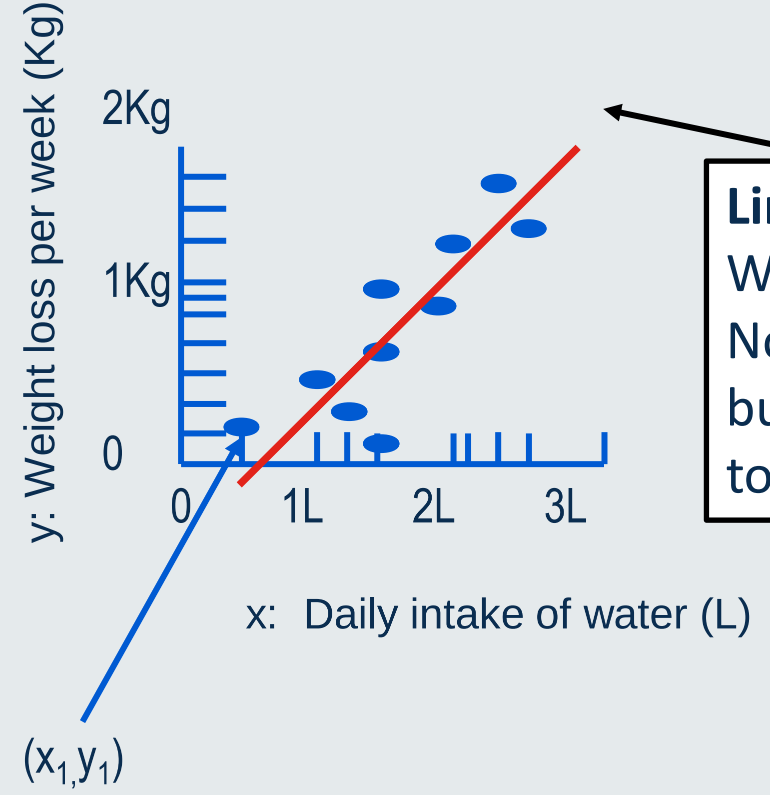
- Understand the difference between an **independent** and **dependent** variable
- Understand the **parameters** of simple linear regression (SLR)
- Interpret the **intercept** and **slope** parameters from a regression equation
- Use the simple linear regression (SLR) parameters to predict future observations
- Understand how to introduce a dummy categorical variable

Previously on ‘Introduction to Statistics’

10 people were studied for the Hypothesis ‘The higher the intake of water, the higher the weight loss’.

- Plotting the data is essential to understand and visually assess the relationship between pairs of continuous variables
- The plot of data points (x,y) with x and y being continuous is called a **scatterplot**

	x	y
(x_1, y_1)	0.5	0.10
(x_2, y_2)	1.0	0.30
(x_3, y_3)	1.2	0.40
	…	…



Linear relationship:
We can draw a line.
Not perfect fit,
but the line is “close”
to the points

Previously on ‘Introduction to Statistics’

We need an objective measure of strength of a linear relationship

Correlation is a statistical concept that refers to how close two variables are to having a linear relationship with each other, or in other words, the strength of their linear relationship. Correlation is a method to quantify the **Direction** and **Magnitude**, of linear association between two continuous variables.

Range of correlation coefficients	Degree of Correlation
0.80 to 1.00	Very strong positive
0.60 to 0.79	Strong positive
0.40 to 0.59	Moderate positive
0.20 to 0.39	Weak positive
0.00 to 0.19	Very weak positive - none
-0.19 to 0.00	Very weak negative - none
-0.39 to -0.20	Weak negative
-0.59 to -0.40	Moderate negative
-0.79 to -0.60	Strong negative
-1.00 to -0.80	Very strong negative

Direction of effect
The co-efficient is positive or negative

Magnitude of effect
The magnitude of the correlation coefficient ranges from -1 to 1, the close to ±1 the stronger the effect

There are two types of correlation coefficients

- Pearson's Correlation Coefficient (normally distributed data)
- Spearman's Correlation Coefficient (skewed or ordinal data)

Simple Linear Regression

In statistical modelling, a regression model is a set of statistical processes for estimating the relationships among variables. These models describe the relationship between variables by fitting a line to the observed data. The relationship is expressed as an equation.

In this session, we will focus on cases where there is a linear relationship between one continuous outcome and one predictor, for which the equation will look like:

$$\boldsymbol{y = \beta_0 + \beta_1 x + \varepsilon}$$

This model is known as the **simple linear regression model.**

Simple Linear Regression

$$y = \beta_0 + \beta_1 x + \varepsilon$$

- $\mathbf{x}$ is called the **independent variable, predictor, explanatory** or **covariate** (continuous or categorical)
- $\mathbf{y}$ is called the **dependent variable, outcome or response**. y **'depends on'** x (always continuous)
- The **intercept** $\boldsymbol{\beta_0}$ is the value that y takes when x is zero.
  - If the intercept is zero then y increases in proportion to x (i.e. double x then y doubles y=x)
- The **slope** $\boldsymbol{\beta_1}$ determines the change in y when x changes by one unit.
  - It is the amount that the dependent variable will increase (or decrease) for each unit increase in the independent variable
- $\boldsymbol{\varepsilon}$ is called the **residual** (distance between the points and the line).
- $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$ are together known as **regression coefficients.**

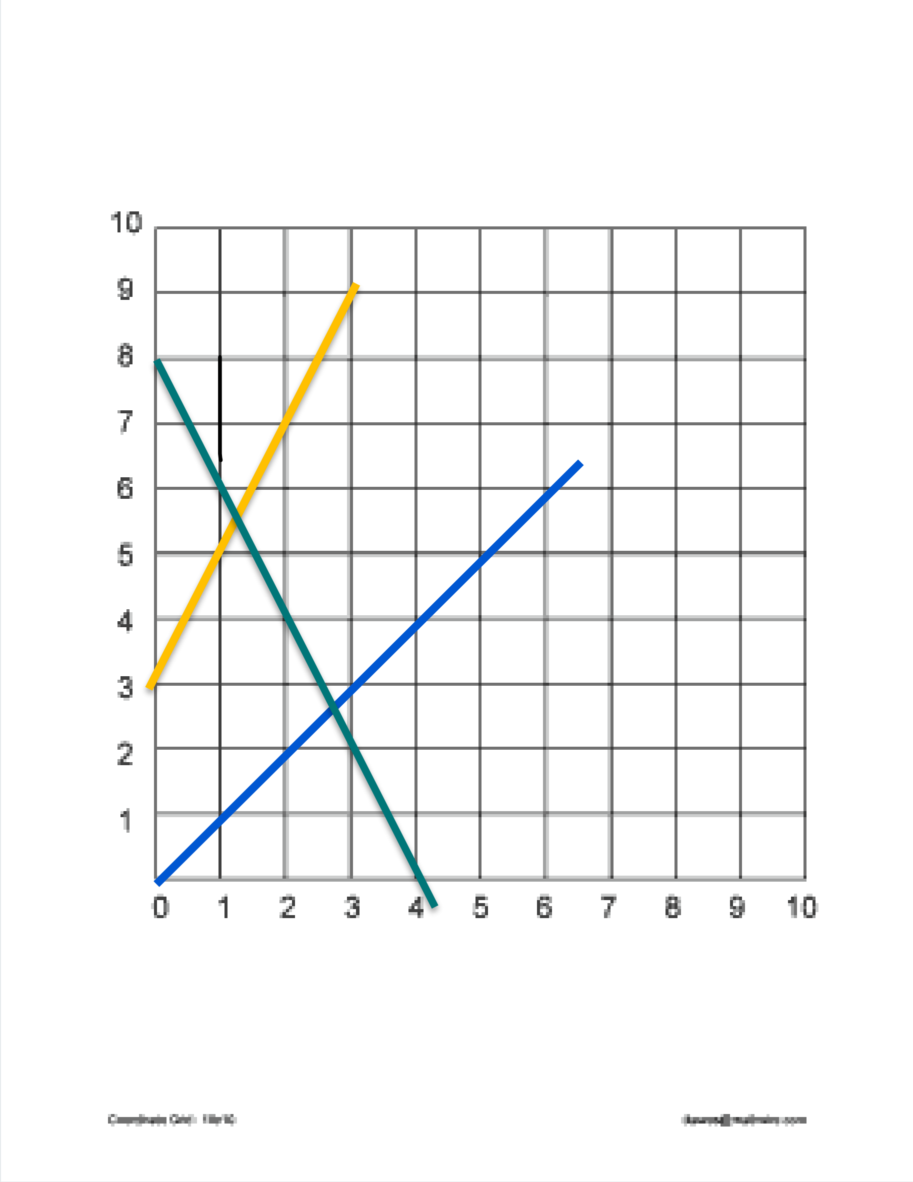
$y=\beta_0 + \beta_1 + \varepsilon$

x	y
1	1
2	2
3	3
…	…
7	7

$y = x$

x	y
0	3
1	5
2	7
…	…
7	17

$y = 3 + 2x$



x	y
0	8
1	6
2	4
…	…
7	-6

$y = 8 - 2x$

β_0 represents where the line intercepts the y axis.

β_1 represent the slope of the line as x increases by one unit how much does y increase or decrease

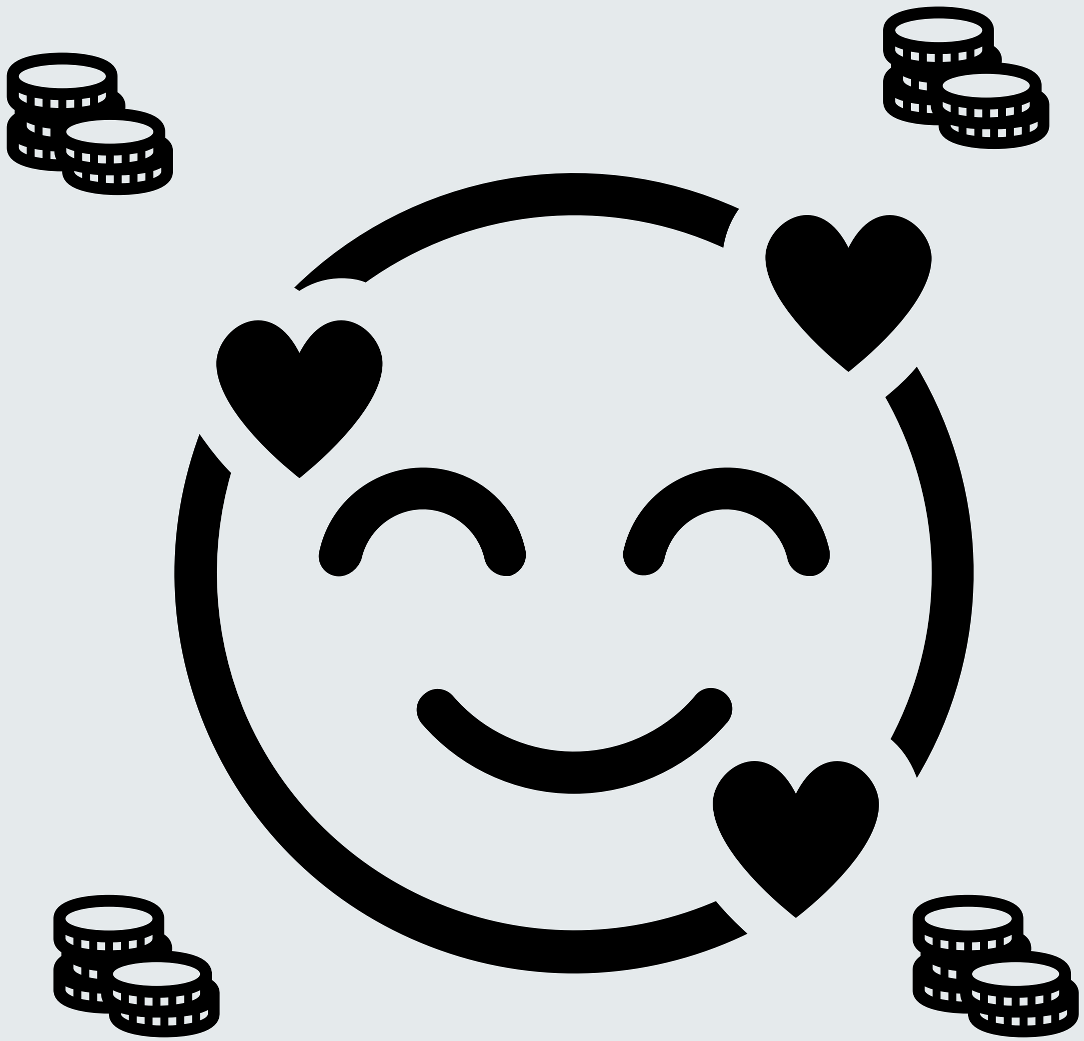
Example

You are a social researcher interested in the relationship between income and happiness. You survey 500 people whose incomes range from £15k to £75k and ask them to rank their happiness on a scale from 1 to 10.

Your independent variable (income) and dependent variable (happiness) are both quantitative, so you can do a regression analysis to see if there is a linear relationship between them.

We can ask

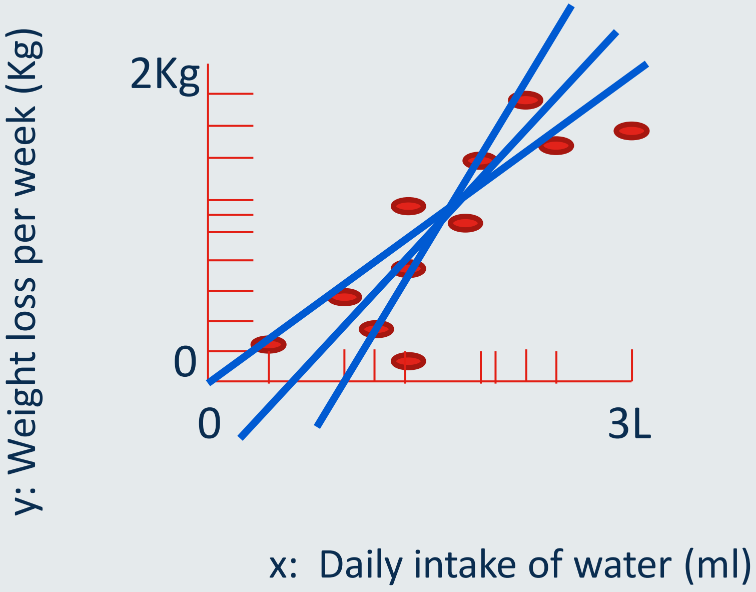
- How strong the relationship is between two variables (e.g. the relationship between income and happiness).
- The value of the dependent variable at a certain value of the independent variable (e.g. the amount of happiness at a certain level of income).



Estimation

Independent variable (x): Daily intake of water

Dependent variable (y): Weight loss per week



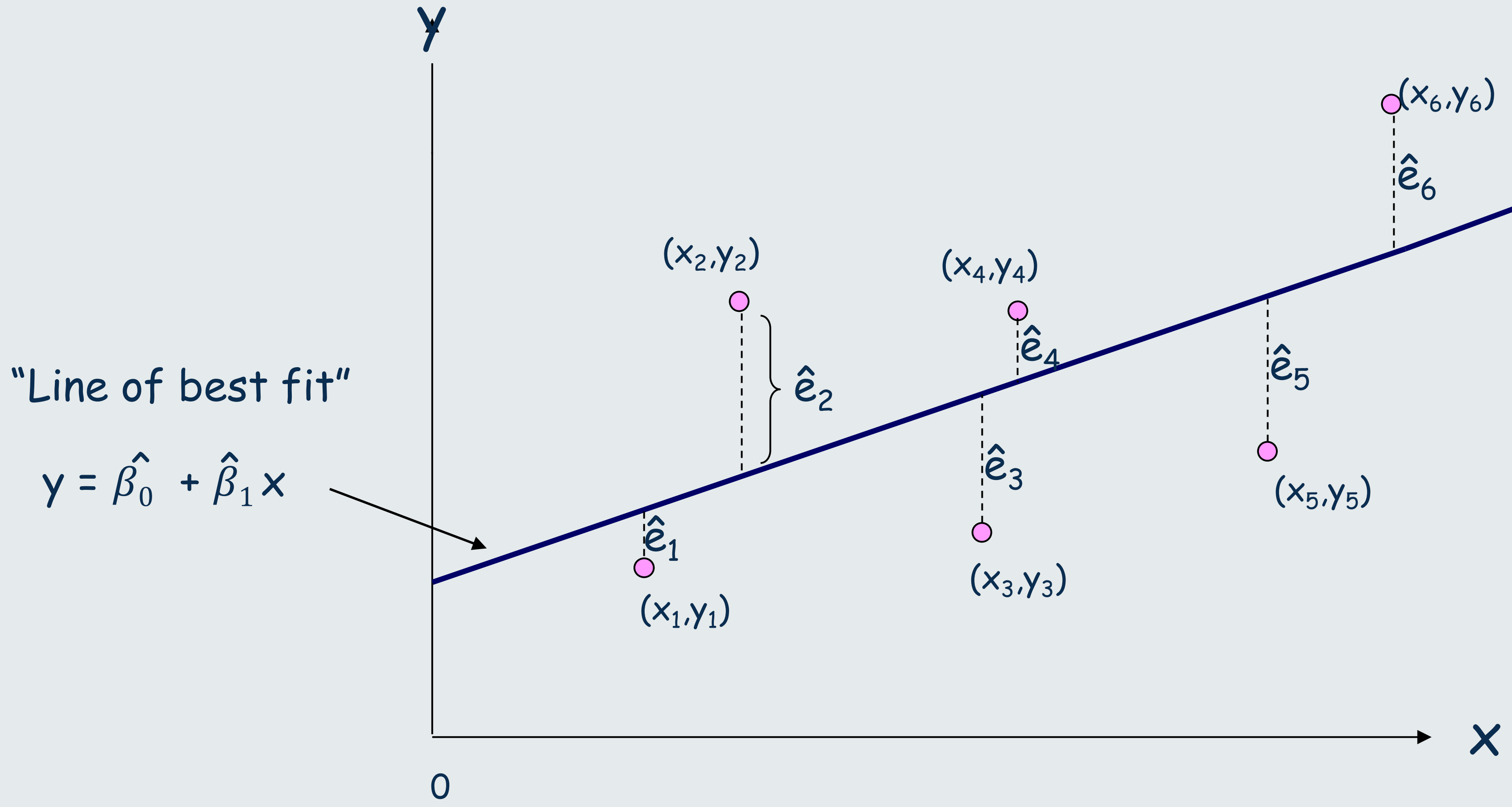
$$y = \beta_0 + \beta_1 x + \varepsilon$$

?

How can we find the best line fitting the cloud of points and therefore find the best estimates for $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_1}$?

Estimation

- The best **linear regression line** is the closest to all data points, i.e. the line that makes the **residual** ε as small as possible.
- **Ordinary Least Squares (OLS)** – Is one method that can be used to estimate the regression line that **minimises** the **squared residuals** ($\boldsymbol{\varepsilon_1^2 + \varepsilon_2^2 + \cdots \varepsilon_n^2}$) to give us the estimates for $\boldsymbol{\widehat{\beta_0}}$ and $\boldsymbol{\widehat{\beta_1}}$.



Simple Linear Regression Model

When to use it

- To measure to what extent there is a linear relationship between two variables

Hypotheses:

- H_0: There is no linear association e.g. the slope β_1 in the population equals to 0
- H_a: There is a linear association e.g. the slope β_1 in the population does not equal to 0

Assumptions:

- There is a linear relationship between the dependent and independent variable
- Residuals (or "errors") ε are independent of one another: the observations in the dataset were collected using statistically valid sampling methods, and there are no hidden relationships among observations
- Residuals follow a Normal distribution, with mean 0 and constant Standard Deviation σ
- Homogeneity of variance (homoscedasticity): the size of the error in our prediction doesn't change significantly across the values of the independent variable.

Formulae – for the curious

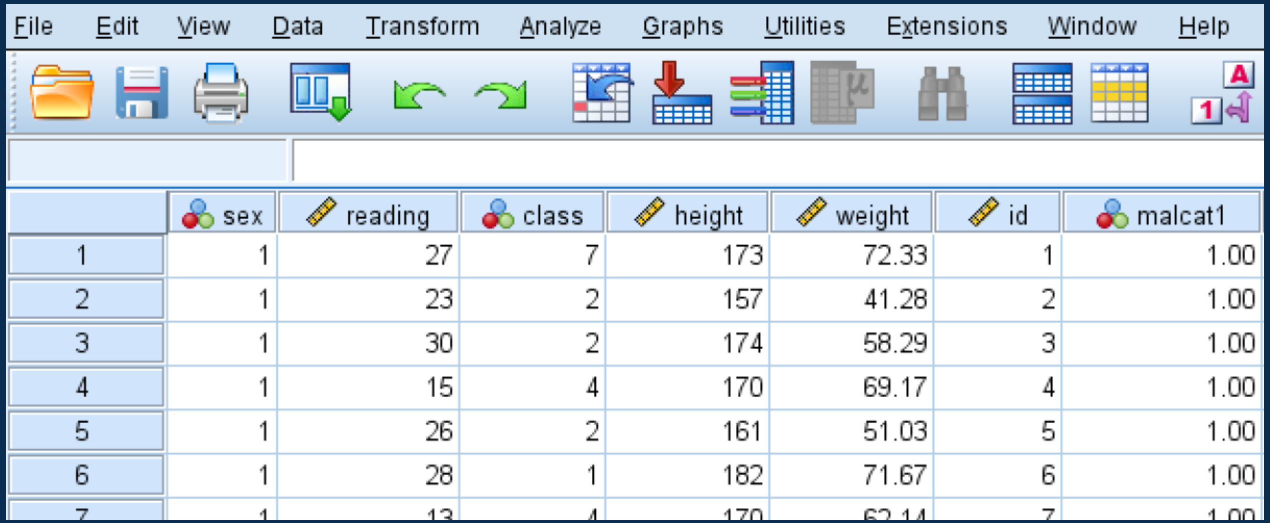
The slope is estimated as $$\widehat{\beta_1} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})\,(y_i - \bar{y})}{\sum_{i=1}^{n}(x_i - \bar{x})^2}.$$

The intercept is estimated as $$\widehat{\beta_0} = \bar{y} - \widehat{\beta_1}\bar{x}$$ $$\left(\ \bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i\ \right)$$

Test Statistic for the hypothesis test $$t = \frac{\widehat{\beta_1}}{\widehat{se}(\widehat{\beta_1})},\ \text{df=n-1}$$

SPSS Slide

Download the data that we are going to use during the lecture. The dataset is the **lecture_6a_data.sav**.


File Edit View Data Transform Analyze Graphs Utilities Extensions Window Help

	sex	reading	class	height	weight	id	malcat1
1	1	27	7	173	72.33	1	1.00
2	1	23	2	157	41.28	2	1.00
3	1	30	2	174	58.29	3	1.00
4	1	15	4	170	69.17	4	1.00
5	1	26	2	161	51.03	5	1.00
6	1	28	1	182	71.67	6	1.00

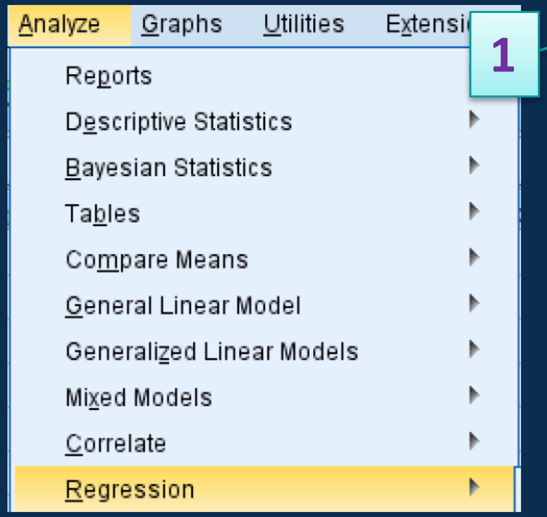
The dataset contains data from 1000 individuals, from the National Child Development Study (NCDS) with respect to their

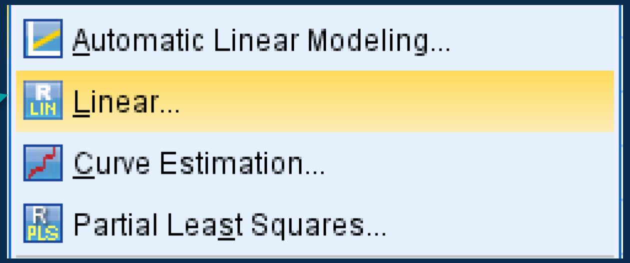
- **sex**: gender of child (1=male, 2=female)
- **height** : height in cm at age 16
- **weight**: weight in kg at age 16
- **reading**: reading score
- **malcat1**: incidence of malaise at 22 years (0=yes, 1 = No)

SPSS Slide: ‘how to’

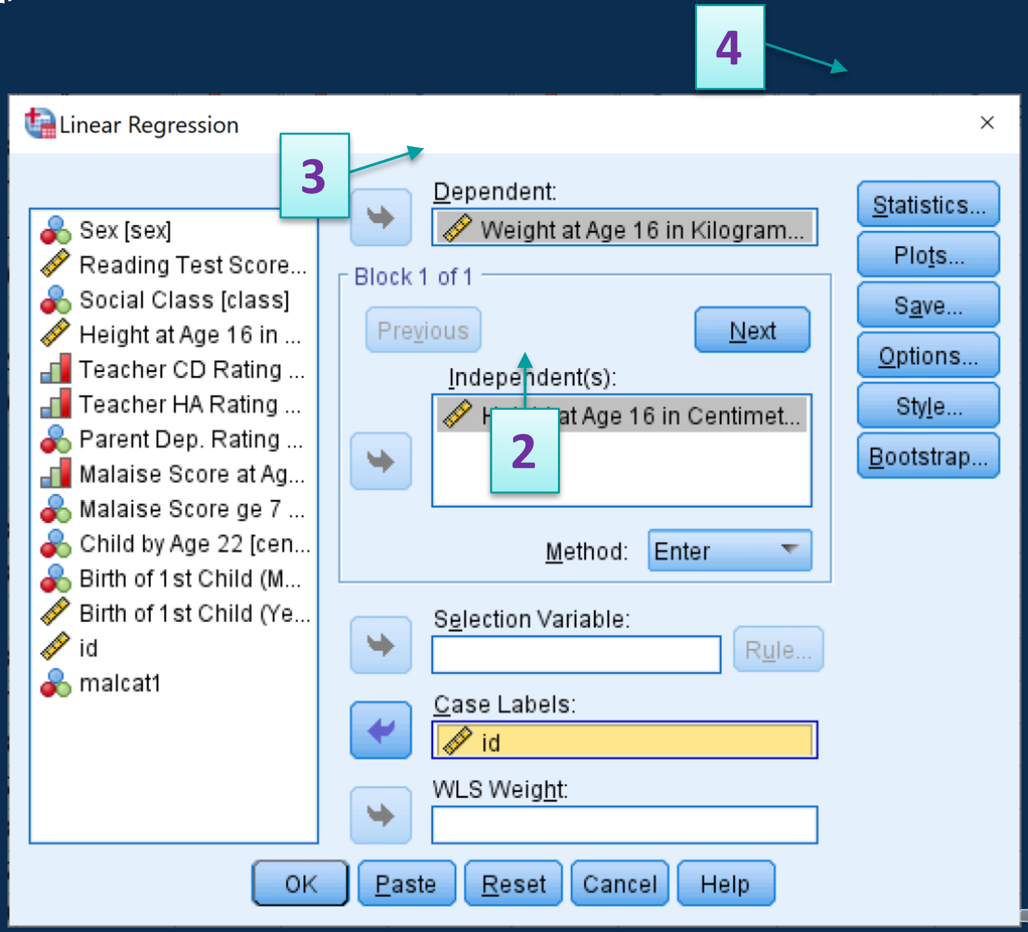
According to the researchers, in the population from which our data came, they believe there is a relationship between weight and height of the 16 year old children

Step 1: Compute a Linear regression model for dependent variable ‘weight’ and independent variable ‘height’ from NCDS data   Use ‘Analyse’ -> ‘Regression’ -> ‘Linear’





Add the two variables, weight in the ‘Dependent’ box and height into the into the ‘independent(s)’ box.
Click on ‘Statistics



SPSS Slide: ‘how to’

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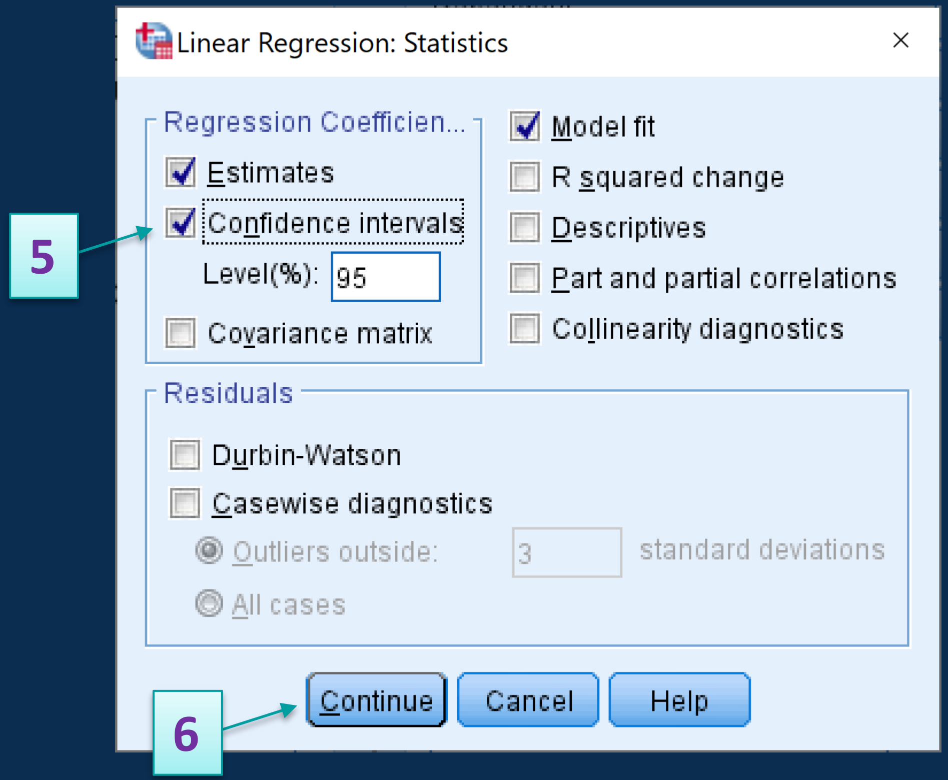
Step 1: Compute a Linear regression model for dependent variable ‘weight’ and independent variable ‘height’ from NCDS data



In the Statistics tab.
Check the ‘Estimates’
Check the ‘Confidence Intervals’
Click on ‘Continue’
Click on ‘OK’

Output and Interpretation Slide

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.520[a]	.270	.270	8.25311

a. Predictors: (Constant), Height at Age 16 in Centimeters

b. Dependent Variable: Weight at Age 16 in Kilograms

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	25172.852	1	25172.852	369.570	.000[b]
	Residual	67977.581	998	68.114		
	Total	93150.434	999			

a. Dependent Variable: Weight at Age 16 in Kilograms

b. Predictors: (Constant), Height at Age 16 in Centimeters

This table provides the R and R^2 values. The R value represents the simple correlation and is 0.520 which indicates a moderate degree of correlation.

The R^2 value indicates how much of the total variation in the dependent variable, weight, can be explained by the independent variable, height. In this case, 27.0% can be explained.

The ANOVA table, reports how well the regression equation fits the data (i.e., predicts the dependent variable). This table indicates that the regression model predicts the dependent variable significantly well ($p<0.001$).

This indicates the statistical significance of the regression model that was run and overall, the regression model statistically significantly predicts the outcome variable (i.e., it is a good fit for the data).

Output and Interpretation

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound
1	(Constant)	-46.764	5.413		-8.639	.000	-57.386	-36.142
	Height at Age 16 in Centimeters	.626	.033	.520	19.224	.000	.562	.689

a. Dependent Variable: Weight at Age 16 in Kilograms

$SE(\beta_1)$

β_0

β_1

The estimated slope coefficient (β_1), suggests a 1cm increase in height is associated with a 0.626kg increase in weight. The units of the slope is kg/cm.

The intercept (β_0), is the extrapolated weight for a 16 year old of zero height.

In addition to getting point estimation for β1, it is possible to calculate a confidence interval for the slope parameter
The confidence interval formula is:

$$95\%\ CI = [\beta 1 - 1.96 \text{x} SE(\beta 1), \beta 1 + 1.96\ \text{x} SE(\beta 1)]$$

E.g. for the NCDS data, a CI for $\beta 1$ can be derived as follows:
Lower limit: 0.626-1.96*0.033=0.562
Upper limit: 0.626+1.96*0.033=0.689
= [0.562, 0.689]

Output and Interpretation

Coefficients[a]

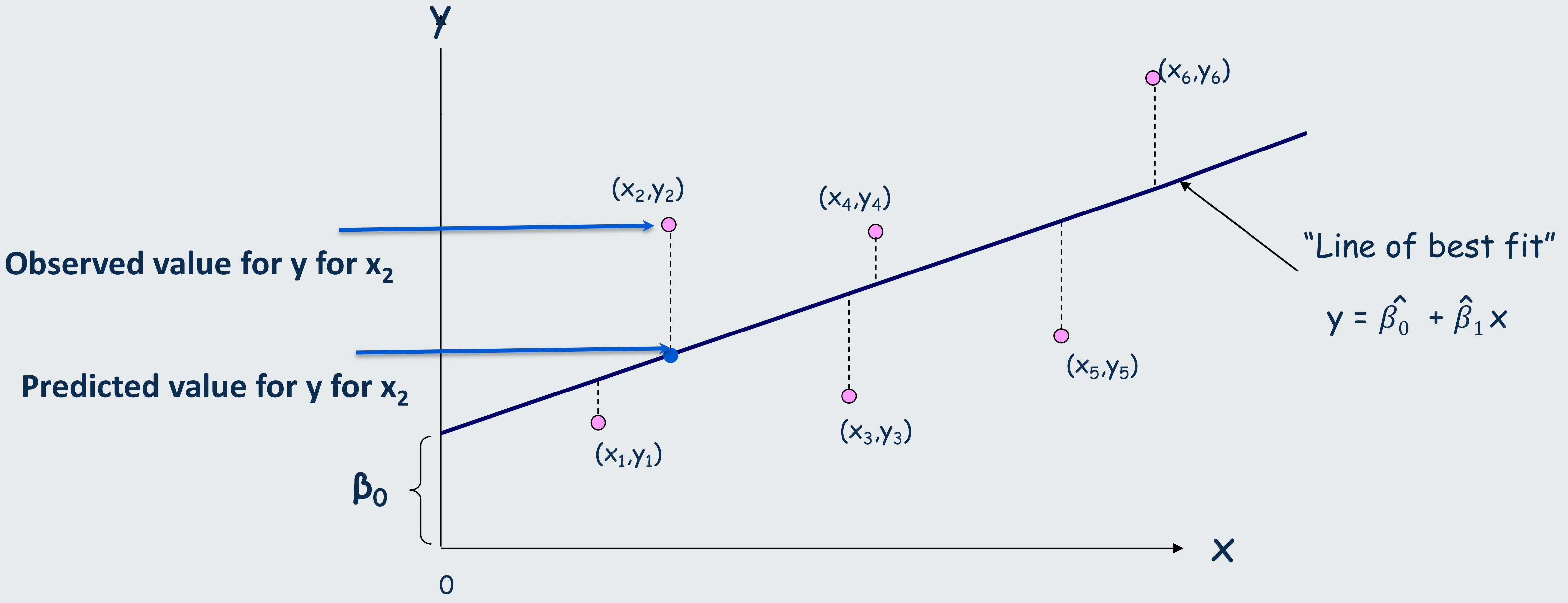
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	-46.764	5.413		-8.639	.000	-57.386	-36.142
	Height at Age 16 in Centimeters	.626	.033	.520	19.224	.000	.562	.689

a. Dependent Variable: Weight at Age 16 in Kilograms

We found a significant relationship between weight and height of 16 year olds with a 1cm increase in height associated with a 0.626kg increase in weight ($\beta 1=0.626$, $t=19.224$, $p<0.001$ 95%CI (0.562, 0.689))

Prediction

Regression models are used to predict new cases.
The predicted value $\hat{y}$ for a new observation x is its corresponding value on the regression line.



Prediction

We can use the regression equation to predict the weight for new case, added to the sample:
If x=186cm for a given 16 years old new case, and knowing that $y=-46.764 + 0.626\,x$,
What would be the child's weight?

We can estimate:

$$
\begin{aligned}
y &= -46.764 + 0.626\,x, \\
y &= -46.764 + 0.626 \times 186 \\
y &= 69.672 \text{ Kg}
\end{aligned}
$$

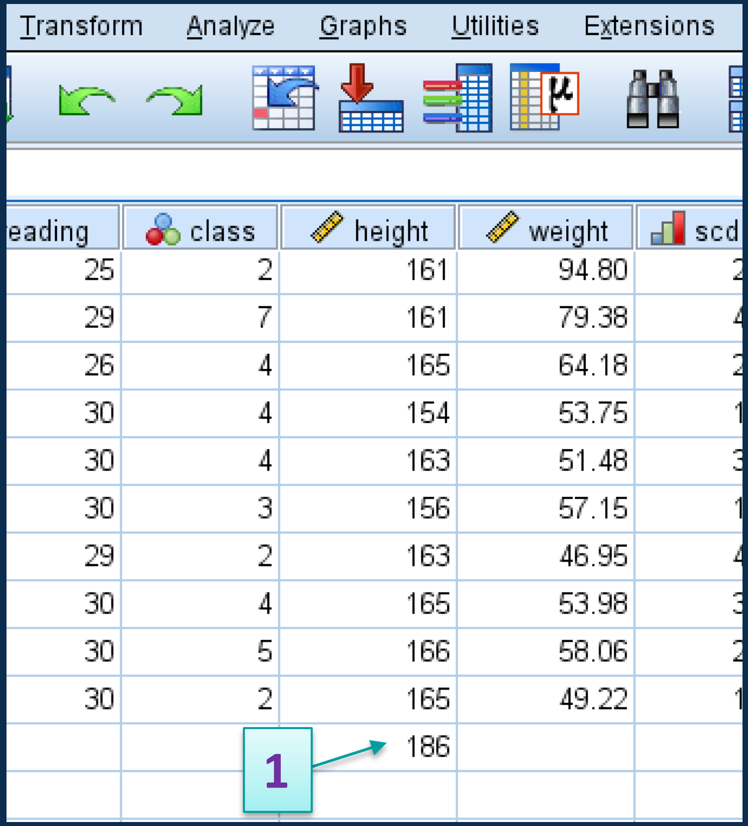
The model predicts a weight of 69.672 Kg for a 16-years old child that is 186 cm tall

In addition to getting predicted values of weight for any given height, it is possible to calculate a confidence interval for that prediction.

SPSS Slide: ‘how to’

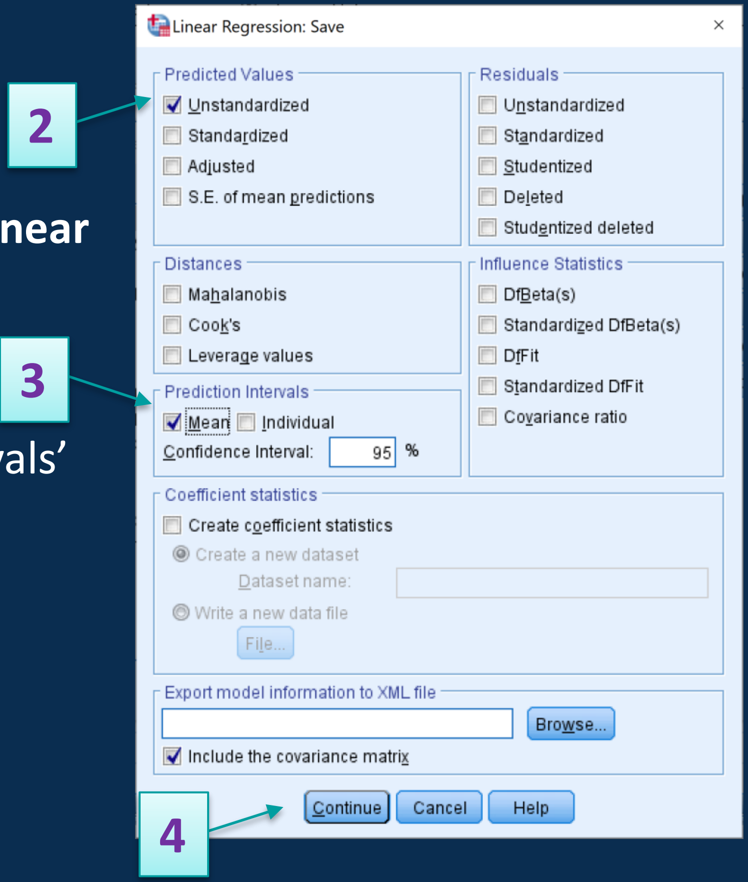
If x=186cm for a given 16 years old new case, and knowing that y=-46.764 + 0.626 x,
What would be expect the child’s weight to be?

Step 1: Add the x-values at which you want to predict y to the y-variable (here height) in the data. Use height= 186 cm



eading	class	height	weight	scd
25	2	161	94.80	
29	7	161	79.38	
26	4	165	64.18	
30	4	154	53.75	
30	4	163	51.48	
30	3	156	57.15	
29	2	163	46.95	
30	4	165	53.98	
30	5	166	58.06	
30	2	165	49.22	
		186		

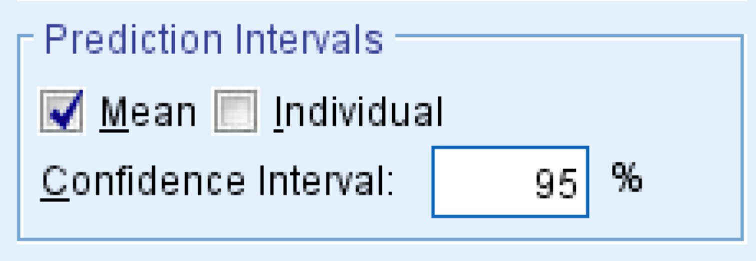
Step 2) Use **Analyse -> Regression -> Linear**
Step 2) Put ‘weight’ in dependent, and ‘height’ in independent.
Click **‘Save’**, select ‘Prediction values’ ‘Unstandardised’ and ‘Prediction intervals’ ‘mean’.
Click on ‘Continue’
Click on ‘OK’



Output and Interpretation

PRE_1	LMCI_1	UMCI_1
53.94261	53.33354	54.55167
53.94261	53.33354	54.55167
56.44463	55.92713	56.96213
49.56407	48.63380	50.49434
55.19362	54.64309	55.74414
50.81508	49.98842	51.64174
55.19362	54.64309	55.74414
56.44463	55.92713	56.96213
57.07013	56.55788	57.58238
56.44463	55.92713	56.96213
69.58024	68.21403	70.94645

The 'Data View' in SPSS you will see three new columns one for the predicted y (PRE_1) $\hat{\mathbf{y}} = \mathbf{69.58\ kg}$ based on the value of 186cm height and the lower (LMCI_1) and upper (UMCI_1) confidence interval limits **95%CI (68.21, 70.95.**



For instance, to predict the average weight of 16 year olds if the height is 186cm use the **confidence interval of the mean**.

To predict the weight of Jasmine, a 16 year old with weight 186cm then use the **confidence interval for the individual.**

Categorical Predictors

What do we do if we have a predictor that is **categorical** ?
Focus on continuous outcome $\mathbf{y}$ = weight and categorical explanatory variable $\mathbf{x}$ = gender.

When x is categorical binary then:

- The regression line connects the mean response in one group with the mean response in the other.
- The slope coefficient simply measures the group difference in means (remember: slope measures predicted change in y when x changes by one unit=switches groups)

Coefficients[a]

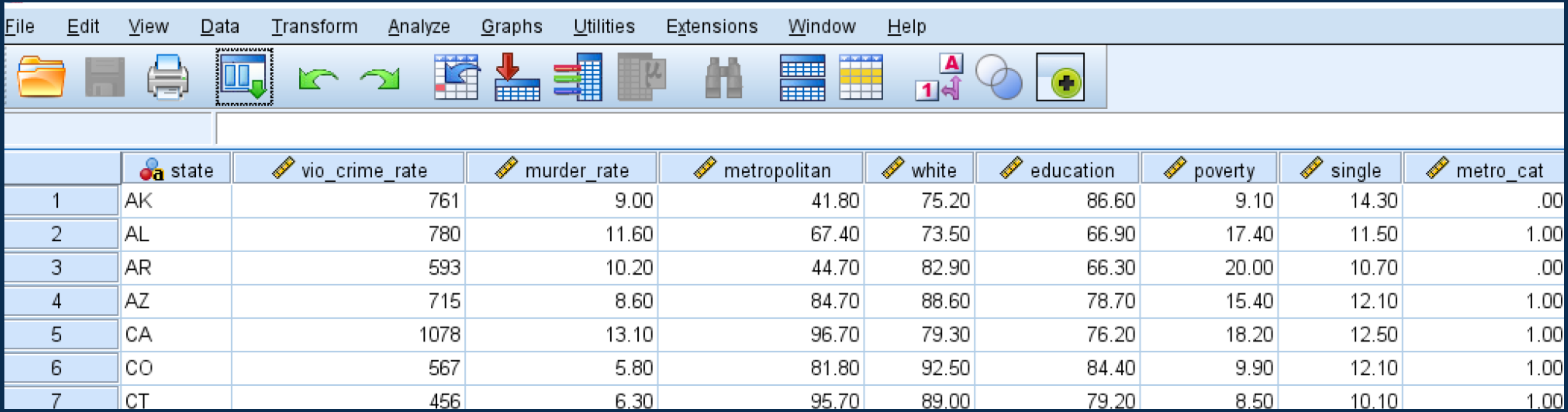
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	64.124	.943		67.971	.000	62.273	65.975
	Sex	-4.607	.593	-.239	-7.763	.000	-5.772	-3.442

a. Dependent Variable: Weight at Age 16 in Kilograms

Represents the difference in means between males and females, as we change x by one unit (move from male to female), the weight changes by 4.607kg. **On average females weigh 4.607kg less than males (β1 =-4.607. t=-7.763, p<0.001, 95% CI (-5.772, -3.442)**

SPSS Slide

Download the data that we are going to use during the lecture. The dataset is the **lecture_6b_data.sav**.



	state	vio_crime_rate	murder_rate	metropolitan	white	education	poverty	single	metro_cat
1	AK	761	9.00	41.80	75.20	86.60	9.10	14.30	.00
2	AL	780	11.60	67.40	73.50	66.90	17.40	11.50	1.00
3	AR	593	10.20	44.70	82.90	66.30	20.00	10.70	.00
4	AZ	715	8.60	84.70	88.60	78.70	15.40	12.10	1.00
5	CA	1078	13.10	96.70	79.30	76.20	18.20	12.50	1.00
6	CO	567	5.80	81.80	92.50	84.40	9.90	12.10	1.00
7	CT	456	6.30	95.70	89.00	79.20	8.50	10.10	1.00

The dataset contains data from 51 US states, measuring the crime rates and background measures for each state with respect to their

- **violent crime**: per 100,000 population
- **murder** : per 100,000 population
- **poverty**: percent below the poverty line
- **single**: percentage of lone parents

Categorical Predictors

What do we do if we have a predictor that has more than 2 **categories**?

Focus on continuous outcome $\mathbf{y}$ = Violent Crime and categorical explanatory variable $\mathbf{x}$ = Urbanicity.

state	urban
AK	Low
AR	Low
IA	Low
ID	Low
KY	Low
ME	Low
AL	Medium
GA	Medium
KS	Medium
MN	Medium
MO	Medium
NC	Medium
AZ	High
CA	High
CO	High
CT	High
DE	High

The variable **urban** is a categorical variable with three levels "**Low**", "**Medium**" and "**High**"

- Categorical variables which are non binary cannot be included directly in a regression model.
- Need to be recoded into a set of dummy variables
- A dummy (indicator) variable is a binary (0,1) variable indicating a category of the predictor variable.
- A predictor with k levels can be coded as k dummy variables
- Only k-1 dummy variables are necessary to fully represent a categorical predictor.

Categorical Predictors

US crime data. The variable urban is a categorical variable with three levels “Low”, “Medium” and “High”
Let’s consider a linear regression for violent_crime and urban

state	urban
AK	Low
AR	Low
IA	Low
ID	Low
KY	Low
ME	Low
AL	Medium
GA	Medium
KS	Medium
MN	Medium
MO	Medium
NC	Medium
AZ	High
CA	High
CO	High
CT	High
DE	High

The variable **urban** is a categorical variable with three levels “**Low**”, “**Medium**” and “**High**”

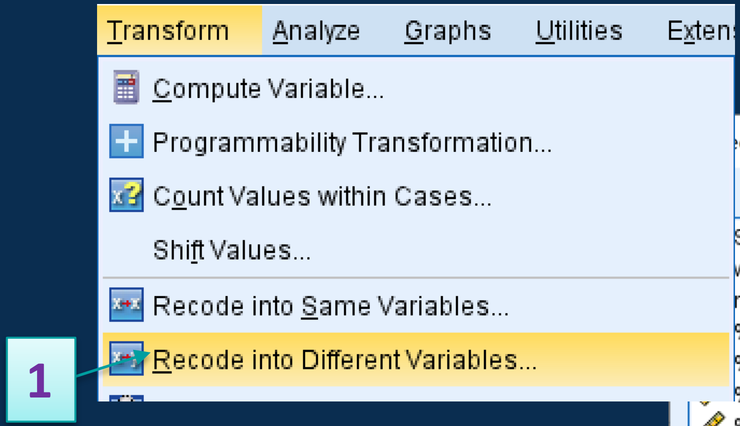
Dummy coding of **`urban`** (*k=3*)

d1	d2	d3
1	0	0
1	0	0
1	0	0
1	0	0
1	0	0
1	0	0
0	1	0
0	1	0
0	1	0
0	1	0
0	1	0
0	1	0
0	0	1
0	0	1
0	0	1
0	0	1
0	0	1

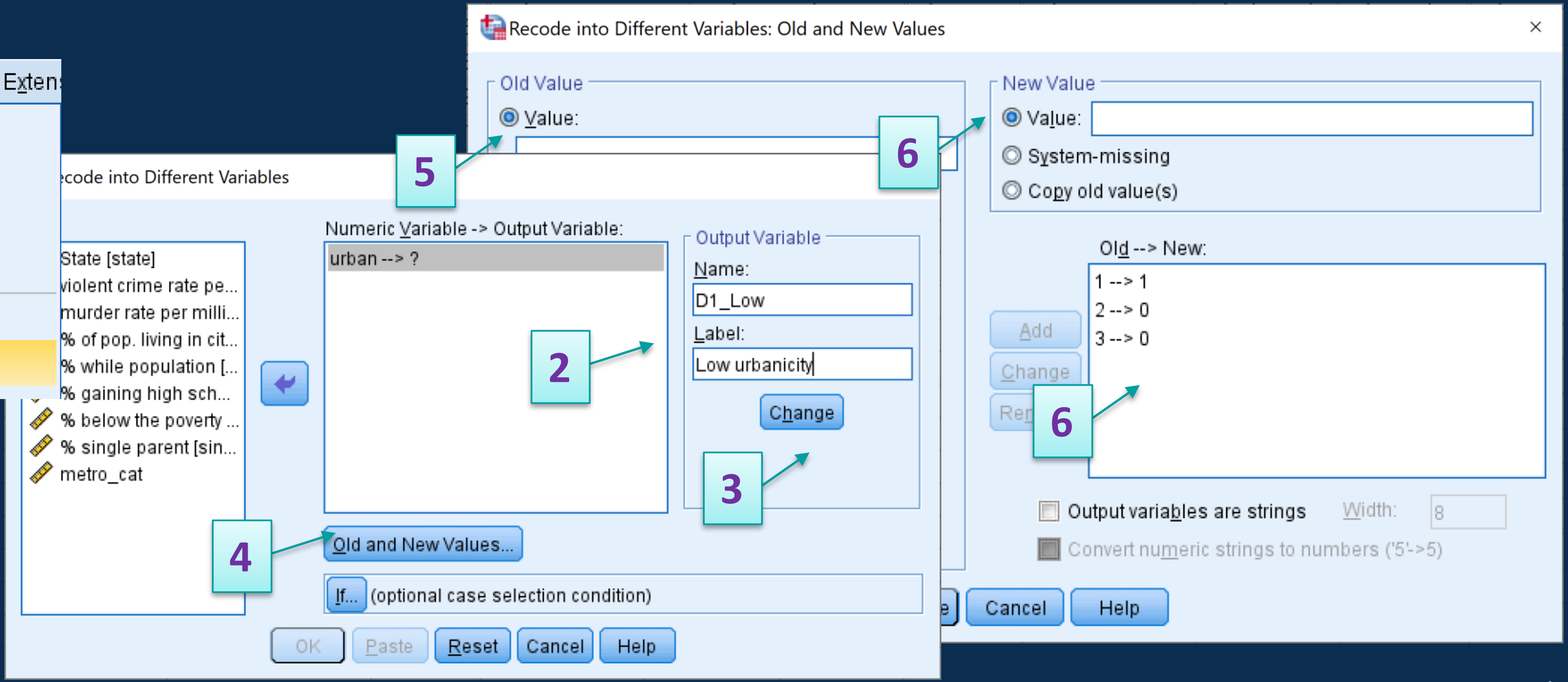
SPSS Slide: ‘how to’

Researchers believe there is a relationship between Violent Crime and the level of urbanicity in an area. The variable urban is a categorical variable with three levels “Low”, “Medium” and “High” and needs to be converted to dummy variables to include in the regression.

Step 1: Generating a dummy variable for “Low” urbanicity level in ‘urban’ variable from US crime dataset (We need to repeat this process to create a dummy variable for “Medium” level)



Use ‘**Transform’ ->’ Recode into Different Variables’**



Output and Interpretation Slide

urban	D1_Low	D2_Med	D3_High
2.00	.00	1.00	.00
3.00	.00	.00	1.00
2.00	.00	1.00	.00
3.00	.00	.00	1.00
3.00	.00	.00	1.00
3.00	.00	.00	1.00
3.00	.00	.00	1.00
3.00	.00	.00	1.00
3.00	.00	.00	1.00
3.00	.00	.00	1.00
3.00	.00	.00	1.00
2.00	.00	1.00	.00
1.00	1.00	.00	.00

Only 2 dummy variables (e.g. d1 and d2) are needed to represent a variable with 3 levels.

The model will be: $violent\_crime = \beta_0 + \beta_1 d_1 + \beta_2 d_2 + \varepsilon$

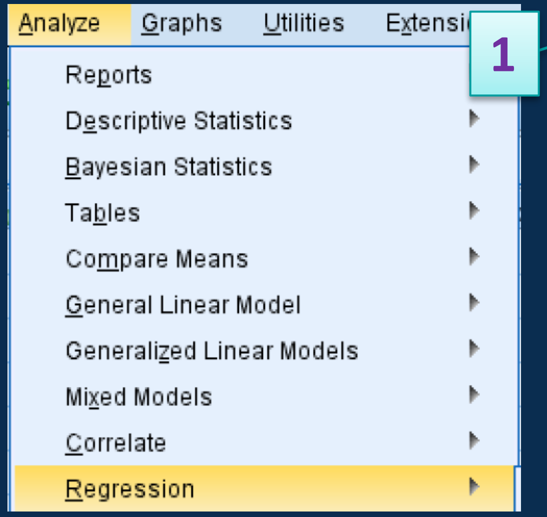
•β_1 will be the difference in mean between “Low” vs. “High” (the latter is called the “reference category”)

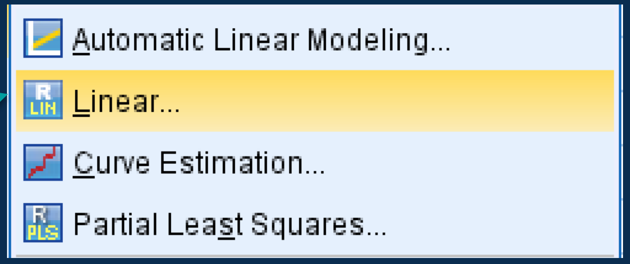
•β_2 will be the difference in mean between “Medium” vs. “High” (the latter is called the “reference category”)

SPSS Slide: ‘how to’

Researchers believe there is a relationship between Violent Crime and the level of urbanicity in an area.

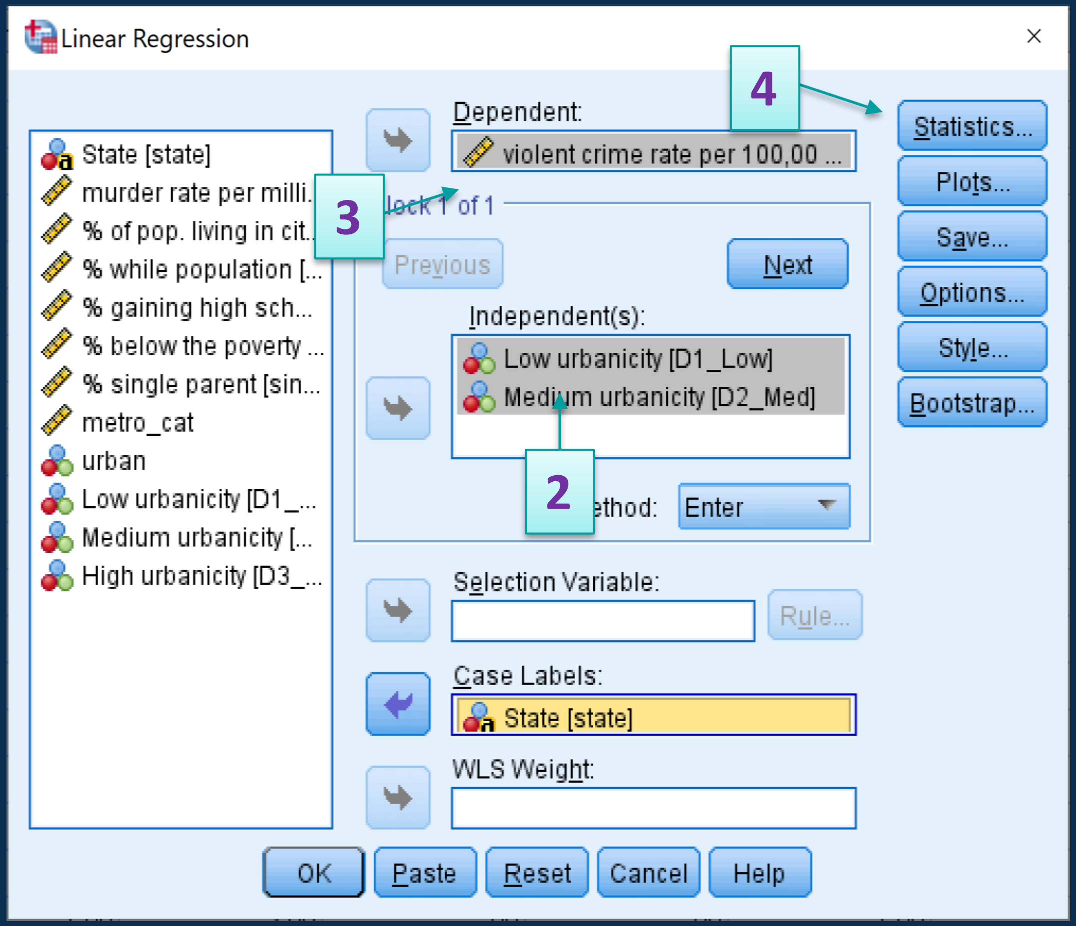
<u>Step 2</u>: Compute a Linear regression model for dependent variable ‘Violent Crime’ and independent variable ‘urban’ using the dummy variables created





Add the two variables, weight in the ‘Dependent’ box and height into the into the ‘independent(s)’ box.

Click on ‘Statistics

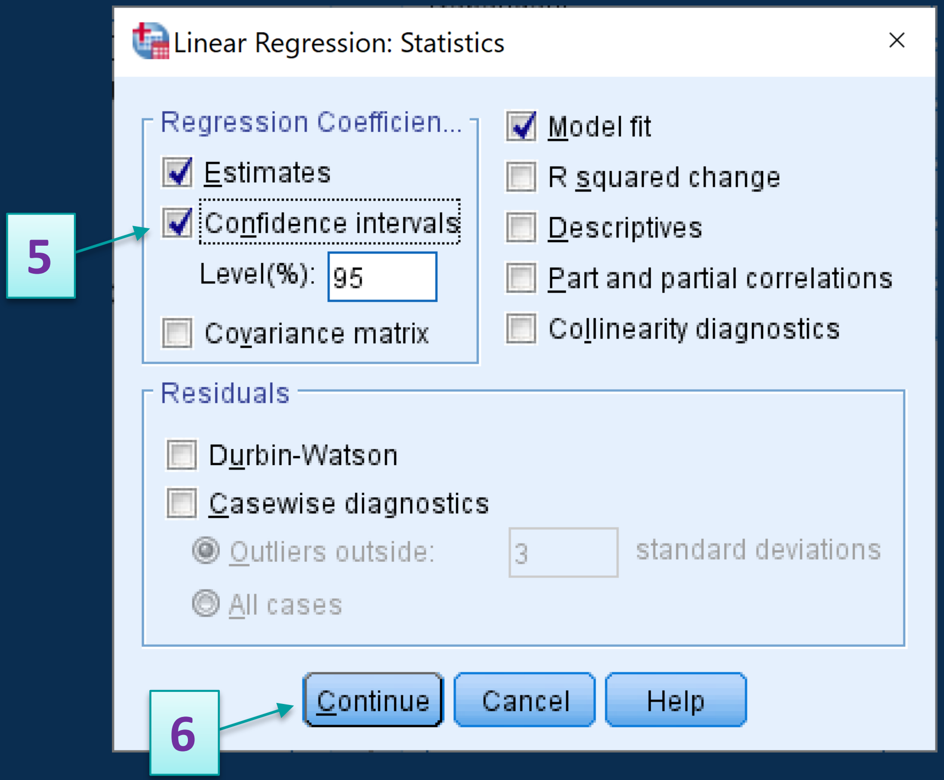


Use ‘Analyse’ -> ‘Regression’ -> ‘Linear’

SPSS Slide: 'how to'

Researchers believe there is a relationship between Violent Crime and the level of urbanicity in an area

Step 2: Compute a Linear regression model for dependent variable 'Violent Crime' and independent variable 'urban' using the dummy variables created



In the Statistics tab.
Check the 'Estimates'
Check the 'Confidence Intervals'
Click on 'Continue'
Click on 'OK'

Output and Interpretation Slide

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.431[a]	.186	.151	410.381

a. Predictors: (Constant), Medium urbanicity, Low urbanicity

b. Dependent Variable: violent crime rate per 100,00 population

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1808632.428	2	904316.214	5.370	.008[b]
	Residual	7915378.052	47	168412.299		
	Total	9724010.480	49			

a. Dependent Variable: violent crime rate per 100,00 population

b. Predictors: (Constant), Medium urbanicity, Low urbanicity

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
		B	Std. Error	Beta			Lower Bound	Upper Bound
1	(Constant)	749.281	72.546		10.328	.000	603.338	895.224
	Low urbanicity	-498.948	182.569	-.368	-2.733	.009	-866.230	-131.666
	Medium urbanicity	-324.531	138.915	-.314	-2.336	.024	-603.991	-45.071

a. Dependent Variable: violent crime rate per 100,00 population

There is a moderate degree of correlation between Violent Crime and Urbanicity r = 0.431. 18.6% of the variation in Violent crime can be explained by Urbanicity. the regression model statistically significantly predicts the outcome variable i.e., it is a good fit for the data.

On average low urbanised areas have 498.95 less cases of violent crime per 100 000 compared to high urbanised areas ($\beta 1$ =-498.948. t=-2.733, p<0.009, 95% CI (-866.230, -131.666) , on average med urbanised areas have 324.53 less cases of violent crime per 100 000 compared to high urbanised areas ($\beta 2$ =-324.531. t=-2.336, p<0.024, 95% CI (-603.991, -45.071)

Knowledge Check

We examined the medical records of participants when they were between 65 and 70 years old, counting the number of health problems they had. Participants were given a questionnaire on how much they've smoked at different times in their life e.g number of cigarettes smoked per day between ages 20 and 50.

The following regression model describes the relationship between health problems (y) and smoking (x)

$$y' = 3.109 + 1.578x \, .$$

- Output from the analysis of the data showed $r = 0.77$
- Effects of both the intercept and slope show $p = .045$ and $p = 0.049$ respectively

1. Write an appropriate Null and Alternative hypothesis for these data.
2. Interpret the coefficients of the regression.
3. How many health problems will a participant be predicted to have if the number of cigarettes they smoke is 10 and 30. Calculate a confidence interval for the prediction given the s.e. is 0.435

Knowledge Check Solutions

We examined the medical records of participants when they were between 65 and 70 years old, counting the number of health problems they had. Participants were given a questionnaire on how much they've smoked at different times in their life e.g number of cigarettes smoked per day between ages 20 and 50.

1. Write an appropriate Null and Alternative hypothesis for these data.
   H0: There is no linear association between health problems and amount of smoking e.g. the slope $\beta1$ in the population equals to 0
   Ha: There is a linear association between number of health problems and amount of smoking e.g. the slope $\beta1$ in the population does not equal to 0

2. Interpret the coefficients of the regression.
   $\beta0 = 3.109$ The intercept ($\beta0$), is the extrapolated number of health problems for a participant who does not smoke, this suggests that if a participant is a non-smoker they will have approx. 3 health problems.
   $\beta1 = 1.578$ The estimated slope coefficient ($\beta1$), suggests a increase of 1 cigarette smoked is associated with a 1.578 increase to number of health problems

3. How many health problems will a participant be predicted to have if the number of cigarettes they smoke is 10 and 30. Calculate a confidence interval for the prediction given the s.e. is 0.435

10 cigarettes will lead to $3.109 + (10 \times 1.578) = 18.89$ health problems
95% CI $(18.89 \pm 1.96 \times 0.435) = (18.04, 19.74)$

30 cigarettes will lead to $3.109 + (30 \times 1.578) = 50.45$ health problems
95% CI $(50.45 \pm 1.96 \times 0.435) = (49.60, 51.30)$

References

Field (2017) Discovering Statistics using SPSS, 5th Ed.
Chapter 8: Correlation
Chapter 9: The Linear Model (Regression)

Agresti and Finlay (2014) Statistical Methods for the Social Sciences, 4th Ed.
Chapter 9: Linear Regression and Correlation

Acock (2018) A Gentle Introduction to Stata, 6th Ed.
Chapter 8: Bivariate correlation and regression

Thank you

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