

Advanced R Unit 3

Sereina Herzog

Institute for Medical Informatics, Statistics and Documentation Medical University of Graz

06.03.2025

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Course Content - Advanced R (Unit 3)

- Statistical tests & models
- ► Simple linear regression
- Statistical models in R
 - R packages
 - Simple linear regression in R



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Which statistical tests and models are suitable for your research questions?

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- measuring level
 - nominal, ordinal, . . .



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 - e.g., difference between . . .



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 - nominal, ordinal, . . .
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 - e.g., difference between . . .
- ▶ study design, ...



Which statistical tests and models are suitable for your research questions?

 \Rightarrow not easy to give an answer



Statistical models in R

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Statistical models in R (part I)

► For almost all well known statistical models there are R packages which will cover them

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Statistical models in R (part I)

- ► For almost all well known statistical models there are R packages which will cover them
- Questions
 - How to find the correct R package?
 - What if there are several?



Statistical models in R (part II)

Answers

- search with the 'correct' key words online, ask colleagues, look which R packages are cited in papers
- R CRAN vs GitHub: CRAN seems to be the more formal of the two
- Keep in mind that R is a open source there is no official check of the content, however.
 - big community
 - ▶ a lot of the packages on CRAN have accompanying peer-reviewed papers



Statistical models in R (part III)

- ► About a R package
 - Who did it?
 - Has it survived a couple of R updates?
 - What does the code look like?
 - How widely used is it? How 'new' is it?
- ► Good sources if problems occur
 - read the documentation of functions in the help
 - online: StackOverflow a question-and-answer website



Statistical models in R (part III)

- ► R packages have often for modelling results
 - plot function
 - summary function

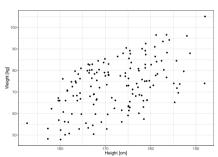
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Example - Height & Weight

What is the relationship between height and weight, respectively can height explain weight?

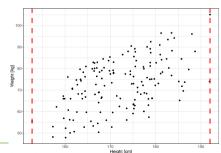




► Regression analysis is used to describe the nature of a relationship using a mathematical equation



- ► Regression analysis is used to describe the nature of a relationship using a mathematical equation
- ► Possibility of prognosis/prediction for an individual patient (incl. CI) within the value range of the predictor





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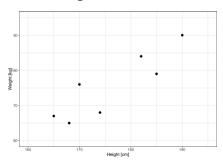
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- method
 - e.g. minimize deviation squares of the observed values from the regression line

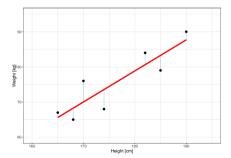


Find a straight line





- ▶ Problem: Find a straight line so that the vertical distance (residuals) between the data points and the straight line is minimized.
- ► Method, e.g., least squares method





As a statistical model

$$Y = \beta_0 + \beta_1 * X$$



As a statistical model

$$Y = \beta_0 + \beta_1 * X$$

As an empirical model with data

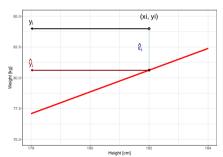
$$y_i = \beta_0 + \beta_1 * x_i + \epsilon_i$$

where ϵ_i describes the error (residual)



$$\hat{y}_i = \hat{eta}_0 + \hat{eta}_1 * x_i$$
 are the predicted values of the regression

$$\hat{\epsilon}_i = \hat{y}_i - y_i$$
 are the residuals of the regression





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- ► For 1) study design question
- For 2) scatter plot
- ► For 3) & 4) looking at residuals

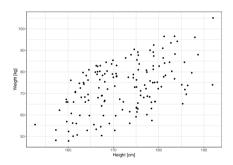


Coefficient of Determination R^2

 R^2 specifies the proportion of variance in the data that is explained by the model

$$R^2=rac{\sum(\hat{y}_i-ar{y})^2}{\sum(y_i-ar{y})^2}$$
 and $0\leq R^2\leq 1$





- 1) Independence ✓
- 2) Linearity ✓

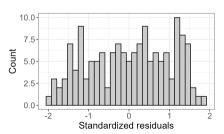


```
res_model <- lm(weight ~ height, data = dt_regression)</pre>
```



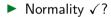
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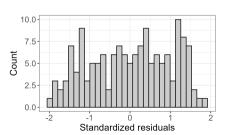
► Normality √?



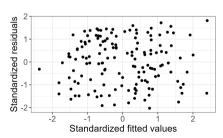


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► Homoscedasticity ✓



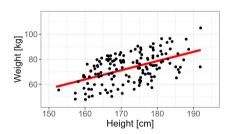


▶ If a model accurately captures the structure in the data, then all that should remain after the model is through making its predictions is random noise!

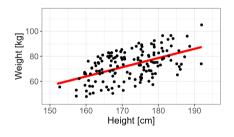


- ▶ If a model accurately captures the structure in the data, then all that should remain after the model is through making its predictions is random noise!
- Why plot residuals vs. fitted values, and not observations?
 - Because residuals and fitted values are uncorrelated by construction
 - Residuals and observations may be correlated—they both depend on observations which would make such plots harder to interpret



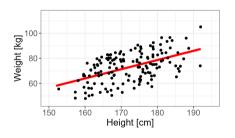






- ► intercept -53.49 (95% CI -87.3 to -19.69)
- ► slope 0.73 (95% CI 0.54 to 0.93)
- $R^2 = 0.27$
- $R_{adj}^2 = 0.265$





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What weight can you expect from a 1.75 m tall person?



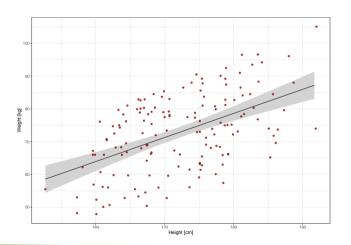
Example - Prediction

```
predict(res_model, newdata = tibble(height = 175),
    interval = "confidence", level = 0.95)
```

```
## fit lwr upr
## 1 74.95 73.25 76.65
```



Example - Uncertainty





ightharpoonup mathematical relationship \neq causality



- ▶ mathematical relationship ≠ causality
- $ightharpoonup R^2$ vs. R_{adj}^2
 - R² tends to increase as more variables are added to the model (even if they don't improve the model significantly)
 - R_{adj}^2 penalizes the addition of unnecessary variables:
 - $R_{adj}^2 = 1 \frac{(1-R^2)(n-1)}{n-p-1}$
 - \triangleright n = number of samples
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- $ightharpoonup R^2$, R_{adi}^2
 - does not indicate whether the model was specified correctly
 - low/high coefficient of determination ≠ bad/good model



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- ▶ Transform X (e.g. $Z = X^2$, $Y = \beta_0 + \beta_1 * Z$)
 - if linearity condition is violated



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- ► Transform Y (e.g. log-transformation of Y)
 - in case of violation of variance homogeneity and/or normal distribution



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- Apply more complex or robust estimation methods
 - e.g. weighted least squares estimation, sandwich estimator, bootstrapping,...



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 - if linearity condition is violated
- ightharpoonup Transform Y (e.g. log-transformation of Y)
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- Apply more complex or robust estimation methods
 - e.g. weighted least squares estimation, sandwich estimator, bootstrapping,...
- Multiple regression: further conditions must be checked (multicollinearity).



Simple linear regression - in R

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Simple linear regression - in R (part I)

```
res_model <- lm(weight ~ height, data = dt_regression)</pre>
```

Simple linear regression - in R



Simple linear regression - in R (part I)

```
res_model <- lm(weight ~ height, data = dt_regression)
```

- ► *lm*() from *stats* package
- 'Fitting Linear Models'
- ▶ **Description:** *Im* is used to fit linear models, including multivariate ones. It can be used to carry out regression, single stratum analysis of variance and analysis of covariance (although *aov* may provide a more convenient interface for these).

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Simple linear regression - in R (part II)

Usage:

Usage

```
lm(formula, data, subset, weights, na.action,
method = "qr", model = TRUE, x = FALSE, y = FALSE, qr = TRUE,
singular.ok = TRUE, contrasts = NULL, offset, ...)
```

▶ **Value:** *Im* returns an object of class "*Im*" or for multivariate ('multiple') responses of class c("*mIm*", "*Im*").



Simple linear regression - in R (part III)

res model

```
##
## Call:
## lm(formula = weight ~ height, data = dt_regression)
##
## Coefficients:
## (Intercept) height
## -53.495 0.734
```



Simple linear regression - in R (part IV)

summary(res_model)

```
##
## Call:
## lm(formula = weight ~ height, data = dt regression)
## Residuals:
      Min
               10 Median
                                     Max
## -20 118 -8 445 1 229
                           8 483 17 674
## Coefficients:
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -53.49479 17.10539 -3.127 0.00212 **
## height
                0.73396
                        0.09922
                                   7.397 9.6e-12 ***
## ---
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
##
## Residual standard error: 9.967 on 148 degrees of freedom
## Multiple R-squared: 0.2699, Adjusted R-squared: 0.265
## F-statistic: 54.72 on 1 and 148 DF, p-value: 9.602e-12
```



Simple linear regression - in R (part VI)

```
coef(summary(res_model))
```

```
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) -53.4947946 17.10538524 -3.127366 2.124137e-03
## height 0.7339631 0.09922269 7.397130 9.601925e-12
```

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Exercise Simple linear regression - in R

- ► Work through 'Unit 3 Exercise 1' (no pdf)
 - UNIT3_ex1_linregression_vYYYYMMDD.Rmd

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Links



Links (I)

- ► Introduction to R
 - R for Data Science (https://r4ds.hadley.nz/)
- ► Plots using ggplot
 - Overview with further links to course material: https://ggplot2.tidyverse.org/
- Display tables using flextable
 - flextable bool https://ardata-fr.github.io/flextable-book/
 - Function references https://davidgohel.github.io/flextable/reference/index.html
- knit_child()
 - link (https://bookdown.org/yihui/rmarkdown-cookbook/child-document.html)



Links (II)

- ▶ Download R
 - CRAN (https://cran.r-project.org/)
- ► Download RStudio
 - RStudio Desktop (https://posit.co/download/rstudio-desktop/)