University of Zurich[UZH]

MAKERERE UNIVERSITY

Data Analysis with R:
Day 3

Sonja Hartnack, Terence Odoch & Muriel Buri

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Why do we need Statistics?

Repeatability of results:
Statistical science allows us to estimate what might happen if an experiment was repeated - but without having to actually repeat it!

Why do we need Statistics?

- Study results must be shown to be robust, i.e. real and not due to random chance

- Best way to demonstrate this is to repeat the same experiment/study many times each with **different** subjects (animals) drawn from the **same study population** and show that the result is truly repeatable

- It is generally totally impractical, in terms of both time and resources, to repeat an experiment many times!

Why do we need Statistics?

- Instead of repeating the experiment many times **probability theory i.e. statistics** is used to **estimate** what might have happened if the experiment had been repeated
- A mathematical model is used to fill this “data gap”
- Generally the most difficult task in statistics is to decide what “model” is most appropriate for a given experiment

What is Statistics? - A definition

A set of analytical tools designed to quantify uncertainty

- If an experiment or procedure is repeated, how likely is it that the new results will be similar to those already observed?

- What is the likely variation in results if the experiment was repeated?

What is Statistics? - A definition

The key scientific purpose of statistics

- to provide **evidence** of the existence of some “effect” of scientific interest
- i.e. evidence based medicine

As a reminder: The importance of study design

Even the most sophisticated statistical analyses cannot rescue a poorly designed study

$\rightarrow$ unreliable results

$\rightarrow$ inability to answer the main research question

Putting Statistics in Context

- The vast majority of analyses can be done in a straightforward fashion - just remember and always use common sense as a guide - be skeptical!

- It is very easy to get “lost” in the statistical software and technical jargon, which differs markedly between different software packages. Terminology can also differ greatly between textbooks...

- Wikipedia is as good a resource as any for finding out about different statistical tests and terminology

Exploratory Data Analysis

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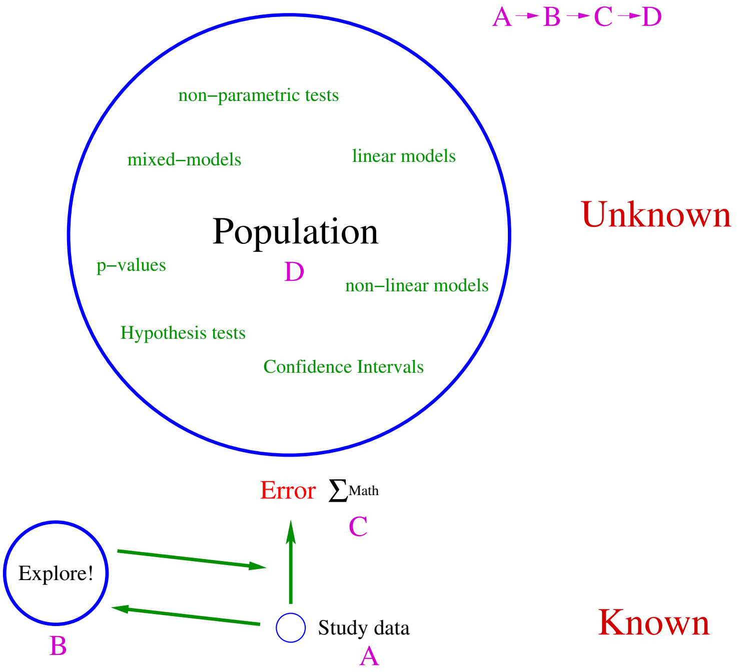
- What explorations are done depends on the objective of the study - the research question(s)
- Helps to decide what kind of formal statistical analyses might be most appropriate for the data available
- What a simple descriptive analysis **does not** provide is evidence of whether the observed treatment effects are large enough to be notable once sampling variation has been accounted - that is the role of formal analyses, e.g. hypothesis testing



A → B → C → D
non−parametric tests
mixed−models
linear models
Unknown
Population
D
p−values
non−linear models
Hypothesis tests
Confidence Intervals
Error
∑Math
C
Explore!
Study data
B
A
Known

Continuous (Integers / Numeric) Data Summaries

- `Mean` - a measure of location. Always examine the average value of the response variable(s) for the different "treatment" effects in your data
- `Median` - a robust single value summary of a set of data (50% quantile point) - most useful in highly skewed data or data with outliers
- `Standard deviation (sd)` - a measure of spread, how variable the data are
- `Standard error of the mean (se)` - an estimate of how far the sample mean is likely to be from the population mean
- and others: `min, max, range, IQR, ...`

Continuous (Integers / Numeric) Data Summaries

```r
mean(x) # mean

median(x) # median

sd(x) # standard deviation

min(x) # minimum

max(x) # maximum

range(x) # range

IQR(x) # interquartile range
```

Continuous Data Summaries

standard deviation

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

standard error

$$se = \frac{s}{\sqrt{n}}$$

Continuous Data Summaries

Combination of continuous and continuous

- `Correlation coefficient` - a measure association between two continuous variables (common but somewhat limited)

Pearson's correlation coefficient r

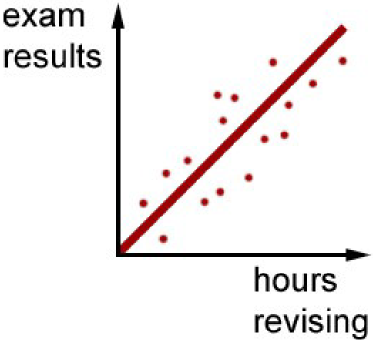
$$r=\frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i-\bar{Y})^2}}$$

$\bar{X}$: mean of variable x

$\bar{Y}$: mean of variable y

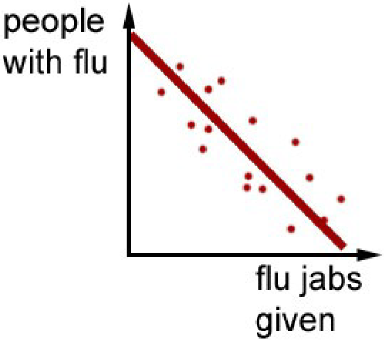
Correlation coefficient

Combination of continuous and continuous



POSITIVE CORRELATION

- people who do more revision get higher exam results.
- revising increases success.



NEGATIVE CORRELATION

- when more jabs are given the number of people with flu falls.
- flu jabs prevent flu.

Correlation coefficient

Combination of continuous with continuous / ordinal

```r
# Test for Association/Correlation Between
# Paired Samples
cor.test(data$x, data$y, method = "pearson")
cor.test(data$x, data$y, method = "spearman")

# Scatterplot(s)
pairs(data$x ~ data$y)
pairs(data)
```

Correlation coefficient
Combination of continuous with factors

```r
tapply(data$x.cont, data$y.fac, mean)

tapply(data$x.cont, data$y.fac, median)

tapply(data$x.cont, data$y.fac, sd)
```

Ordinal Data Summaries

- `Median` - a robust single value summary of a set of data (50% quantile point) - most useful in highly skewed data or data with outliers

- `e.g.10th and 90th percentile` - a measure of spread, how variable the data are

```
quantile(x, probs = c(0.1, 0.9))
```

- `proportions` - e.g. percentage per grade

```
prop.table(table(data$x.fac))
prop.table(table(data$x.fac, data$y.fac))
```

Nominal Data Summaries

- `proportions` - percentage within the different categories
- `contingency tables` e. g. 2x2

```r
table(data$x.fac)
table(data$x.fac, data$y.fac)
prop.table(table(data$x.fac))
prop.table(table(data$x.fac, data$y.fac))
```

Exercise 8

How to deal with missing values in R? (1/3)

- In R, missing values are represented by the symbol **NA** (not available).
- Impossible values (e. g., dividing by zero) are represented by the symbol **NaN** (not a number).
- Ask yourself why a **NA** and / or **NaN** occurs!

How to deal with missing values in R? (2/3)

- Testing for Missing Values

```r
vec1 <- c(1, 2, 3, NA)
is.na(vec1) # returns a vector (FALSE, FALSE, FALSE, TRUE)
# The TRUE indicates the position of the NA in vec1.
```

- Recoding Values to Missing

```r
# recode specific values (e. g. 0.001) to missing for variable x
# select rows where x is 0.001 and recode value in column x with NA
dat$x[dat$x == 0.001] <- NA
```

How to deal with missing values in R? (3/3)

- Excluding Missing Values from specific function calls

```
a <- c(1, 2, NA, 3)
mean(a) # returns NA
mean(a, na.rm=TRUE) # returns 2
```

- Check for complete cases with function `complete.cases(...)`

```
# list rows of data that have missing values
dat[!complete.cases(dat),]
subdat <- dat[complete.cases(dat),]
```

- Create new dataset without missing data with function `na.omit(...)`

```
new.dat <- na.omit(dat)
```

How to check your data for plausibility?

- Ask yourself what can go wrong?
- Implausible values?
- Impossible values?
- Logical errors?

Exercise 9A: Plausibility Checks

Exercise 9B: Missing Values

Exercise 10