DATA HANDLING AND ASSUMPTIONS

Making the Most of Your Data



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Aarhus University

25/03/2020

- 1 Data Etiquettes
 - Data Recording
 - Data Storing
 - Data Handling
 - Data Mining
 - Data Sharing
- 2 Statistical Assumptions
 - Normality
 - Independence
 - Homogeneity of Variances

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Why Care?

Biostatisticians often use 70% of their time to handle data and just 30% to actually analyse it.

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- Proper data collection and data handling ensure accurate results
- Proper data collection cuts down on data handling time
- Proper data handling will make reproducing an analysis much easier

What to consider?

- Which data format to use
- What kind of data to record
- How data values are recorded/stored
- What kind of data values are feasible

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Guidelines for data recording:

- When collecting categorical data, know what values the variables are allowed to take
- When collecting continuous data, know which range the variable values can fall into
- Make sure everyone involved in data collection is on the same page
- Make regular back-ups of your data set

- Preparing content-aware excel files for data entry
 - Only allow pre-defined values to be entered
 - Need some excel macro writing
- Using a cloud-service featuring version control for data storage

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The Decimals

Always use a dot to indicate decimals

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To NA Or Not To NA?

Never enter NA values manually into your data

 \rightarrow They cause problems in R.

Entering 0?

If a 0 value has meaning in your set-up, \textit{enter] it!

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Redundancy Or Sparsity?

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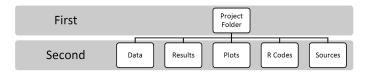
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The only files allowed in your first hierarchy level are

- R master file
- Manuscript master file



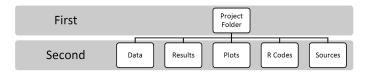
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Using the **README file**, one can identify what information is contained within the data set and thus decide:

- What type/class a data record should be of
- Which variables may be redundant
- Which data records exceed their variable-specific feasible thresholds
- Where to get comparative data sets from

Data Mining should then focus on:

- Identifying problems within the data records
- Explorative data analyses

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Descriptive Statistics:

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Recording Data Collection - The README File

Documenting data recording is just as important as proper data collection!

To do so, one usually uses a **README** file containing the following

- Project Name and Summary
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Peer-to-Peer:

- Raw data
- Code
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- Base assumption: The data is normally distributed
- If p-value < chosen significance level, the data is **not** normally distributed
- Very sensitive to sample size

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The QQ Plot In Theory

- Method for comparing two probability distributions by plotting their quantiles against each other
- If the two distributions being compared are similar, the plot will show the line y = x.
- Compare the data distribution to the normal distribution

Theory:

- Even the smallest dependence in you data can turn into heavily biased results (which may be undetectable).
- A dependence is a connection between/within the data.
- The assumption of independence relies on the absence of any connection in your data that haven't been accounted for in your approach (accounting for it is difficult).

Independent data

- Between Groups
 Groups of data records should be pulled from different individuals.
- Within Groups
 Data values within the same group are not to influence one another.
- Within Individuals
 Data values recorded for one individual should not influence each other. This is often an issue with repeated measurement approaches.

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Homogeneity of Variances

Particularly important for t-Tests and ANOVAs

- Assumption: Data from separate groups have same variance
- **Test**: leveneTest() in the car package.

```
## Levene's Test for Homogeneity of Variance (center = median)
## Df F value Pr(>F)
## group 1 337 <2e-16 ***
## 1998
## ---
```

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Particularly important for t-Tests and ANOVAs

- **Assumption**: Data from separate groups have same variance
- **Test**: leveneTest() in the car package.