Week-14:
Course wrap-up

phase IV

What we have notably studied

- R and data science-oriented environment (tidyverse).
- Descriptive statistics.
- Foundations to Null Hypothesis Significance Testing.
- Inferential statistics for different problem designs (e.g. one continuous variable, two continuous variables, etc).
- Modelling relationship with regression.
- Nonparametric inferential testing.
- Multiple testing correction.

What we have not covered, and you should probably do in the future

EFFECT SIZES

- We should not rely solely on p-values to guide our research conclusions: enough large sample sizes can almost any result significant.
- Our results should be reported along with measures that quantify the size of the effect studied without taking sample size into account.
- E.g. **Cohen's *d*** for one- and two-sample t-tests:

$$t = \frac{\hat{\mu}_1 - \hat{\mu}_2}{\hat{\sigma}/\sqrt{N}}$$

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$$t = \frac{\hat{\mu}_1 - \hat{\mu}_2}{\hat{\sigma} / \cancel{\sqrt{N}}} \longrightarrow d = \frac{\hat{\mu}_1 - \hat{\mu}_2}{\hat{\sigma}}$$

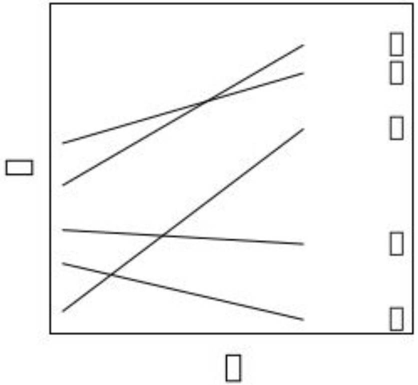
What we have not covered, and you should probably do in the future

MODELS FOR CLUSTERED OR PANEL DATA

- Sometimes, our data might have some inherent underlying structure (e.g. a population of students from different schools).
- We may want to incorporate this structure to the parameter estimation (**Mixed-effects models**)

$$
\begin{aligned}
y_i &= \alpha_{j[i]} + \beta_{j[i]} x_i + \epsilon_i, \quad \text{for students } i = 1, \ldots, n \\
\alpha_j &= a_0 + b_0 u_j + \eta_{j1}, \quad \text{for schools } j = 1, \ldots, J \\
\beta_j &= a_1 + b_1 u_j + \eta_{j2}, \quad \text{for schools } j = 1, \ldots, J.
\end{aligned}
$$

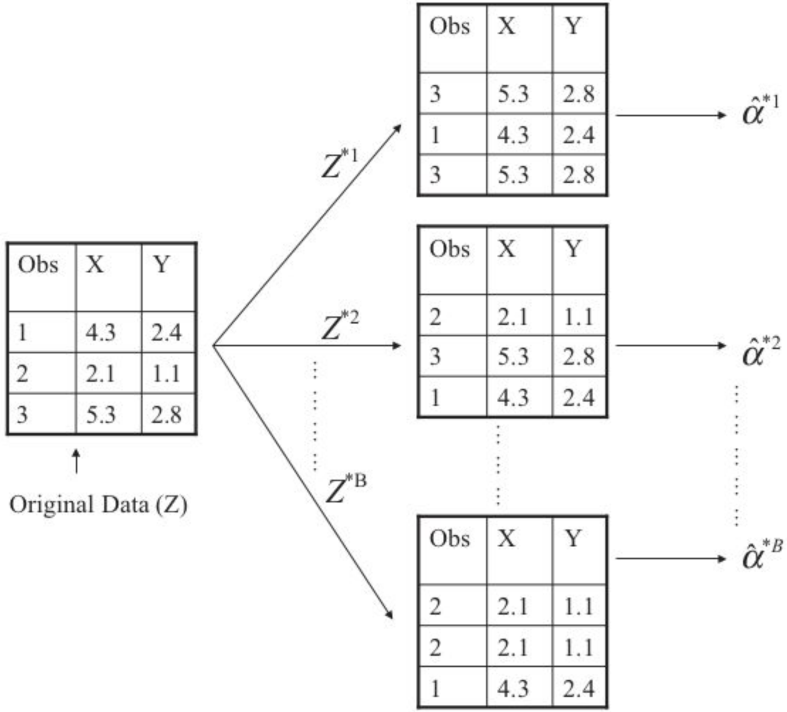
Varying intercepts and slopes



What we have not covered, and you should probably do in the future

BOOTSTRAPPING

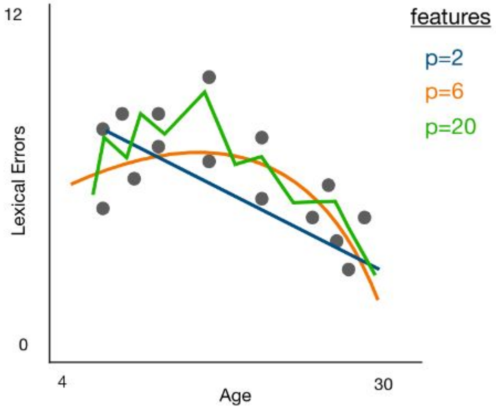
- ➢ It is a powerful **resampling method** that allows you to simulate the sampling distribution of **any** measure assuming that your population looks the same as your sample.
- ➢ Very useful for instance to build **confidence intervals** without relying to any specific distribution.

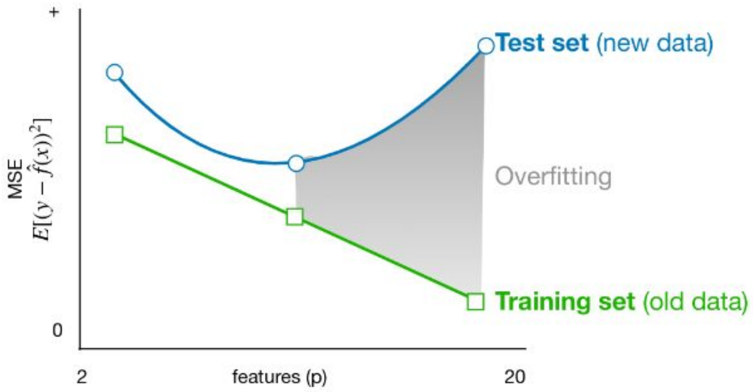


What we have not covered, and you should probably do in the future

EFFECTS GENERALIZABILITY

- ➢ The model that best describes our data needs not to behave well on new data!
- ➢ We need models with the appropriate complexity that generalize well.
(**Sign up for Prof. Verstynen's course on Data Science**!)





What we have not covered, and you should probably do in the future

BAYESIAN STATISTICS

- The statistics covered in this course belongs to what is called **frequentist perspective**.
- **Frequentist statistics**: probabilities are inherent properties of the system.
- **Bayesian statistics:** probabilities are measure of uncertainty or subjective belief in the outcomes.

What we have not covered, and you should probably do in the future

BAYESIAN STATISTICS

- In contrast to frequentists, bayesians can estimate probabilities for the hypotheses!

Likelihood **Prior**

$$P(H|D) = \frac{P(D|H) \cdot P(H)}{P(D)}$$

Posterior

Evidence

THE END

"Statistical thinking will one day be as necessary for efficient citizenship as the ability to read and write."

Samuel S. Wilks