BSc in Cognitive Science
Methods 1: Introduction to Experimental Methods, Statistics, and Programming [147201U009]

This program is still in draft version. Last updated: August 28, 2021

Course description:
Cognitive science is an intrinsically empirical and data-analytical field of study: we collect data (often by running experiments) in order to better understand human cognition. But experiments only work if they are carefully designed, and empirical data can only be made sense of if we have the right tools to interpret them. Aim of this course is therefore to endow you with in-depth and hands-on knowledge of three foundations of experimental and analytical work in the cognitive sciences:

(1) the basic principles of empirical research and experimental design, which will allow you to create well-controlled scientific studies that generate reliable evidence for your hypotheses;
(2) statistical tools (within the realm of the so-called general linear model), which will enable you to always choose the best way to approach your data analysis;
(3) the programming languages Python/PsychoPy (which we will use to create fully-custom experimental procedure in computer code) and R (which we will use to run all our statistical analyses).

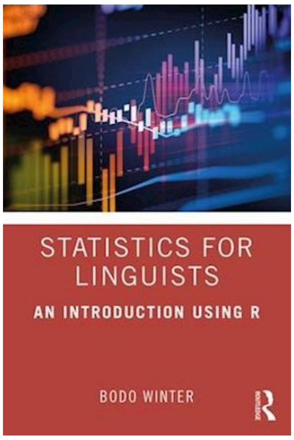
Lastly, you will learn how to interpret and report your statistical findings in order to answer your initial research questions. This course constitutes the first part of a three-part course together with Methods 2 in the second semester and Methods 3 in the third semester.

You can access the AU study regulations for this course here.

Practical information:
Teacher: **Fabio Trecca** (AU profile) (e-mail)
Instructor: **Sigurd Fyhn Sørensen** (e-mail)
Time and place:
Lectures: mostly on Tuesdays, 14-16, but check timetable.au.dk
Classes: mostly on Thursdays, 10-12 (Class 1) and 12-14 (Class 2) , but check timetable.au.dk

The Tuesday lectures will be focused on theoretical aspects of experimental design and data analysis, whereas the Thursday practical classes will consist of hands-on practice with the topics discussed in the lectures.

Literature:
Almost all readings in this course will be from this handbook: Winter, B. (2019). Statistics for linguists. Routledge. You can buy the book on Saxo.dk for 349,95 DKK. I will make the first two chapters available as PDF on Brightspace in case you In a few occasions, the readings will be articles and chapters from other sources (you will find the links to these in the Course schedule below; note that you may have to be on campus/connected via VPN to open some of the links). The Course



schedule section below differentiates between "Primary readings", which are mandatory and should be read before class (and ideally also quickly refreshed after class); and "Secondary readings", which are not mandatory but nonetheless highly suggested if you want to gain a more in-depth understanding of the topic.

Software:

In this course we will make large use of two computer programs (and their relative programming languages). We will mainly be using R, which is an open-source environment/programming language for conducting statistical analyses of data. The default R environment is not very user-friendly though: for this reason, we will also be using RStudio, a nicer and much more user-friendly graphical interface that runs on top of R (RStudio will only run if R is already installed on your computer). One easy way of getting started with R/RStudio is by reading Chapter 3 ("The R environment") of our handbook and trying out the examples that are provided there. You will also get a lot of hands-on experience with R/RStudio during our practical exercises.

The other programming language/environment we will be using is Python. Python does not come with a dedicated software editor like RStudio: you can use any text editor (yes, even RStudio!) to write and run Python code (although there are some good editors out there that are designed for Python such as IPython Notebooks, PyCharm, and Spyder). To program experiments, we will be using an extension of Python called PsychoPy3, which is a stand-alone software designed specifically for creating and running psychological/behavioral experiments using Python code. We will not be reading any specific literature for Python, but you are welcome to check out the many good materials that are available on the web (e.g., Learn Python The Hard Way and Automatize the boring stuff with Python). As for PsychoPy3, you are encouraged to have a look at the eBook Programming Experiments in Python and PsychoPy3 by Kristian Tylén and Christina Evans. We will also make occasional use of JASP, which is also open-source, so go ahead and download it!

Useful resources from the web:

R LABS (YouTube channel with plenty of R tutorials)
Brandon Foltz (YouTube channel with a lot of video explanations of statistical concepts)
StatQuest (Website and YouTube channel with a lot of funny but effective video explanations of statistical concepts)

Exam:

The exam is in the form of: (1) lecture participation (cf. the general rules of the academic regulations here); and (2) a portfolio exam consisting of four assignments carried out during the semester. Detailed instructions on the portfolio assignments will be published on Brightspace throughout the semester. Half of the assignments will be individual and half will be group assignments (which you will do in cooperation with your study group). Portfolio assignments are submitted on Brightspace.

Preliminary topics and deadlines for the portfolio assignments are (these are subject to change):

1) Data mining report on "personality test" data from the intro day. Deadline 29/9, 23.59 (individual)
2) PsychoPy script for two-condition reading time experiment + correlation and t-test analysis of data from reading experiment. Deadline 26/10, 23.59 (group)
3) Report on multi-condition group experiment. Deadline 16/11, 23.59 (individual)
4) Logistic regression analysis. Deadline 30/11, 23.59 (group)

At the end of the semester, the five assignments should be compiled into one single PDF-file and submitted to the AU digital system. Deadline is 13/12/2021. Instructions for digital submission of exam papers can be found here. If you have any formal questions about the exam, please contact Lotte Fisker Rasmussen (artslfr@au.dk).

Course schedule:

Lecture 1
Introduction to research design
Tue Aug. 31st, 14-16 (Week 35)

In our first lecture, we will discuss how the cognitive sciences are an intrinsically analytical field of study, and how statistical testing and modeling therefore constitute a central tool of the trade for every scientist interested in the study of human thinking behavior. We will discuss different research methods and approaches within the cognitive science, the different kinds of evidence they can provide, and the strengths and weaknesses associated with each of them.

Practical Exercises 1
The R/RStudio environment
Wed Sep. 1st, 15-17 (Class 1)
Thu Sep. 2nd, 14-16 (Class 2)

In the first class, we will introduce ourselves to basics of the programming language R and the RStudio environment. We will discuss and try out various basic procedures, such as how to assign various values to variables, lists and data frames and how to access these values again in order to manipulate and use them. You will also be provided with general guidelines for practical exercises, some advice on coding and helpful resources.

Primary readings:
- Handbook, Chapter 1: *Introduction to R*

Lecture 2
Data collection: What to measure, and how to measure it
Tue Sep. 7th, 14-16 (Week 36)

How can we answer questions about human cognition by collecting and analyzing empirical data? What are *measurements*, *variables*, and *distributions*, and why are they important? How do we make sure we measure what we really want to measure? How many different types of data are there? All these questions (and more) will be addressed in this lecture.

Primary readings:
- Handbook, Chapter 2: *The Tidyverse and Reproducible R Workflows*

Practical Exercises 2
Data mining 1: Organizing data
Thu Sep. 9th, 12-14 (Class 1)
Thu Sep. 9th, 14-16 (Class 2)

We continue working with RStudio. In this class, we will get started with some basic tools for *data mining*, i.e. the practice of exploring and working with data sets with the purpose to discover patterns and insights. More specifically, we will learn how to import, index, explore and transform so-called two-dimensional data frames. We will also learn how to extract relevant subsets of data that meet certain criteria. Please make sure to download the CogSciPersonalityTest2020Data before this class.

Lecture 3

Practical Exercises 3

Building statistical models
Tue Sep. 14th, 14-16 (Week 37)

When we do statistics, we build mathematical models of the phenomena under scrutiny (e.g., a specific kind of behavior we may be interested in) from the empirical data we have collected. These models are crucial, as they help us narrow huge and messy data into something that we can more easily understand. In this lecture, we will explore the concept of *statistical models*, and we will get acquainted with very basic types of statistical models that are normally used to describe data: mean, median, standard variation, and standard error.

Primary readings:
- Handbook, Chapter 3: *Descriptive Statistics, Models, and Distribution*

Data mining 2: Summarizing data
Thu Sep. 16th, 10-12 (Class 1)
Thu Sep. 16th, 12-14 (Class 2)

We will continue with the data mining exercises from the previous week, adding a few new tools and functions to our repertoire. We will also start looking at how the tools we have learned so far can be effectively supplemented with data visualization (i.e., graphs and charts), which is a very important part of the data mining process. It is much easier to find patterns in data if we can visualize them graphically!

Lecture 4
Parametric tests and their assumptions
Tue Sept. 21st, 10-12 (Week 38)

Many different statistical tools are usually available in a cognitive scientist's toolbox, but the choice of which tool to use in which occasion depends on the purposes of our analyses, and on the kind of data we are dealing with. How do we make sure we choose the right one? The data will tell us: this is because each test builds on different assumptions about the nature of the data, so different types of data afford the use of different statistical tools. In this lecture, we will get acquainted with these assumptions.

Primary readings:
- Field, Discovering Statistics Using R, Chapter 5: *Exploring assumptions*
- Handbook, Chapter 5: *Correlation, Linear, and Nonlinear Transformations*

Practical Exercises 4
Data mining 3: Visualizing data
~~Thu Sep. 23rd, 10-12 (Class 1)~~
~~Thu Sep. 23rd, 12-14 (Class 2)~~
This class is canceled because of the cabin trip. You will do the exercises individually.

As we have already experienced, data are often quite noisy, and just looking at numbers won't tell us much. Here, we will follow up on the previous class and talk about how any analysis of experimental data should therefore start (and end, actually) with data visualization. Visualizations have the power to present the essence of your otherwise complex data in a glance. You can inspect if there are problems with the distribution, unexpected outliers or any other data abnormalities. We will acquaint ourselves with the R package 'ggplot2' and investigate how we can use visualization tools to explore assumptions (and even make transformations) of non-normal data.

Python/PsychoPy3 Workshop
Wed Sept. 29th – Fri Oct. 1st (Week 39)
Time and place: TBA

Teacher: **Kristian Tylén** (AU profile)

This is an intensive 3-day workshop introducing the programming language, Python, with special focus on its PsychoPy3 package, which can be used to program and run experiments in experimental psychology and cognitive science. Programming in Python/PsychoPy allows us to present different types of stimuli in controlled ways and record real-time responses from participants. The same programming tools will be used later in the study program with eye-trackers and fMRI brain scanners to control stimulus presentation and response recording. The workshop is intended to be very practice-oriented and hands-on.

In preparation for the workshop, please make sure to install the PsychoPy3 standalone version here.

Also, it will be a great advantage if you go through chapter 1 and 2 of Kristian's eBook Programming Experiments in Python and PsychoPy3 and try out some of the code examples.

Lecture 5
Correlations: Looking at relationships in our data
Tue Oct. 5th, 14-16 (Week 40)

Until this point, we will have dealt with so-called *descriptive statistics* — i.e., summary models that tell us something about what our data looks like. But what if we want to look deeper into the data in order to deduce properties of underlying relationships between our variables, and even to test hypotheses we may have about the data? This is where we begin to move into the world of so-called *inferential statistics*. Statistical inference allows us to learn things about the data we are working with and to generalize to the larger population it came from. A very common tool in inferential statistics is correlation analysis: measuring the degree to which variables are associated with or dependent on each other. We will learn how to measure correlation in R using our experimental data and discuss whether correlation implies

Practical Exercises 5
Correlation analysis in R
Thu Oct. 7th, 10-12 (Class 1)
Thu Oct. 7th, 12-14 (Class 2)

Based on data from a reading time experiment that you will have collected during the PsychoPy workshop, we will investigate a number of variables and how they affect our reading pace. This will require us to employ newly acquired correlation analysis techniques in R. These analyses of our own data — including the accompanying graphs — will make up the second part of the portfolio exam.

causality.

Primary readings:
- Field, Discovering Statistics Using R, Chapter 6: *Correlation*

Additional materials:
- Spurious correlations (very funny, check it out)

Lecture 6
Inferential statistics and hypothesis testing
Tue Oct. 12th, 14-16 (Week 41)

Correlation does not always imply causation. However, in cognitive science research, we are mostly interested in cause-effect relations. How can we test hypotheses about causes and effects? This requires carefully designed experiments in which we manipulate one or more variables (the so-called *independent variables*) and then assess the impact of our manipulation on another variable (the so-called *dependent variable*). In this lecture, we will discuss different types of experimental design (e.g., within-subject vs. between-subject designs), and we will look at concepts like randomization and sampling. We will then get acquainted with the *t*-test, which is a common tool for hypothesis testing.

Primary readings:
- Handbook, Chapter 9: *Inferential Statistics 1: Significance Testing*
- Handbook, Chapter 10: *Inferential Statistics 2: Issues with Significance Testing*

Practical exercises 6
The *t*-test
Thu Oct. 14th, 10-12 (Class 1)
Thu Oct. 14th, 12-14 (Class 2)

We will keep working with our reading time data, but this time we will contrast two experimental conditions using *t*-tests. Specifically, we will use *t*-test to see whether violations of expectations can disrupt the reading pace by comparing reading time between two texts that differ only by one word. The *t*-test will help us determine whether the difference between the two conditions is “statistically significant”, or simply due to chance.

Week 42 **Fall break**

Lecture 7

Practical exercises 7

The linear model
Tue Oct. 26th, 14-16 (Week 43)

We can take the idea behind correlation to the next level and look at how we can *estimate* the value of one dependent variable from one independent variable. This is called *regression*, because it allows us to regress (= lead back) one variable to another. The power of regression analysis even goes beyond the data we have collected, as it allows us to make *predictions* about data that we haven't observed. In the first of four lectures about regression analysis, we will get acquainted with the basics of the model and learn to implement it in R.

Primary readings:
- Handbook, Chapter 4: *Introduction to the Linear Model: Simple Linear Regression*
- Lindeløv, J. K. (2019). Common statistical tests are linear models (or: how to teach stats)

Simple linear regression
Thu Oct. 28th, 10-12 (Class 1)
Thu Oct. 28th, 12-14 (Class 2)

In the class we will explore a new dataset that includes information about child aggression outcomes and background factors that are possibly associated with it. We will learn how to run linear regression models on this data, how to understand the outputs, and finally how to interpret our findings.

Lecture 8
Multiple regression with numerical and categorical predictors
Tue Nov. 2nd, 14-16 (Week 44)

Sometimes we are interested in predicting how our dependent variable changes in relation to not just one, but multiple independent variables. In these cases, we turn to multiple regression, which allows us to estimate the predictive value of each variable both independently or as they interact with each other. We will focus particularly on one statistical tool that is commonly used in these situations — the ANOVA (ANalisys Of VAriance) model — which is a variant of multiple regression.

Primary readings:
- Handbook, Chapter 6: *Multiple Regression*
- Handbook, Chapter 7: *Categorical Predictors*

Practical exercises 8
ANOVA for model comparison
Thu Nov. 4th, 10-12 (Class 1)
Thu Nov. 4th, 12-14 (Class 2)

We will recap theory on ANOVA and learn how to run it in RStudio. We will also have a brainstorm about the Portfolio 4 assignment.

Lecture 9
Repeated-measures design and multilevel regression
Tue Nov. 9th, 14-16 (Week 45)

In experimental psychology and cognitive science, we mostly design experiments in which multiple measurements are collected from the same participant — e.g., by subjecting the participant to multiple trials and multiple conditions within our experiment. In such cases, we will not only have to deal with variance across conditions and/or across participants (which we have addressed using either linear or multiple regression), but also *within* the same participant. In order to handle these different types of variance, we resort to a specific type of regression models called multilevel regression models (aka. *linear mixed-effects models*).

Primary readings:
- Handbook, Chapter 14: *Mixed Models 1: Conceptual Introduction*

Practical exercises 9
Linear mixed-effects models
Thu Nov. 11th, 10-12 (Class 1)
Thu Nov. 11th, 12-14 (Class 2)

We will conduct a small repeated-measures experiment — the “emotional Stroop test” — and discuss how to construct the analysis using mixed effects models (with the *lme4* and *lmerTest* packages for R). You can download the PsychoPy script for the experiment here.

- Handbook, Chapter 15: *Extended Example, Significance Testing, Convergence Issues*

Additional materials:
- https://www.jove.com/video/53720/the-emotional-stroop-task-assessing-cognitive-performance-under
- https://en.wikipedia.org/wiki/Emotional_Stroop_test

Lecture 10
Logistic regression
Tue Nov. 16th, 14-16 (Week 46)

Linear and multiple regressions are amazing tools, but they only work if the outcome of our study (i.e., our dependent variable) is a continuous variable. But what if our outcome variable is a binary value — e.g., true/false, 1/0, male/female? These outcomes are indeed quite common in our field of study. To predict this kind of data from either continuous or categorical variables (e.g., predicting our biological sex based on what we had for dinner last night), we rely on an extension of linear regression called *logistic regression*.

Primary readings:

Practical exercises 10
Logistic regression in R
Thu Nov. 18th, 10-12 (Class 1)
Thu Nov. 18th, 12-14 (Class 2)

We will look at a case study on sound symbolism that requires us to do multiple logistic regression (link to the experiment). We will practice how to make logistic regression work in RStudio and how to make sense of its output. The data and tools from this class will be used in Portfolio 5.

- Handbook, Chapter 12: *Generalized Linear Models 1: Logistic Regression*

Additional materials:
- This video tutorial about logistic regression by Josh Starmer @ StatQuest (make sure to check out some of his other videos too)

Lecture 11
Interaction analysis
Tue Nov. 23rd, 14-16 (Week 47)

TBA

Primary readings:
- Handbook, Chapter 8: *Interactions and Nonlinear Effects*

Practical exercises 11
Interactions and nonlinear effects
Thu Nov. 25th, 10-12 (Class 1)
Thu Nov. 25th, 12-14 (Class 2)

TBA

Lecture 12
Content analysis
Tue Nov. 30th, 14-16 (Week 48)

As cognitive scientists, we may sometimes be interested in investigating issues that can be hard to measure objectively and quantitatively. For instance, we may be interested in analyzing written texts (newspapers, books, web pages, etc.) or pieces of oral communications (radio and TV programs, speeches, interviews, etc.) with the intent of evaluating how emotionally charged, creative, or left-wing vs. right-wing they are. In such cases, we may want to turn to content analysis, a method that allows us to summarize subjective judgments in relation to different types of content into quantitative measurements for statistical analysis. To achieve this goal, content analysis relies on *coding* (i.e., counting) of various aspects of the content. Coding is normally carried out by multiple, independent *coders* using standardized procedure and schemes. This allows us to quantify the level of agreement between different judgments of the content

Practical exercises 12
Coding qualitative data in R
Thu Dec. 2nd, 10-12 (Class 1)
Thu Nov. 2nd, 12-14 (Class 2)

We will practice how to turn a qualitative material into measurable units by means of human coding. As judges of the material might produce different results, *inter-coder reliability* is a fundamental measure in studies that rely on human coders. Vast differences could point to various underlying factors, such as problematic experimental design or significant differences between participants that should not be overlooked. In this class, we will learn how to assess inter-coder reliability in R.

Coding scheme
Coding template
The data

(so-called *inter-coder reliability*), thus reducing the subjectivity of the measurement.

Primary readings:
- Canavagh, S. (1997) Content analysis: concepts, methods and applications.

Secondary readings:
- Krippendorff, K. (2004). Content analysis. An introduction to its methodology. Thousand Oaks, CA: Sage Publications. Chapter 2 and 4