

Methods 3: Multilevel Statistical Modeling and Machine Learning

Week 1: *Introduction and Why are we here?*
September 14, 2021

by: Lau Møller Andersen

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Outline

- 1) The overall idea of the course
- 2) Presenting the instructor and myself
- 3) Getting to know your names
- 4) Academic regulations (*studieordning*) and exam
- 5) How much do you remember?

The foundations we build on

- You have now learnt to code (*Methods 1*), and you have learnt about the General Linear Model (*Methods 2*)
- You can thus evaluate any given model

From Jonas Lindeløv

Common statistical tests are linear models

Last updated: 28 June, 2019. Also check out the [Python version!](#)

See worked examples and more details at the accompanying notebook: <https://lindeloev.github.io/tests-as-linear>

	Common name	Built-in function in R	Equivalent linear model in R	Exact?	The linear model in words	Icon
Simple regression: $\text{lm}(y \sim 1 + x)$	y is independent of x P: One-sample t-test N: Wilcoxon signed-rank	t.test(y) wilcox.test(y)	$\text{lm}(y \sim 1)$ $\text{lm}(\text{signed_rank}(y) \sim 1)$	✓ for N > 14	One number (intercept, i.e., the mean) predicts y. - (Same, but it predicts the <i>signed rank</i> of y.)	
	P: Paired-sample t-test N: Wilcoxon matched pairs	t.test(y1, y2, paired=TRUE) wilcox.test(y1, y2, paired=TRUE)	$\text{lm}(y_2 - y_1 \sim 1)$ $\text{lm}(\text{signed_rank}(y_2 - y_1) \sim 1)$	✓ for N > 14	One intercept predicts the pairwise $y_2 - y_1$ differences. - (Same, but it predicts the <i>signed rank</i> of $y_2 - y_1$.)	
	y ~ continuous x P: Pearson correlation N: Spearman correlation	cor.test(x, y, method='Pearson') cor.test(x, y, method='Spearman')	$\text{lm}(y \sim 1 + x)$ $\text{lm}(\text{rank}(y) \sim 1 + \text{rank}(x))$	✓ for N > 10	One intercept plus x multiplied by a number (slope) predicts y. - (Same, but with <i>ranked x</i> and <i>y</i>)	
	y ~ discrete x P: Two-sample t-test t.test(y1, y2, var.equal=FALSE) Welch's t-test N: Mann-Whitney U wilcox.test(y1, y2)	t.test(y1, y2, var.equal=TRUE) t.test(y1, y2, var.equal=FALSE) wilcox.test(y1, y2)	$\text{lm}(y \sim 1 + G_2)^4$ $\text{gls}(y \sim 1 + G_2, \text{weights}=\dots)^4$ $\text{lm}(\text{signed_rank}(y) \sim 1 + G_2)^4$	✓ ✓ for N > 11	An intercept for group 1 (plus a difference if group 2) predicts y. - (Same, but with one variance <i>per group</i> instead of one common.) - (Same, but it predicts the <i>signed rank</i> of y.)	
Multiple regression: $\text{lm}(y \sim 1 + x_1 + x_2 + \dots)$	P: One-way ANOVA N: Kruskal-Wallis	aov(y ~ group) kruskal.test(y ~ group)	$\text{lm}(y \sim 1 + G_2 + G_3 + \dots + G_N)^4$ $\text{lm}(\text{rank}(y) \sim 1 + G_2 + G_3 + \dots + G_N)^4$	✓ for N > 11	An intercept for group 1 (plus a difference if group $\neq 1$) predicts y. - (Same, but it predicts the <i>rank</i> of y.)	
	P: One-way ANCOVA	aov(y ~ group + x)	$\text{lm}(y \sim 1 + G_2 + G_3 + \dots + G_N + x)^4$	✓	- (Same, but plus a slope on x.) <i>Note: this is discrete AND continuous. ANCOVAs are ANOVAs with a continuous x.</i>	
	P: Two-way ANOVA	aov(y ~ group * sex)	$\text{lm}(y \sim 1 + G_2 + G_3 + \dots + G_N + S_2 + S_3 + \dots + S_K + G_2*S_2 + G_3*S_3 + \dots + G_N*S_K)^4$	✓	Interaction term: changing sex changes the y ~ group parameters. <i>Note: $G_{2 \dots N}$ is an indicator (0 or 1) for each non-intercept levels of the group variable. Similarly for $S_{2 \dots K}$ for sex. The first line (with G) is main effect of group, the second (with S) for sex and the third is the group * sex interaction. For two levels (e.g. male/female), line 2 would just be "S2" and line 3 would be S2 multiplied with each G.</i>	[Coming]
	Counts ~ discrete x N: Chi-square test	chisq.test(groupXsex_table)	Equivalent log-linear model $\text{glm}(y \sim 1 + G_2 + G_3 + \dots + G_N + S_2 + S_3 + \dots + S_K + G_2*S_2 + G_3*S_3 + \dots + G_N*S_K, \text{family}=\dots)^4$	✓	Interaction term: (Same as Two-way ANOVA.) <i>Note: Run glm using the following arguments: glm(model, family=poisson())</i> As linear-model, the Chi-square test is $\log(y) = \log(N) + \log(\alpha) + \log(\beta) + \log(\alpha\beta)$ where α and β are proportions. See more info in the accompanying notebook	Same as Two-way ANOVA
	N: Goodness of fit	chisq.test(y)	$\text{glm}(y \sim 1 + G_2 + G_3 + \dots + G_N, \text{family}=\dots)^4$	✓	(Same as One-way ANOVA and see Chi-Square note.)	1W-ANOVA

https://lindeloev.github.io/tests-as-linear/linear_tests_cheat_sheet.pdf

... so what is left to learn?

Overall idea of the course

- **Master complex data:** build models that work despite missing data entries, and which model the nested and hierarchical structures of the data
- **Create generalisable models:** do model comparisons and learn the difference between *explanation* and *prediction*
- **Reduce the dimensionality of data:** extract the meaningful dimensions of data and separate it from the noise

Overall idea of the course

- The aim is that you learn the practical skills (not just the theory), such that you yourself can build and evaluate models in *R* and *Python*.
- In a wider sense, the idea is that you should be able to critically assess models and understand their advantages and limitations.

My expectations towards you – the do's!

- Do show up for the lectures and classes!
- Do the exercises and the assignments and hand them in on time!
- Do take responsibility for your learning!
- Do ask questions if things are unclear!
- Do challenge me!
- Do make sure that I provide a foundation of learning for you all!

Who are we?

Instructor

- Emil Trenckner Jessen
 - Master's degree student (1st semester)



Lecturer

[Front Page](#)
[Publications & CV](#)
[Workshops](#)
[Open Science](#)
[Teaching Material](#)

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Denmark



LAU MØLLER ANDERSEN

Postdoc: Karolinska Institutet 2015-2019:
working on on-scalp MEG and
somatosensation

PhD: Aarhus University 2016
Thesis: Spatio-temporal localization and
task specificity in the search for neural
correlates of perceptual consciousness

MSc (Cum Laude): University of
Amsterdam 2011
Programme: Brain and Cognitive
Sciences

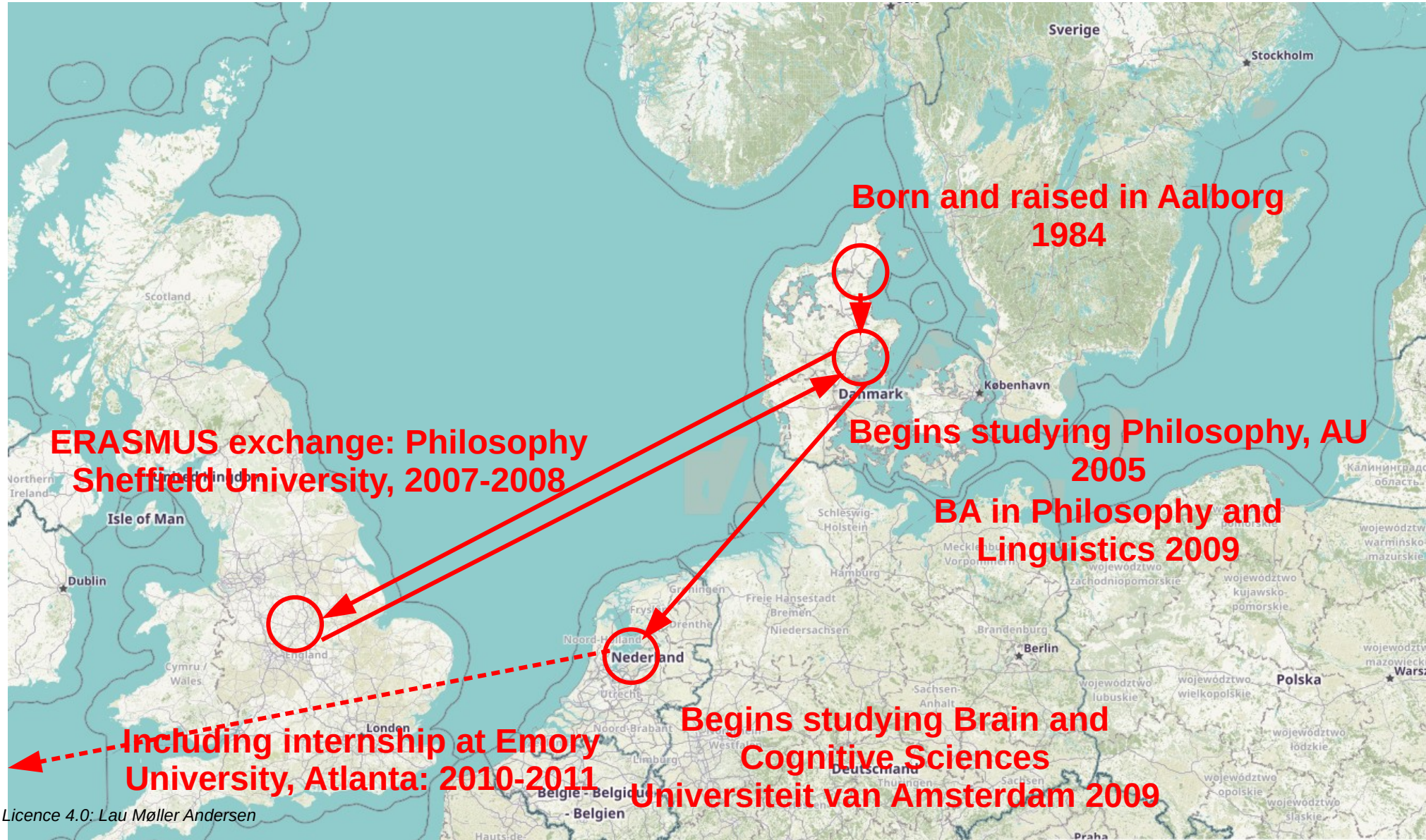
BA: Aarhus University 2009
Programmes: Philosophy and Linguistics



ABOUT ME

I am a post-doc working at CFIN (Center of Functionally Integrative Neuroscience) at Aarhus University, Denmark and I am a fellow at the Aarhus Institute of Advanced Studies (AIAS). I'm interested in anything related to **magnetoencephalography** (MEG), but **sensory expectations, consciousness, cerebellar MEG** and **on-scalp MEG** must be highlighted among my interests. I have also worked and published on on-scalp MEG and **machine learning**. Finally, I take a keen interest in coding using language such as **MATLAB, Python** and **R** and have published tutorial papers on how to do MEG analysis in **FieldTrip** and **MNE-Python**.

©Villy Fink Isaksen CC-BY-SA 4.0 [file link](#)



**Born and raised in Aalborg
1984**

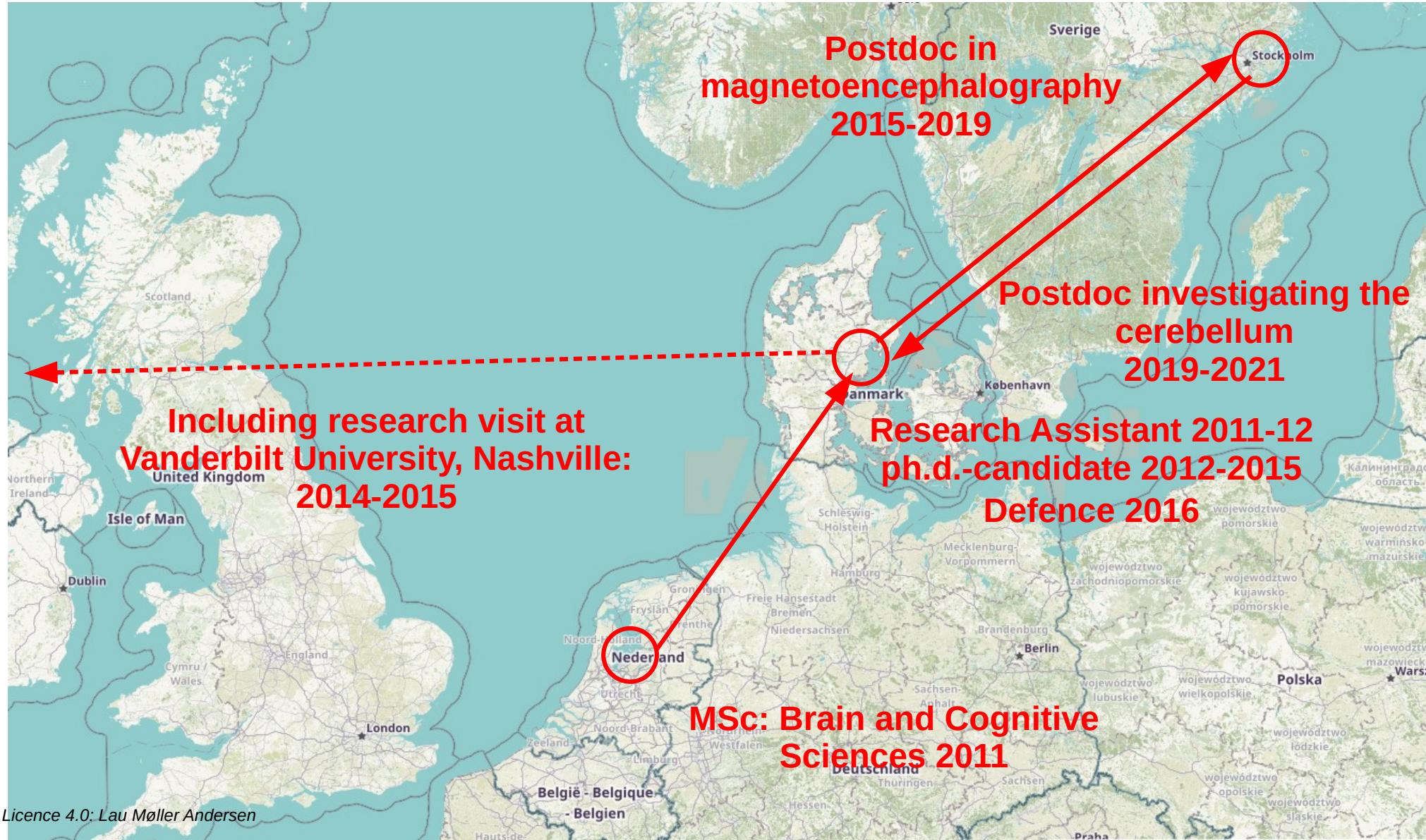
**Begins studying Philosophy, AU
2005**

**BA in Philosophy and
Linguistics 2009**

**Begins studying Brain and
Cognitive Sciences
Universiteit van Amsterdam 2009**

**ERASMUS exchange: Philosophy
Sheffield University, 2007-2008**

**Including internship at Emory
University, Atlanta: 2010-2011**



**Postdoc in
magnetoencephalography
2015-2019**

**Postdoc investigating the
cerebellum
2019-2021**

**Including research visit at
Vanderbilt University, Nashville:
2014-2015**

**Research Assistant 2011-12
ph.d.-candidate 2012-2015
Defence 2016**

**MSc: Brain and Cognitive
Sciences 2011**

2021 – onwards

Department of Cognitive Science

Examples of my interests

Classifying when visual stimuli become consciously perceptible using *machine learning*

Occipital MEG Activity in the Early Time Range (<300 ms) Predicts Graded Changes in Perceptual Consciousness FREE

Lau M. Andersen ✉, Michael N. Pedersen, Kristian Sandberg, Morten Overgaard

Cerebral Cortex, Volume 26, Issue 6, June 2016, Pages 2677–2688, <https://doi.org/10.1093/cercor/bhv108>

Published: 24 May 2015

Examples of my interests

Finding the somatosensory
activation to absent
stimulation using
magnetoencephalography



NeuroImage
Volume 184, 1 January 2019, Pages 78-89



Somatosensory responses to nothing: An MEG
study of expectations during omission of tactile
stimulations

Lau M. Andersen  , Daniel Lundqvist

 [Show more](#)

<https://doi.org/10.1016/j.neuroimage.2018.09.014>

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Examples of my interests


Providing pipelines for
group analysis in *Python*
and *MATLAB*

PROTOCOLS ARTICLE

Front. Neurosci., 22 January 2018 | <https://doi.org/10.3389/fnins.2018.00006>



Group Analysis in MNE-Python of Evoked Responses from a Tactile Stimulation Paradigm: A Pipeline for Reproducibility at Every Step of Processing, Going from Individual Sensor Space Representations to an across-Group Source Space Representation

 Lau M. Andersen*


NatMEG, Department of Clinical Neuroscience, Karolinska Institutet, Stockholm, Sweden

PROTOCOLS ARTICLE

Front. Neurosci., 01 May 2018 | <https://doi.org/10.3389/fnins.2018.00261>



Group Analysis in FieldTrip of Time-Frequency Responses: A Pipeline for Reproducibility at Every Step of Processing, Going From Individual Sensor Space Representations to an Across-Group Source Space Representation

 Lau M. Andersen*

NatMEG, Department of Clinical Neuroscience, Karolinska Institutet, Stockholm, Sweden

Examples of my interests

Benchmarking new technologies in *magnetoencephalography*



Examples of my interests

Using *mixed effects modelling*



Consciousness and Cognition

Volume 71, May 2019, Pages 59-69



Visual expectations change subjective experience without changing performance

Lau Møller Andersen ^{a, b, ✉}, Morten Overgaard ^b, Frank Tong ^c

[Show more](#) ✓

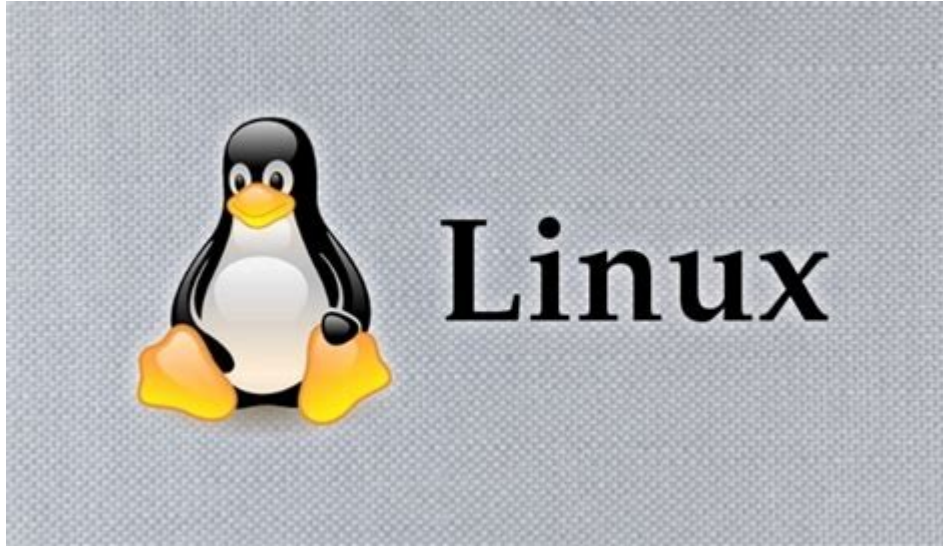
+ Add to Mendeley Share Cite

<https://doi.org/10.1016/j.concog.2019.03.007>

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LibreOffice – (I work in Linux)

- Slides will be in odp- or pdf-format.



<https://www.libreoffice.org/download/download/>

... and I avoid Google as much as I can



Search engine



CryptPad
Online document
collaboration



File management
and version
control

Getting to know your names

I am **L**au and I brought a
Lama with me

Languages



<https://cran.r-project.org/mirrors.html>



My recommendation:

<https://docs.conda.io/en/latest/miniconda.html>

Python environment

Create environment (yml-file can be downloaded from GitHub)

```
(base) lau@lau:~$ conda env create -f methods3_environment.yml
```

Activate environment

```
(base) lau@lau:~$ conda activate methods3
```

This course

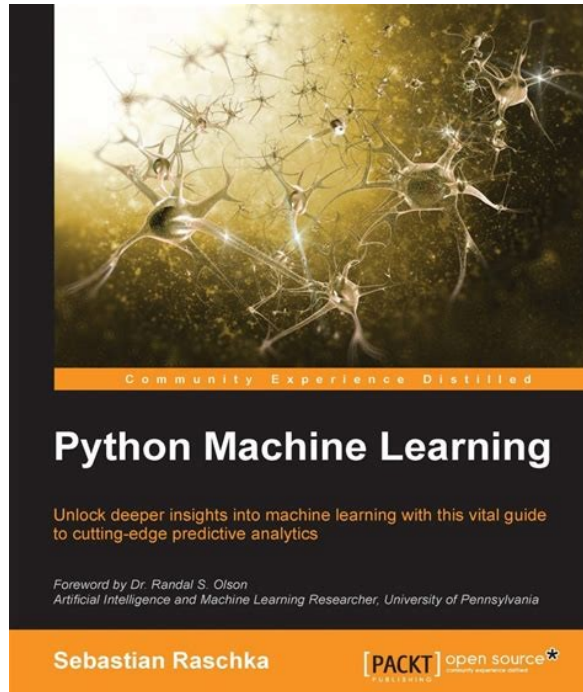
R

Linear mixed
models

Python

Machine
learning

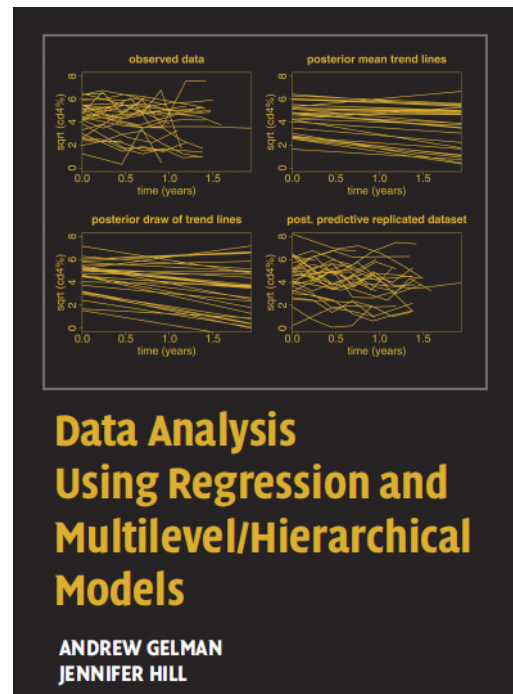
Book for latter half



- Has been ordered from Stakbogladden
 - Support the local book stores and not space cowboys

Not necessary – but really good if you are interested

- Can be ordered from Stakbogladen
 - Let me know if you are interested!
 - Support the local book stores and not space cowboys



Programming languages interpret *human readable code*, such that complex operations can be performed in a systematic way

Example – estimating π

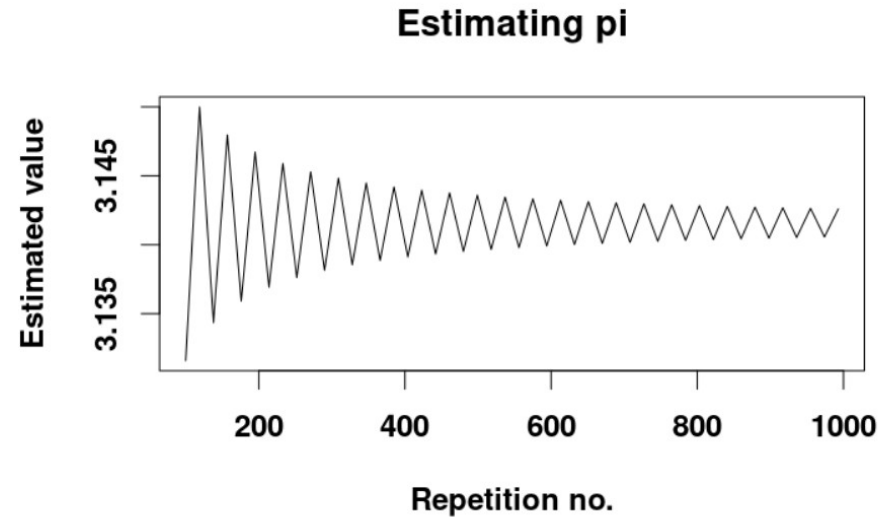
$$\pi = 4 \cdot \sum_{n=1}^{\infty} (-1)^{n+1} \cdot \frac{1}{2n-1} = 4 \cdot \left(\frac{1}{1} - \frac{1}{3} + \frac{1}{5} - \frac{1}{7} + \frac{1}{9} - \frac{1}{11} \dots \right)$$

[https://da.wikipedia.org/wiki/Pi_\(tal\)](https://da.wikipedia.org/wiki/Pi_(tal))

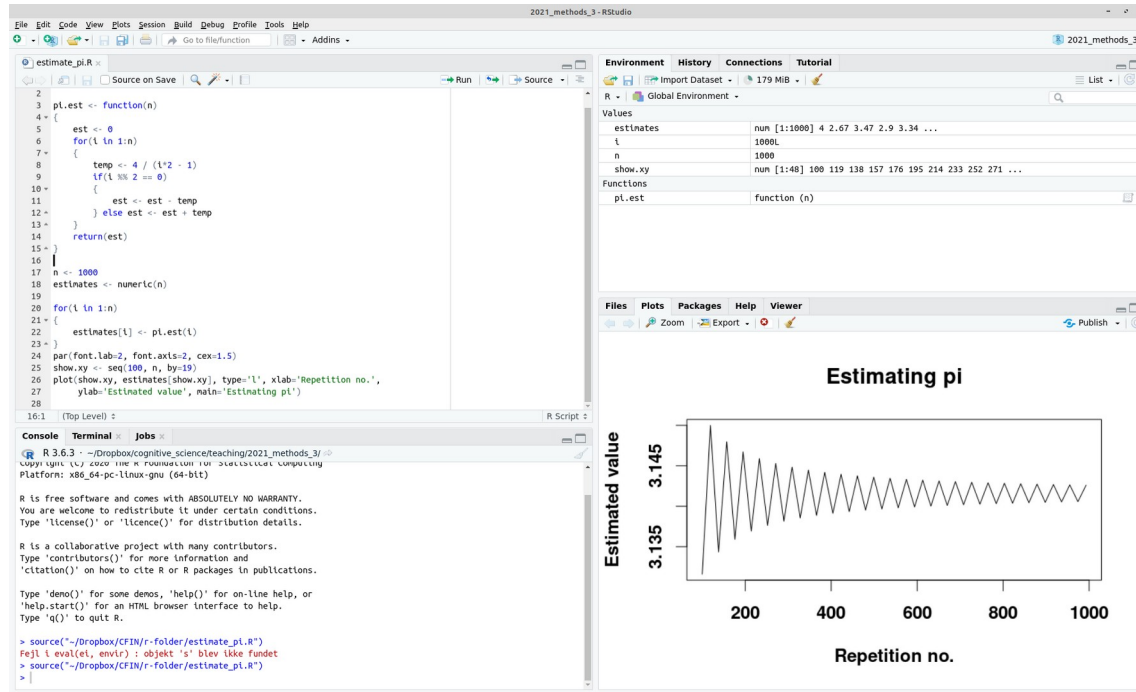
Scripts and output

```
estimate_pi.R x
Source on Save

2
3 pi.est <- function(n)
4 {
5   est <- 0
6   for(i in 1:n)
7   {
8     temp <- 4 / (i*2 - 1)
9     if(i %% 2 == 0)
10    {
11      est <- est - temp
12    } else est <- est + temp
13  }
14  return(est)
15 }
16 s
17 n <- 1000
18 estimates <- numeric(n)
19 |
20 for(i in 1:n)
21 {
22   estimates[i] <- pi.est(i)
23 }
24 par(font.lab=2, font.axis=2, cex=1.5)
25 show.xy <- seq(100, n, by=19)
26 plot(show.xy, estimates[show.xy], type='l', xlab='Repetition no.',
27       ylab='Estimated value', main='Estimating pi')
28
```

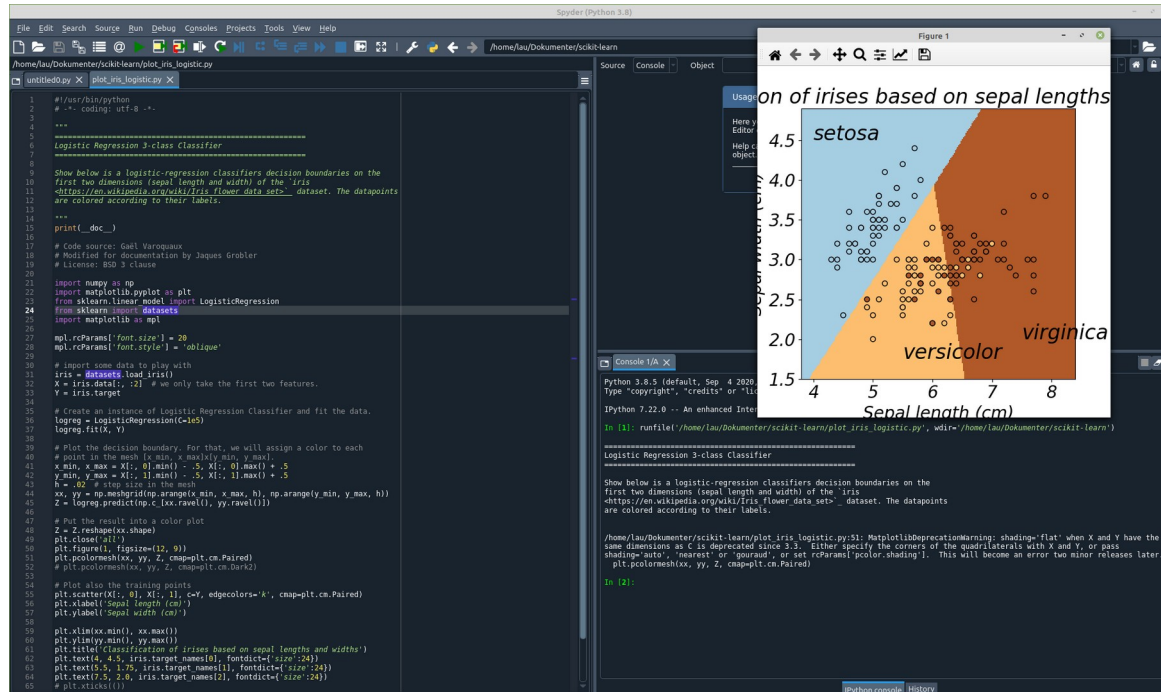


RStudio – Integrated Development Environment



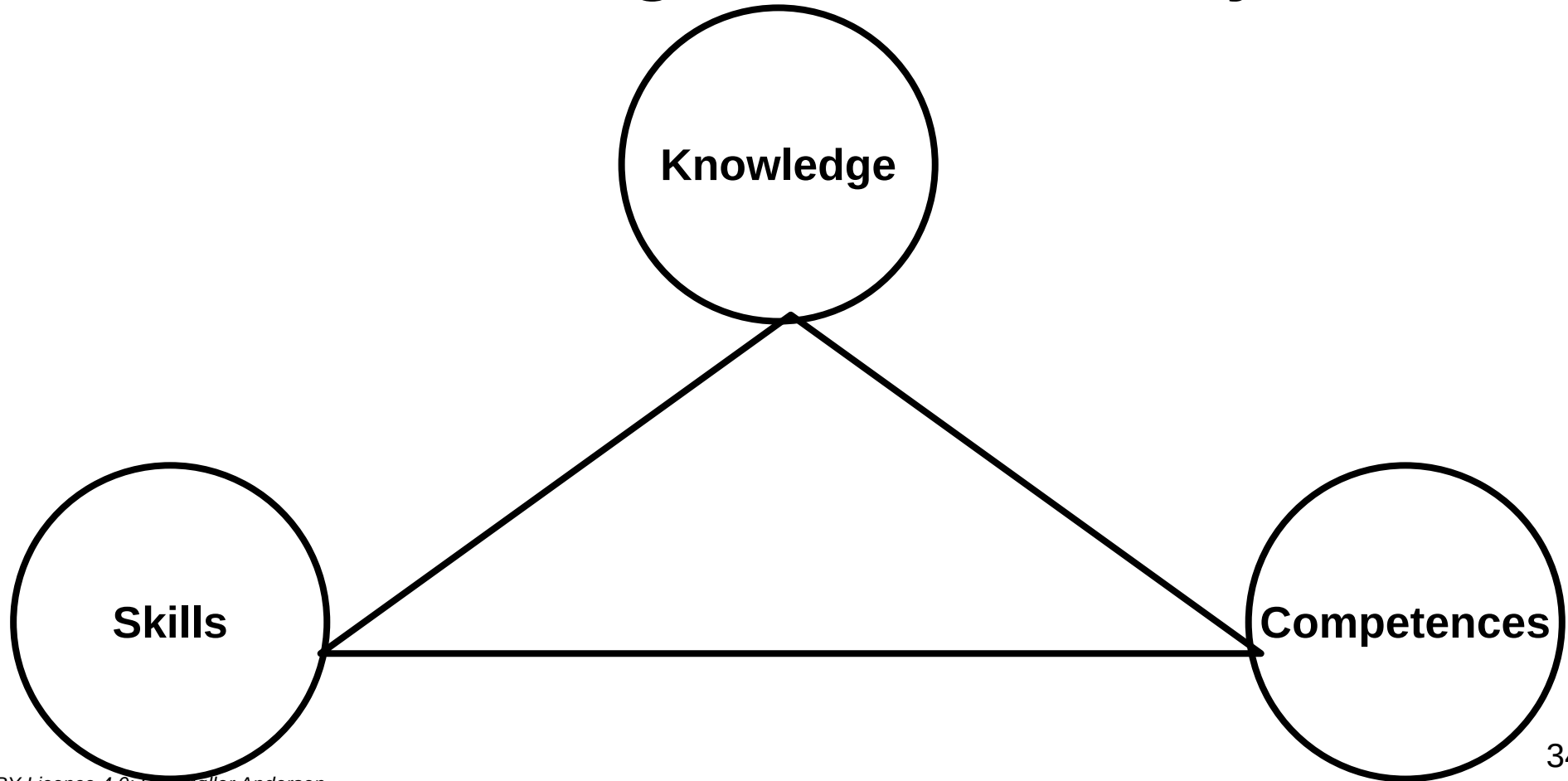
<https://www.rstudio.com/products/rstudio/download/>

Spyder - Integrated Development Environment



Part of installed environment

Academic regulations – objectives



Academic regulations – objectives

Knowledge:

- demonstrate understanding of statistical techniques relying on the Generalised Linear Model
- demonstrate understanding of hierarchical modeling methods
- demonstrate understanding of basic machine learning concepts.

Academic regulations – KNOWLEDGE

You should thus be able to answer questions like:

What is logistic regression?

*What are some naturally
occurring hierarchies within
research data?*

*What is a mixed-effects
model?*

What is cross-validation?

Academic regulations – objectives

Skills:

- build and evaluate models of hierarchically structured data
- integrate machine learning procedures in data analysis
- communicate analysis processes, results and interpretation.

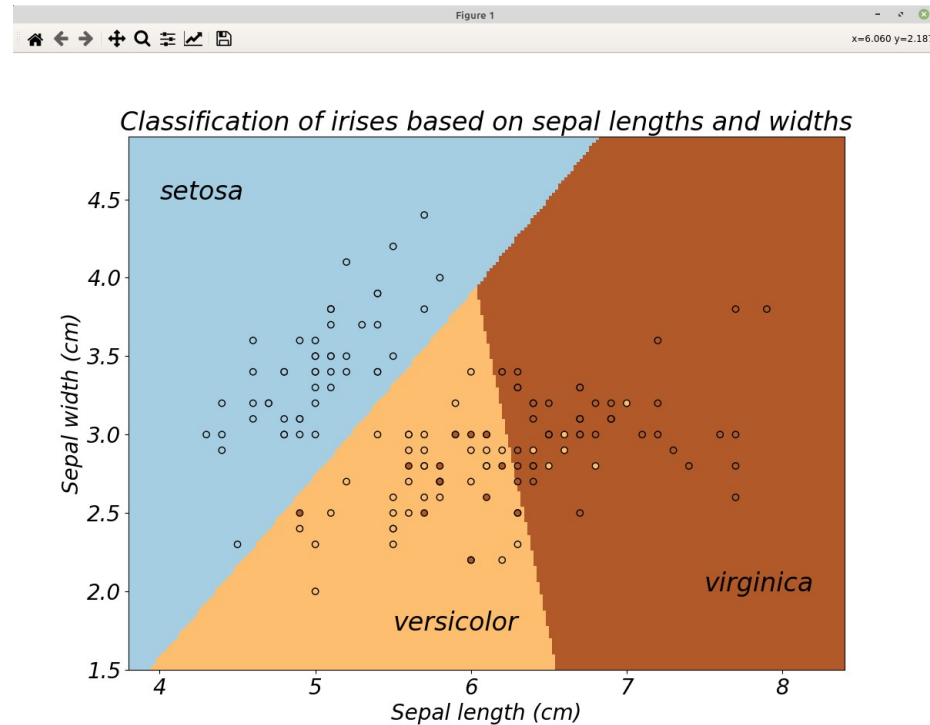
Academic regulations – SKILLS

*build and evaluate models of
hierarchically structured data*

```
Linear mixed model fit by REML ['lmerMod']  
Formula: Height ~ Gender + (1 | Family)  
Data: height
```

Academic regulations – SKILLS

*integrate machine learning procedures
in data analysis*



Academic regulations – SKILLS

*communicate analysis processes,
results and interpretation*

(Andersen et
al., 2019)

Mixed model analyses ([McCulloch & Neuhaus, 2005](#)) were applied to investigate how top-down expectations (No. of Possible Targets) affected subjective experience and objective performance. We performed model comparisons between models that did or did not include the relevant fixed effects and interactions to find the best compromise between an explanatory and a parsimonious model. This was done using the log-likelihood ratio between two models because this ratio approximates a chi-square distribution. A chi-square test can thus be used to assess whether two models differ significantly, where the test statistic is the log-likelihood-ratio and the degrees of freedom is the difference in free parameters of the two models.

Academic regulations – objectives

Competences:

- independently decide on data analysis methods, given a data set and a research question
- justify decision making when pre-processing messy data for data analysis.

Difference between *skills* and *competences*:
Skills are specific
Competences are more generic

Academic regulations – COMPETENCES

*independently decide on data analysis
methods, given a data set and a
research question*

*justify decision making when pre-
processing messy data for data analysis.*

EXAMPLE QUESTION: Can native
Danish speakers tell apart soft d's (ð)
and l's if they are embedded in
English speech, e.g.
maðfunction/malfunction

EXAMPLE DATA: Dataset with
response times and discrimination
responses



Exam; portfolio

- Ongoing assignments to be solved in small groups
 - Will be done in *R Markdown* (.Rmd)
- Final portfolio:
 - Revised assignments, handed in as short reports with reproducible code on GitHub
 - Assignment 1: Using mixed effects modelling to model hierarchical data (Winter & Grawunder, 2012)
 - Assignment 2: Mixed effects modelling of response times, response counts, and accuracy (Andersen et al., 2019)
 - Assignment 3: Using logistic regression to classify subjective experience from brain data
 - Assignment 4: Dimensionality reduction, finding the signal among the noise

Re-examination

Will be done during the summer (tip: stay on schedule, such that you can enjoy your summer)

The structure of lectures

- Tuesdays 11.00-13.00 (NB: Academic quarter)
- A mix between the general theoretical framework and a few formulas
- Code will be incorporated
- Group discussions
- Please don't hold back on your questions
- Slides will be shared *after* the lecture

The structure of a practical exercise

- Wednesdays 10.00-12.00 and 16.00-18.00
- The practical exercises are led by either Emil or me.
 - An introduction to the task
 - Group work (3-4 people)
 - Data and an instructions file are shared
 - Intermittent discussion of pressing issues
- Feedback is given per assignment and collectively

The structure of a practical exercise

- You will be separated into two groups
 - Emil and I will take turns leading the instructor sessions
 - Your time slot is fixed, either 10-12, (Class 2) or 16-18 (Class 1)
 - We, Emil and Lau, show up alternately.
 - Lau: 10-12 – Weeks 3, 5, 7 and 9
 - Emil: 10-12 – Weeks 2, 4, 8, 10
 - Together: Weeks 1 (intro), 6 (mid-way evaluation), 11 (final evaluation)

Homework

- Focus is on developing data analysis and reporting skill
- Readings:
 - Mainly covers background and are sometimes more in-depth than the lectures
 - One have-to-read
 - ... and some recommended (that are not strictly necessary)
- Practical exercises and assignments
 - Hand them in on GitHub on the following Monday (23:59)

Questions about homework and the subject in general

- Lau: Office hours between 8 and 9 on Mondays
- We, Emil and I, collect questions during the week and try to answer them in the classes
- <https://cryptpad.fr/pad/#/2/pad/edit/U21qNTbLgfKriGZU1bnmDE2o/>

Student counsellors

You can contact any of us for help - but each of us has an academic specialisation, so we may refer you to another student counsellor for certain questions. If we can't answer your questions, we will normally be able to direct you to someone who can.



Sofia Madsen

- Scandinavian
Languages
and Literature

Josephine
Brunsgaard

- Cognitive Science

Kristina Duun

- Linguistics and
Cognitive Semiotics

Emilie Vinther

- Experience
Economy and Culture
Of Events

The course plan

Week 1: *Introduction and Why are we here?*, September 14 & 15

Instructor sessions: *Setting up R and Python and recollection of the general linear model*

Week 2: *Linear Mixed Effects Models*, September 21 & 22

Instructor sessions: *Modelling random effects – and how do they differ from fixed effects?*

Week 3: *Generalized Linear Mixed Effects Models*, September 28 & 29

Instructor sessions: *What to do when the response variable is not continuous?*

Week 4: *Explanation and Prediction*, October 5 & 6

Instructor sessions: *Why are good explanations sometimes bad?*

Week 5: *Evaluating and comparing models*, October 12 & 13

Instructor sessions: *How do we assess how models compare to one another?*

Week 6: *Mid-way evaluation and Machine Learning Intro*, November 2 & 3

Instructor sessions: *Moving the goal away from explanation towards prediction and getting Python running*

Week 7: *Linear regression revisited (machine learning)*, November 9 & 10

Instructor sessions: *How to constrain our models to make them more predictive*

Week 8: *Logistic regression (machine learning)*, November 16 & 17

Instructor sessions: *Categorizing responses based on informed guesses*

Week 9: *Dimensionality Reduction, Principled Component Analysis (PCA)*, November 23 & 24

Instructor sessions: *What to do with very rich data?*

Week 10: *Organising and preprocessing messy data*, November 30 and December 1

Instructor sessions: *How to clean up?*

Week 11: *Final evaluation and wrap-up of course*, December 7 & 8

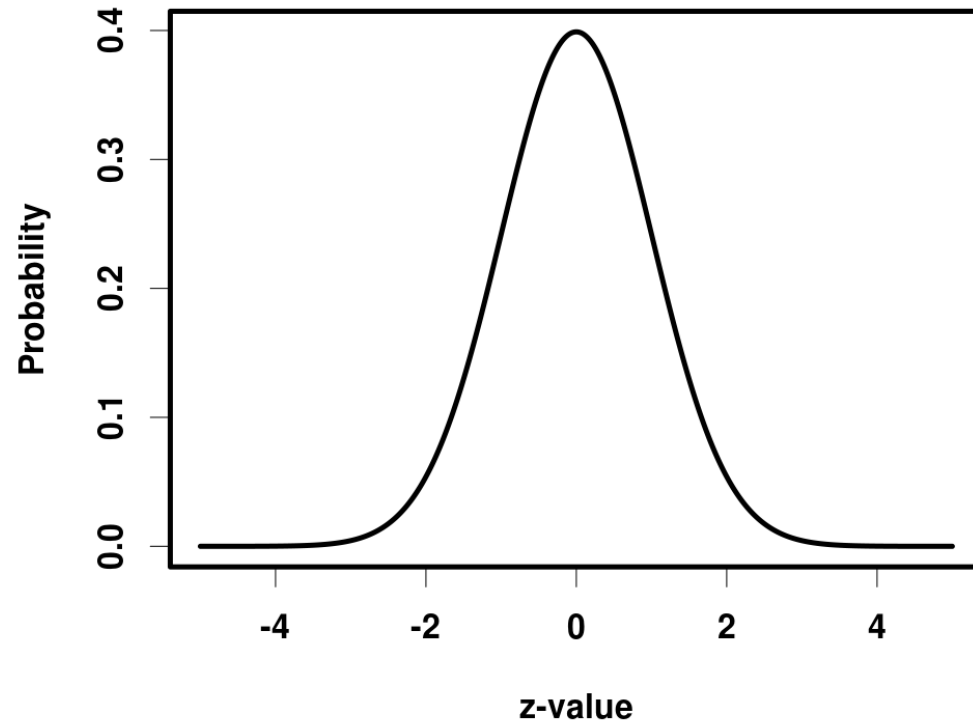
Instructor sessions: *Ask anything!*

What do you remember?

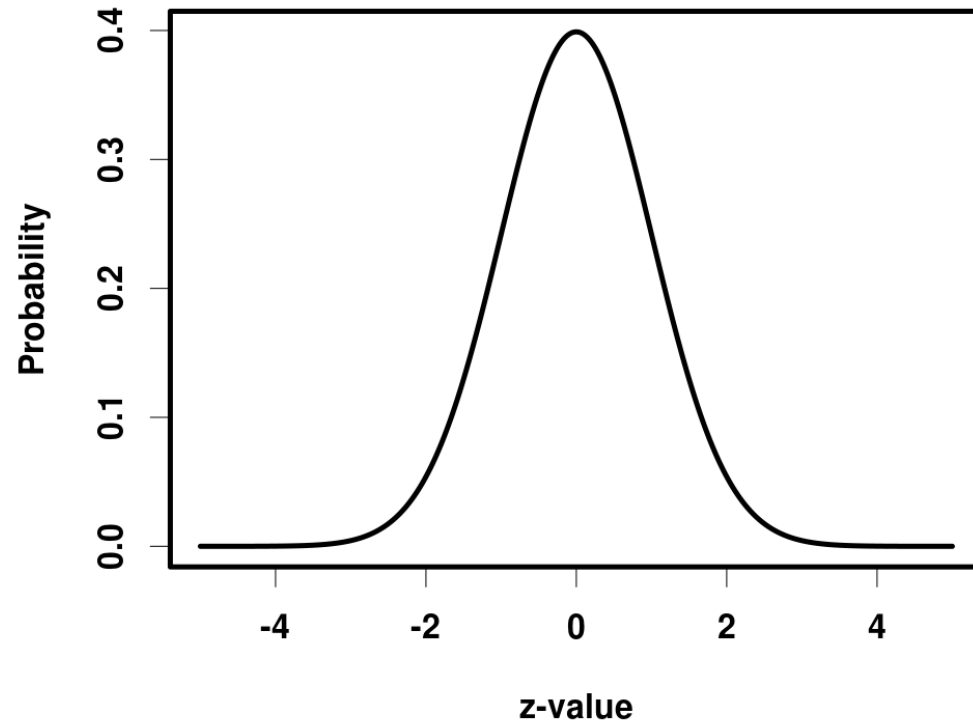
Group discussions

- What does a z -value express?
- What does a p -value express?
- What is the relation between a t -value and a z -value?
- What do the following symbols signify in these equations?
 - $Y = X \beta + \epsilon$
 - $\hat{\beta} = (X^T X)^{-1} X^T Y$

What does a z-value express?



Normal Distribution



$$Z = \frac{\bar{X} - P}{SE}$$

$$SE = \frac{\bar{\sigma}}{\sqrt{n}}$$

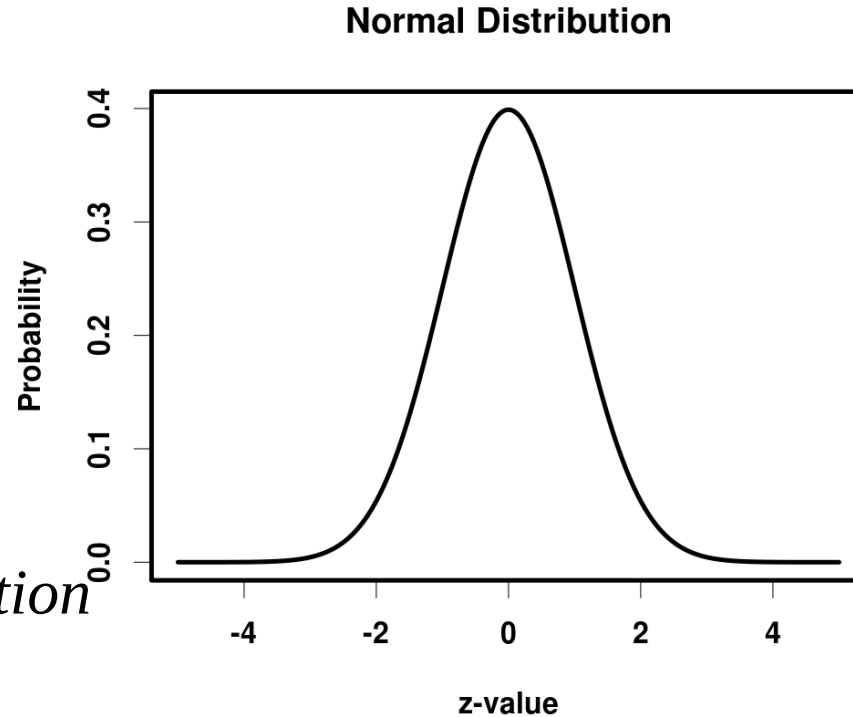
\bar{X} : sample mean

P : population mean

SE : standard error

$\bar{\sigma}$: estimated standard deviation

n : number of observations



$$Z = \frac{\bar{X} - P}{SE}$$

$$SE = \frac{\bar{\sigma}}{\sqrt{n}}$$

\bar{X} : sample mean

P : population mean

SE : standard error

$\bar{\sigma}$: estimated standard deviation

n : number of observations

If we are testing the null hypothesis, then what is z ?

$$P = 0$$

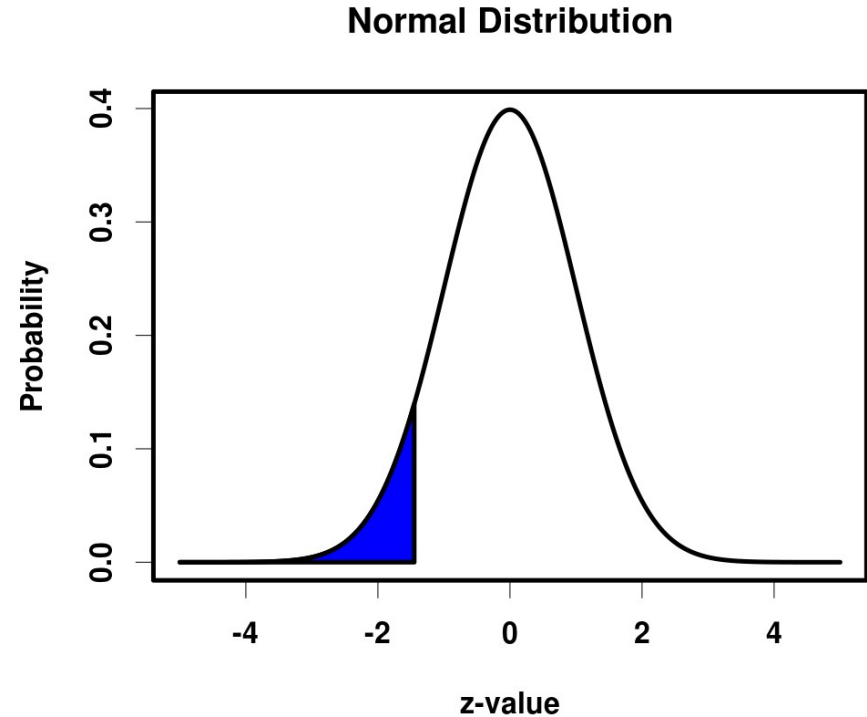
$$z = \frac{\bar{X}}{SE}$$

What does a p -value express?

When assuming the truth of the null hypothesis, the p -value is the probability of observing a given z -value or one that is more extreme.

If $z = -1.45$,
what is p then?

The area of the
blue curve, $p =$
 0.0735



Bonus questions:

- 1) what is the total area under the curve equal to?
- 2) why does the p -value *not* say about the truth of the null hypothesis?

What is the relation between a t -value and a z -value?

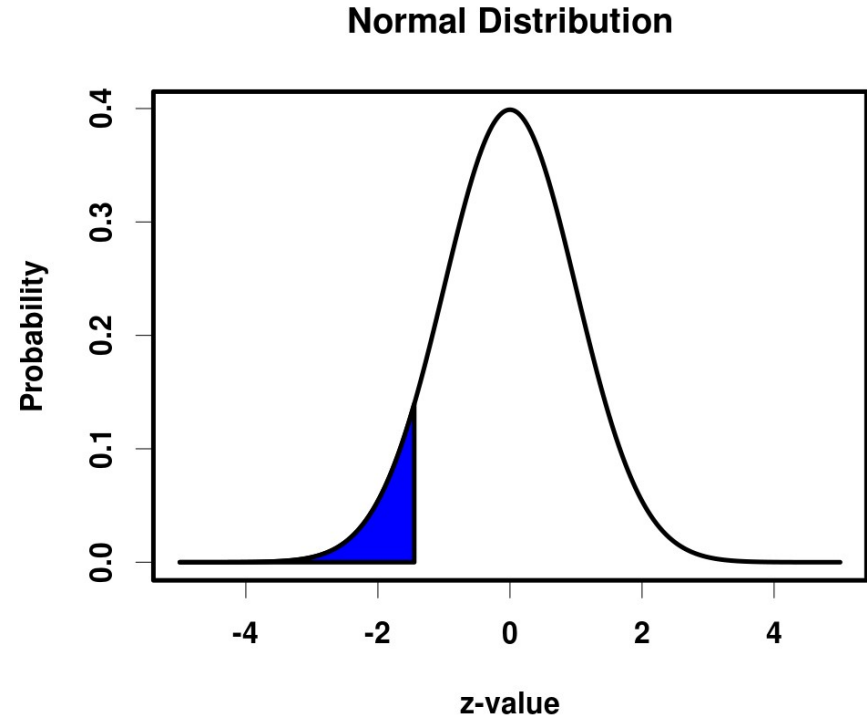
It is the identity relation

$$t = \frac{\bar{X} - P}{SE} = z$$

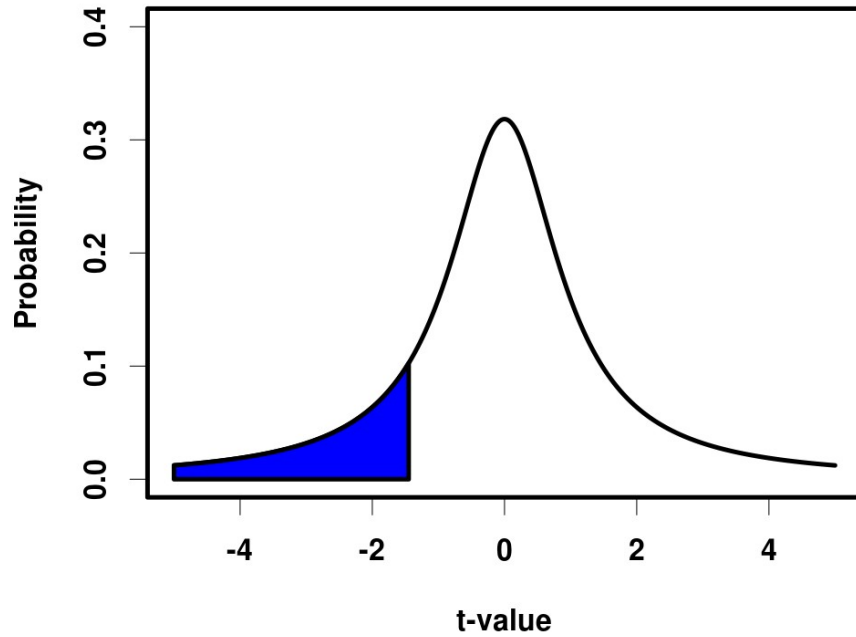
... But the p -values associated with t - and z -values differ. For t -values, the p -values depend on the degrees of freedom; for the z -values, they do not

Crucial assumption when you are performing a z-test is that the population variance is known. When this is not known a *t*-test is more appropriate, as it takes the uncertainty of the estimated variance into the equation

We normally do not know the population variance

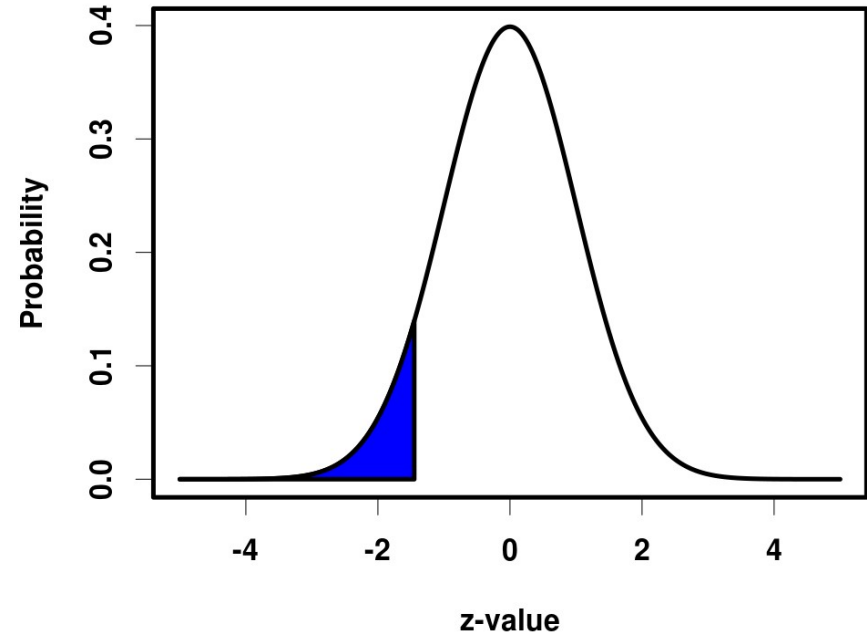


t-distribution, df=1



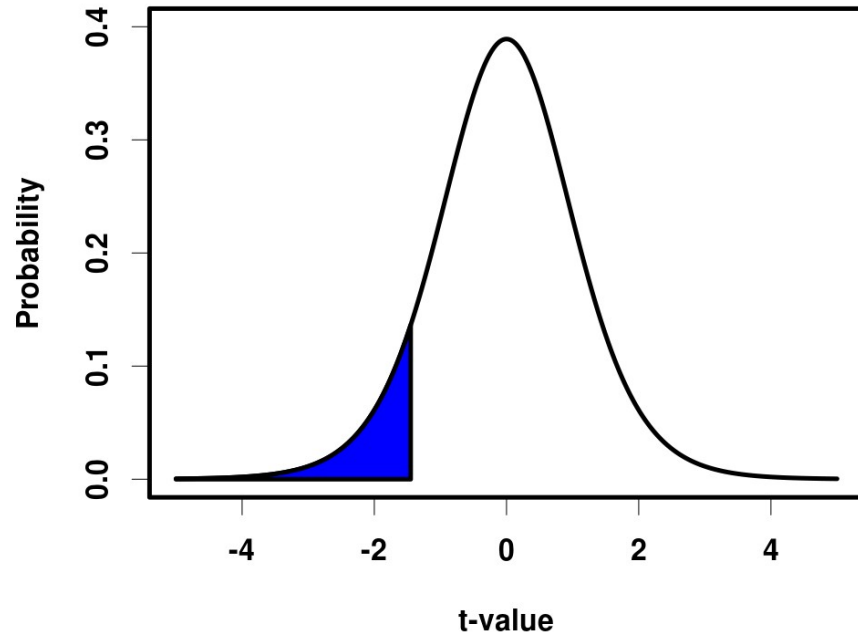
$$p = 0.192$$

Normal Distribution



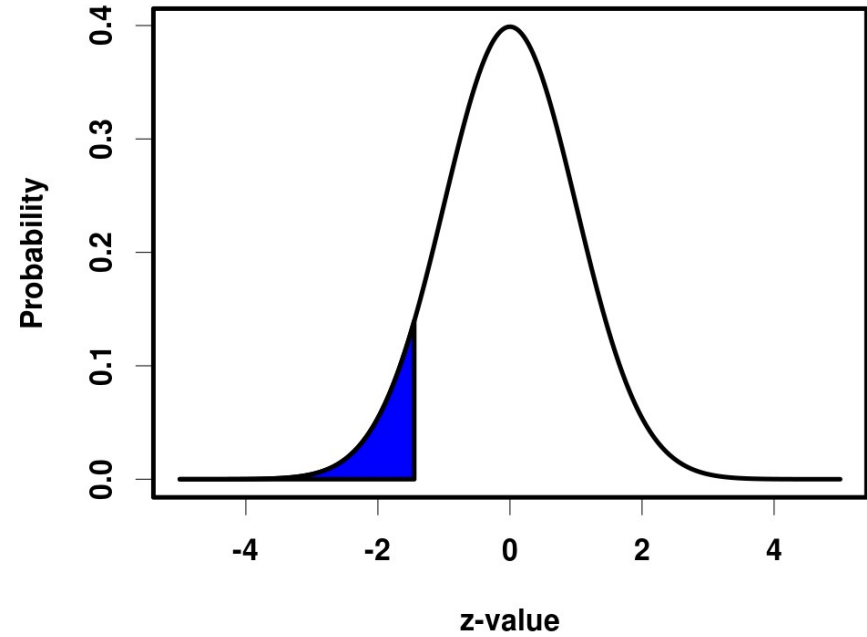
$$p = 0.0735$$

t-distribution, df=10



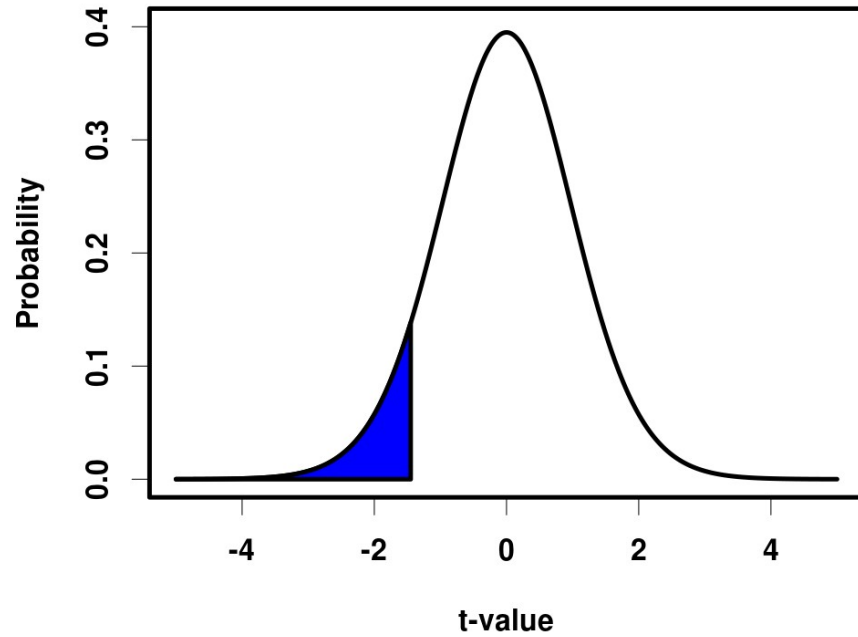
$$p = 0.0888$$

Normal Distribution



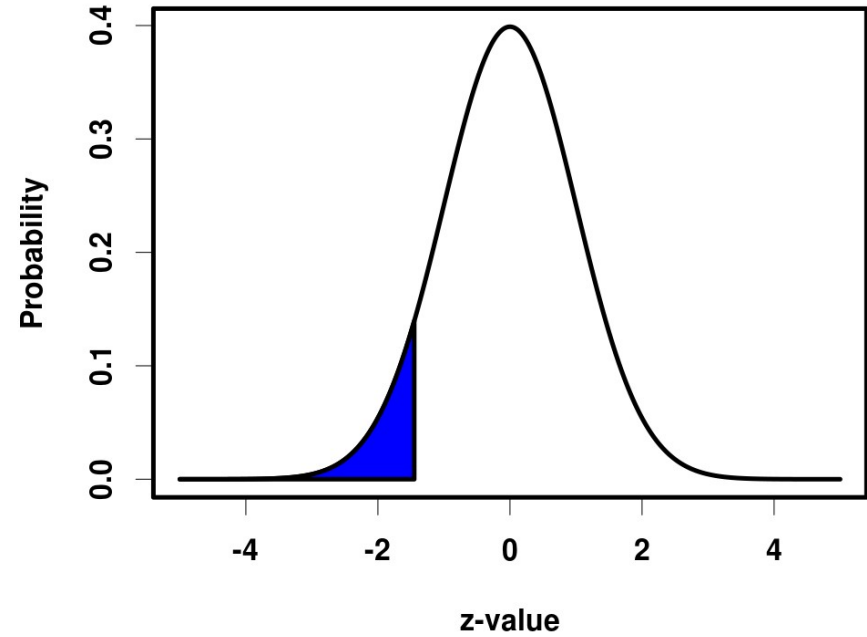
$$p = 0.0735$$

t-distribution, df=25



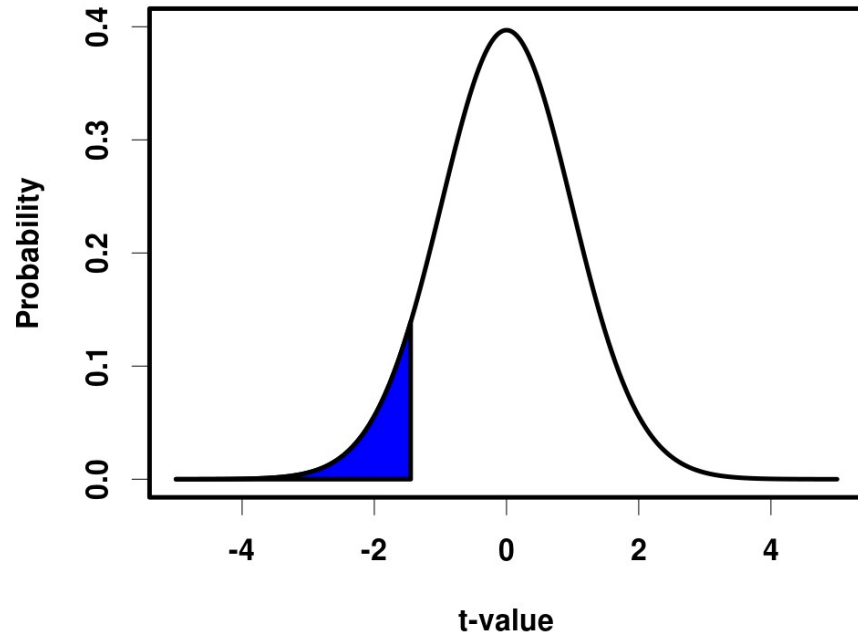
$$p = 0.0797$$

Normal Distribution



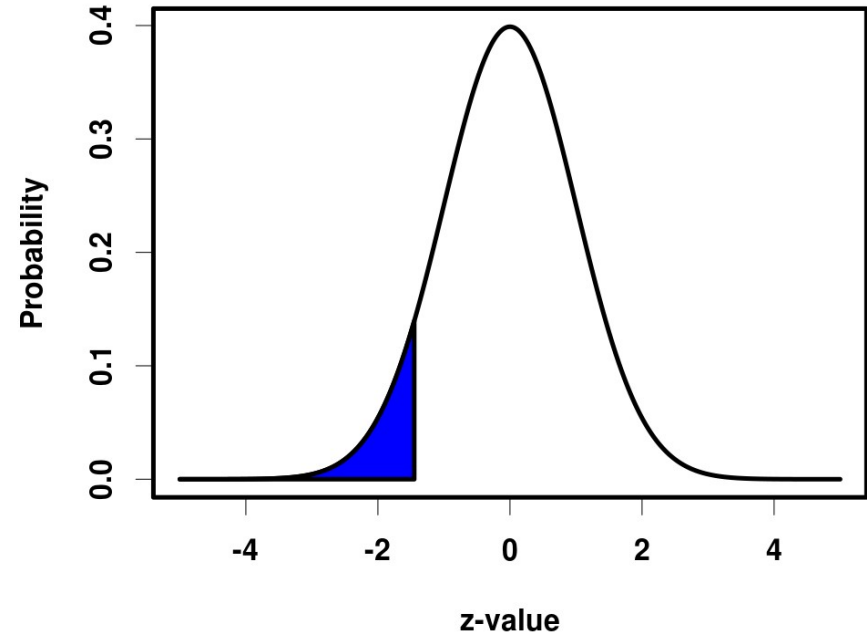
$$p = 0.0735$$

t-distribution, df=50



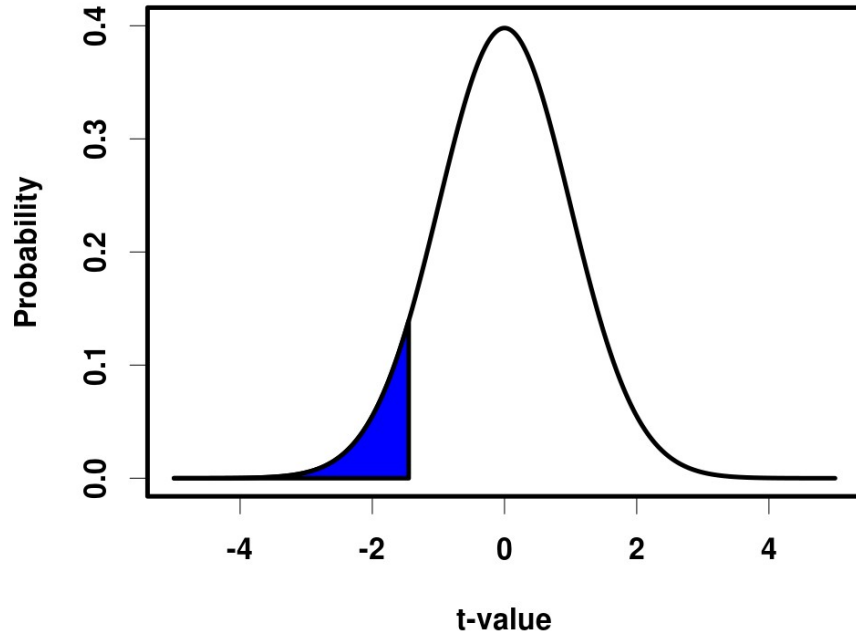
$$p = 0.0767$$

Normal Distribution



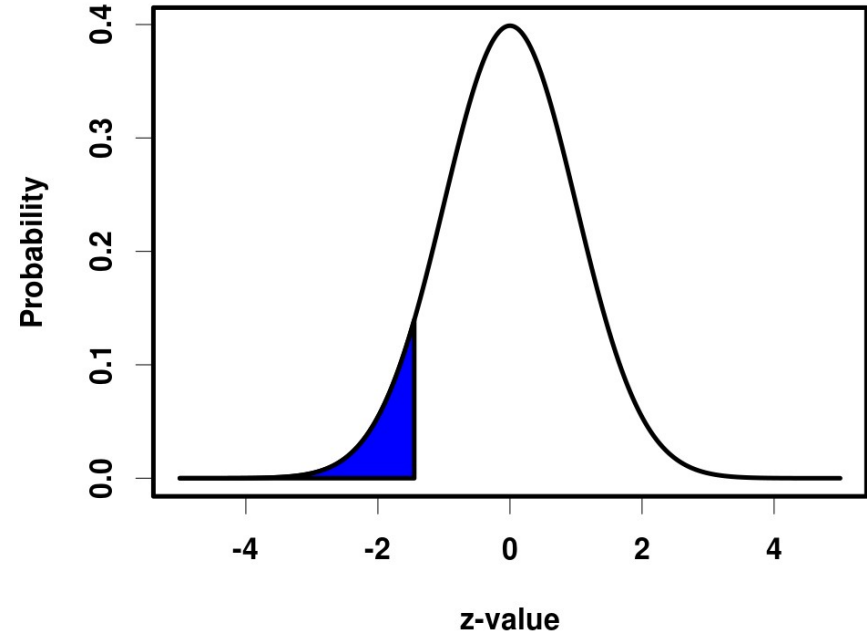
$$p = 0.0735$$

t-distribution, df=100



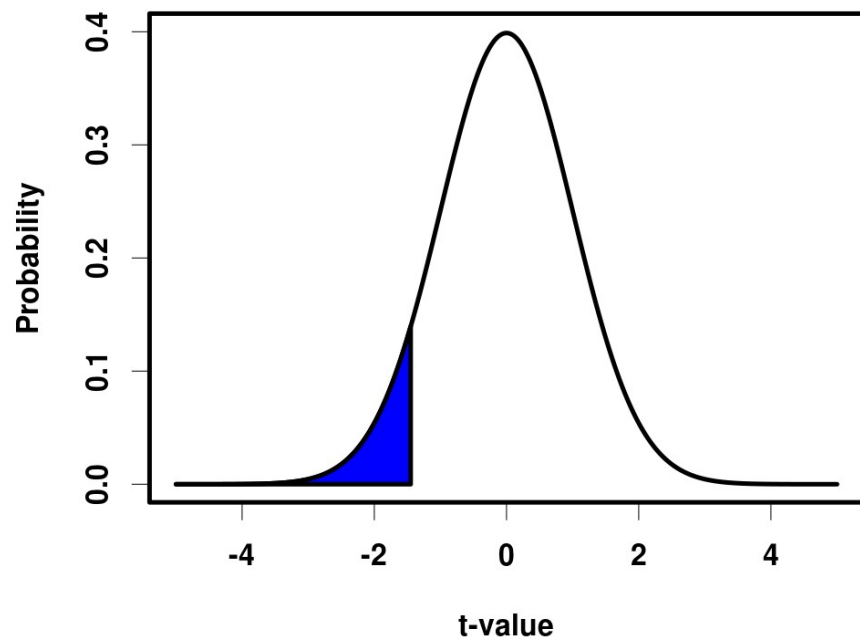
$$p = 0.0751$$

Normal Distribution



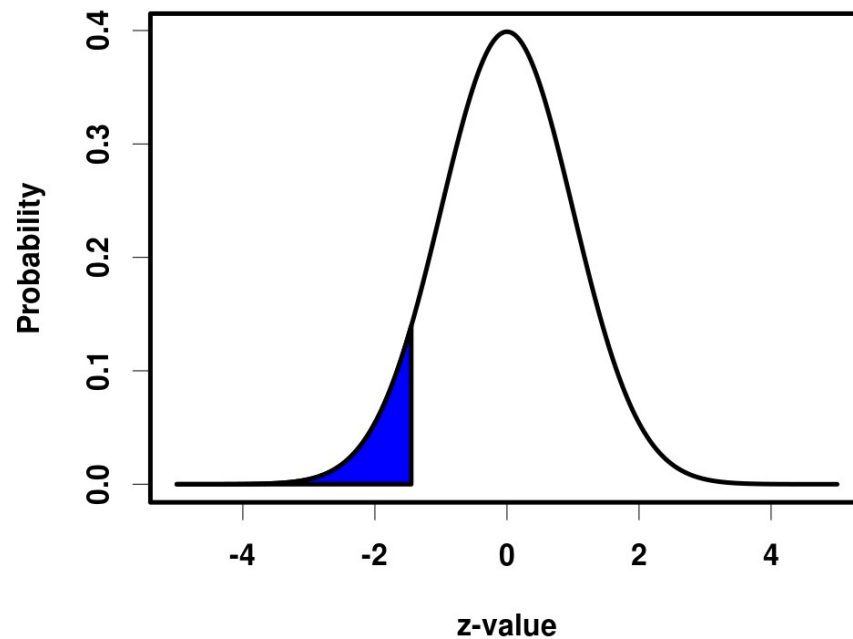
$$p = 0.0735$$

t-distribution, df=1000



$$p = 0.0737$$

Normal Distribution



$$p = 0.0735$$

Bonus question:

Which distribution does the t -distribution converge on when the degrees of freedom goes towards infinity?

What do the following symbols signify in these equations?

$$Y = X \beta + \epsilon$$

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

$Y = X\beta + \epsilon$ (The General Linear Model)

Y : a column vector with J observations (known)

X : the design matrix (known), size: $J \times L$

β : a column vector with L (unknown) model parameters

ϵ : a column vector with J residuals

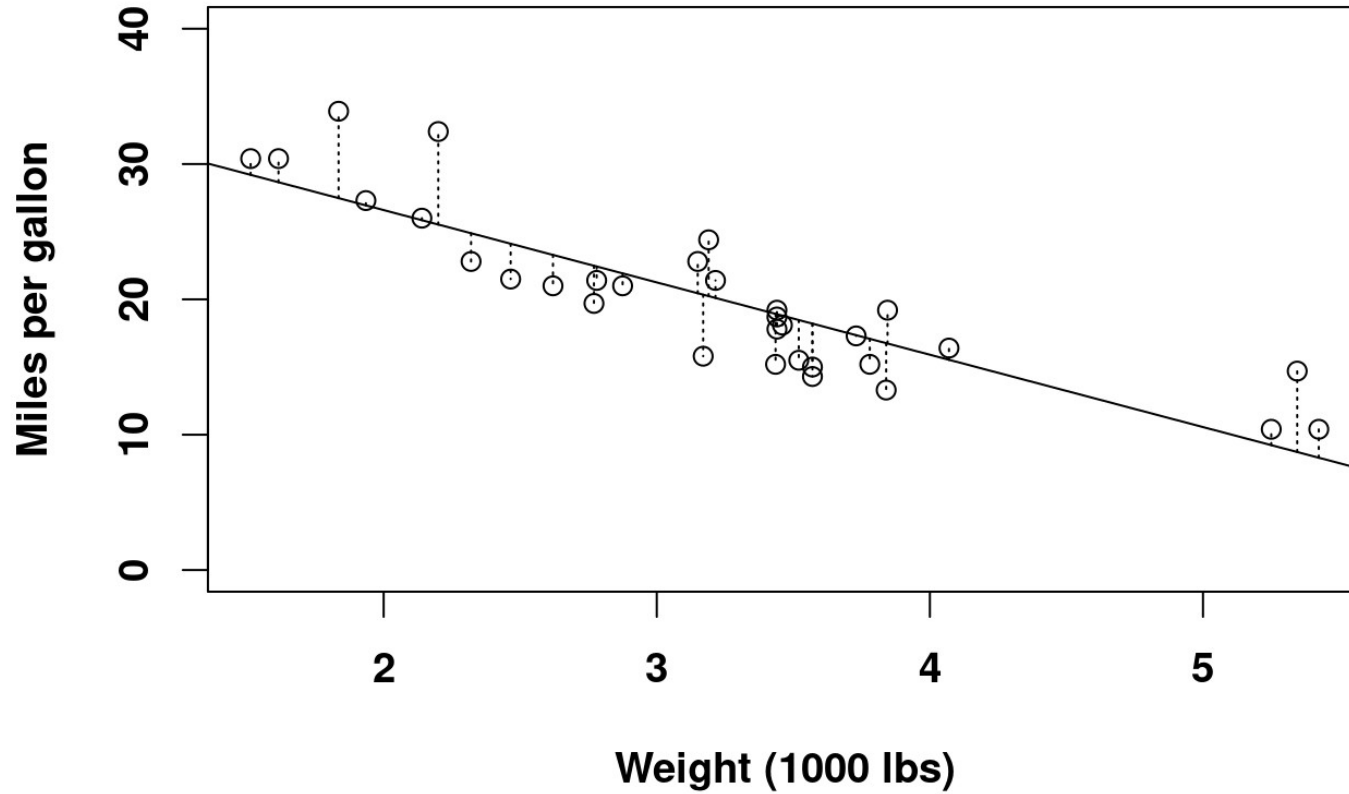
$$\hat{\beta} = (X^T X)^{-1} X^T Y \text{ (least squares solution)}$$

$\hat{\beta}$: the estimated L model parameters

X^T : the transpose of the design matrix

$(X^T X)^{-1}$: the inversion of the $L \times L$ matrix

Linear regression (mtcars)



Next time

- Introducing mixed effects modelling
 - Fixed effects
 - Random effects
 - Nested effects

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