Week 1: Introduction & Organization

MATH-516 Applied Statistics

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Section 1

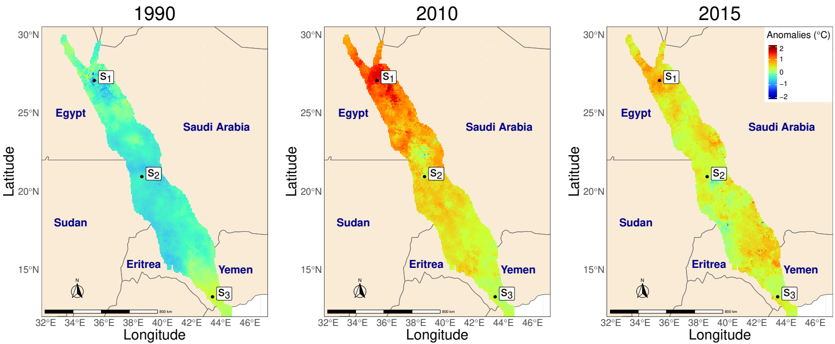
Introduction

Why Applied Statistics

- Data are everywhere!
  - Large amount of data that come with **uncertainty** and **variability**
  - We want to learn something about these data, but what?

Why Should I Learn Applied Statistics?

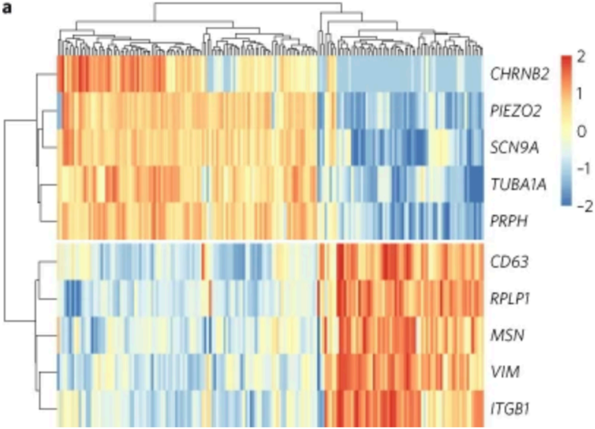
To understand spatial and temporal (climate change) dependencies



Source: Castro-Camilo et al. (2020)

Why Should I Learn Applied Statistics?

To understand variability in gene expressions



Source: Schwartzentruber et al. (2018)

Job of a Statistician

Understand a complex world by describing it in relatively simple terms that capture essential aspects of its structure, and provide us some idea of how uncertain we are about that knowledge

- think about uncertainty and bias (anticipate and reduce it)
- build models emulating nature
  - inference about the models leads to conclusions about nature – but what if the model is a poor representation of nature?
- provide *interpretable* models allowing for rational conclusions
  - prediction vs. information extraction
  - all models are wrong $\Rightarrow$ critical model validation
- estimate variation ($\Rightarrow$ confidence/credible intervals, significance)
- draw conclusions from data
- traditional role: statisticians invited to analyze existing data
  - e.g., does the existing data contain the desired information?
- modern role: collaborative step-by-step
  - from acquisition of data to presentation of results
  - interdisciplinary communication

Domains of Application

- actuarial science
- biostatistics (medicine, pharma, genetics, etc.)
- business
- chemometrics
- econometrics
- epidemiology
- finance
- geostatistics
- machine learning and AI
- official statistics (demography, surveys, etc.)
- psychology
- quality control
- reliability
- physics
- signal processing
- ...

Why Models?

We build models in order to

- 1. understand the nature (of intelligence),
- 2. predict the future, and
- 3. control the world. [or was it rule the world?]

– Patrick Winston (former director of the AI lab at MIT)

1. is the main goal of applied statistics
    - interpretation
    - parsimony
2. is the main goal of AI
    - average accuracy
3. is just to slam the message home

All models are wrong, but some are useful.

– George Box

Section 2

Organisation

Organisation

- This course: a taste of real world problems and challenges for future statisticians
- Emphasis on models and inference: we overview several techniques of statistical modelling, and discuss real life problems
- Project based evaluation:
  - you will be challenged to use these tools to learn from the data
- This course is problem-driven, and hence you are responsible for understanding what are the appropriate models to analyse the data and to implement these computationally
  - reproducibility of the analysis and effective and rigorous communication of your analyses are assumed acquired from MATH-517

Classes

Lectures

- Teacher: Linda Mhalla
- Time: Monday 13:15-15:00 (biweekly)
- Place: MA A3 31

Exercises

- Teacher: Amit Sawant
- Time: Monday 14:15-17:00
- Place: MA A3 31

A schedule can be found here

Prerequisites

Learning Prerequisites (from the course book):

- REQUIRED COURSES
  - Regression Methods
  - **Statistical Computation and Visualisation** (MATH-517)
- RECOMMENDED COURSES
  - Time Series
  - Statistical Inference

Prerequisites

Learning Prerequisites (from the course book):

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  - Regression Methods
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- RECOMMENDED COURSES
  - Time Series
  - Statistical Inference

Learning Prerequisites (my strong personal recommendation):

- required course:
  - **Statistical Computation and Visualisation** (MATH-517)
- somewhat helpful courses:
  - Regression Methods
  - Time Series
  - Statistical Inference

Content

- **Week 1**: Intro
  - Project 1: Snow particles
- **Week 3**: Linear Mixed Models
  - Project 2: TBD
- **Week 5**: Causal Discovery
  - Project 3: TBD
- **Week 7**: Generalised Linear Models
  - Project 4: TBD
- **Week 9**: Extreme Value Theory
  - Project 5: TBD
- **Week 11**: Statistical Consulting
  - Project 6: TBD
- Weeks 13 and 14: **Oral Exam**
  - Discussion of your submitted projects

Project deadlines: Project assigned on (Monday of) Week X has a deadline on Monday evening of Week $X+2$, i.e. there are always 2 weeks per project.

Project grading: See the detailed criteria here.

Project Submission

R/RStudio, Markdown/Quarto (or eventually LaTeX) and GitHub will be needed

- submissions are made through GitHub Classroom (see dedicated tutorial on the MATH-517 course website)

Evaluation

The grade will reflect on the quality of the projects, which are expected to

- identify questions of interest
  - some will be provided during the description of the project
- choose appropriate models to analyse the data
  - demonstrate understanding of the models used
- implement the models in `R` or `Python`
  - though this is preferably not displayed in the report
- critically evaluate shortcomings of your models (model diagnostics)
  - a good solution may be to provide more than one model at first and eventually compare those
- use a final model to answer the questions of interest

Evaluation

It is imperative that the final report is

- readable
  - figures need to have self-explanatory captions, appropriate font size, and be generally of a decent quality
  - there should be no code in the report, unless it significantly improves clarity of the report (e.g., `R` table instead of a Latex table is permitted for simplicity) and even in such a case it has to be verbally explained around any code chunk what it actually does
- reproducible
  - i.e., the `R` Markdown file can be run again on a different machine inside a copy of your Github repo
  - code is well commented

This makes projects iterative work, where most of the work done (e.g., data exploration and model selection) is underrepresented in the final report

Report Writing

Some (paraphrased) quotes:

- If a work is not compiled into a report, it does not exist. If the report is not readable and reproducible, the work is useless.
- Think about what you want to write and then write it as clearly and economically as possible. That is all there is to academic writing.

Report Writing

- The length of the reports should not exceed 15 pages, all included.
- The reports should include:
  - An abstract
  - An introduction presenting the problem
  - A description of the data
  - An exploratory analysis of the data (with some relevant plots)
  - A statistical description of the method(s) used to analyse the data
  - An interpretation of the results (with some relevant plots)
  - A conclusion and a discussion

Evaluation

- 6 projects in total (for you to choose from)
  - specific data and tasks to perform
  - done individually[1], but exchange of ideas (but not the code) is encouraged
- 4 projects will form your chosen portfolio
  - Project 1 is mandatory
  - Project 3 is mandatory
  - Project 5 is mandatory
  - One from Projects 2-4-6
- Project 1 (linked heavily to MATH-517) gets a detailed feedback
- The second chosen project gets as well a detailed feedback
- All projects are subject to discussion during the final oral examination
- This course is "without withdrawal" (submit Project 1 $\equiv$ commit)

[1] This is subject to modification if number of enrolled students is high. Oral examination is individual regardless of the number of students.

References

- Wood (2017) Generalized Additive Models: an Introduction with R (2nd ed.)
  - even though mainly about GAMs, this book has a short and practical exposition to linear models and GLMs that has a value of its own
  - computational flavor
- Davison (2003) Statistical Models
  - nice reference due to the content breadth; is self-contained , but no `R` code
- Gelman & Hill (2006) Data Analysis Using Regression and Multilevel/Hierarchical Models
  - focuses very much on interpretation
  - eloquent/lengthy and not always to the point (or precise)
- Wickham & Grolemund (2017) R for Data Science
  - useful guide to `tidyverse`, i.e., data exploration and manipulation
- Coles (2001) An Introduction to Statistical Modeling of Extreme Values
- Peters, Janzing and Schölkopf (2017) Elements of Causal Inference

Use of AI tools: some guidelines

Topic	EPFL rule
Permitted use	AI tools may be used to support learning, e.g., understanding concepts, debugging, language assistance
Transparency	Any use of AI in assessed work must be **clearly disclosed**. Undisclosed use is not allowed
Authorship	AI-generated content must **not be presented as your own work**. You remain the author and are responsible for the submission
Plagiarism	Submitting AI-generated text or code without disclosure counts as **plagiarism** under EPFL regulations (Lex 1.3.3, Article 4)
Scientific validity	You must **verify all AI outputs**. Incorrect, unjustified, or hallucinated claims remain your responsibility
Writing & structure	Over-reliance on AI-generated structure or wording (generic phrasing, bullet-only reports, unsupported claims) is unacceptable
Data & privacy	Do not upload confidential, proprietary, or third-party content to public AI tools

A Quick Poll

What are your expectations from this course?

- want/need to get out of it
- Click here to answer