

# Week 1: Introduction & Organization

## MATH-516 Applied Statistics

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# Section 1

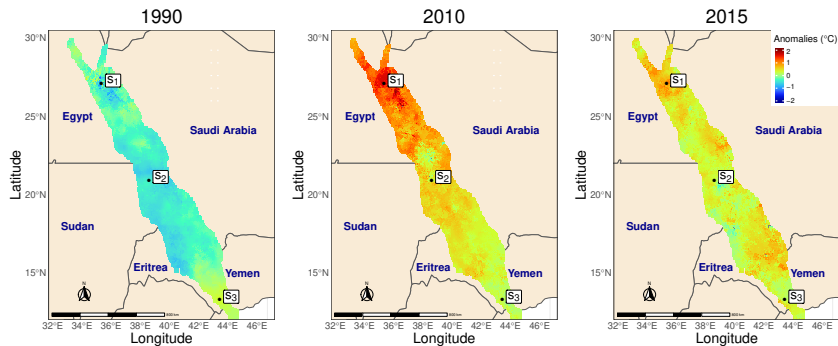
## Introduction

# 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?

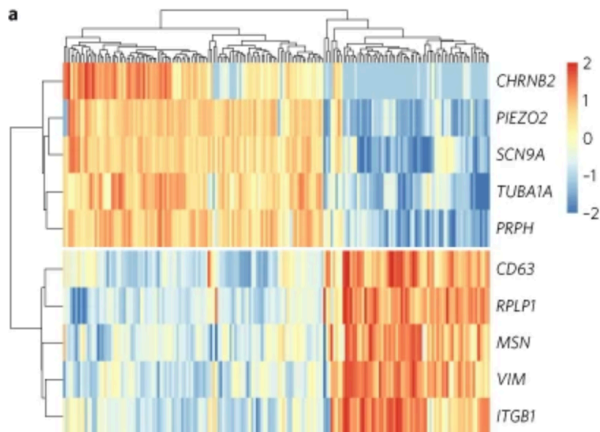
To understand spatial and temporal (climate change) dependencies



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 variation 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 uncertainty ( $\Rightarrow$  confidence/credible intervals, significance)
- draw conclusions from data
- traditional role: statisticians invited to analyse 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

## 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

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  - 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](#))

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

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.

- 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<sup>1</sup>, 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)

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<sup>1</sup>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
<b>Permitted use</b>	AI tools may be used to support learning, e.g., understanding concepts, debugging, language assistance
<b>Transparency</b>	Any use of AI in assessed work must be clearly disclosed. Undisclosed use is not allowed
<b>Authorship</b>	AI-generated content must not be presented as your own work. You remain the author and are responsible for the submission
<b>Plagiarism</b>	Submitting AI-generated text or code without disclosure counts as plagiarism under EPFL regulations (Lex 1.3.3, Article 4)
<b>Scientific validity</b>	You must verify all AI outputs. Incorrect, unjustified, or hallucinated claims remain your responsibility
<b>Writing &amp; structure</b>	Over-reliance on AI-generated structure or wording (generic phrasing, bullet-only reports, unsupported claims) is unacceptable
<b>Data &amp; privacy</b>	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](#)