

# Week 1: Introduction & Organization

## MATH-516 Applied Statistics

Linda Mhalla

2024-02-19

# Section 1

## 1. Introduction

# 1.1 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?

## 1.2 Why Should I Learn Applied Statistics?

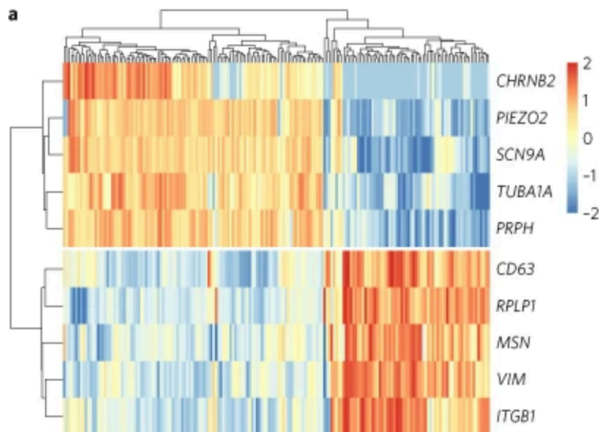
To understand spatial and temporal (climate change) dependencies



Source: [Castro-Camilo et al. \(2020\)](#)

# 1.3 Why Should I Learn Applied Statistics?

To understand variability in gene expressions



Source: [Schwartzentruber et al. \(2018\)](#)

## 1.4 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 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

# 1.5 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
- ...

# 1.6 Why Models?

We build models in order to

- ① understand the nature,
- 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

### 2. Organization

## 2.1 Organization

- 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 analyze 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

## 2.2 Classes

### Lectures

- Teacher: Linda Mhalla
- Time: Monday 13:15-14:00 and Wednesday 13:15-14:00 (biweekly)
- Place: MA A1 10

### Exercises

- Teacher: Almond Stöcker
- Time: Monday 13:15-16:00
- Place: CM 0 12

A schedule can be found [here](#)

## 2.3 Prerequisites

Learning Prerequisites (from the course book):

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

## 2.3 Prerequisites

Learning Prerequisites (from the course book):

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

Learning Prerequisites (my strong personal recommendation):

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

## 2.4 Content

- **Week 1:** Intro
  - Project 1: Snow Data
- **Week 3:** Poisson Regression
  - Project 2: Climate-related Disasters
- **Week 5:** Logistic Regression
  - Project 3: TBD
- **Week 7:** Linear Mixed Models
  - Project 4: Calorie Expenses in the Human Body
- **Week 9:** Causal Inference
  - Project 5: Tübingen Datasets
- **Week 11:** Extreme Value Theory
  - Project 6: The Vargas Tragedy or Rainfall data in Switzerland
- **Week 12:** Statistical Consulting
  - Project 7: TBD
- **Week 14: Oral Exam**
  - discussing your submitted projects

**Project deadlines:** Project assigned on (Monday of) Week  $X$  has a deadline on Sunday evening of Week  $X + 1$ , i.e. there are always 2 weeks per project.

## 2.5 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](#))

## 2.6 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 analyze the data
  - demonstrate understanding of the models used
- implement the models in R
  - though this is probably 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



## 2.7 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

## 2.8 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.

## 2.9 Report Writing

- The length of the reports should be between 8 and 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

## 2.10 Evaluation

- 7 projects in total (for you to choose from)
  - specific data and tasks to perform
  - done individually, but exchange of ideas (but not the code) is encouraged
- 5 projects will form your chosen portfolio
  - Project 1 is mandatory
  - at least one from Projects 2-3
    - you will get a detailed feedback on this one
  - at least one from Projects 4-5
  - at least one from Projects 6-7
- Project 1 (linked heavily to MATH-517) gets a grade of its own (not provided), the rest will be graded during the final oral examination
- This course is “without withdrawal” (submit Project 1  $\equiv$  commit)

## 2.11 References (for the 1st half of this course)

- 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

## 2.12 A Quick Poll

What are your expectations from this course?

- want/need to get out of it
- [Click here to answer](#)

