Week 1: Introduction & Organization

MATH-516 Applied Statistics

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Section 1

Introduction

History of Statistics

Etymology:

- 1749: science of dealing with data about the condition of a state or community
    - from German *statistik*

Example:

- 1890 US Census data would take 13 years to be processed by hand
    - new census every 10 years
    - roughly the scale of today's "big data"
- Herman Hollerith (1860-1929) working for the Census Bureau
    - proposed using punch cards to be counted by a machine using the recent discovery of electricity
    - perfect analog to the computer data storage format
    - "Hollerith's Machine" lead to the foundation of IBM

History of Statistics

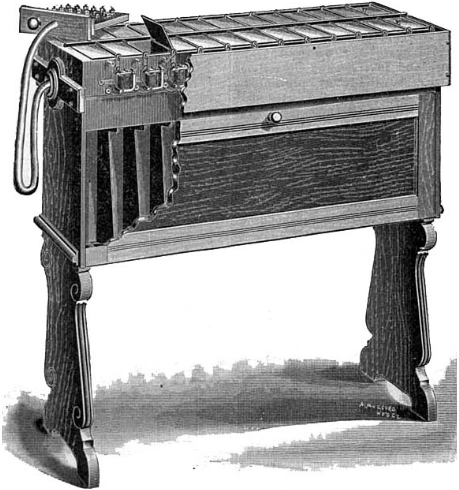


Fig. 3.—Sorting Machine.

Hollerith's Electric Sorting and Tabulating Machine.

Today

- applied statistics
- data analytics
- data science
- machine learning
- artificial intelligence

Inference vs. prediction?

Boring vs. cool?

Complicated models vs. simple solutions?

Quite confusing...

David Donoho (2015) 50 years of Data Science

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

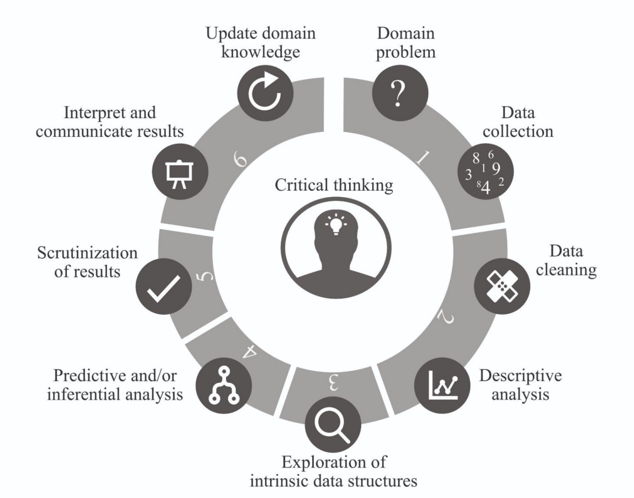
All models are wrong, but some are useful.

– George Box

Job of a Statistician

- think about uncertainty
- estimate variation ($\Rightarrow$ confidence intervals, significance)
- avoid bias (not entirely possible, but 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 emulation of nature?
- provide *interpretable* models allowing for rational conclusions
  - prediction vs. information extraction
  - all models are wrong $\Rightarrow$ critical model validation
- draw conclusions from data
  - this is rather vague since almost everything is data
- traditional role: statisticians invited to analyze existing data
  - problems such as: does the existing data set contain the desired information?
- modern role: collaborative step-by-step
  - from acquisition of data to presentation of results
  - interdisciplinary communication
- exploratory vs. confirmatory analysis

Cycle of (Data-driven) Science



credit: Bin Yu, Rebecca Barter

Domains of Application

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

Section 2

Organization

Classes

Lectures

- Teacher: Tomas Masak
- Time: Monday 13:15-15:00
- Place: MA A1 10

Exercises

- Teacher: Charles Dufour
- Time: Wednesday 10:15-12:00
- Place: GC D0 386

Actually, it should be

- 1 h of lecture +
- 3 h of project work

Prerequisites

Learning Prerequisites (from the course book):

- REQUIRED COURSES
  - Regression Analysis (a.k.a. regression methods)
  - **Statistical Computation and Visualization** (MATH-517)
- RECOMMENDED COURSES
  - Time Series
  - Statistical Inference

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  - 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

Content

- **Week 1**: Intro
  - Project 1: Snow Data
- Week 2: Linear Models - Practical Recap
- **Week 3**: Logistic Regression
  - Project 2: Online Shopping Data
- Week 4: Generalized Linear Models
- **Week 5**: Poisson Regression
  - Project 3: Premier League Data
- Week 6: TBD
- **Week 7**: Mixed Models
  - Project 4: U.S. Presidential Elections
- Free Week: Easter Holidays
- **Week 8**: Time Series
  - Project 5: Global Warming
- Week 9: Time Series Regression

Content (cont.)

The remainder is subject to changes:

- **Week 10**: Extreme Value Theory
  - Project 6: TBD
- Week 11: more EVT
- **Week 12**: Functional Data Analysis
  - Project 7: First Wave of Covid in the US
- Week 13: Functional PCA
- 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.

Project Submission

RStudio + R Markdown + Github:

- create **private** `AppStat-SCIPER` folder on Github
  - share the folder with users `TMasak` and `dufourc1`
- one sub-folder `Project-X` for every project, containing
  - the data used
  - `rough_work.Rmd` and the resulting `rough_work.html`
  - `Project-X.Rmd` and the resulting `Project-X.html`, which is the final report to be graded
  - optionally external scripts containing demanding calculations and `.RData` files storing their
  - grading based on `Project-X.html`, other files are for **reproducibility** and cross-checking
- check out an example project
  - we will go through it on Week 2

Moodle: link to the `Project-X` folder will be submitted to the respective Moodle assignment.

Evaluation

The grade will reflect on the quality of the final report, which is expected to

- identify questions of interest
  - some will be provided during the lectures together with the data
- choose appropriate models to analyze the data
  - demonstrate understanding of the models used
- implement the models in R
- critically evaluate shortcomings of your models (model diagnostics)
  - a good solutions provides more than one model at first and eventually compares 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 does (the reader is not expected to understand R commands)
- reproducible
  - i.e. the R Markdown file can be run again on a different machine inside your Github repo
  - code contains comments

This makes projects iterative work, where most of the work done 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.*

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 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, the rest will be graded during final examination

$$\textbf{Final Grade} = ab$$

where $a \in \{0, 0.25, 0.5, 0.75, 1\}$ is the grade for Project 1, and $b \in [1, 6]$ is the grade for your portfolio to be determined during the oral exam.

- this course is "without withdrawal" (submit Project 1 $\equiv$ commit)

Section 3

Project 1

Data

- data from a PhD student at the Laboratory of Cryospheric Sciences at EPFL, essentially snow-flake diameters
  - shared with the permision of the authors of this paper
- the total number of particles measured (variable `particles.detected`) and the fraction (variable `retained [%]`) of particles belonging to each diameter bin (given by `startpoint` and `endpoint`)
  - only binned data are available (and the grid is not equidistant)

```
##   X startpoint endpoint retained.... particles.detected
## 1 1      0.000    0.060          3.3             705044
## 2 2      0.060    0.065          0.8             705044
## 3 3      0.065    0.070          0.9             705044
## 4 4      0.070    0.076          1.1             705044
## 5 5      0.076    0.082          1.3             705044
## 6 6      0.082    0.089          1.3             705044
```

The Goal

Simulate diameters from a distribution, which is as close as possible to the observed data, in order to study aeolian transport of snow using certain numerical models.

- i.e. the goal is to do Monte Carlo: **how to simulate snow-flake diameters that are compatible with the data?**
- it is assumed that a mixture of two log-normal distributions is a good model.

Tasks for You

1. Is the assumption viable, i.e. is bi-log-normal distribution a reasonable model for the data?
   - simple exploration of the data
2. Fit the bi-log-normal distribution in order to be able to simulate the data easily.
   - jittering and EM algorithm
   - optimization (e.g. local search starting from the jittered EM result)
   - Bayesian approach
3. Test whether the diameters come from a bi-log-normal distribution.
   - parametric Bootstrap

MATH-517 Content

- Week 1: Introduction & Software
- Week 2: Ethics & Reproducibility
- Week 3: Data Exploration & Graphics
- **Week 4: Kernel Density Estimation**
- Week 5: Local Polynomial Regression
- **Week 6: Cross-validation**
- **Week 7: EM Algorithm**
- **Week 8: EM Algorithm**
- **Week 9: Monte Carlo**
- **Week 10: Bootstrap**
- **Week 11: Bootstrap**
- **Week 12: Bayesian Computations**
- **Week 13: Bayesian Computations**
- Week 14: $\emptyset$
  - weeks in bold are pertinent to Project 1
  - Weeks 1-3 established the workflow needed for all the projects