

# Bayesian Learning

M2 Data Science  
1<sup>st</sup> semester



# Audience

Minimal background in mathematics and statistic

- analysis and calculus (integral, derivatives, study of functions, ... )
- basic statistical concepts (expectation, median, covariance, distributions, ... )

Minimal knowledge of statistical modeling

- e.g. regression (for many concepts we will see a new formulations)

Basic expertise with Python and Jupyter Notebook

- installing new packages
- writing basic code and running pipelines
- knowledge of standard libraries (numpy, pandas, scikit-learn)
- use of git

# The course

Based on lessons and notebooks

Additional reading material and references are provided at each lesson

All the material available at the course website

<https://marcolorenzi.github.io/teaching.html>

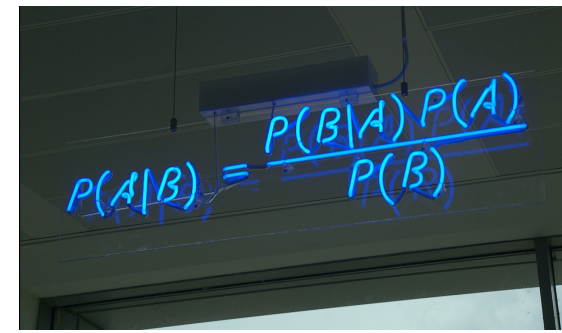
## 10 lessons

Mid-term assessment

Final oral exam

- theory, exercises, paper discussion

# Why Bayesian modeling?


$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Practical methods for making inference from data using probability models for:

- Quantities we observe
- Quantities we wish to learn

Explicit use of probability for quantifying uncertainty in inference



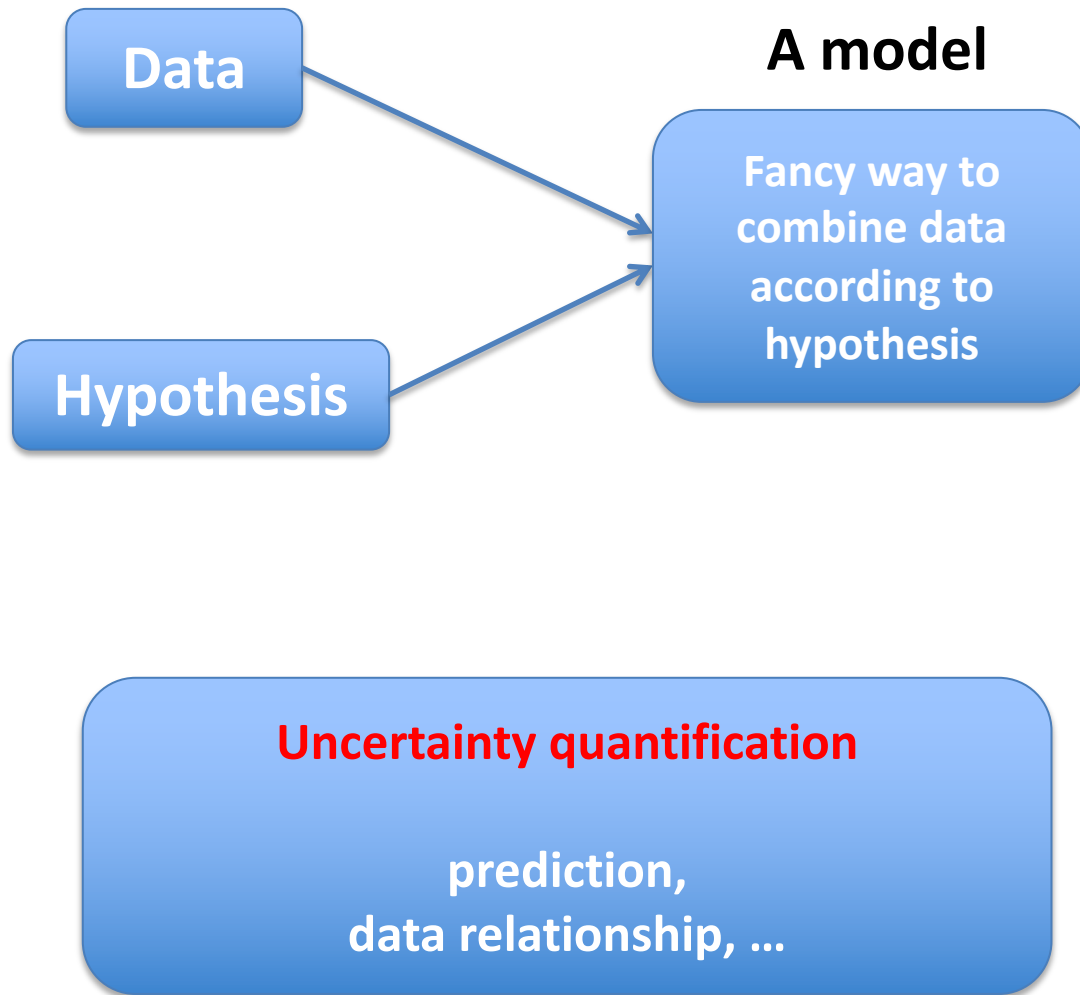
Portrait of Bayes used in a 1936 book, but it is doubtful whether the portrait is actually of him.

From wikipedia

Pierre-Simon Laplace



# The common denominator



# An increasing success in several disciplines

- Important whenever uncertainty is critical  
healthcare, weather forecast, sociology, epidemiology, ...
- Principles tools to integrate hypothesis about the world
- Today many theoretical and computational approaches available to solve Bayesian problems

Maths and calculus: closed forms, variational approximations

Computational methods: sampling

# Course overview

Basics of Probability and Bayesian Modeling

Basic models and distribution families

A practical take on Bayesian inference

regression, classification

Model Approximation

Sampling methods

**Questions?**