

Big Data and Data Science

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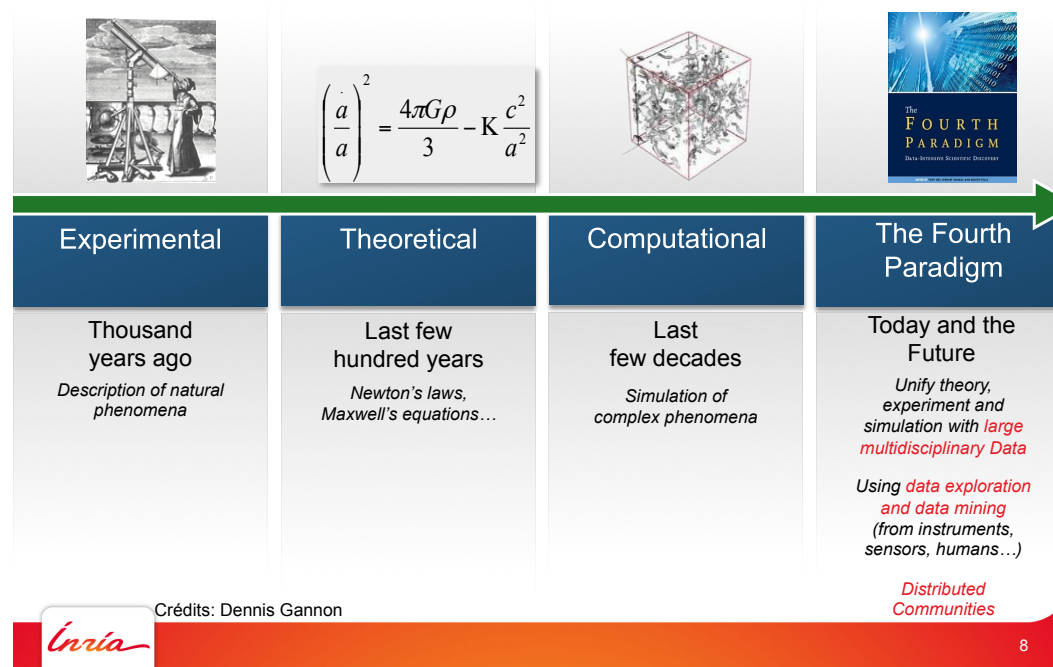
Intro to ML

The 4th paradigm

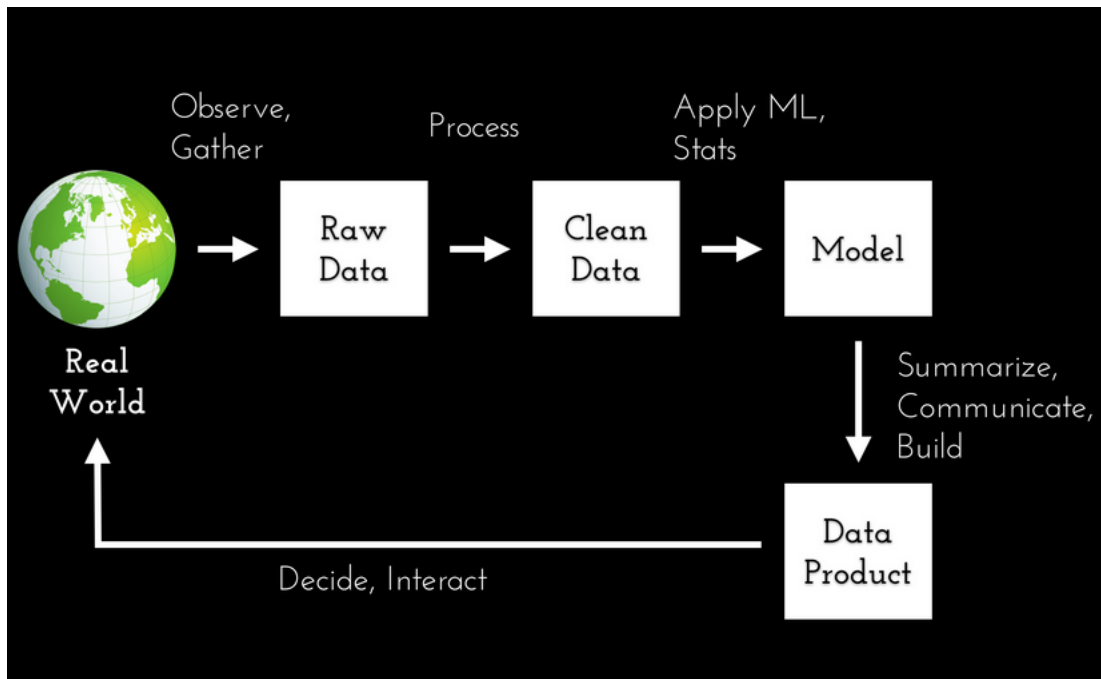
1. The scientific methodology: (three pillars)
 - (a) Experiments
 - (b) Theory
 - (c) Simulation
2. The 4th paradigm: science from the data
 - (a) the data deluge - instruments, connected objects, internet, etc. (exponential growth)
 - (b) data science... "let the data speak "

4th paradigm

La “science des données”, 4^e paradigme de la découverte scientifique



Data Science

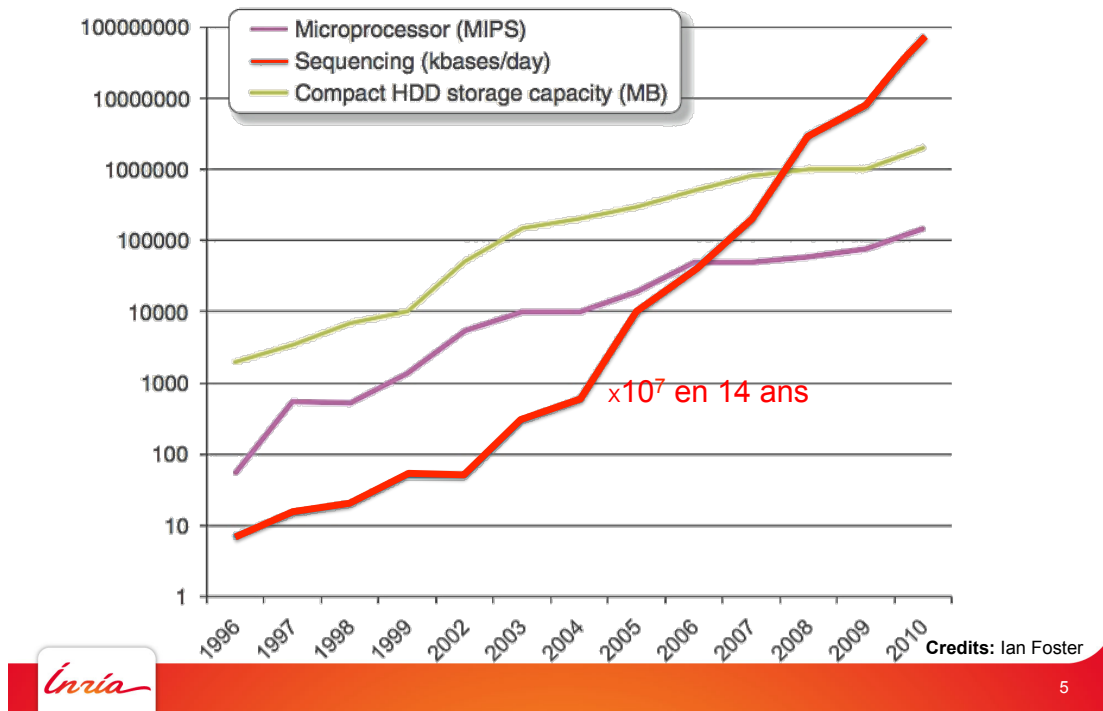


The 4 “V’s” of Big Data

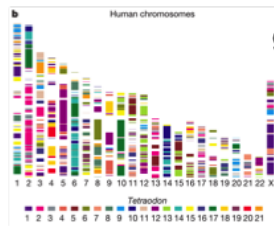
1. Volume
2. Variety
3. Velocity
4. Veracity

Volume

Explosion des données en bioinformatique

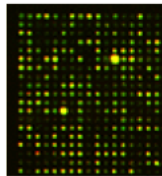


Variety



génomique

NGS



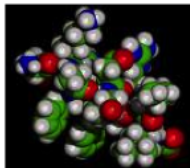
transcript-
omiques

marrays
RNASeq



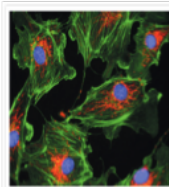
protéomiques
métabolomiques

spectro.
masse



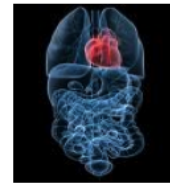
structurales

cristallo.
RMN



images
biologiques

microscopie



images
médicales

IRM



cliniques

cohortes
biobanques



biblio-
graphiques

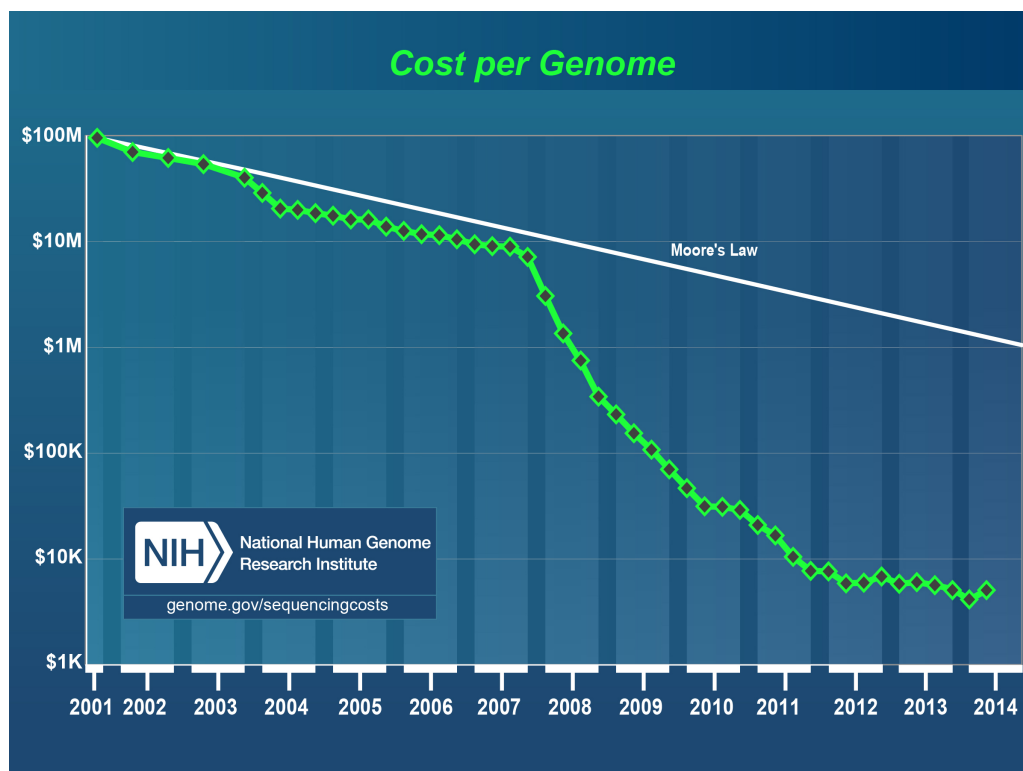


environ-
nementales

Velocity



600 Gb/run
~ 5 Go/h



Veracity

- trust, integrity, quality, transparency
- security
- confidentiality
- protection of private life
- intellectual propriety

Big Data and Statistics

- For both, we want to learn from the data...
- **Statistiques** analyze primary data (experimental, samples) and try to verify hypotheses.
- **Big data** attempts to use secondary data (observations) to deduce the hypotheses and hence to create new insights.
- **Conclusion** : the 2 approaches are complementary and should proceed hand-in-hand... to facilitate and provide tools for decision-making based on the data. The 2 fields should be united to draw **reliable onclusions** from **available data**.
- A lack of expertise in statistics can (and has - eg. using omic data...) led to fundamental errors!
 - ⇒ clinical trials cancelled for an anti-cancer treatment;
 - ⇒ effect of GMO on cancer;
 - ⇒ Google flu... (correlation vs causation!)

Statistics for Big Data

- ✓ General skills of a “data scientist”:
 - statistics
 - linear algebra
 - programming
- ✓ Complementary skills:
 - data preparation (“data wrangling, munging, scraping”)
 - modeling
 - visualization
 - communication

Statistical Inference

- ✓ The data represent **traces** of real-world processes that depend on the way we collect the data.
- ✓ Two sources of uncertainty:
 - random character of the process itself,
 - uncertainty due to the data collection method
- ✓ The process that leads us from the world to the data, then from the data to the world, is called **statistical inference**
 - procedures, methods, theorems that allow us to extract information from data that come from a random/stochastic process

Populations and Samples

Definition 1. A *population* is the set of all the objects (observations) being studied. Their number is denoted by N .

Definition 2. A *sample* is a subset, of size n , $n \leq N$, drawn from the population. We examine these observations to draw conclusions and infer things about the population.

For *Big Data*:

✗ $N = \text{ALL} \text{ ???}$

✗ Correlation \implies Causation ???

Models

Definition 3. *A **model** is an attempt to understand and represent the nature of reality. It is a construction from which all superfluous details have been eliminated.*

CAVEAT :

- “Models are models, not reality!”
- “All models are wrong, but some are useful.”

Statistical Models

We seek the underlying process...

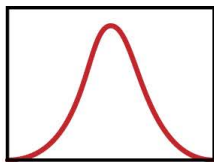
- ✓ What comes first?
- ✓ What influences what?
- ✓ What is the cause of what?
- ✓ What would be a test of his?

How to construct a model

- ✓ Exploratory data analysis (see below)
 - calculate basic statistics
 - draw graphics
 - obtain intuition
- ✓ Probability distributions

- the foundations of classical statistical models
- not all processes generate data that resemble known distributions (Gauss, Poisson, Weibull, etc.), but many do
- these laws attribute a probability to a subset of possible outcomes by means of a corresponding function

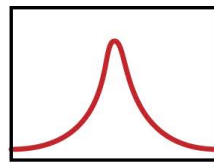
Law/distributions of Probability



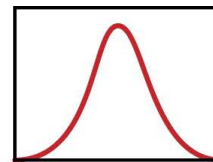
Normal Distribution



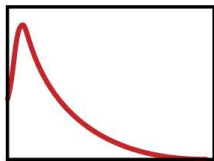
Uniform Distribution



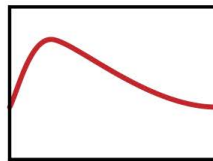
Cauchy Distribution



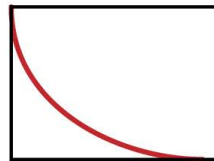
t Distribution



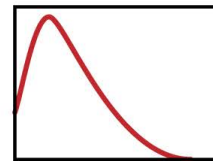
F Distribution



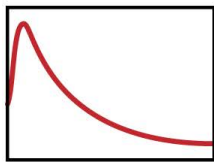
Chi-Square Distribution



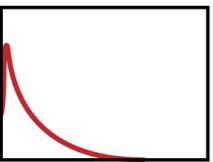
Exponential Distribution



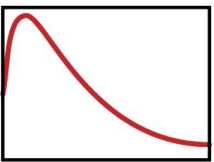
Weibull Distribution



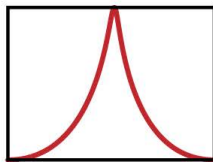
Lognormal Distribution



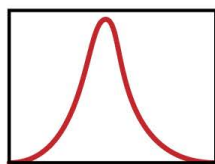
Birnbaum-Saunders
(Fatigue Life) Distribution



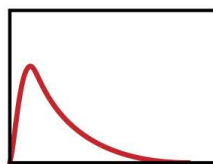
Gamma Distribution



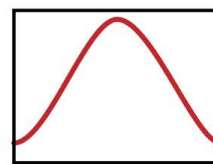
Double Exponential
Distribution



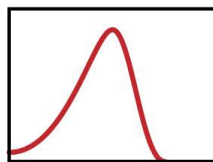
Power Normal Distribution



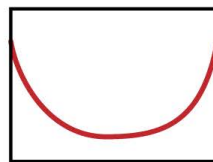
Power Lognormal
Distribution



Tukey-Lambda Distribution



Extreme Value Distribution



Beta Distribution

References

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<http://www.deeplearningbook.org>