

Analyser, comprendre le monde  
Complémentarité entre apprentissage et visualisation

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*Inria*  
INVENTEURS DU MONDE ALPHÉRIQUE

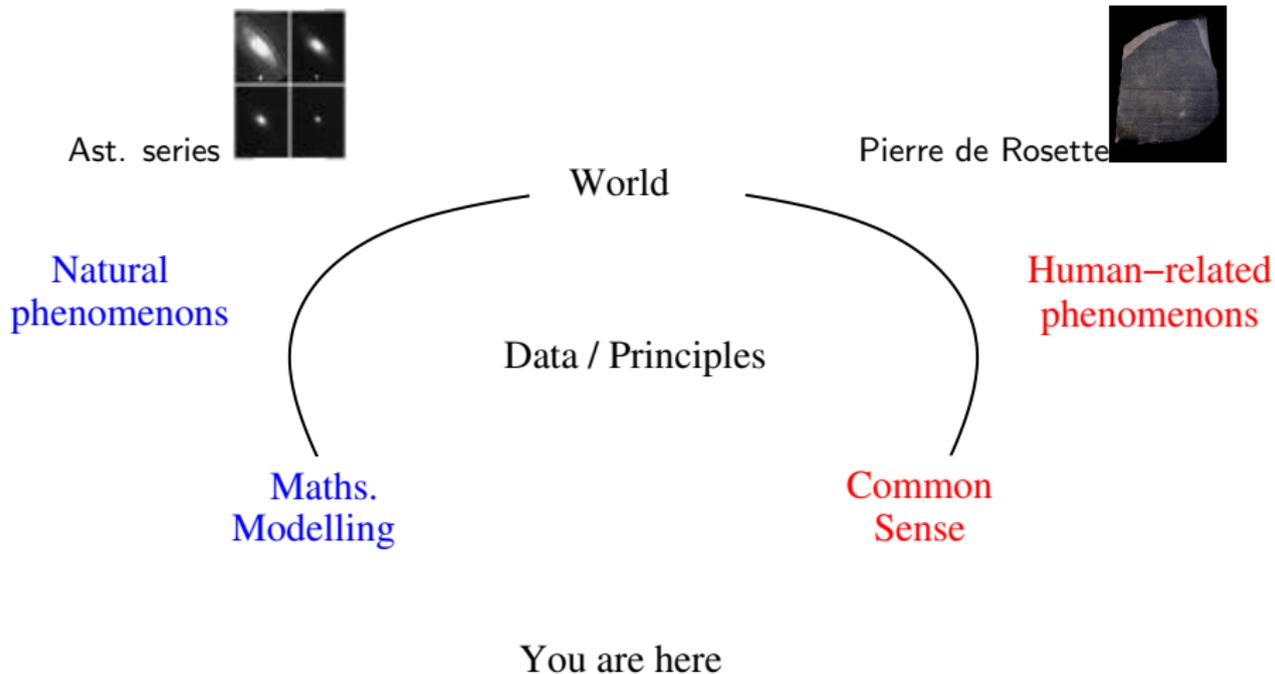
## Machine Learning in general

Our team: AO/TAU, LISN, CNRS, INRIA, UPSaclay

ML-IHM complementarity, 2 case studies

Cartolabe: today, to-morrow

# Learning, XVIII-XIX<sup>e</sup> centuries



# Learning, XXI<sup>e</sup> century



Sc. data

Google™

Natural  
phenomenons

World

Human-related  
phenomenons

Data / Principles

Maths.  
Modelling

Common  
Sense

You are here

# Types of Machine Learning problems

WORLD – DATA – USER

Observations

+ Target

+ Rewards

Understand  
Code

Predict  
Classification/Regression

Decide  
Action Policy/Strategy

Unsupervised  
LEARNING

Supervised  
LEARNING

Reinforcement  
LEARNING

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# New Artificial Intelligence

## A Case of Irrational Scientific Exuberance

- ▶ Underspecified goals Big Data cures everything
- ▶ Underspecified limitations Big Data can do anything (if big enough)
- ▶ Underspecified caveats Big Data and Big Brother

## TAU goals

## *T*Ackling the Underspecified

- ▶ Learn trustable models
- ▶ Mix data **and** knowledge in basic sciences principles, models, softwares
- ▶ Characterize the learning landscape an end and a mean to knowledge transfer

## Three scientific pillars

- ▶ Enforcing fairness and robustness
- ▶ ML with/for scientific modelling
- ▶ Learning to learn

Fair AI

From data assimilation to NN-based Numerical Analysis

## Main three application domains

- ▶ Energy
- ▶ Human and Social Sciences
- ▶ Numerical Engineering

## Organization of challenges

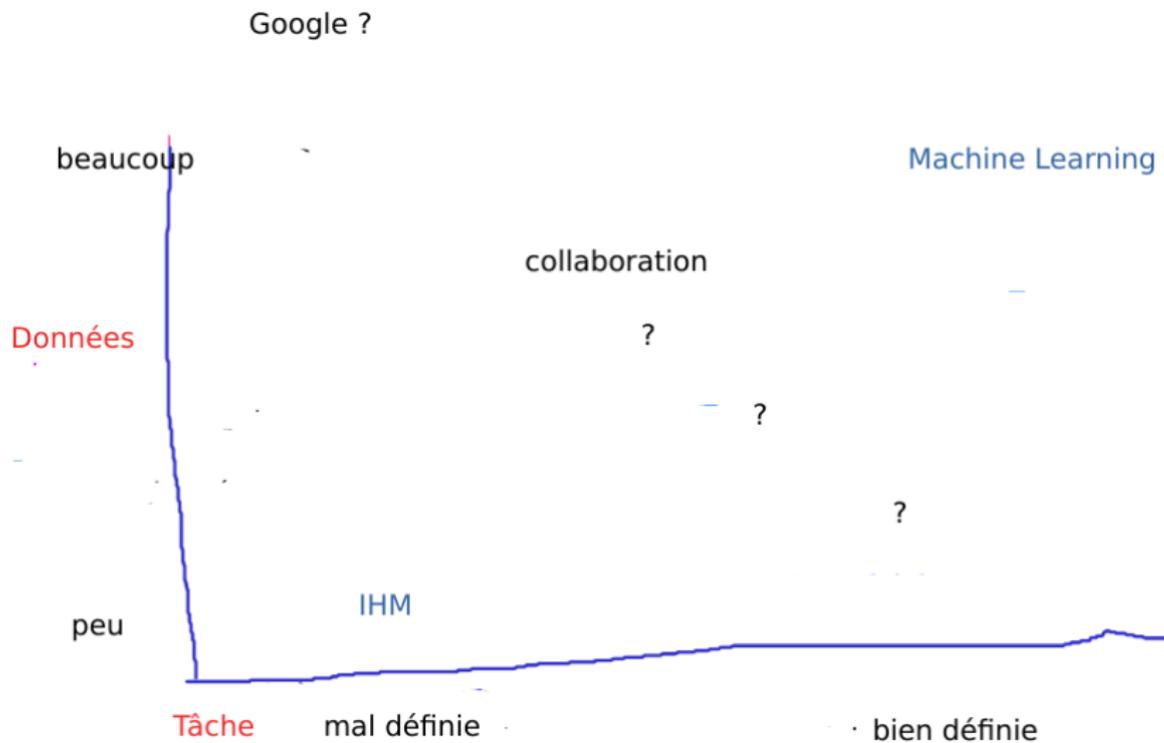
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# ML - IHM : Complémentarité



# Exploratory Data Analysis

## Clustering

- ▶ Input: data
- ▶ Desired output: making sense of it...
- ▶ How:
  - ▶ Divide and conquer
  - ▶ Visualize = project in 2-3 D.

## Issues

- ▶ Which distance ?
- ▶ Which projection criterion ?

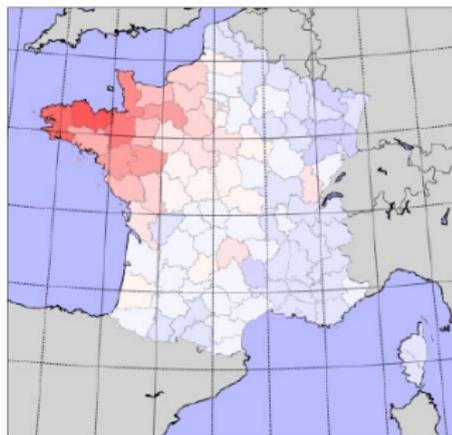
# Case study 1: Nutriperso

Coll. O. Allais, P. Caillou, A. Constantinescu, K. Gasnikova

## The Kantar data

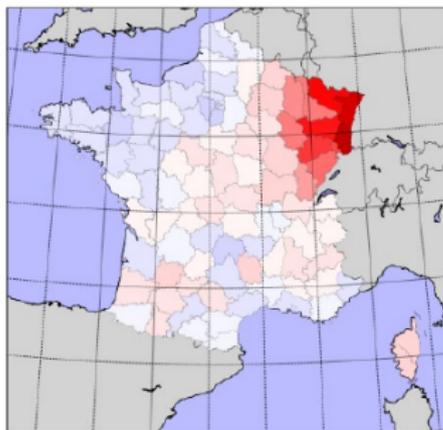
- ▶ A wealth of data: 20,000 households, 180,000 food items
- ▶ Goal: assess impact of food on health.

**Identify (elements of) diets:** some have a geographical support



Thym frais, Fromage camembert,  
Beurre, Cidre, Café, Produit sucrant,  
Lait, Crème fraîche, Vinaigre, Rillettes

PRESIDENT, PAYSAN BRETON,  
COIC.ESCALE BRETONNE, GRAND  
FERMAGE. SAN MARCO.



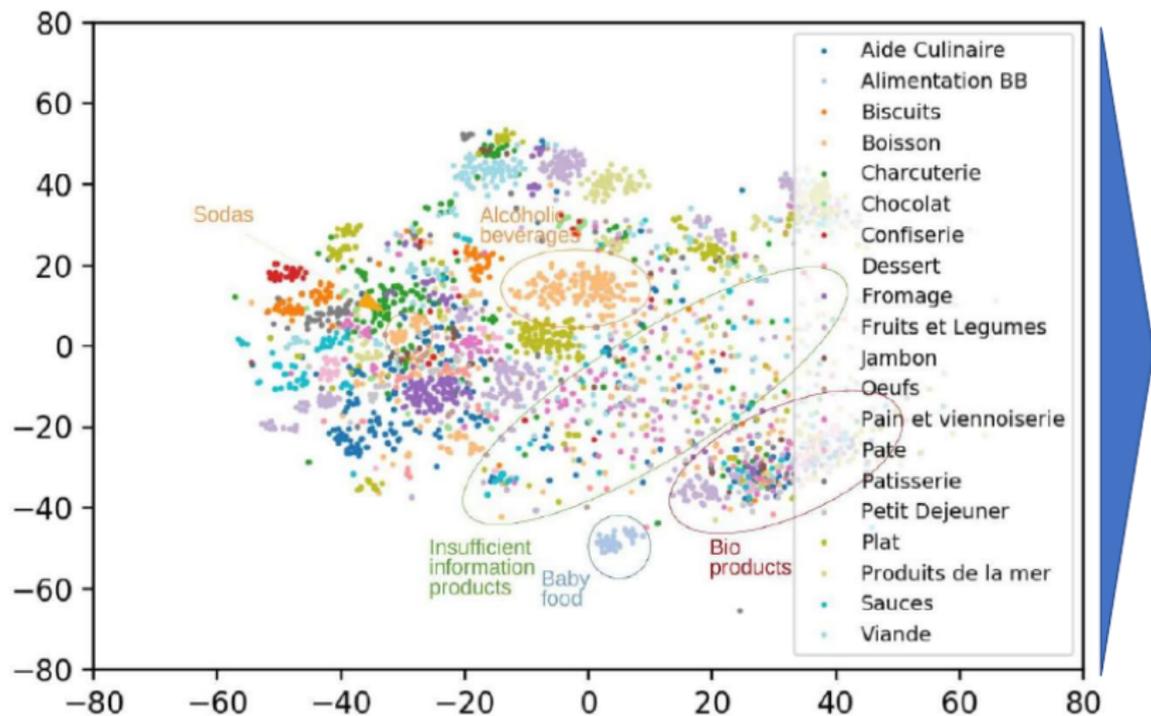
Gelée A Préparer, Féculé, Aide A  
La Pâtisserie, Jambon surgelé,  
Chapelure, Farine, Bouillon Et  
Court-Bouillon, Autre aide culinaire

SCHMIDT, GEO, ADAM, TEMPE,  
KAUEFFERS, AGNES/CUSENIER

# Case study 1: Nutriperso, foll'd

Coll. O. Allais, P. Caillou, A. Constantinescu, K. Gasnikova

## Localize types of food

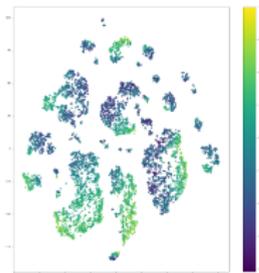


## Case study 2: Eurostate

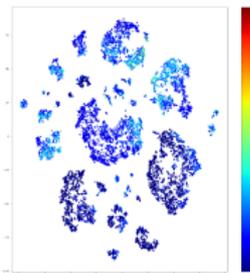
Coll. N. Schwencke, E. Ollion

### The SRCV data

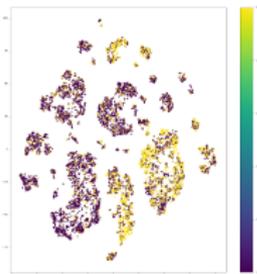
- ▶ A wealth of data: 10,000 households, 1,000 + features
- ▶ Goal: describe population.



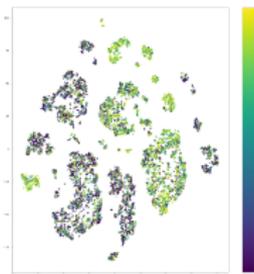
Age



N. persons



Gender



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## Current ML pipeline: CARTOLABE-DATA

### From words/vectors to dimensionality reduction

- ▶ Each entity (article, author, lab)  $\rightarrow$  a vector in  $\mathbb{R}^d$
- ▶ Method
  - ▶ Singular Value Decomposition
  - ▶ Latent Dirichlet Allocation
  - ▶ BERT
- ▶ Hyper-parameter: number of dimensions  $d$

choice ?

### Naming regions

- ▶ Most frequent & discriminant terms
- ▶ Manually tuned to avoid nonsense

# Next

## The need

- ▶ There is no such thing as a good distance for all
- ▶ Learn the distance
- ▶ More generally: Interactive intent modelling

Ruotsalo et al. 18

## From usages to expectations

- ▶ How to get feedback ?
- ▶ Asking scores ? :-)
- ▶ Providing summaries