

An informal walk in the world of mathematical optimization

Oliver Smithies and Leverhume Lecture I, November 2015

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- University of Florence, Italy
- University of Namur, Belgium

Mathematics : a universal language

My objectives :

- Show (by examples) that optimization is a language in which a large number of complex and interesting problems can be solved.
- Share my enthusiasm and amazement at the variety and scope of its applications.
- Spend some intellectually stimulating moments in your company.

The menu

- 1 Objectives and concepts
- 2 Methods et means
- 3 An history-rich discipline
- 4 Optimization in action
 - in industry and technology
 - in sciences
 - in human society
- 5 Conclusions

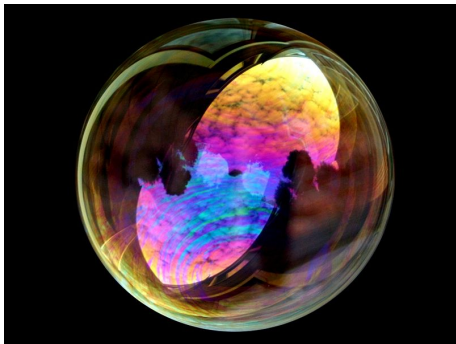
What is mathematical optimization ?

Use mathematics to

make the best choice under constraints

best \Rightarrow criterion, **objective function** (**maximize/minimize**)
choice \Rightarrow **variables** whose values we are free to choose
constraints \Rightarrow **restrictions** on the admissible variables' values

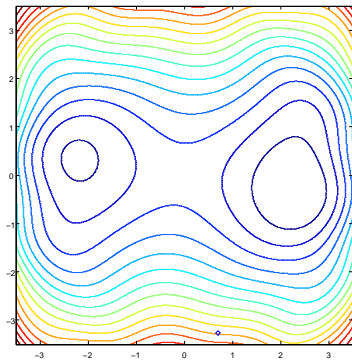
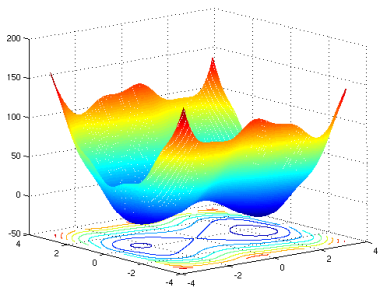
Nature optimizes



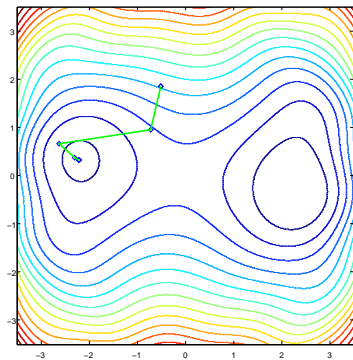
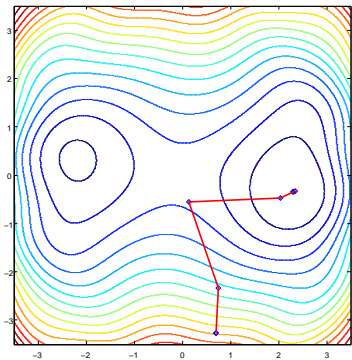
Humans optimize (every day)



Methods : a mountaineering vision ...



Methods : the path to the lake



The means

Powerful computers :



IBM Blue Gene

Optimization pioneers

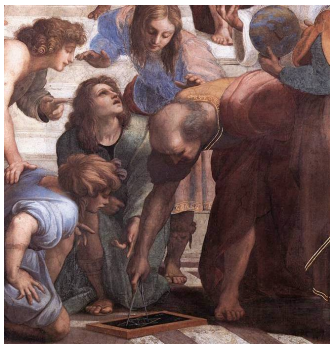
“Nous sommes comme des nains juchés sur des épaules de géants, de telle sorte que nous puissions voir plus de choses et de plus éloignées que n’en voyaient ces derniers. Et cela, non point parce que notre vue serait puissante ou notre taille avantageuse, mais parce que nous sommes portés et exhaussés par la haute stature des géants.”

“We are like dwarves standing on the shoulders of giants, so that we may see more and further afar than they could. And not because our sight is powerful or because we are tall, but only because we are carried and raised by the high stature of the giants.”

Bernard de Chartres (1130-1160)

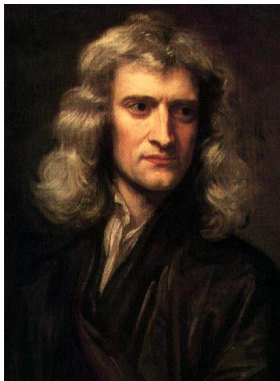
Euclide (300 BC)

Al-Khwarizmi (783-850)



Isaac Newton (1642-1727)

Leonhard Euler (1707-1783)

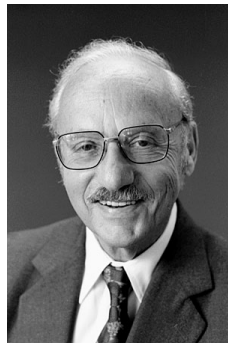


J. de Lagrange (1735-1813)

Friedrich Gauss (1777-1855)



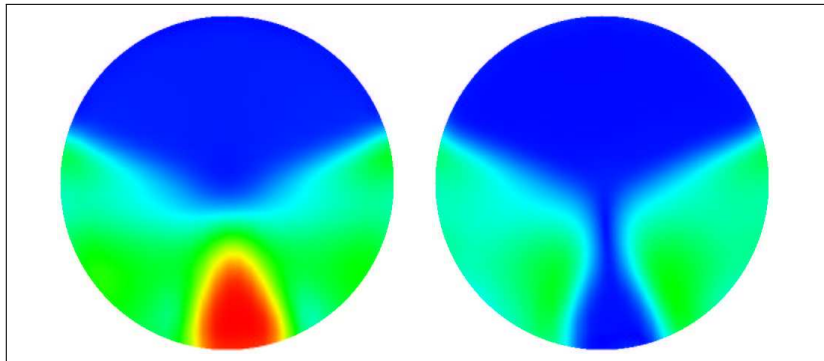
Augustin Cauchy (1789-1857) George Dantzig (1914-2005)



Design of progressive lenses (1)

Specification of modern progressive lenses :

vary the lens's optical power while minimizing astigmatism



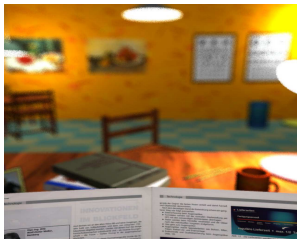
Loos, Greiner, Seidel (1997)

Design of progressive lenses (2)

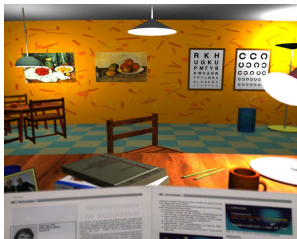
What can be done :



without correction
long distance



short distance
with progressive lenses



Design of progressive lenses (3)

Is this problem nonlinear (\approx difficult)?

If the urface of the lens is given by $z = z(x, y)$, the **optical power** is

$$p(x, y) = \frac{N^3}{2} \left[\left(1 + \left[\frac{\partial z}{\partial x} \right]^2 \right) \frac{\partial^2 z}{\partial y^2} + \left(1 + \left[\frac{\partial z}{\partial y} \right]^2 \right) \frac{\partial^2 z}{\partial x^2} - 2 \frac{\partial z}{\partial x} \frac{\partial z}{\partial y} \frac{\partial^2 z}{\partial x \partial y} \right]$$

where

$$N = N(x, y) = \frac{1}{\sqrt{1 + \left[\frac{\partial z}{\partial x} \right]^2 + \left[\frac{\partial z}{\partial y} \right]^2}}$$

The **surface astigmatism** is then given by

$$a(x, y) = -2 \sqrt{p(x, y) - N^4 \left(\frac{\partial z}{\partial x} \frac{\partial z}{\partial y} - \left[\frac{\partial^2 z}{\partial x \partial y} \right]^2 \right)}$$

Sterilization of baby food (1)

A very standard problem in the food industry :

keep a max of vitamins while eliminating a given fraction of the bacteria

heat the food in vapour- or hot-water autoclaves



Sachs (2003)

Sterilization of baby food (2)

Model : coupled partial differential equations (PDEs)

Concentration of micro-organisms and other nutrients :

$$\frac{\partial C}{\partial t}(x, t) = -K[\theta(x, t)]C(x, t),$$

where $\theta(x, t)$ is temperature, and where

$$K[\theta] = K_1 e^{-K_2 \left(\frac{1}{\theta} - \frac{1}{\theta_r} \right)} \quad (\text{Arrhenius equation})$$

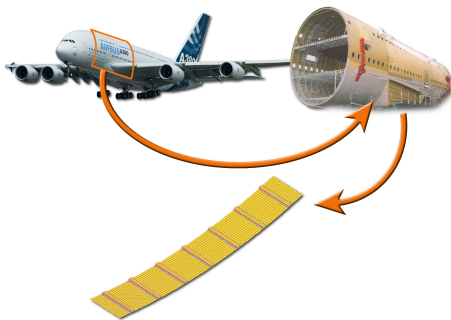
Temperature evolution :

$$\rho c(\theta) \frac{\partial \theta}{\partial t} = \nabla \cdot [k(\theta) \nabla \theta],$$

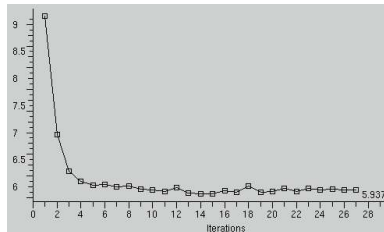
(with suitable **boundary conditions** : refrigerant, initial temperature, Idots)

Structural design for aeronautics

minimize fuselage weight while maintaining structural integrity



SAMTECH (2009)

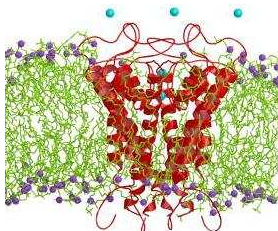


mass reduction
during optimization

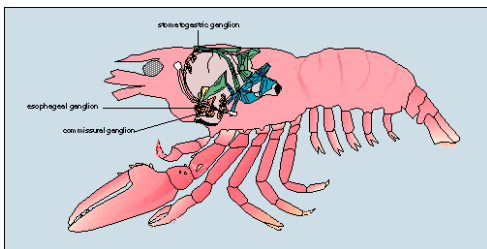
A parameter estimation problem in biology (1)

A model for a potassic channel in a neurone's membrane :

Sansom (2001)



But where are these neurones? In a spiny Pacific lobster (*Panulirus interruptus*)! Simmers, Meyrand and Moulin (1995)



A parameter estimation problem in biology (2)

After collecting **experimental data**
(applying a current to the cell) :

estimate the model's parameters in order to best fit the data

The model (for the biologists) :

- Activation : p independent **gates**
- Deactivation : n_h gates with different **dynamics**
- $n_h + 2$ **coupled PDEs** for voltage, activation level and partial inactivation levels
- 5-points BDF integrator for ≈ 50000 time steps
- \Rightarrow **very nonlinear!**

Data assimilation in weather forecasting (1)

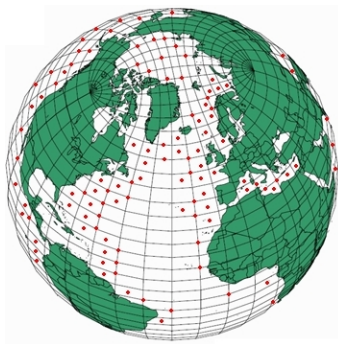


(Attempt to) predict. . .

- tomorrow's weather
- average temperature in the ocean for the coming month
- future gravity field
- next currents in the ionosphère
- . . .

Data assimilation in weather forecasting (2)

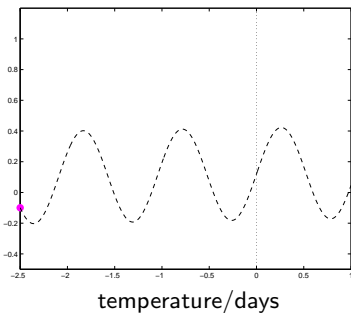
Data : temperature, wind, pressure, ... everywhere and at all times !



Contains more than **1.000.000.000** variables !

Data assimilation in weather forecasting (3)

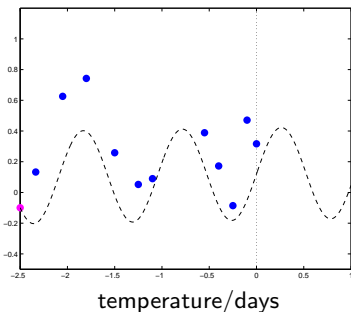
The principle :



- **Situation** known 2.5 days ago and “background” forecast

Data assimilation in weather forecasting (3)

The principle :

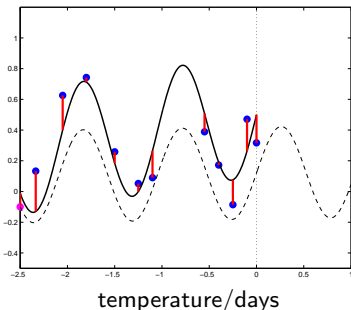


- **Situation** known 2.5 days ago and “background” forecast
- **Temperature** for the past 2.5 days

Data assimilation in weather forecasting (3)

The principle :

Minimize the error between model and past observations



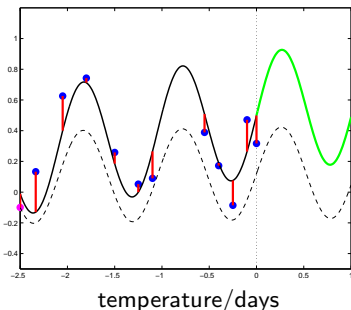
- **Situation** known 2.5 days ago and “background” forecast
- **Temperature** for the past 2.5 days
- Run the model to **minimiser** distance between model prediction and observations

$$\min_{x_0} \frac{1}{2} \|x_0 - x_b\|_{B^{-1}}^2 + \frac{1}{2} \sum_{i=0}^N \|\mathcal{HM}(t_i, x_0) - b_i\|_{R_i^{-1}}^2.$$

Data assimilation in weather forecasting (3)

The principle :

Minimize the error between model and past observations

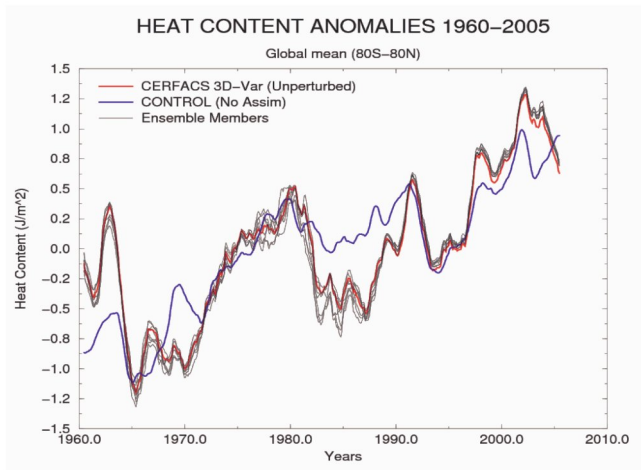


- **Situation** known 2.5 days ago and “background” forecast
- **Temperature** for the past 2.5 days
- Run the model to **minimiser** distance between model prediction and observations
- **Predict** tomorrow's temperature

Data assimilation in weather forecasting (4)

Analysis of the heat content in the ocean :

CERFACS (2009)



Musch better fit !

Image denoising (1)

Consider an **image** with random **noise** (incorrect of pixel blackness) proportional to signal strength.

HQuestion ; reconstruct the original blackness levels

use the pixels' values as much as possible
while minimizing sharp transitions (gradients)

This yields the optimization problem

$$\min_u \sum_{ij \in \Omega} (u_{ij} - z_{ij} \log(u_{ij})) + \alpha \int_{\Omega} \|\nabla u\|$$

where

$$z_{ij} = u_{ij} + n f(u_{ij})$$

and n is a Gaussian noise.

Image denoising (2)

Some **spectacular** results : an 512×512 image with **95%** noise

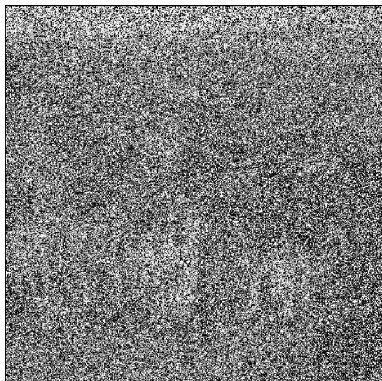
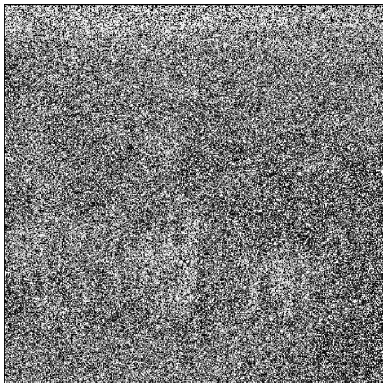


Image denoising (2)

Some **spectacular** results : an 512×512 image with **95%** noise



Chan and Chen (2007)

Reconstruction of hidden objects (2)

- an object \mathcal{O} **hidden** in an opaque medium (ground, water, body ...)
- one **“illuminates”** this object with an electromagnetic plane wave in “all” directions

$$u^{inc}(x, d) = e^{ik\langle x, d \rangle} \quad d \in \mathcal{S}$$

- one measures the **waves reflected** $u^s(x, d)$ by the object in “all” directions

$$\Delta u^s + k^2 u^s = 0 \quad (\text{outside } \mathcal{O})$$

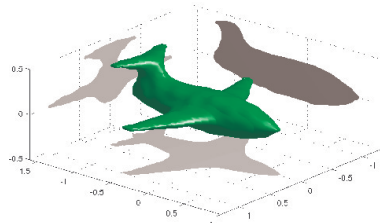
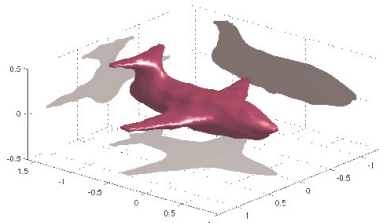
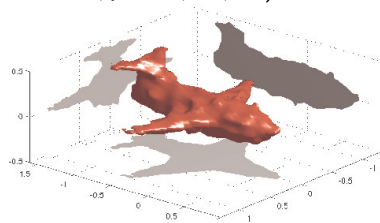
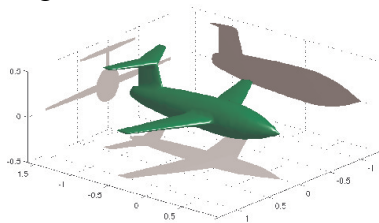
with

$$u = u^{inc} + u^s, \quad u = 0 \text{ on } \partial\mathcal{O} \quad \text{et} \quad \lim_{r \rightarrow \infty} \frac{\partial u^s}{\partial r} = iku^s.$$

Optimize the object's shape \mathcal{O} from the measurements $u^s(x, d)$

Illustration : reconstruction of a plane

The original and its reconstructions ($N = 1002$, $p = 5, 20, 50$)



Optimization, transport et mobility

The context

Analyse de la mobilité quotidienne en Belgique

Modelling the **displacements**



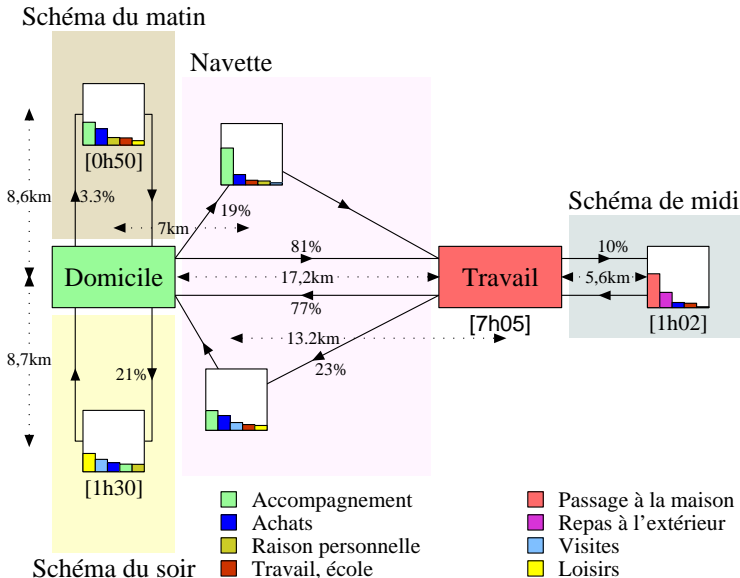
Modelling the **activities**



Modelling behaviours of
individuals/households



Daily mobility : a complex system



Understanding choice strategies in society

Context : simulation of individuals' **mobility** choices
(mode, route, start time, ...)

Random utility theory

Individual i assigns to alternative j the “utility”

$$U_{ij} = [\text{parameters} \times \text{explaining factors}] + [\text{random error}]$$

Illustration :

$$U_{bus} = \text{distance} - 1.2 \times \text{ticket price} - 2.1 \times \text{delay w.r.t. trip by car} + \epsilon$$

Discrete choice models (1)

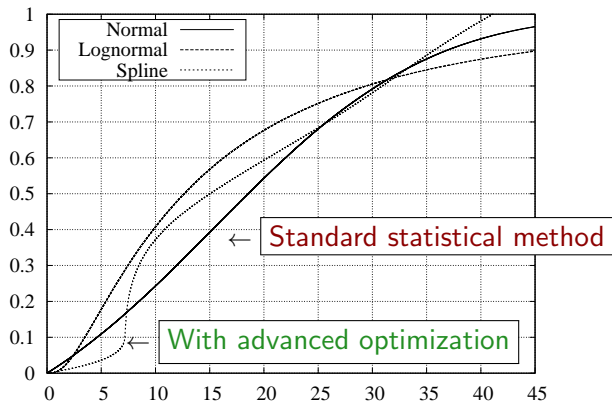
Probability that the individual i chooses alternative j rather than alternative k is given by

$$\text{prob}(U_{ij} \geq U_{ik} \text{ for all } k)$$

Data : mobility surveys ([MOBEL](#), [BELDAM](#), etc.)

find the utility's parameters which
maximize the likelihood of observed behaviours

Discrete choice models (2)



Estimation of the **value of lost time** in traffic congestion
(with and without advanced optimization)

Modelling individuals ?

A major difficulty

- Individual data (often) **unavailable/incoherent**. . .
(cost, privacy regulations, variable sources)

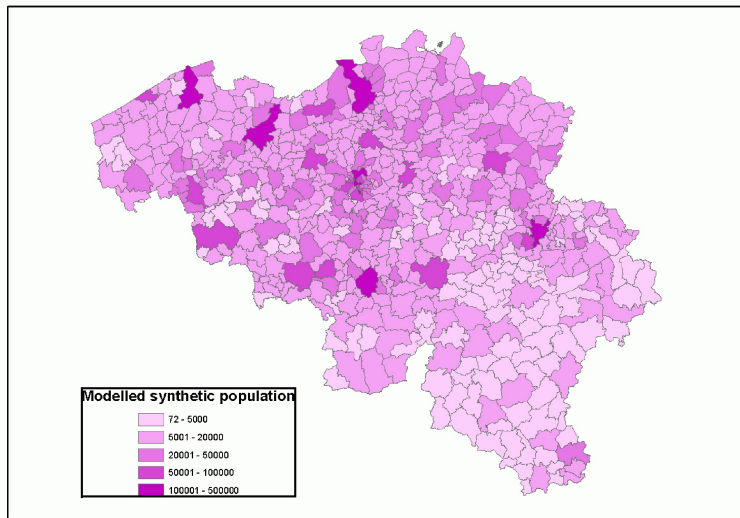
Build a syntetic population

Method

- **maximize** the likelihood of individuals/housholds descriptions
- while maitaining **known statistics** for the real population

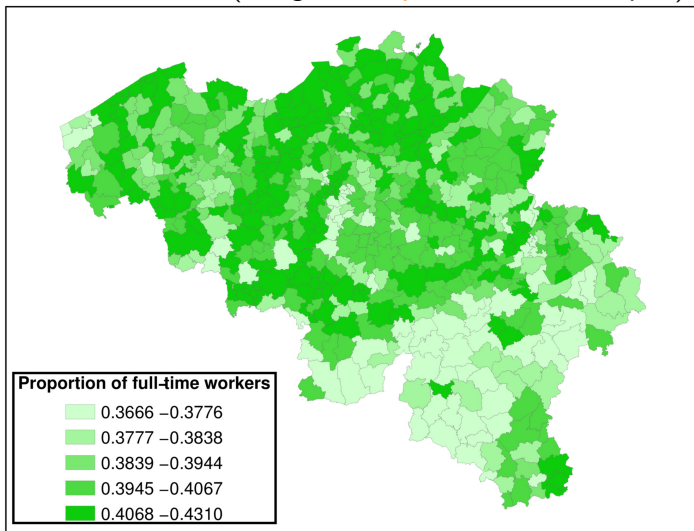
A synthetic population for Belgium

One gets $\approx 10.600.000$ individuals in 4.400.000 households



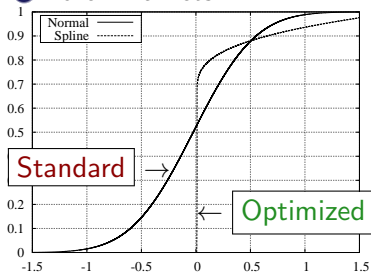
A synthetic population for Belgium

From which one can deduce (using other **optimization** techniques)



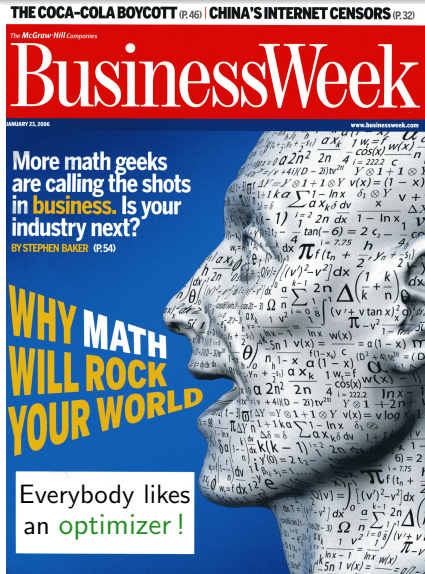
and in finance...

- ① risk management
- ② portfolio analysis
- ③ forex markets



Distribution of the BoJ
investments 1991-2004

- ④ ...



Some conclusions

The mathematical language is astonishingly *flexible, adaptable, elegant and efficient*.

Applied mathematics is a booming area of expertise.

Optimisation and complex system analysis are in the forefront.

A regret : not being able to share (yet) the **fulgurence** of the theory...