

# Webinar



Sciences Economiques et  
Sociales de la Santé et Traitement  
de l'Information médicale  
[sesstim.univ-amu.fr](http://sesstim.univ-amu.fr)



[openhealth-institute.org](http://openhealth-institute.org)

## *Jacques DEMONGEOT*

Professeur, IUF, Institut Universitaire de France, Membre honoraire.  
UGA, Université Grenoble Alpes Professeur Emérite.

**Big data,  
Functional modelling, Time Data.**

juin 2017

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# Big data, Functional modelling, Time data

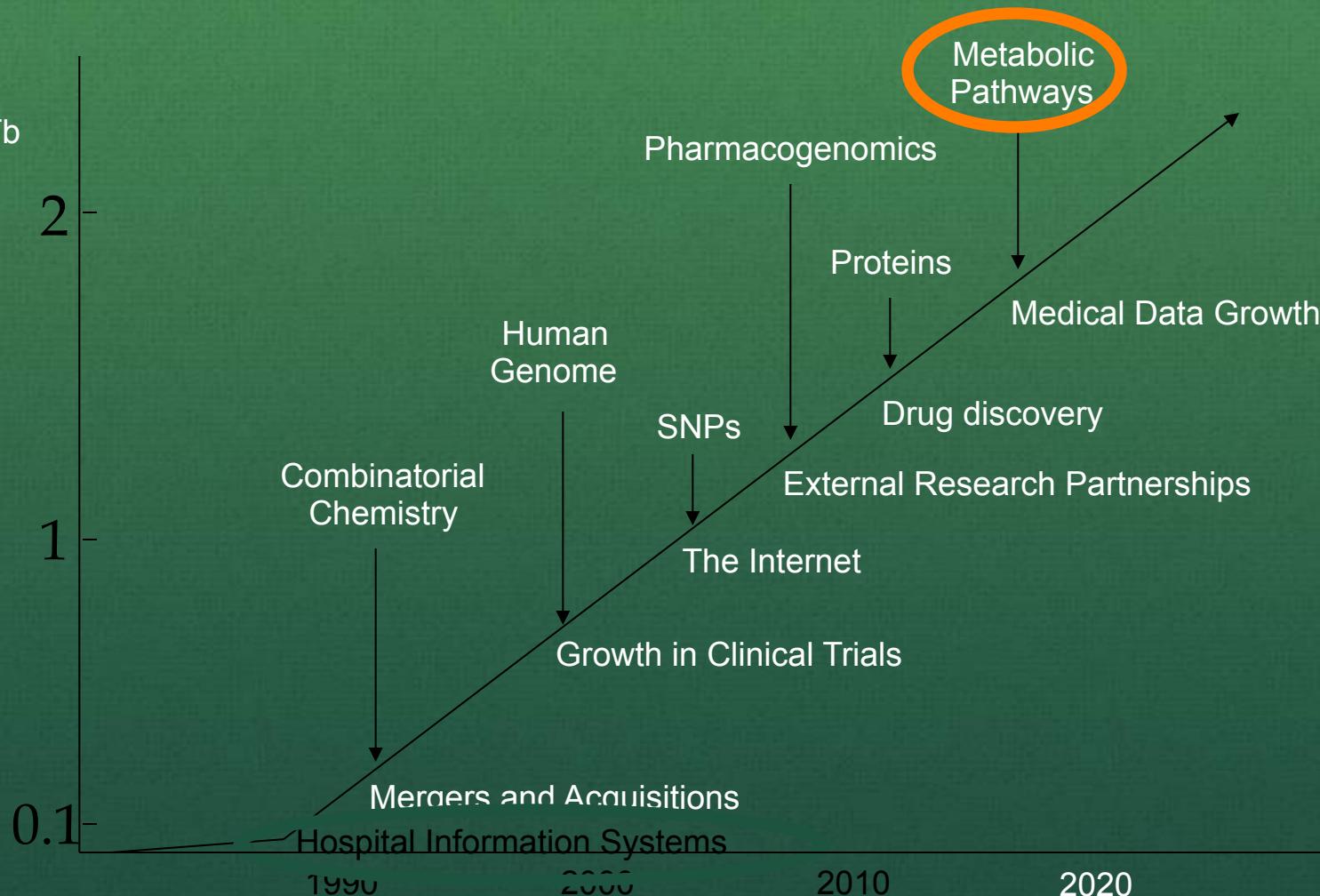
J. Demongeot IUF (honorary) & UGA (emeritus)

# New Health Technologies Produce Data Tsunami

Petabytes of medical data produced pro year in a hospital receiving 200 000 patients / year

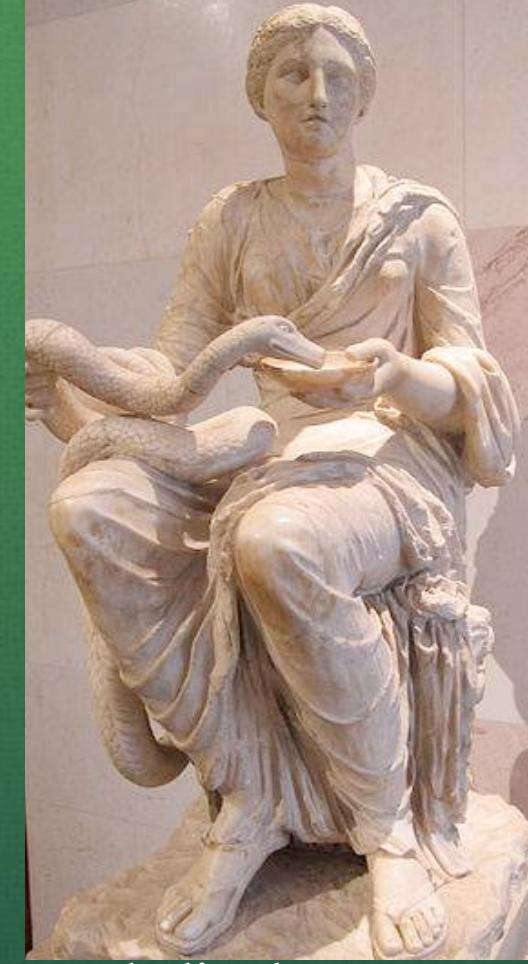
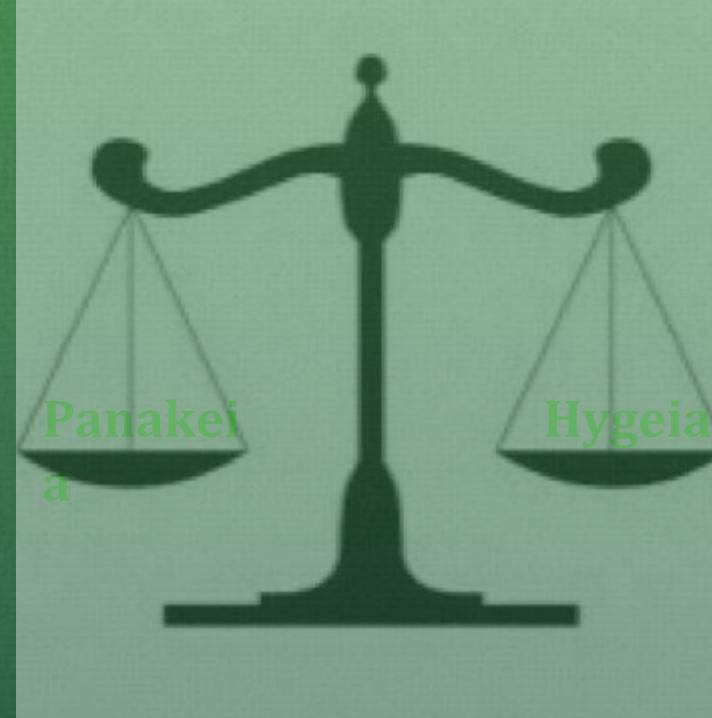
of  
Data

=  
1024 Tb



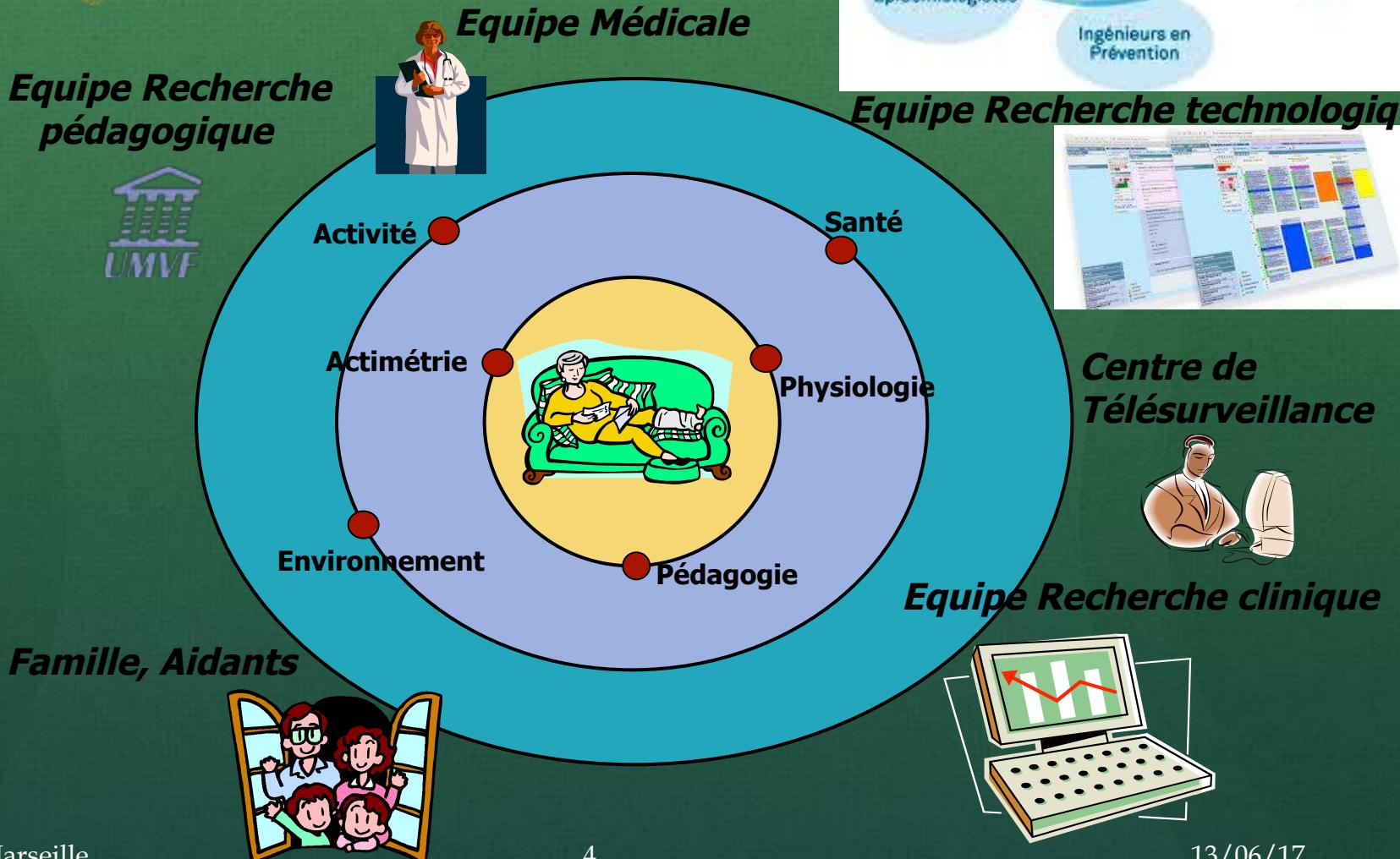


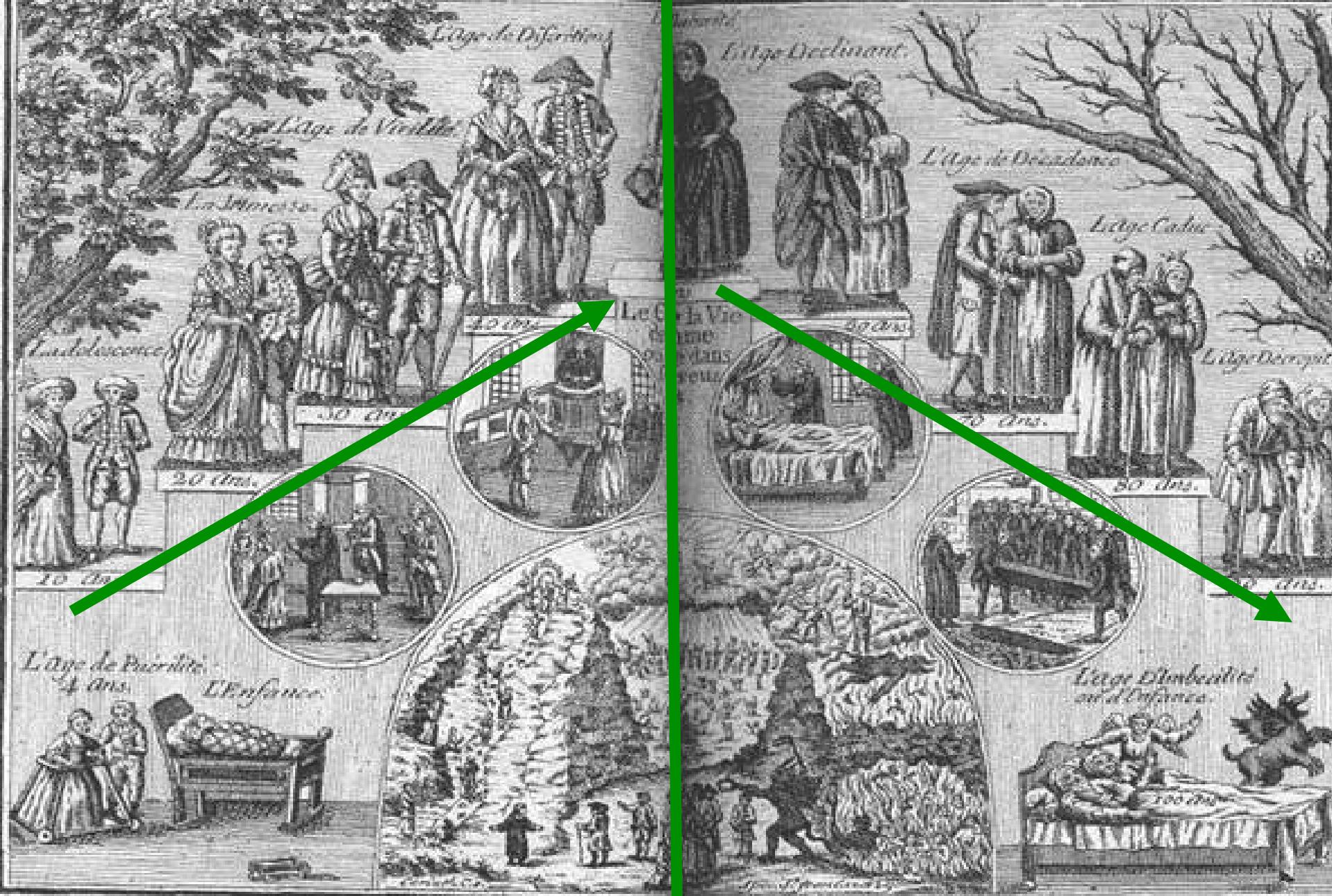
**Le bâton symbolise l'activité  
du médecin qui promène  
sa science secourable**



**Le serpent symbolise la personne  
qui fait le choix de participer  
ou non au soin, prenant ainsi en  
main son propre bien-être**

# e-santé asservie au patient





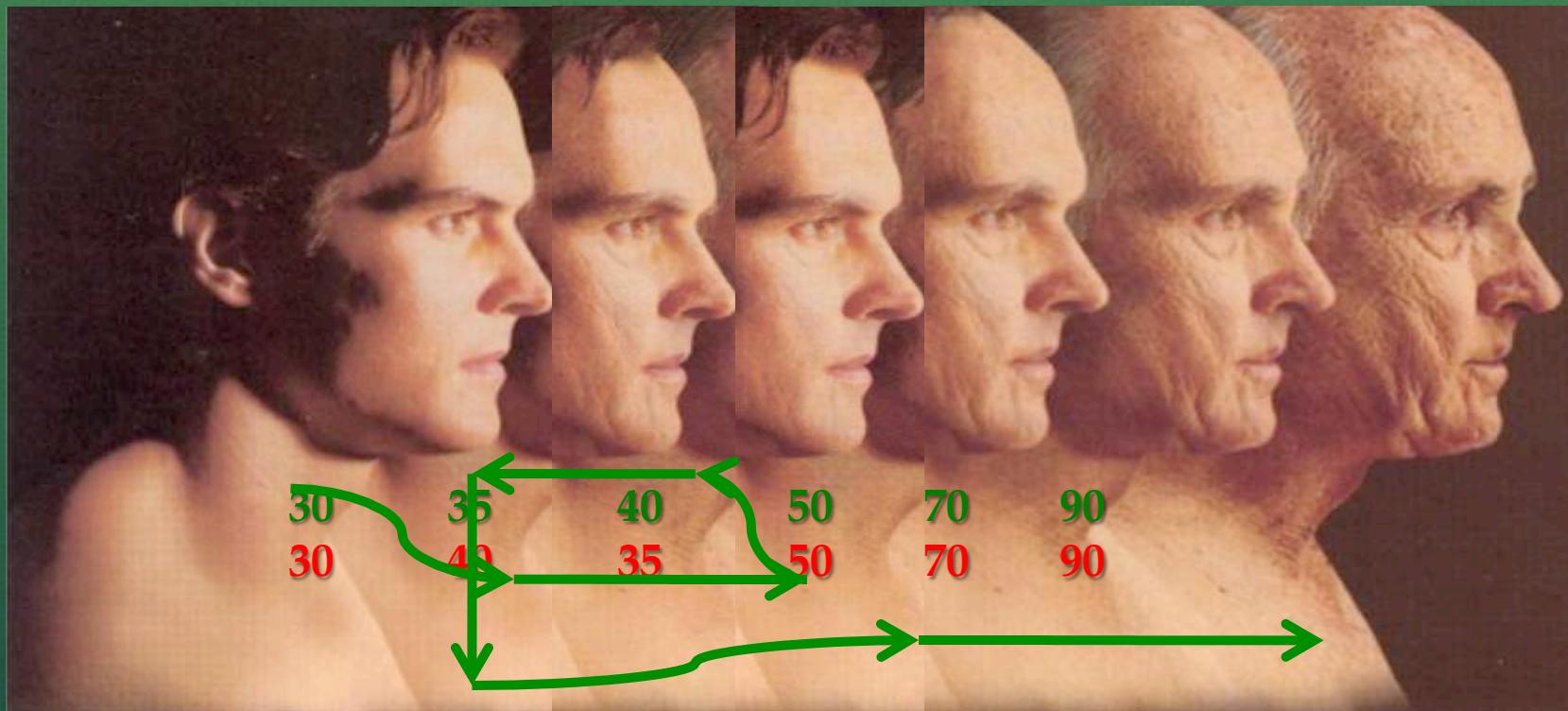
L'Homme commence par l'enfance,  
Et à l'âge de deux ans il devient  
Un petit enfant. L'adolescence.

Si la jeunesse et l'adolescence.  
Dès l'âge de trois ans l'enfant est comparé à un enfant de trois ans.  
L'âge d'adolescence. Il aura l'âge qui va le suivre,  
Et de grande force pour faire plaisir. C'est à dire de la Santé.

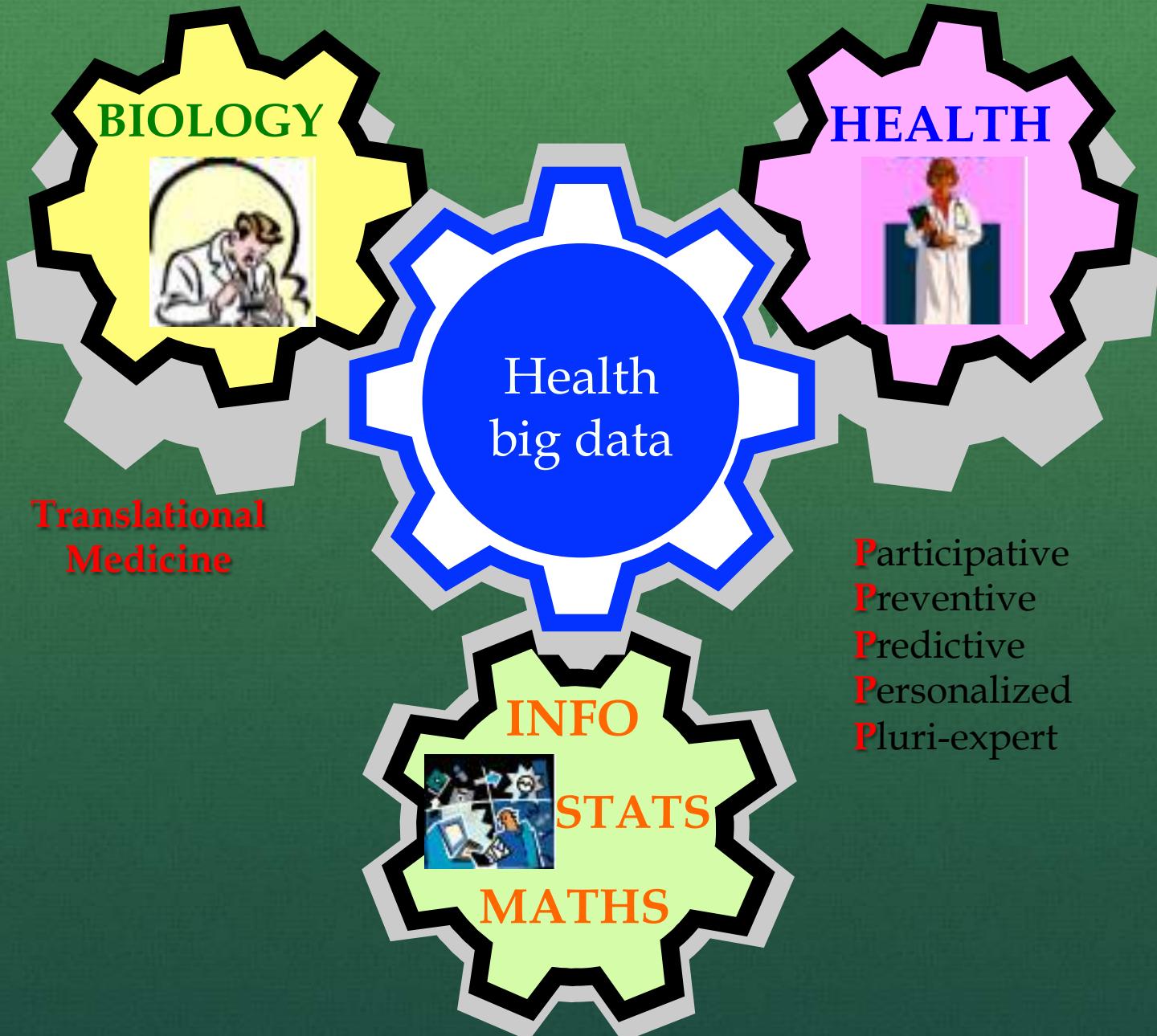
L'âge Caduc et imbecile.  
Il ne peut plus faire rien.  
Plus fort devient tout, mais moins.  
Et le corps devient un autre être.

# Biological Time

## Chronological Time



JD, Acta Bio, 2009



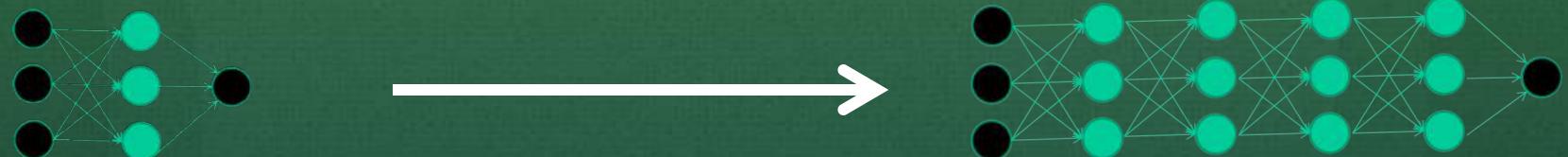
# Methods of investigation, compression & interpretation

## Methods of investigation

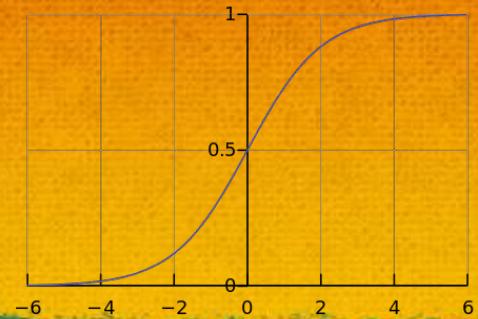
- Classical data analysis
- Deep learning
- No SQL interrogation

**Le “deep learning est une méthode non supervisée, qui utilise un classifieur réseau de neurones à plusieurs couche.**

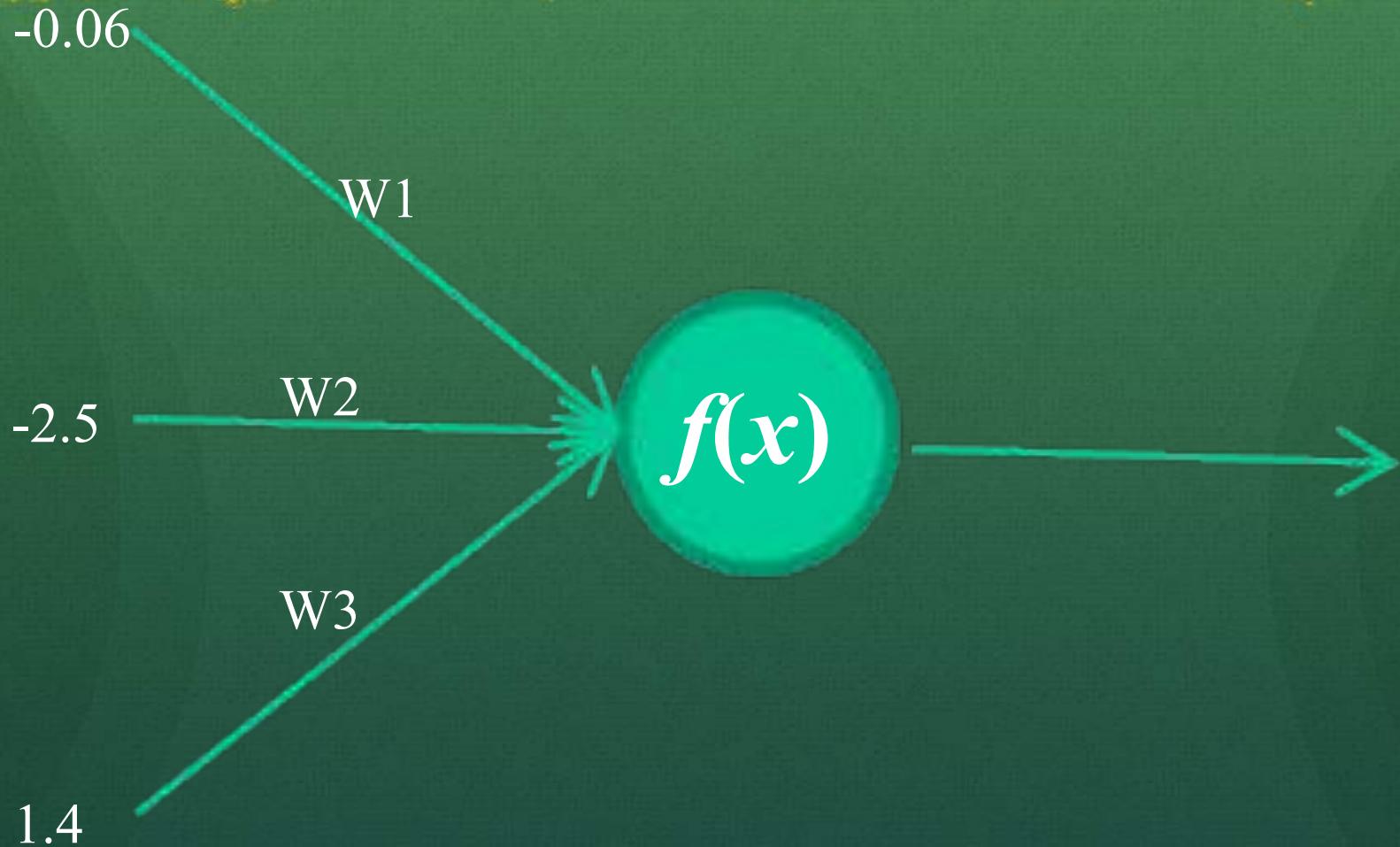
Par rapport aux réseaux classiques  
(Hopfield, Kohonen, etc),  
ajonction de plusieurs couches



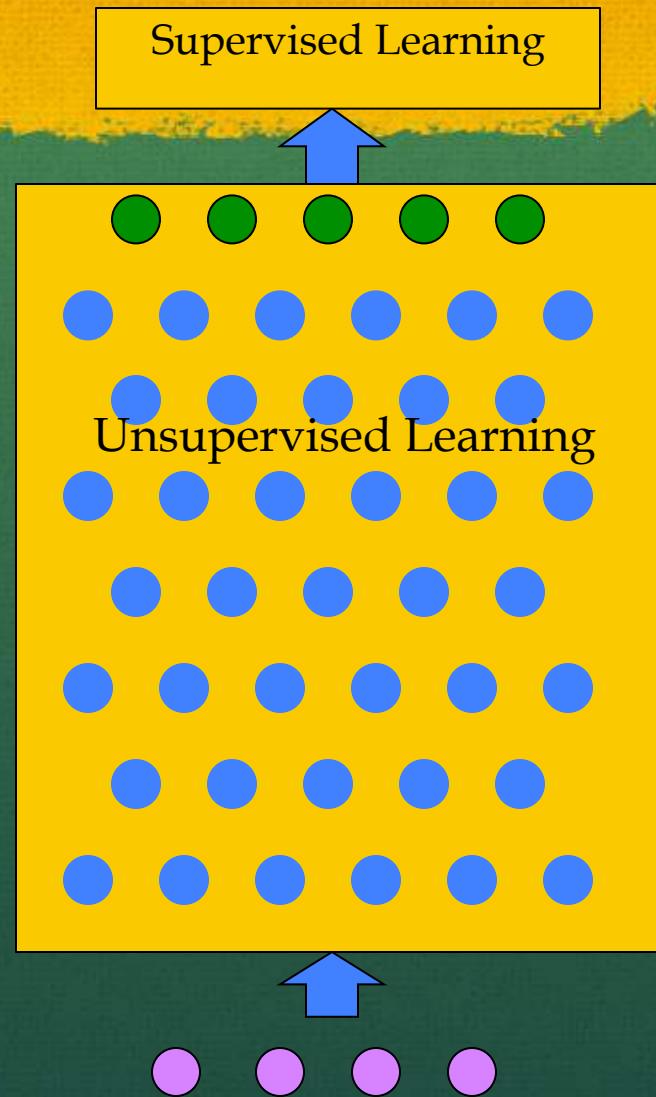
$$f(x) = \frac{1}{1 + e^{-x}}$$



# McCulloch-Pitts 1940



# Deep Learning



# Convolution (L. Schwartz, Y. Lecun)

## Pour régulariser, on convole...

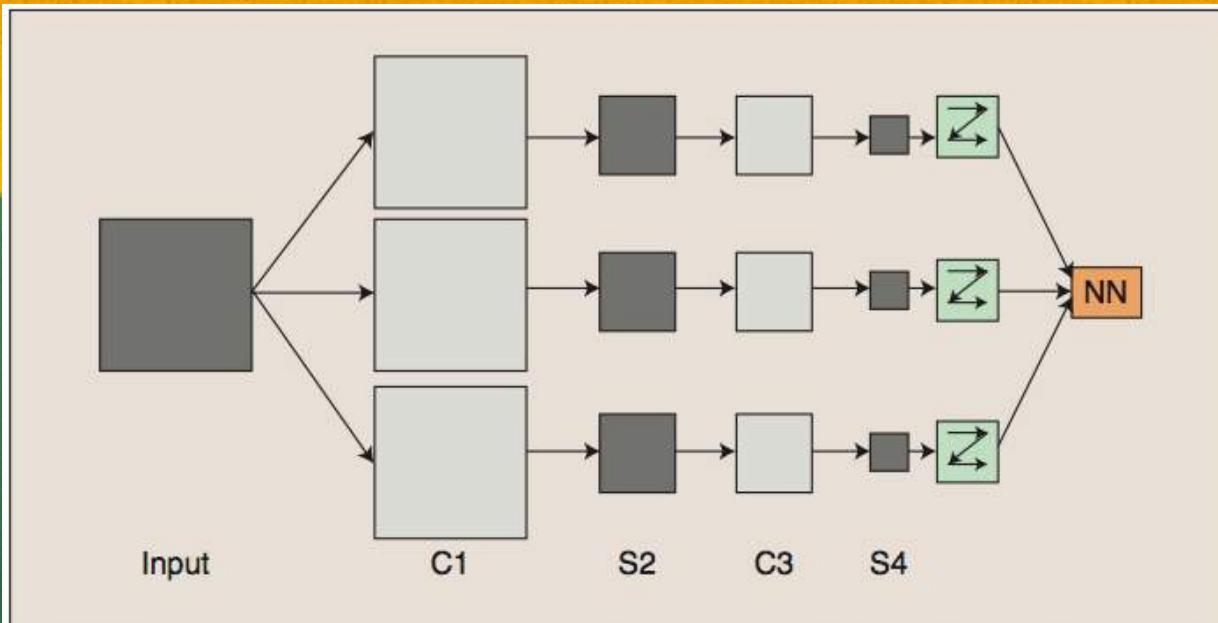
1 <small><math>\times 1</math></small>	1 <small><math>\times 0</math></small>	1 <small><math>\times 1</math></small>	0	0
0 <small><math>\times 0</math></small>	1 <small><math>\times 1</math></small>	1 <small><math>\times 0</math></small>	1	0
0 <small><math>\times 1</math></small>	0 <small><math>\times 0</math></small>	1 <small><math>\times 1</math></small>	1	1
0	0	1	1	0
0	1	1	0	0

Image

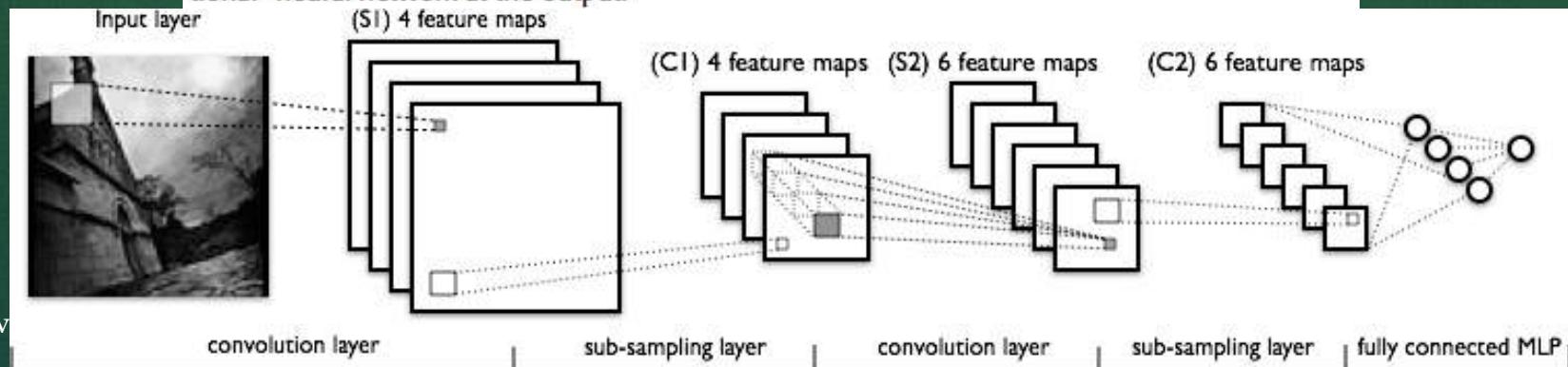
4		

Convolved  
Feature

# Convolutional Neural Networks



**FIGURE 2** Conceptual example of convolutional neural network. The input image is convolved with three trainable filters and biases as in Figure 1 to produce three feature maps at the C1 level. Each group of four pixels in the feature maps are added, weighted, combined with a bias, and passed through a sigmoid function to produce the three feature maps at S2. These are again filtered to produce the C3 level. The hierarchy then produces S4 in a manner analogous to S2. Finally these pixel values are rasterized and presented as a single vector input to the “conventional” neural network at the output.



# Cascade of convolutions

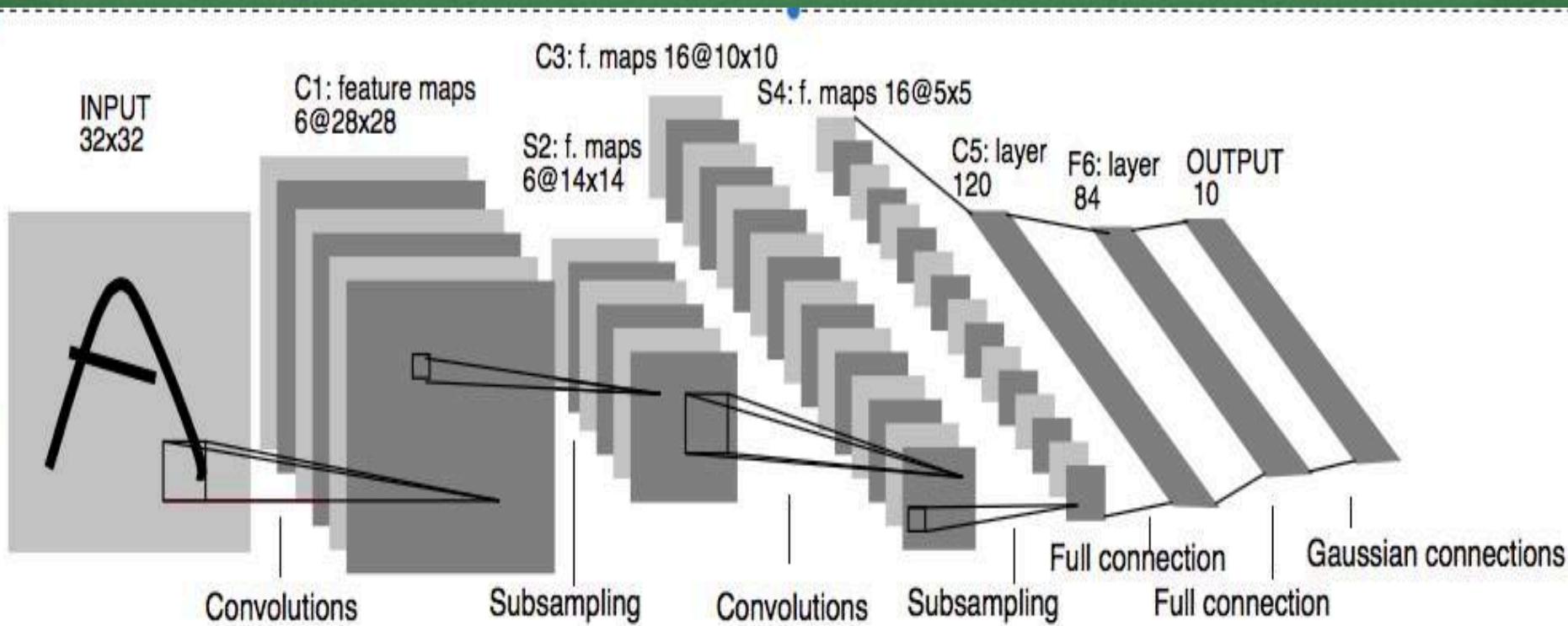
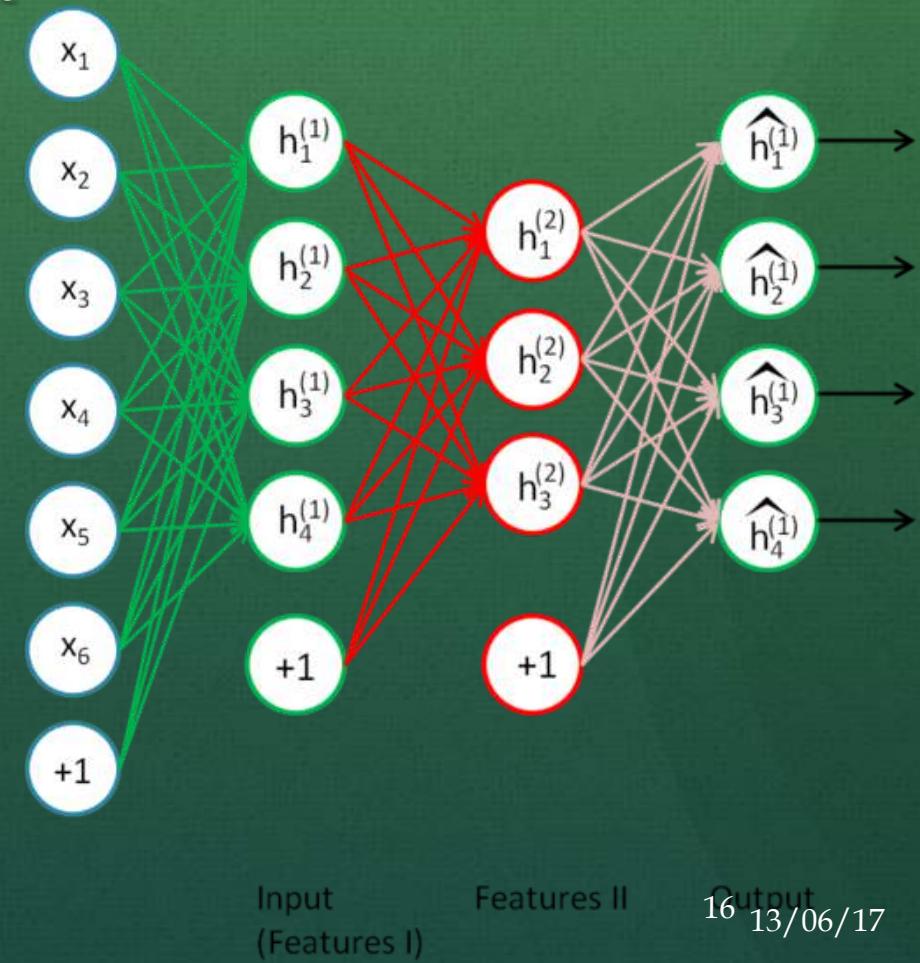
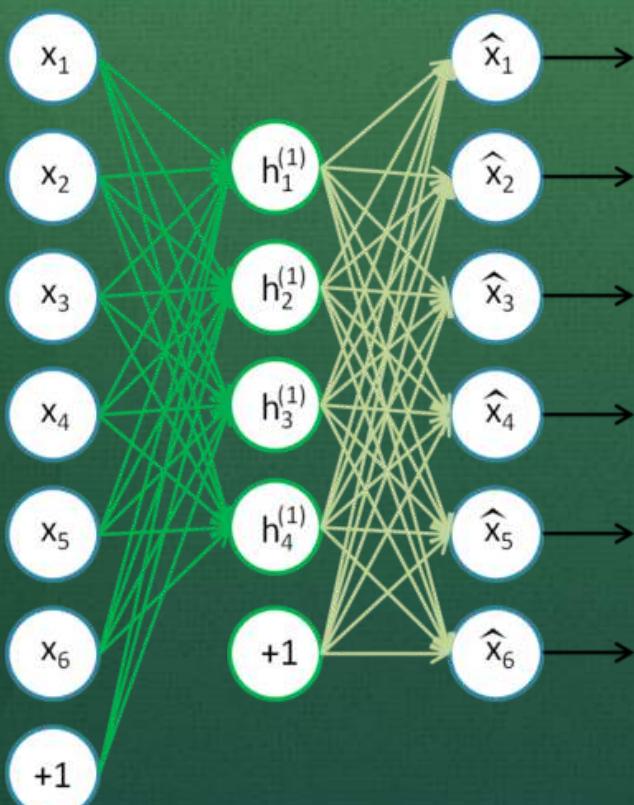


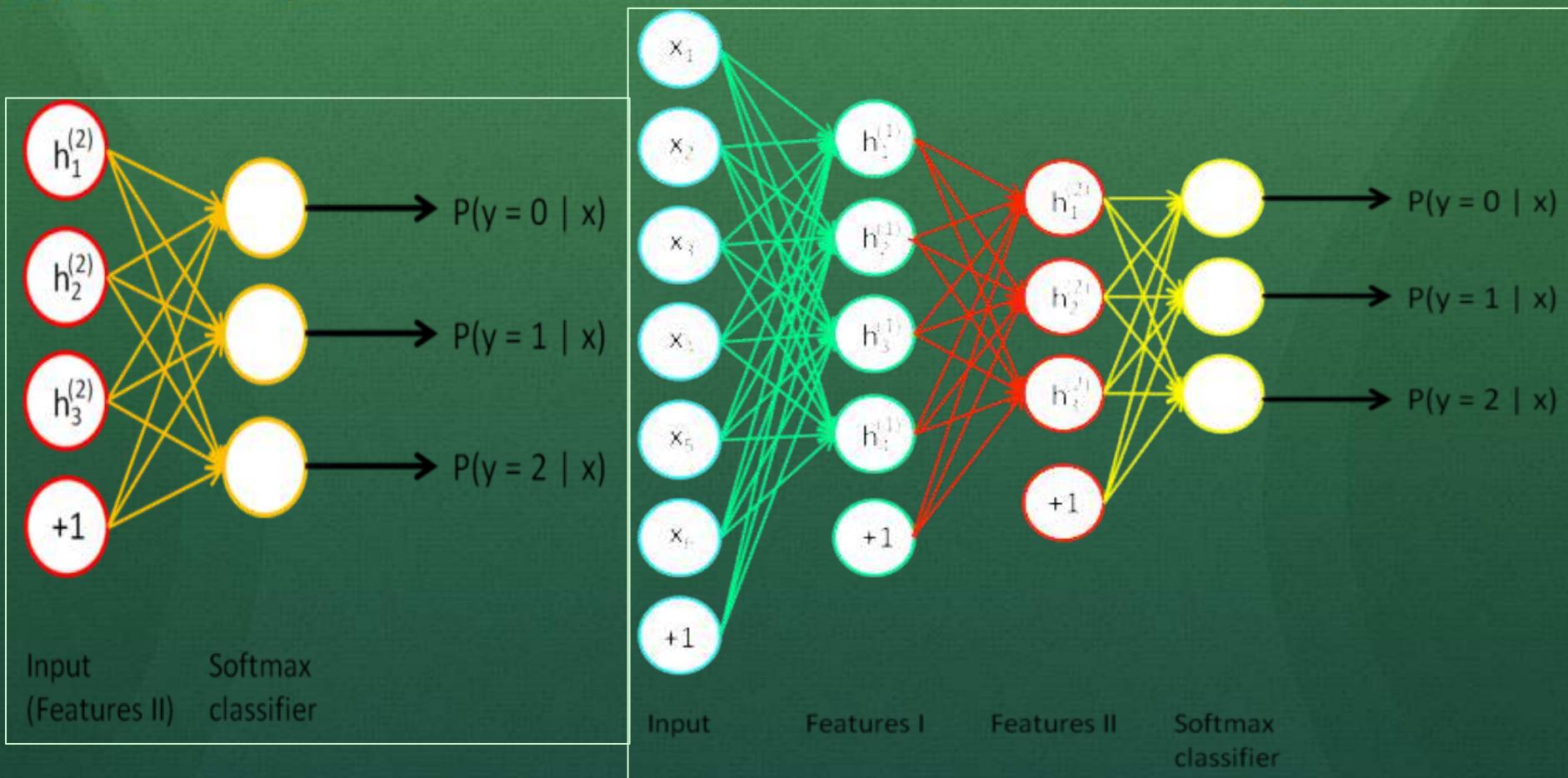
Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

# Stacked Auto-Encoders

- Bengio (2007) - After Deep Belief Networks (2006)
- Stack many (sparse) auto-encoders in succession and train them using greedy layer-wise training
- Drop the decode output layer each time



# Auto-encodeurs empilés



## **Methods of compression**

- Statistical compression
- Model driven compression
- Qualitative ontologic compression

# Statistical compression

for reducing health big data

into a few data representations

based on data analysis restituting

the essential of the medico-social

knowledge

# Influenza Web surveillance in Japan social networks

Eiji Aramaki, Sachiko Maskawa, Mizuki Morita

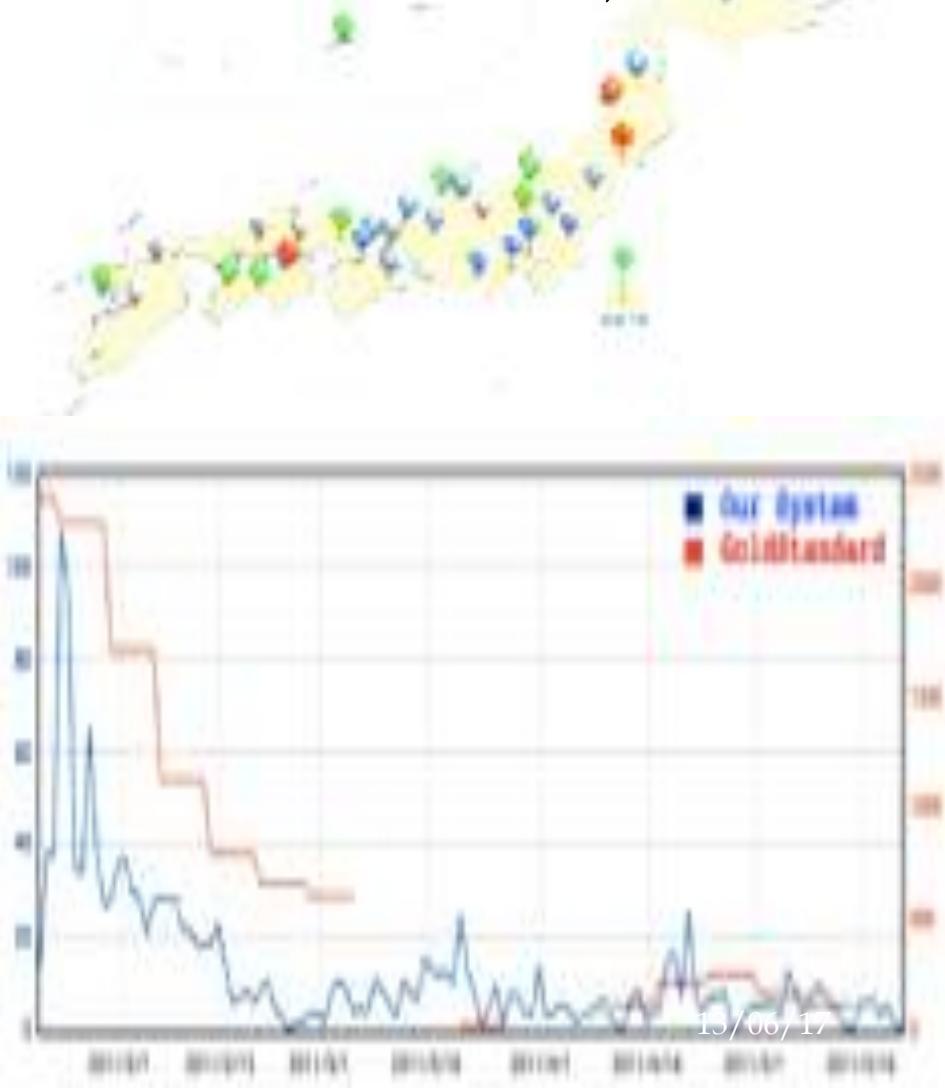
Twitter Catches The Flu: Detecting Influenza Epidemics using Twitter

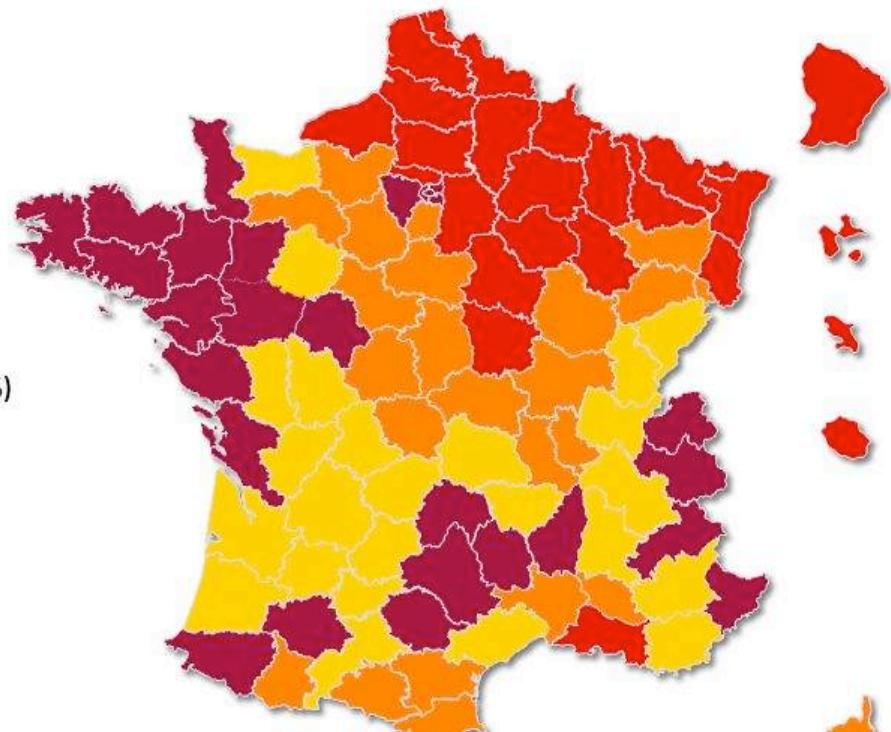
EMNLP (*Empirical Methods on Natural Language Processing*), 1568-1576 (2011)

## *INFLU kun GP surveillance*

*Tweet data*

*Google data*

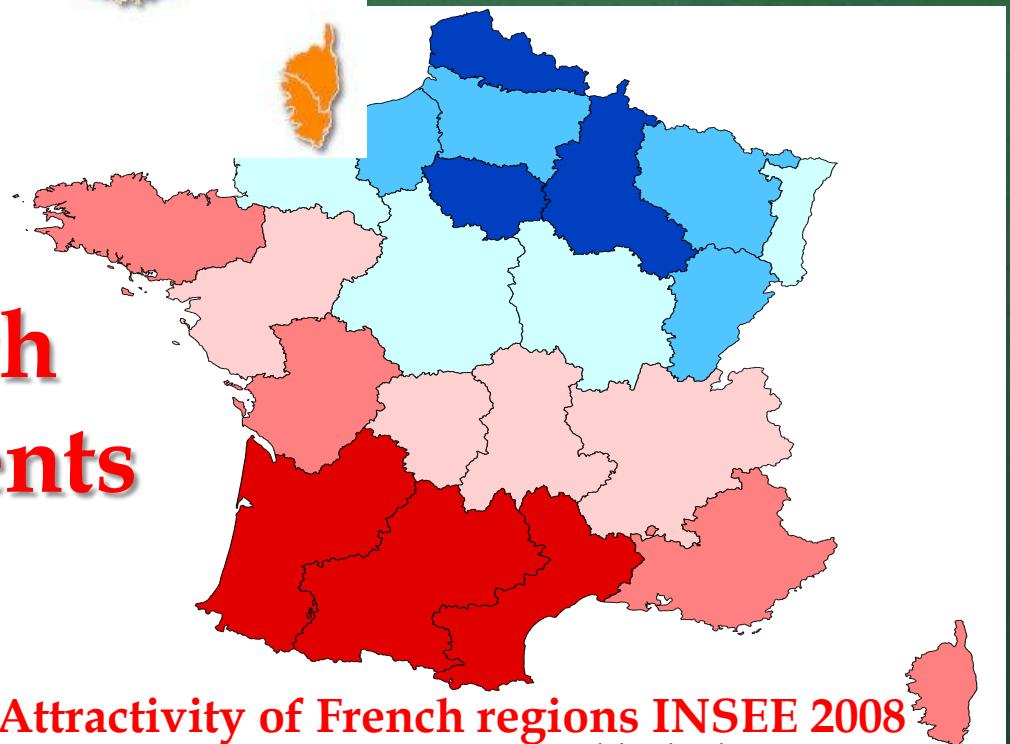




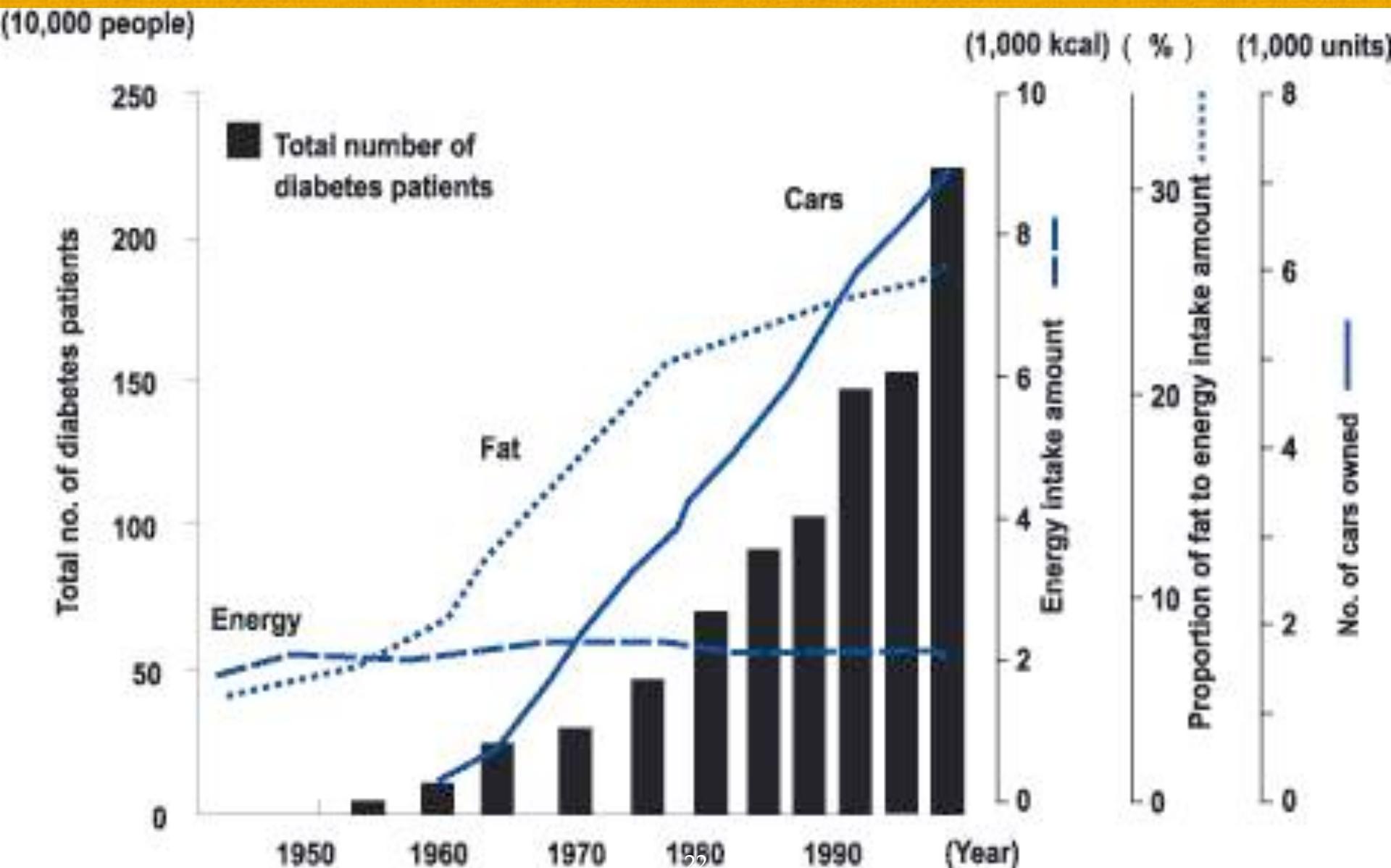
Type II diabetes prevalence OECD 2008



# South-North French medico-social gradients

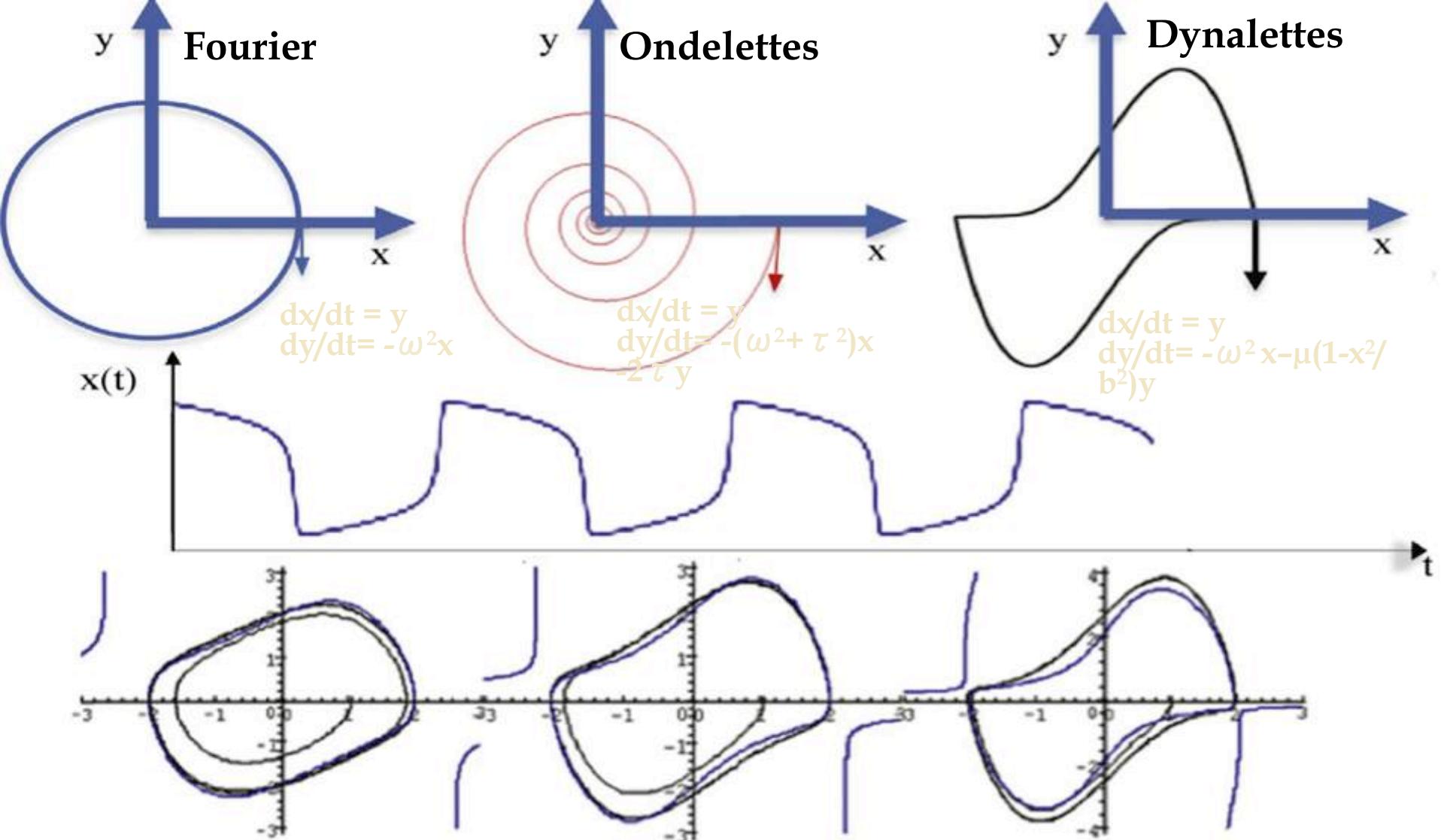


# Type II Diabetes increase in Japan



# Model driven compression

**Generalization of the Fourier & wavelets approach**



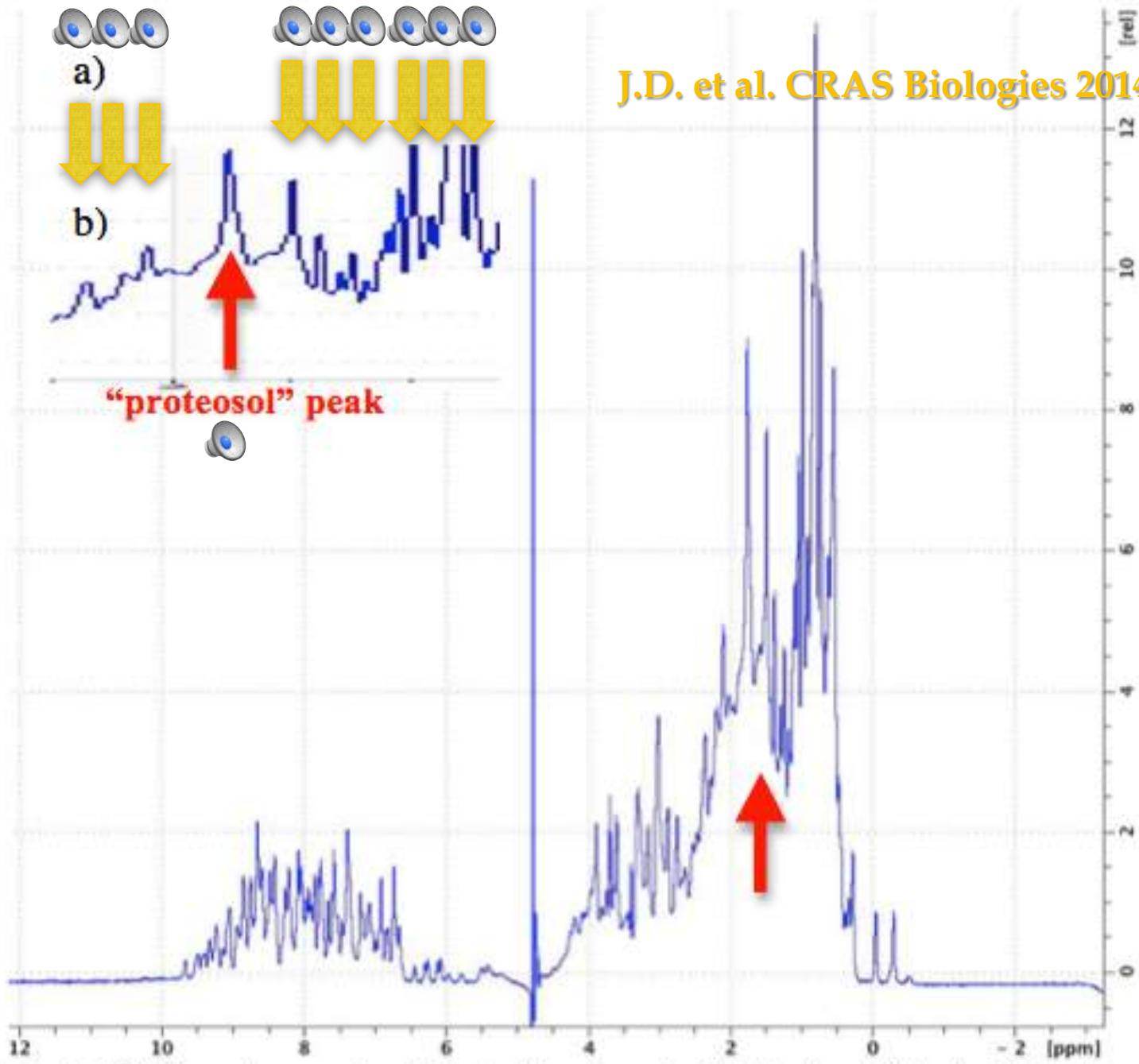


Fig. 1: a) original protein NMR spectroscopy signal; b) extraction of a peak called "proteosol" to be isolated and processed by the Dynalet transform (red arrow).

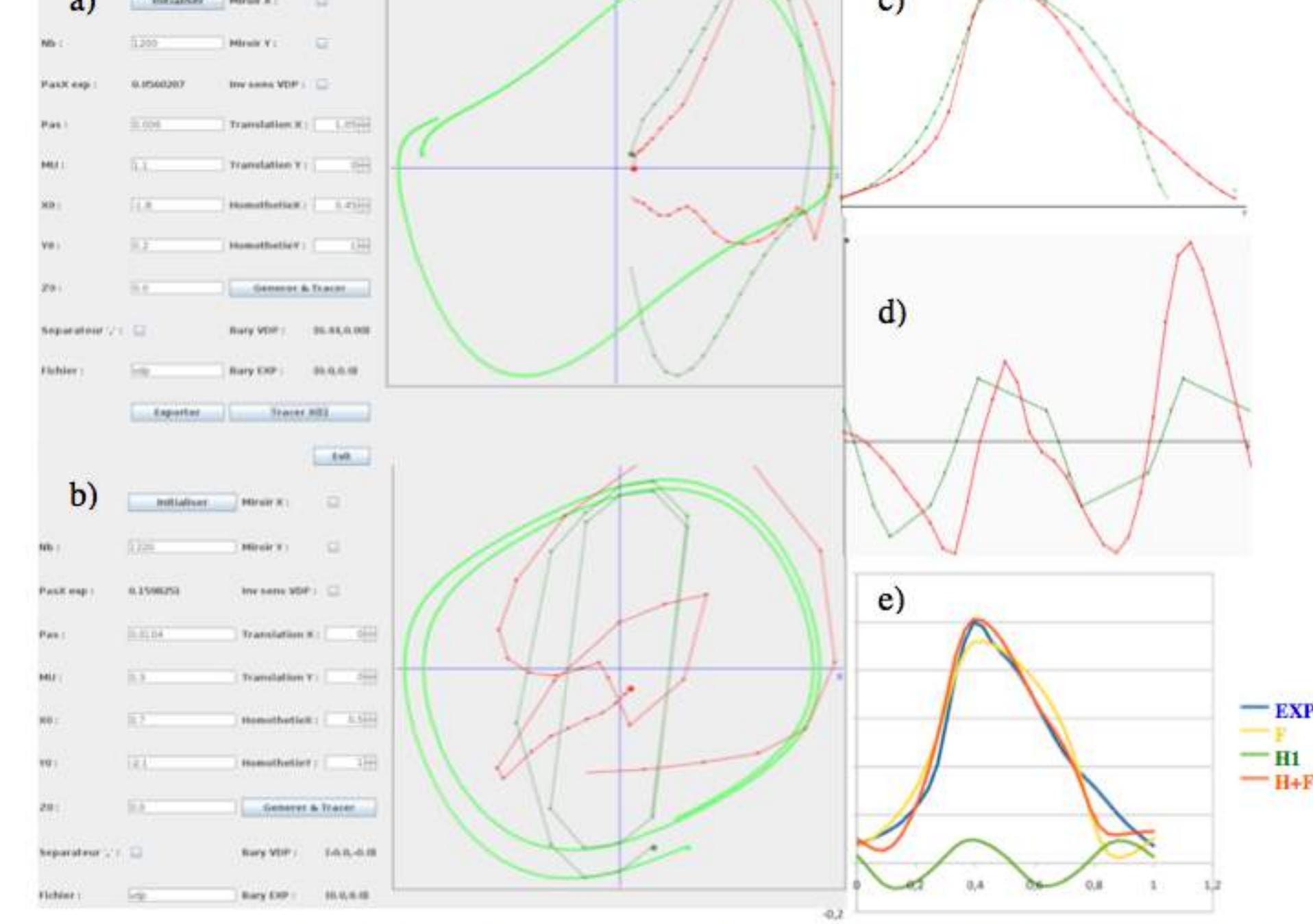


Fig. 2: a) original empirical protein signal of Fig. 1 (in red) matched with the van der Pol limit cycle (in dark green); b) first harmonic signal matched with the first harmonic of the van der Pol signal; c) fundamental temporal original signal (in red) matched with the van

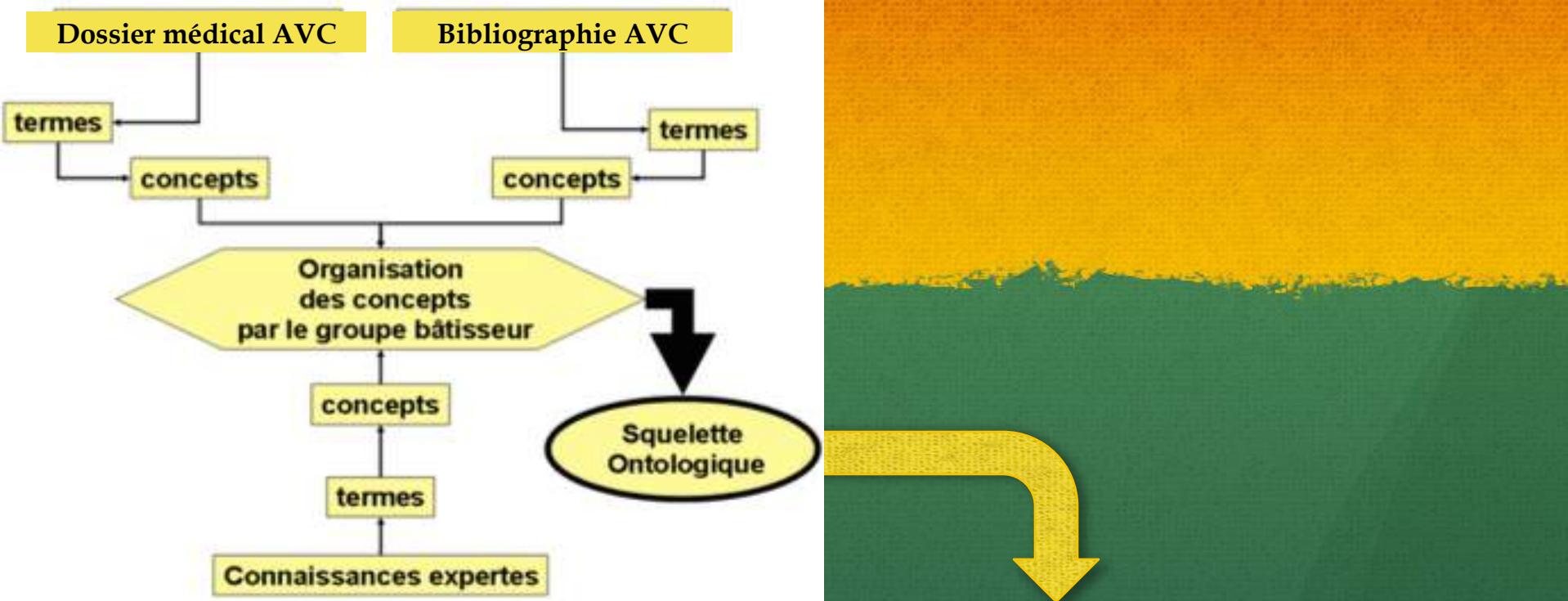
# Qualitative ontologic compression

## into logic representations

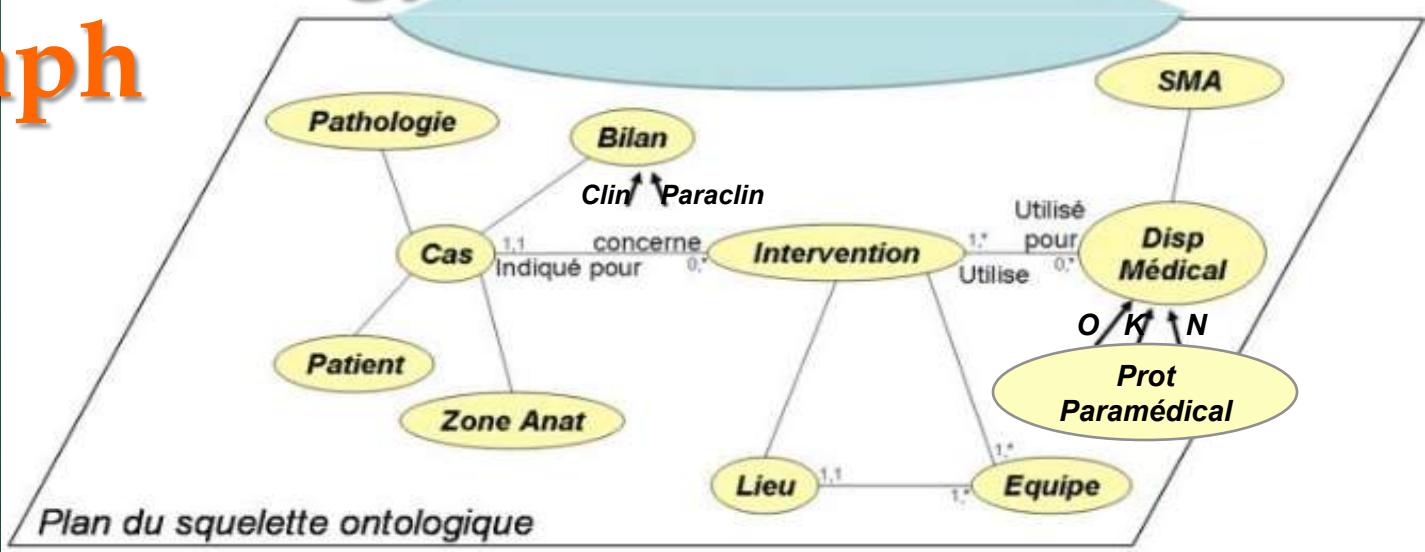
based on

semantic analysis and

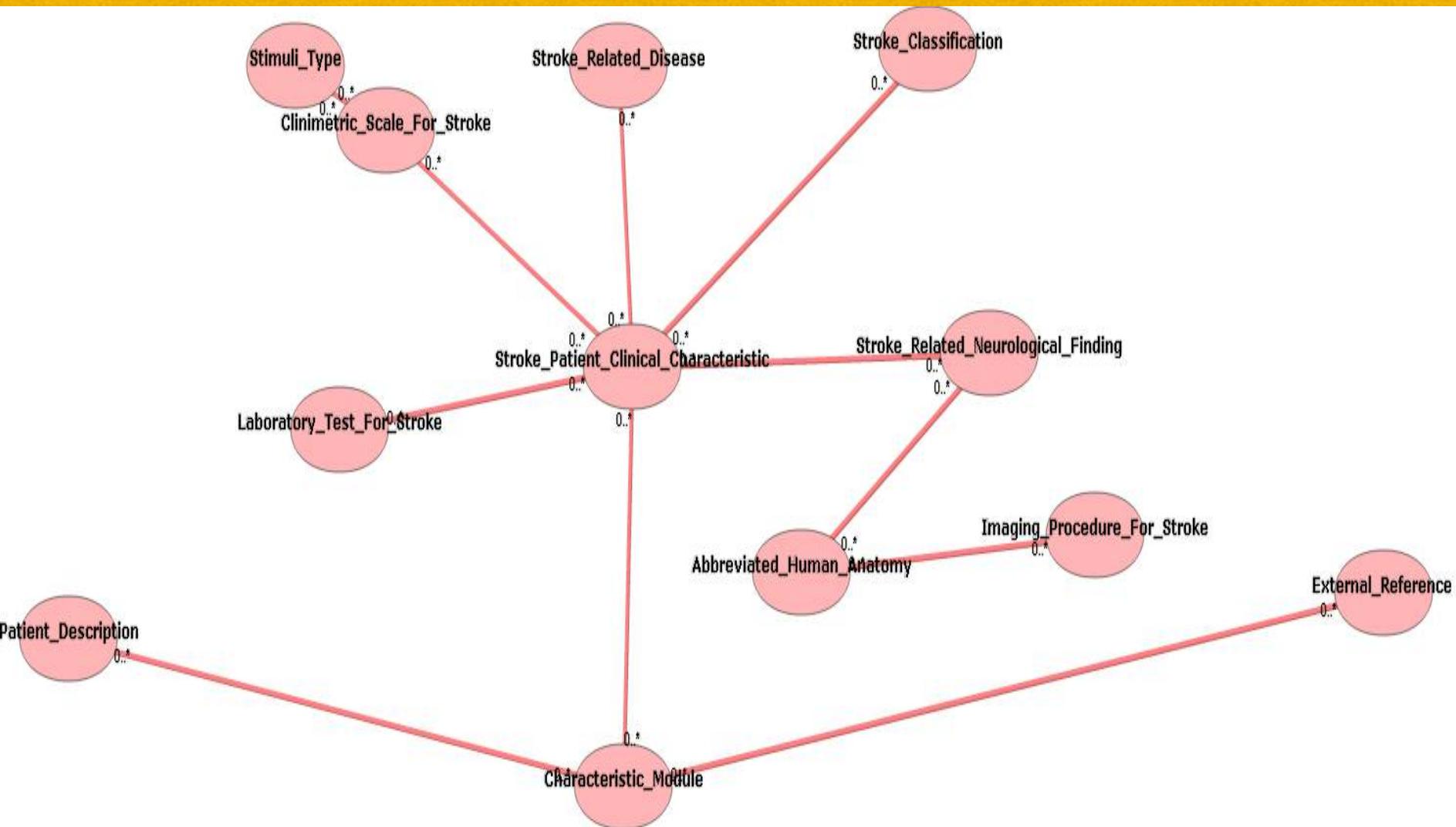
ontologic representation



# Concepts ontology graph



# Ontology building tools



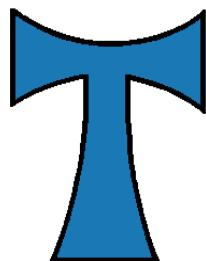
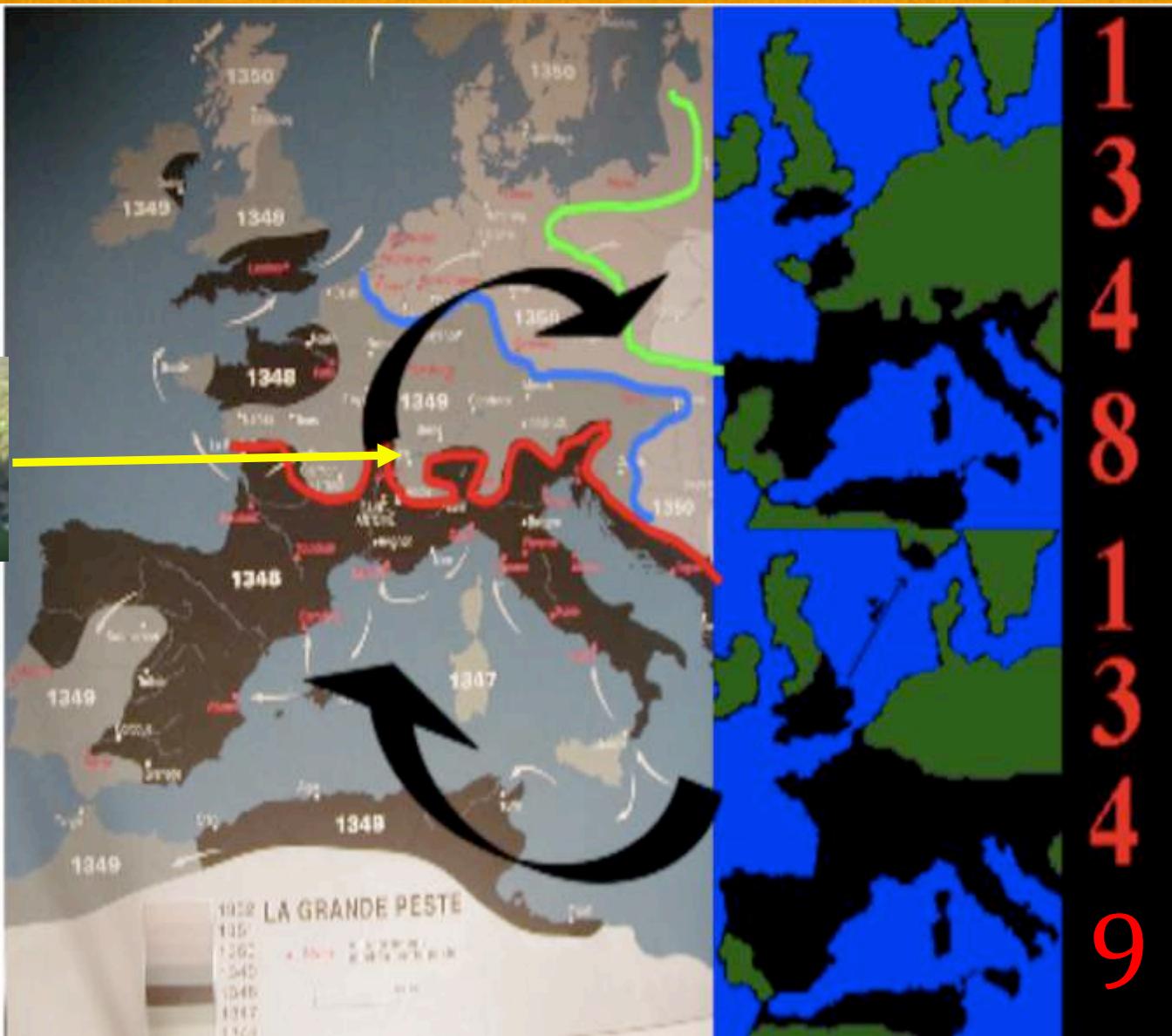
## **Methods of interpretation**

- Differential modelling
- Automata & Multi-Agent modelling
  - Functional modelling

# Differential modelling

# Voies commerciales



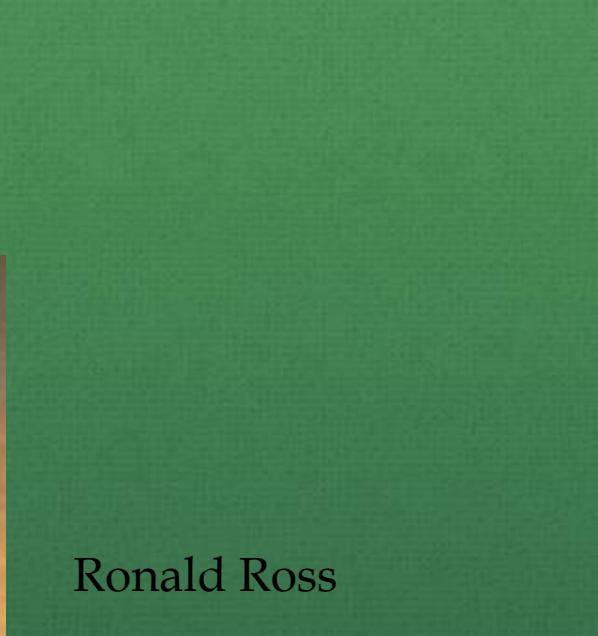




Daniel Bernoulli



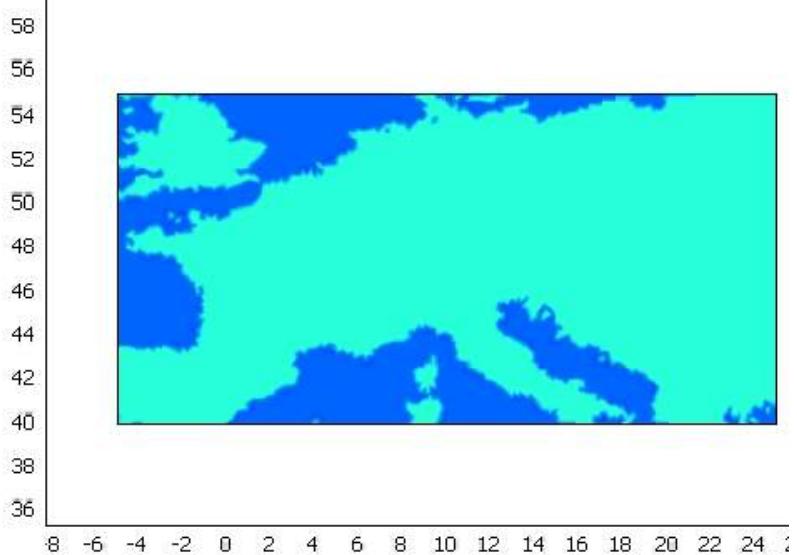
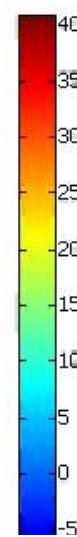
Jean d'Alembert



Ronald Ross

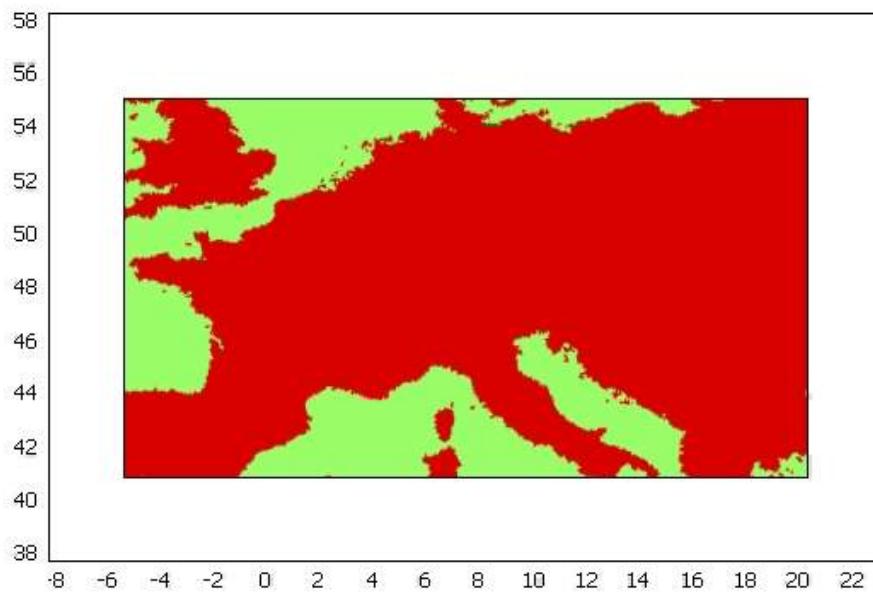
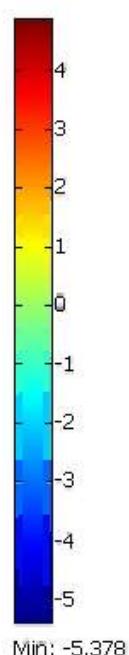
Time=0  
Surface: u

Max: 40.92



Time=0  
Surface: u

Max: 4.882

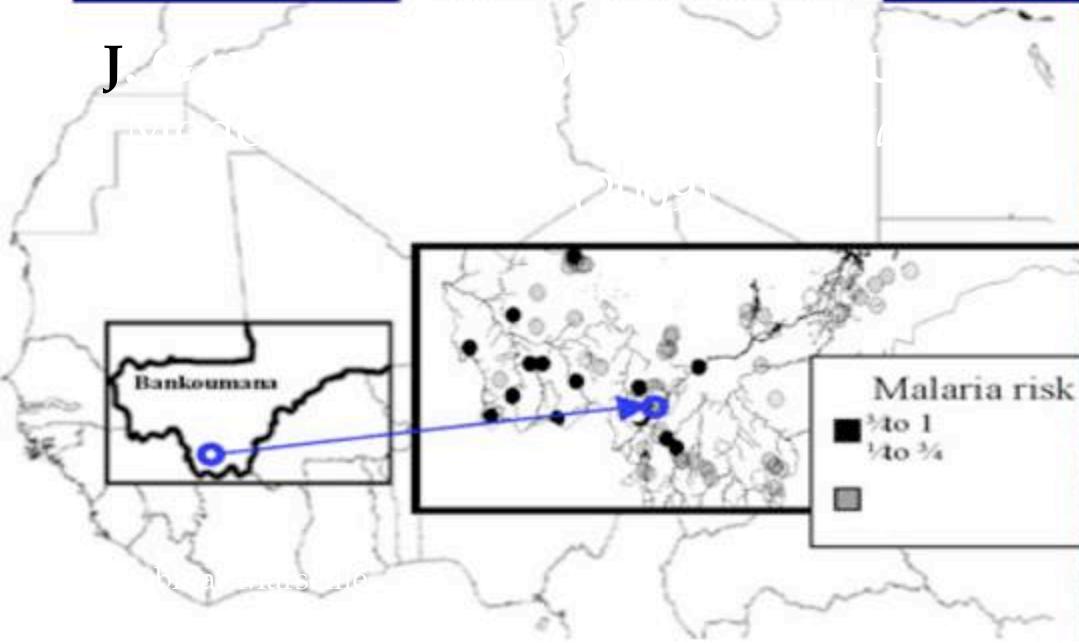




## MODELISATION



A. Turing



P. Ambroise-Thomas

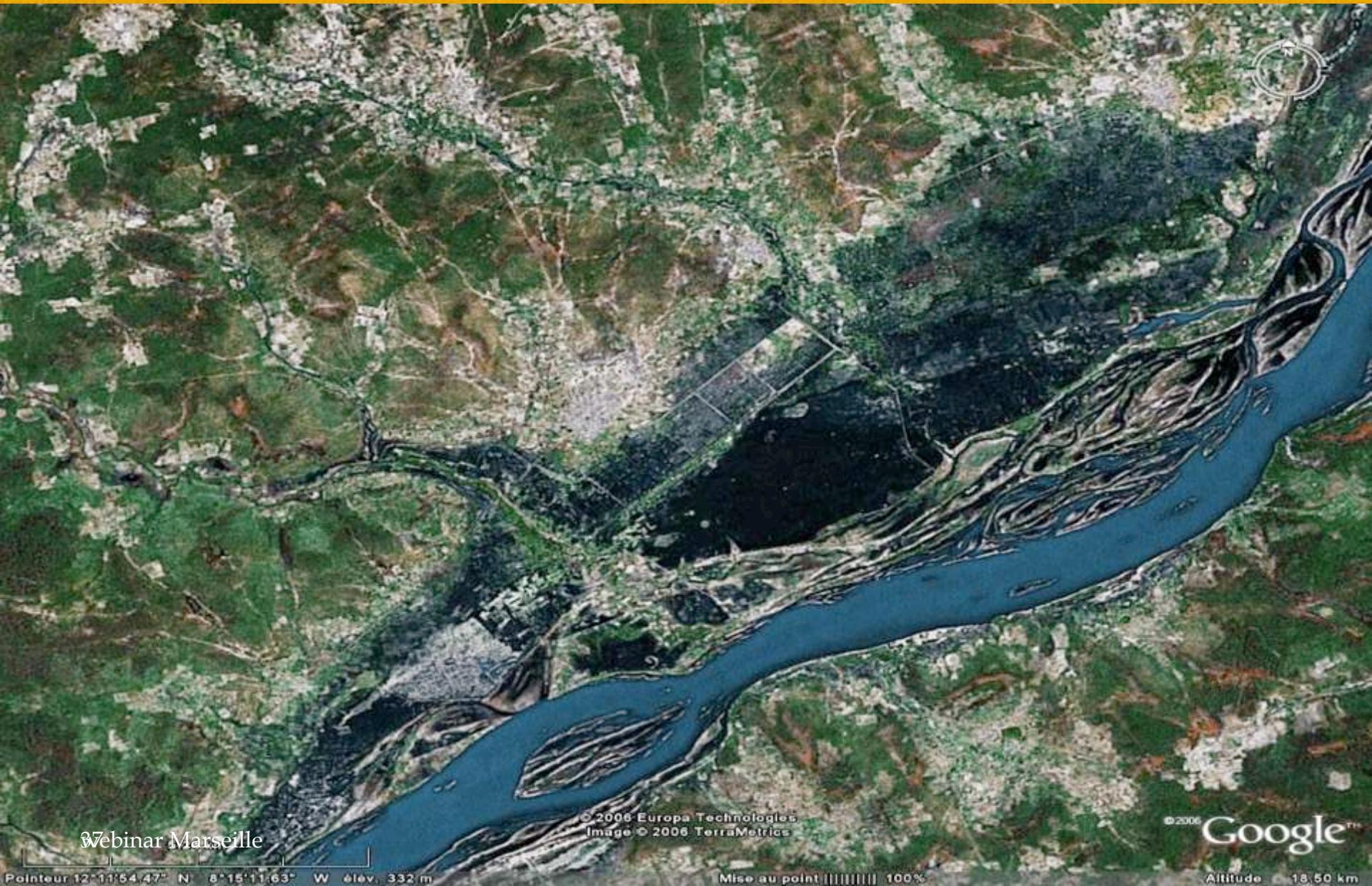


## MATHEMATIQUES

À Alger, j'ai abandonné mes premières amours les mathématiques dites pure pour « entrer en médecine »



# Bancoumana (Mali): selon quel gradient progresse la maladie?



# Spatial problem

Fractal perimetric superficial backwater



$2\pi r$  perimetric phreatic backwater

Niger

# Endemic prevalence

Prévalence = Proportion des personnes ayant ou ayant eu la maladie dans un échantillon et une durée donnés

$$\frac{dS(t)}{dt} = -\mu \alpha \beta A_i(t) S(t) + \sigma R(t)$$

$$\frac{dI(t)}{dt} = +\mu \alpha \beta A_i(t) S(t) - (\eta_1 + \gamma) I(t) + \eta_2 G(t)$$

$$\frac{dG(t)}{dt} = +\eta_1 I(t) - (\eta_2 + \gamma) G(t)$$

$$\frac{dR(t)}{dt} = +\gamma (I(t) + G(t)) - \delta R(t)$$

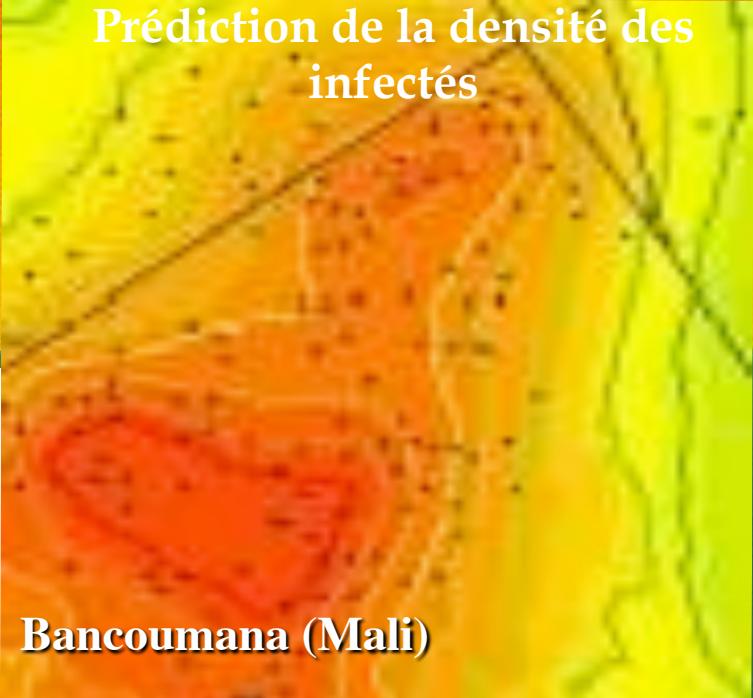
$$\frac{\partial A_s(x, t)}{\partial t} = \varpi - \alpha \zeta G(t) A_s(x, t) - \xi A_s(x, t) + D_i \Delta A_s(x, t)$$

$$\frac{\partial A_g(x, t)}{\partial t} = +\alpha \zeta G(t) A_s(x, t) - (\xi + \nu) A_g(x, t) + D_g \Delta A_g(x, t)$$

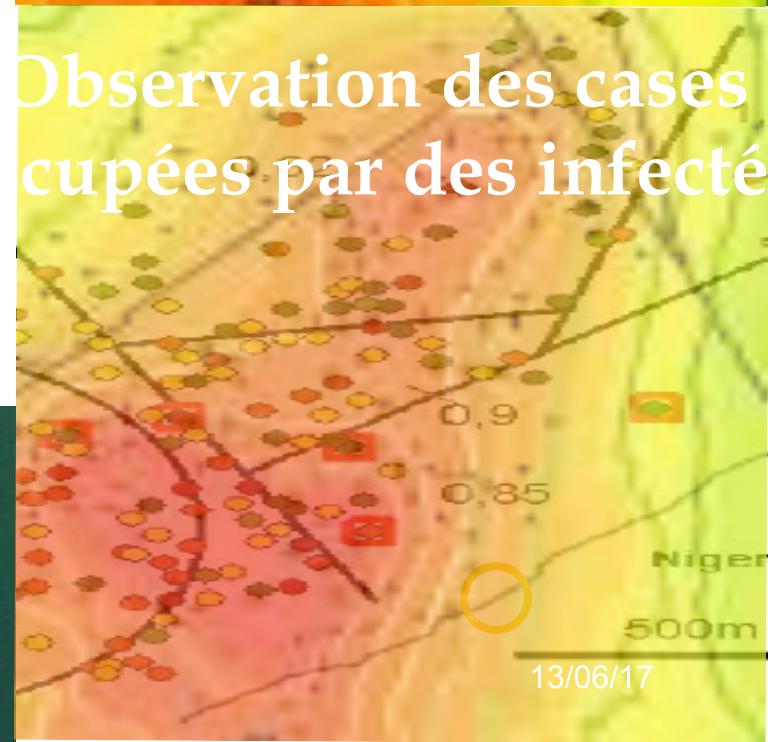
$$\frac{\partial A_i(x, t)}{\partial t} = \nu A_g(x, t) - \xi A_i(x, t) + D_s \Delta A_i(x, t)$$

J. GAUDART,..., J. D. & O.K. DOUMBO,  
Modelling malaria incidence. *Malaria J.*, 8, 61 (2009).

Prédiction de la densité des infectés

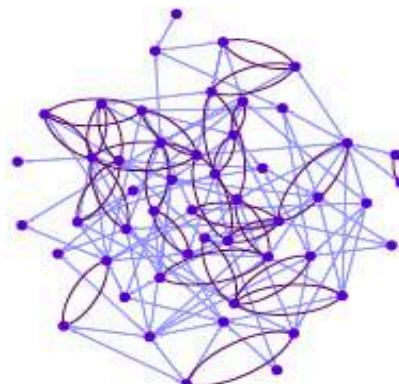


Observation des cases cupées par des infecté

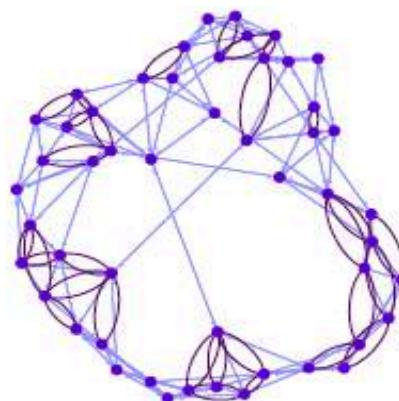


# Automata modelling

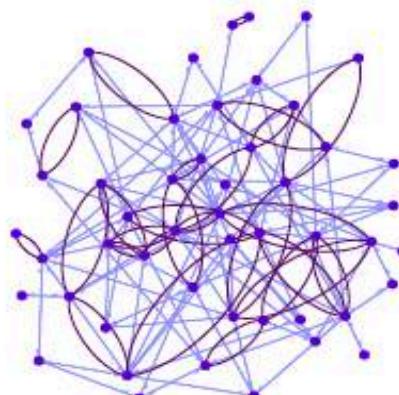
# Social networks



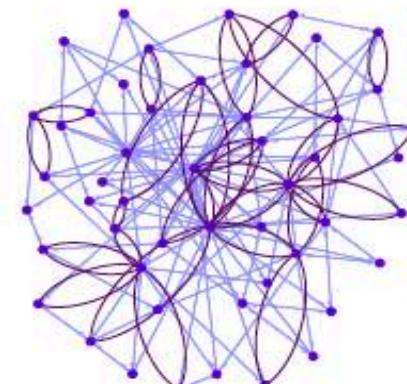
(a) ALEATOIRE



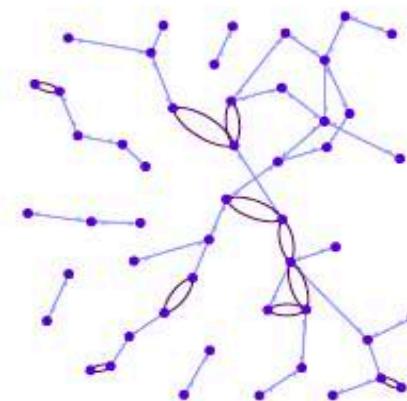
(c) SMALL WORLD



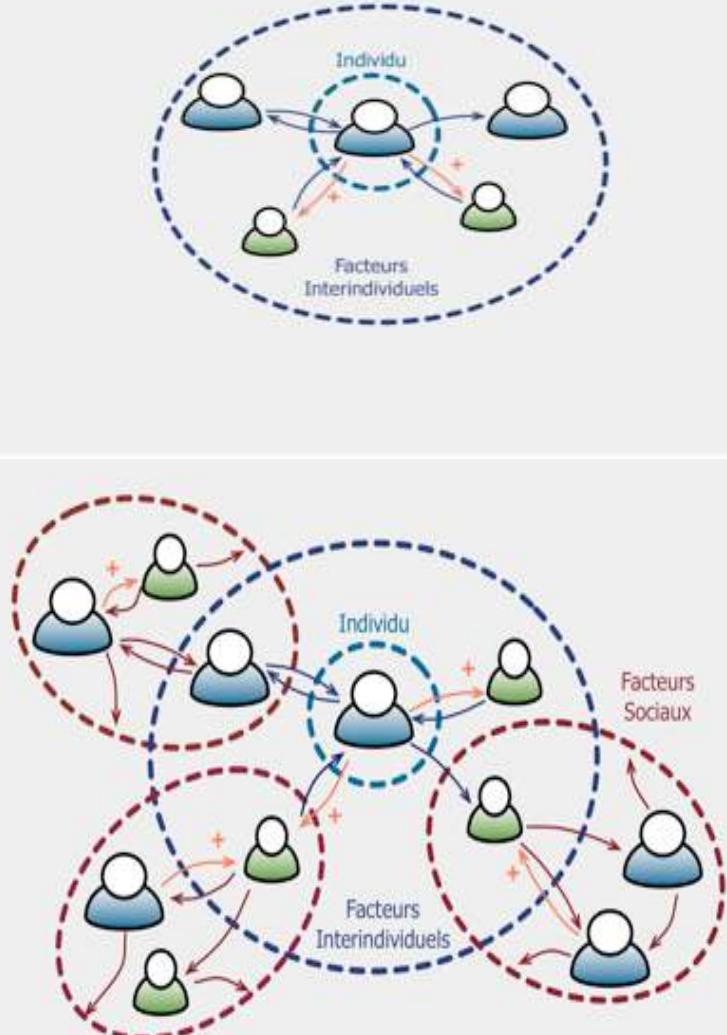
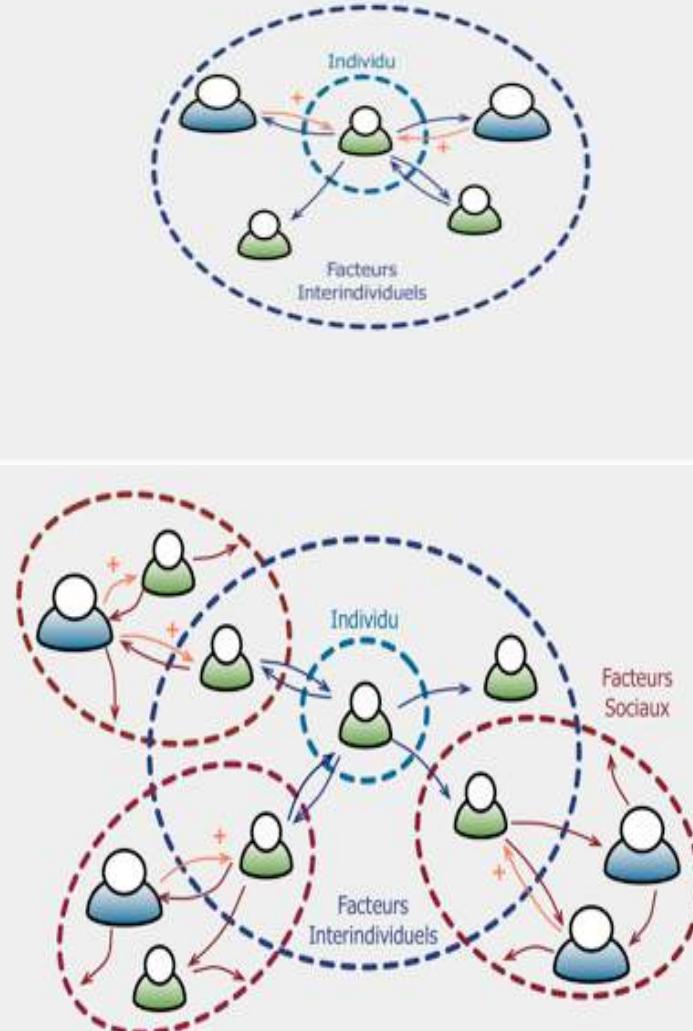
(e) EMPIRIQUE 2



(b) SCALE -FREE



(d) EMPIRIQUE 1

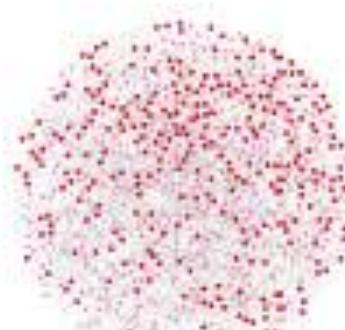


# Empirical networks

# Obesity

DYNAMIQUE HOMOPHILIQUE

EMPIRIQUE 1



Obesity dynamics

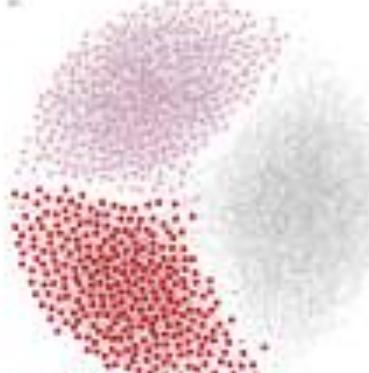
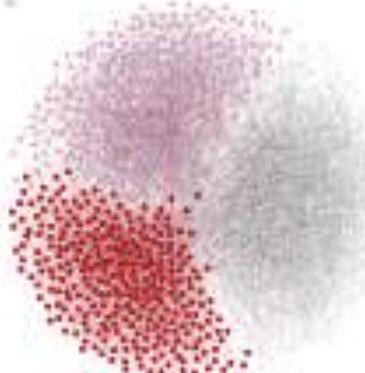
*C. Taramasco*

(a) RÉSEAU INITIAL

(b) RÉSEAU AU TEMPS = 80

(c) RÉSEAU FINAL

EMPIRIQUE 2  
homophilic graphs

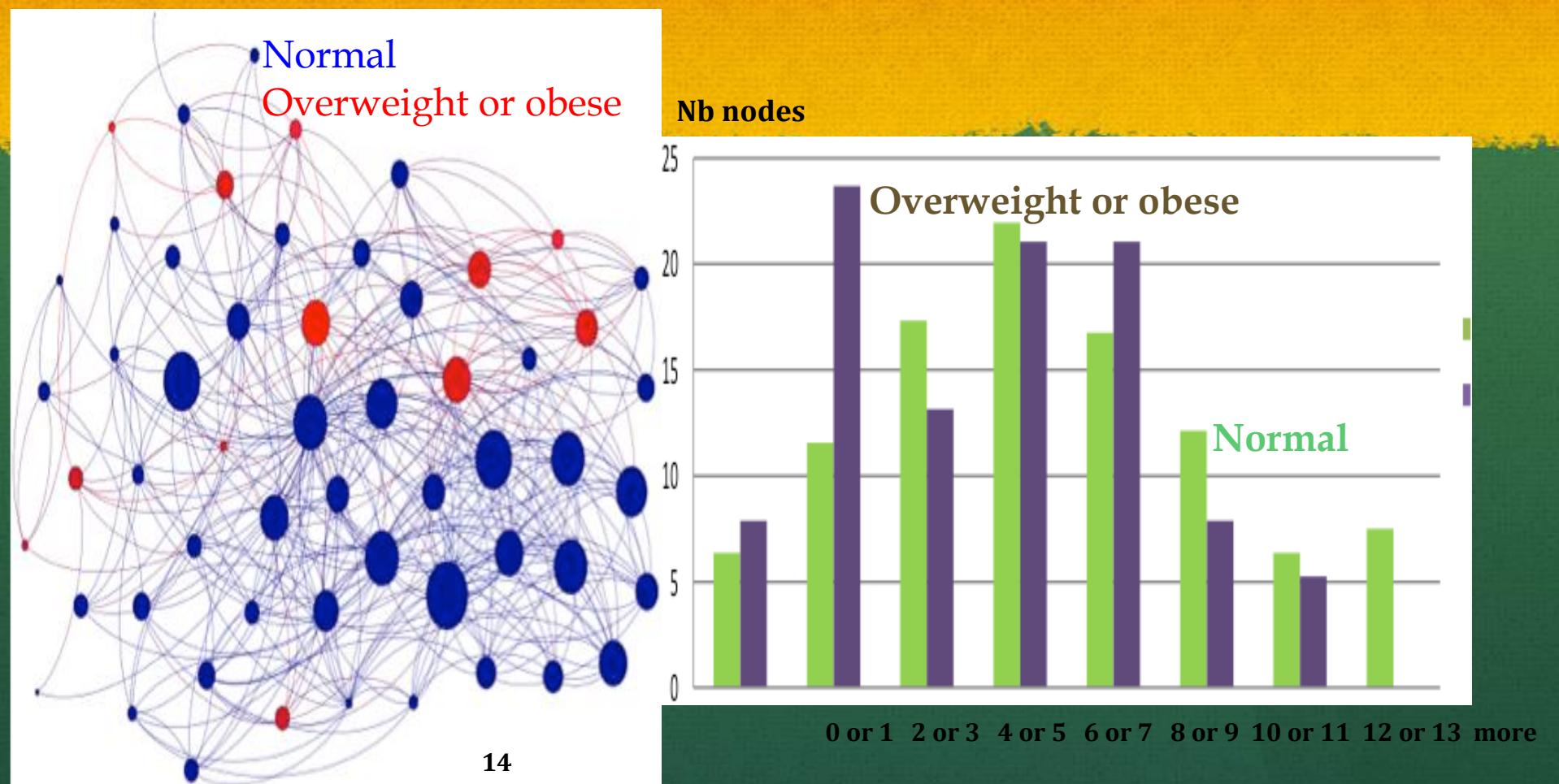


(d) RÉSEAU INITIAL

(e) RÉSEAU AU TEMPS = 60

(f) RÉSEAU FINAL

# Friendship network at highschool



**Bimodal distribution of friend's numbers in abnormal population of highschool**



STEAMSURFING  
BY VITALISEUR DE MARION

S'INSCRIRE

SE CONNECTER

FR

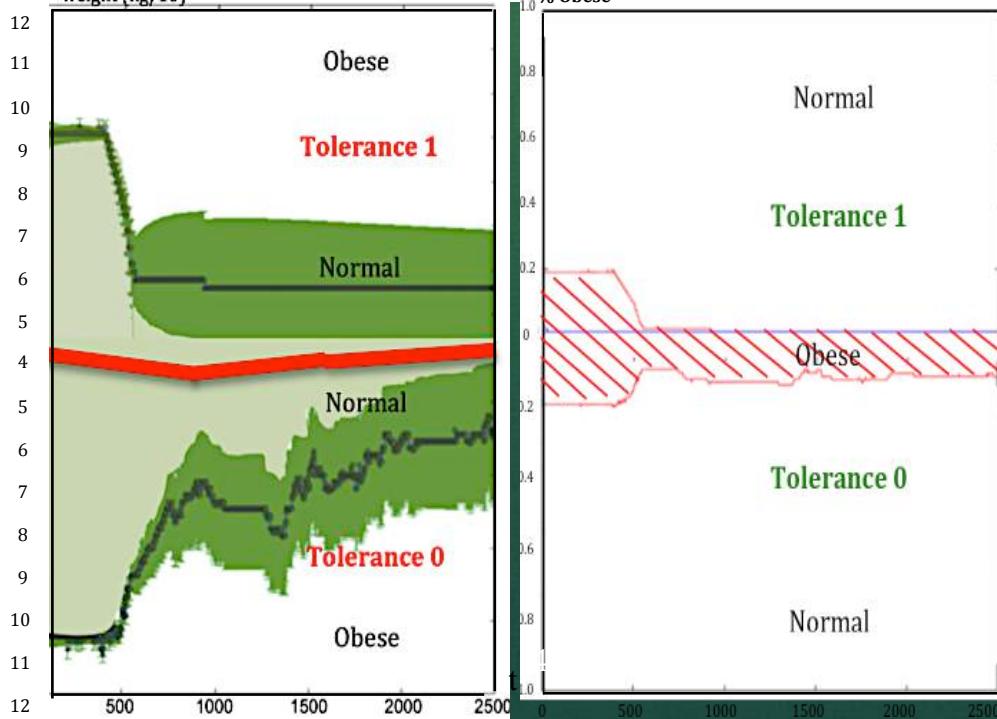
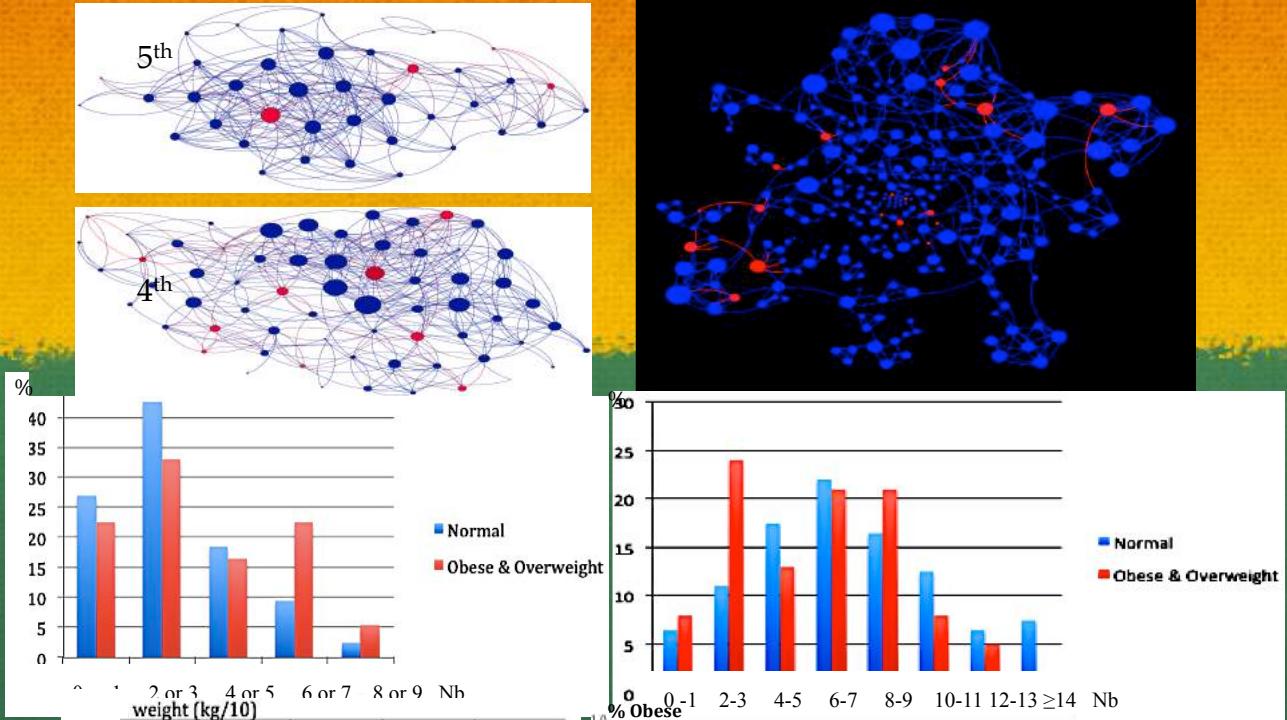
EN



Créez, partagez, vivez  
vos exigences alimentaires

# Suivi de l'obésité au collège

webinar Marseille



13/06/17

# Functional modelling

For reducing big data related to

a metabolic pathway

into a few number of attractors

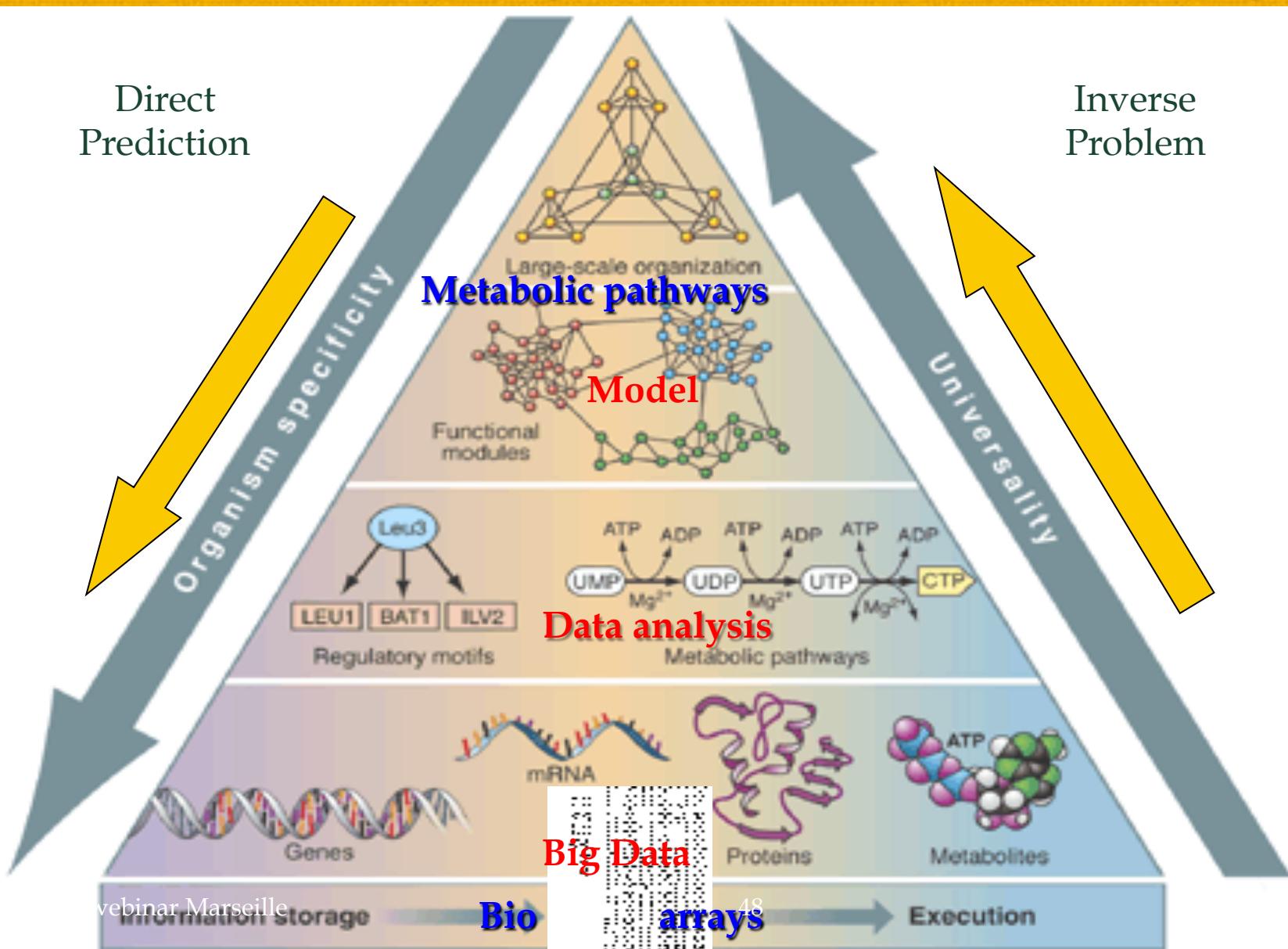
related to the circuits of its

interaction graph

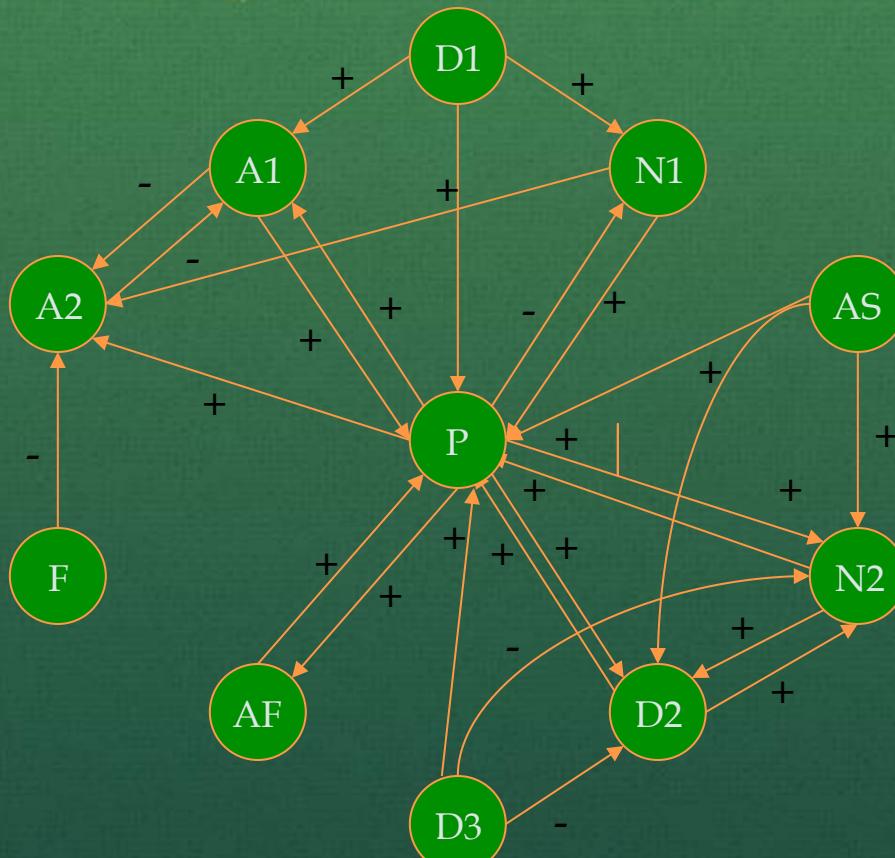
# Life's complexity: from bio-arrays to metabolic pathways

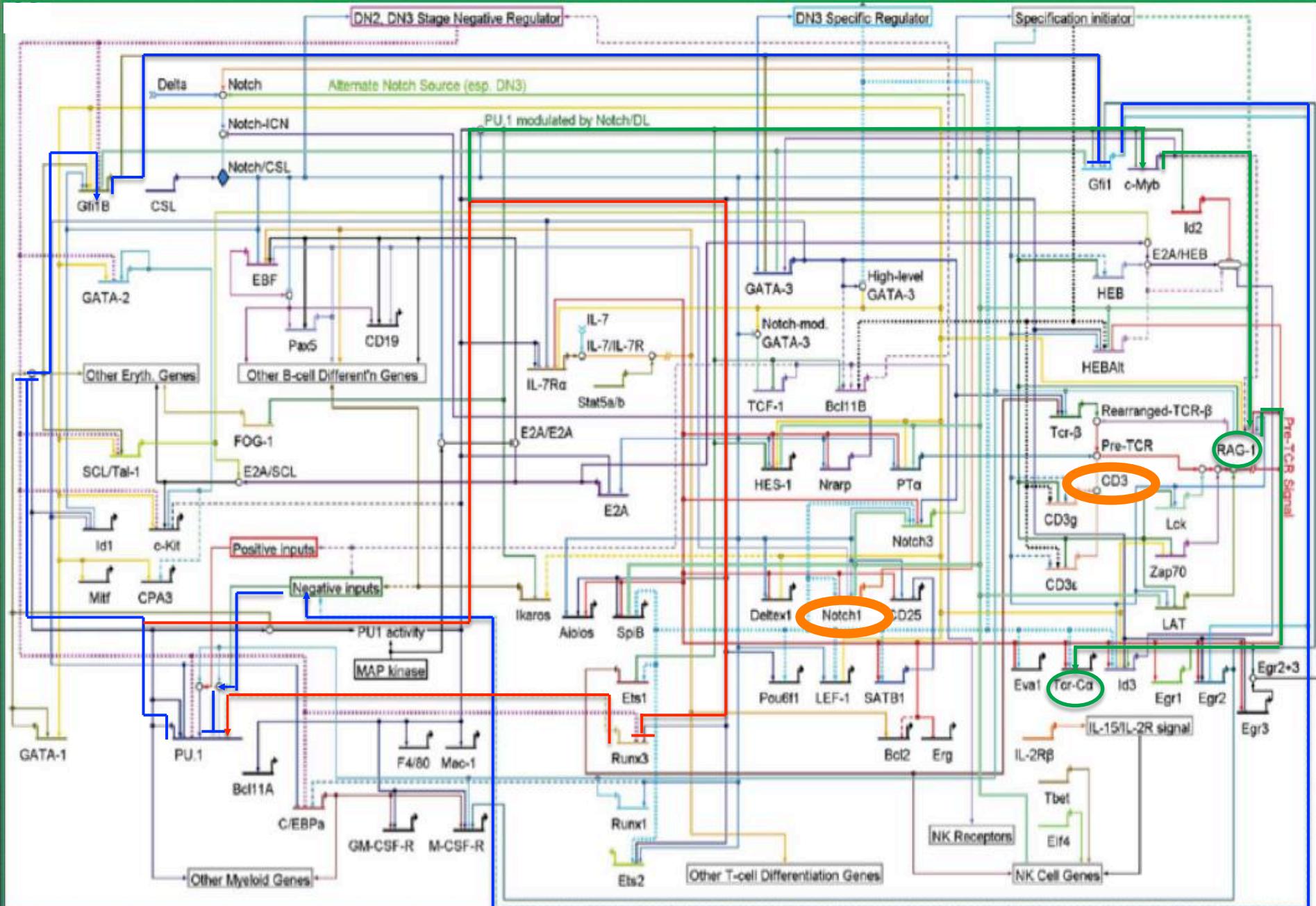
Direct  
Prediction

Inverse  
Problem



# Social Interaction network





## RAG control pathway

webinar Marseille

C. Georgescu, PNAS 2008; JD, A. Elena, M. Noual, S. Sené & F. Thuderoz J. Theor. Biol. 2011

# Attractor Nb of positive circuits of length $r$ tangent to negative of length $l$

$\ell \setminus r$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	$T_\ell^-$
1	1																1
2		1															1
3	1	1	2														2
4	1	2	1	2													2
5		2	1	2	2	4											4
6	1	1	3	3	2	6											6
7	2	2	3	2	4	3	10										10
8	2	3	2	8	3	4	6	16									16
9	3	2	2	3	5	9	7	7	30								30
10	2	4	3	4	17	7	7	10	11	52							52
11	4	3	5	6	7	7	11	11	16	19	94						94
12	3	4	9	2	7	42	11	33	17	23	28	172					172
13	5	6	7	7	11	11	16	19	24	28	39	46	316				316
14	6	7	7	10	11	17	105	23	28	38	46	60	75	586			586
15	7	7	10	11	4	17	24	28	44	125	60	66	97				1096
16	7	10	11	33	19	23	28	278	46	60	75	88					2048
17	11	11	16	19	24	28	39	46	60	75	97						3856
18	11	17	17	23	28	6	46	60	729	96							7286
19	16	19	24	28	39	46	60	75	97								13798
20	19	23	28	32	125	60	75	88									26216
21	24	28	44	46	60	66	10										49940
22	28	38	46	60	75	96											95326
23	39	46	60	75	97												182362
24	46	60	66	88													349536
25	60	75	97														671092
26	75	96															1290556
27	97																2485534

JD, M. NOUAL, S. SENE  
Discrete Applied Maths 2014

$$\gcd(\ell, r) =$$

$1$

$2$

$3$

$4$

$5$

$6$

$7$

$8$

$9$

$$\ell = r$$

$$\ell = 3 \times r / 2$$

$$\ell = 2 \times r$$

$$\ell = 4 \times r$$

# Conclusion

- Toward a personalized patient time recording
- and at the population level, a spatiotemporal observation
- followed by the steps of big data compression, modelling and interpretation
- with restitution of information to patient and to population