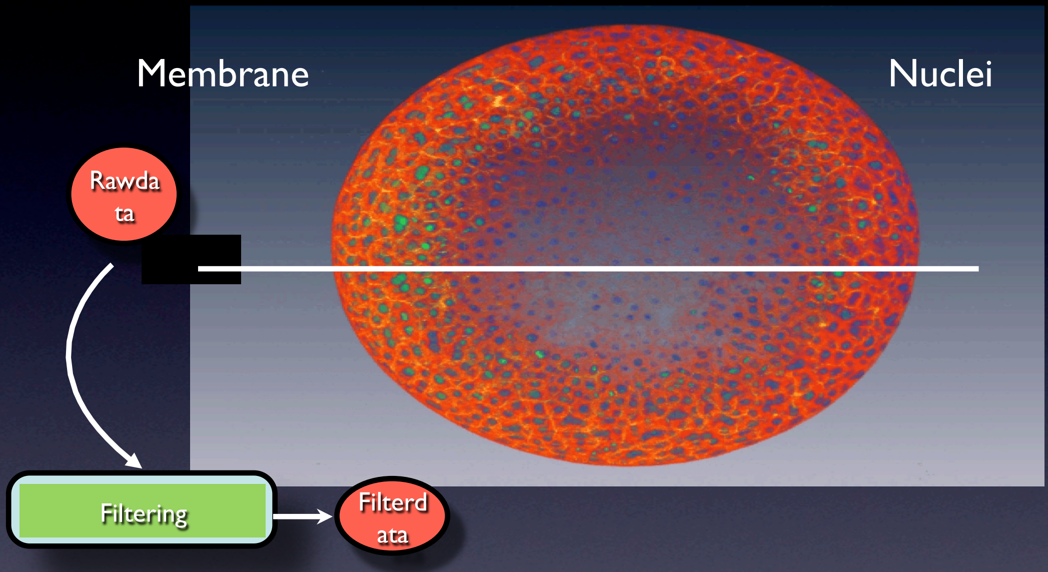
Foundations of CSS : Phenomenological & Theoretical Multi-scale Reconstruction

Paul Bourgine
CNRS-Ecole Polytechnique
Complex Systems Digital Campus (CS-DC)

INCT'2013

Workflow

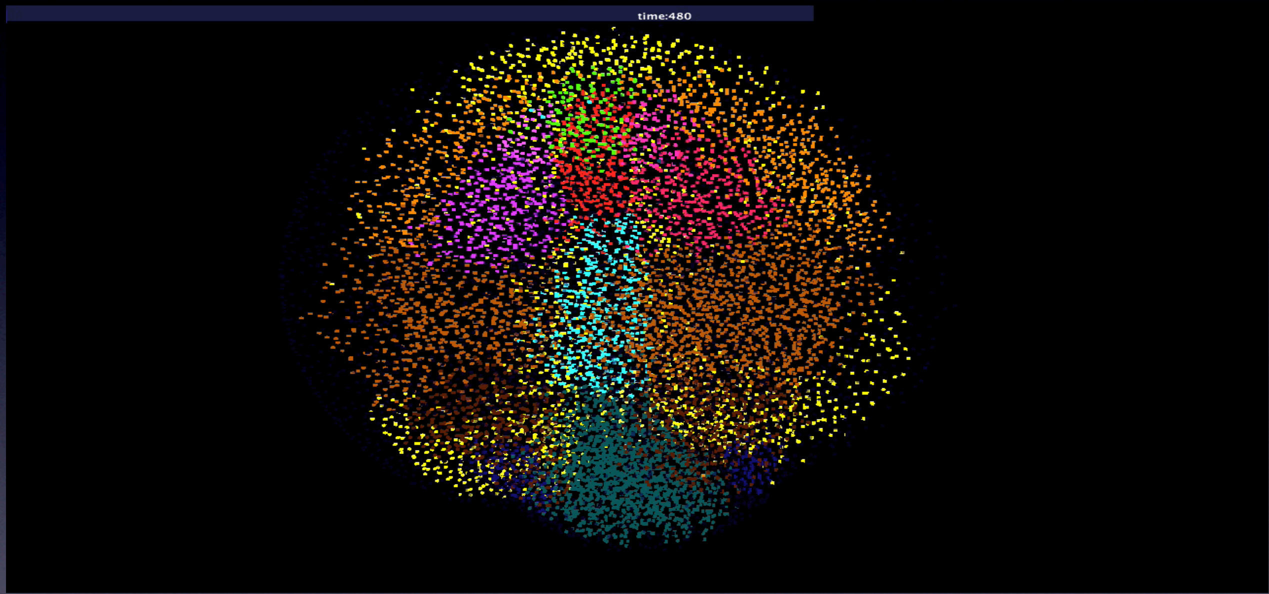


DMDG Bratislava
Karol Mikula
Robert Čunderlík
Olga Drblíková
Mariana Remešíkova

Filtering Methods :
- Perona Malik
- Mean Curvature Flow
- Geodesic Mean Curvature Flow
- Gradient Anisotropic Diffusion
- Twister Segment Filtering

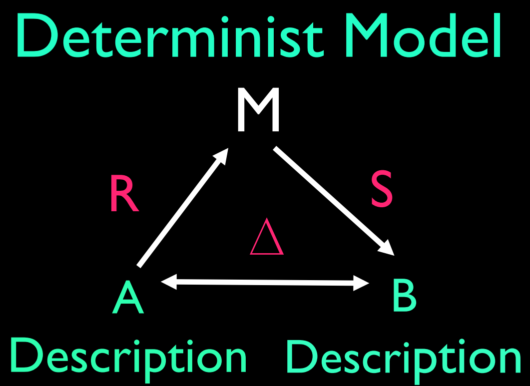
Luengo-Oroz, M, **Faure, E,** Lombardot, B, & Sance, R. *Twister Segment Morphological Filtering. A New Method for Live Zebrafish Embryos.* Confocal Images. IEEE ICIP, Jan. 2007

Tracking and Visualization



Phenomenological Reconstruction

Reconstruction with determinist grammars

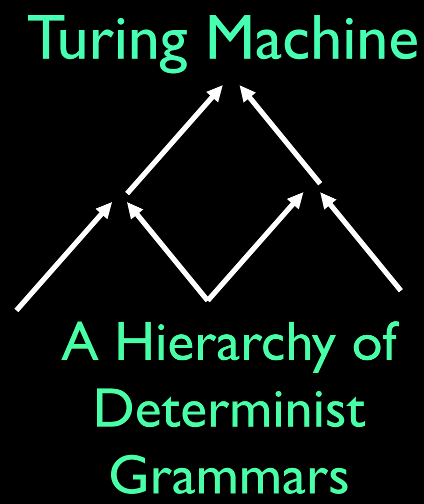


Occam's rasor :

'small' determinist model M that reconstructs the description

△ deterministic = 0

(the 'smallest' in Chaitin Kolmogorov definition of 'complexity')



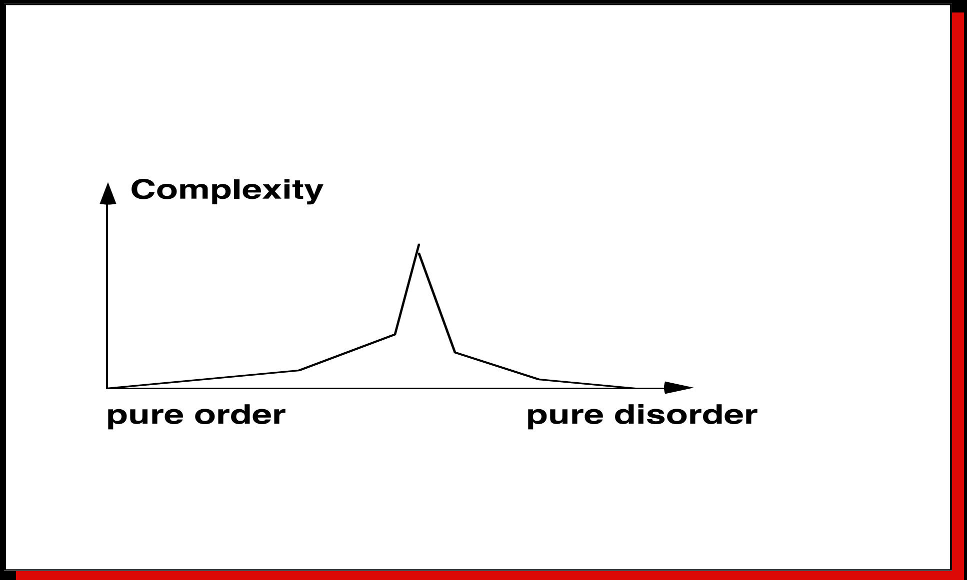
Reconstruction of a «pure» disorder

- A pure disorder : a long random series of 0/1
- 011001010010111….

Between Crystal and Smoke

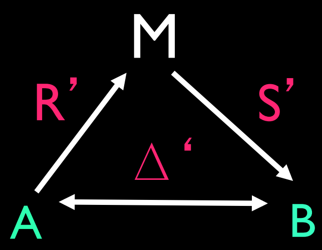
Henri Atlan

A fundamental idea is that complexity arises between pure order and pure disorder



Reconstruction of a «pure» disorder

Stochastic Model



Description Description

$\Delta'(A,B)=0$

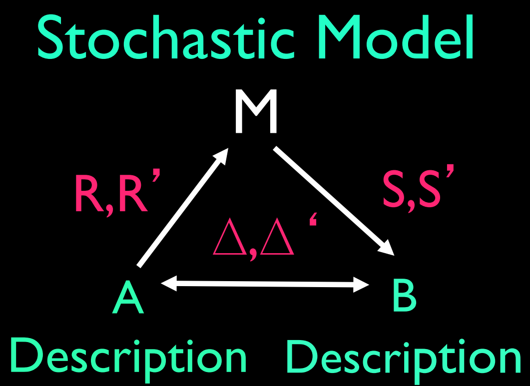
- A pure disorder : a long random series of 0/1
- 011001010010111....

e.g. Kulback-Liebler distance

$\Delta(p,q) = \Sigma\, p_k \,\mathrm{Log}(q_k/p_k) + q_k \,\mathrm{Log}(p_k/q_k)$

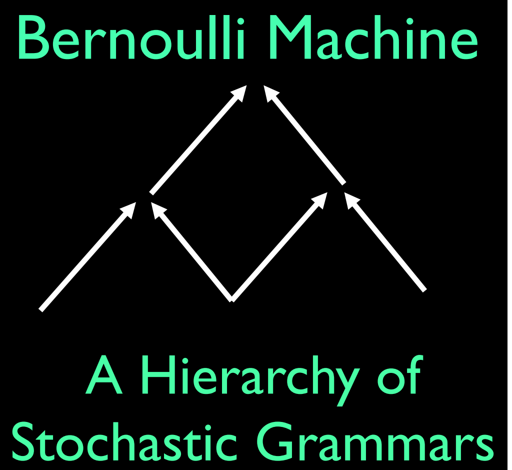
$\Delta(p,q)=0$ iff $p=q$; symmetric

Reconstruction with stochastic grammars



Occam's rasor : a 'small' stochastic model M such that :

Δ deterministic = 0
Δ' stochastic = 0



Discrete Multiscale Stochastic Process

Mazurka 1

Mazurka 2

Data Assimilation by Model

Knowing the multimodal optical flow a= *{a1 (red), a2(green), ..}*
Find the unknow *y* : velocity field *v*, the cell lineage *g*,viscosity, ..

- Optical Flow & Registration : $\varepsilon_m^f(x,t) = \nabla_t f_m + v(x,t).\nabla_x f_m$
- Continuity equation : $\varepsilon^{c}(x,t) = \nabla.v$
- Continuum Mechanics : $\varepsilon^{cm}(x,t) = \partial_t v + \nabla.(V \otimes V - \frac{\sigma}{\rho})$
- Nuclei&Cells, Divisions detection : $\varepsilon^{ncdd}(x_i,t_i)$
- Tracking & Fractal Brownian: $\varepsilon_i(r,t) = v'_i(r,t) = v_i(t) - V(r,t)$

Problem 1 : y=argmax P(ε(y)|a)

Hypothesis : all random variables have spherical symmetries

Problem 2 : y=argmax $e^{-\int_{X\times T} dxdt \sum_k \varepsilon_k^T \Lambda_k^{-1} \varepsilon_k}$ with $\Lambda_k(x,t) = Cov(\varepsilon_k(x,t)\varepsilon_k(x,t)^T)$

Problem 3 : y=argmin $\int_{X\times T} dxdt \sum_k \varepsilon_k^T \Lambda_k^{-1} \varepsilon_k$

Problem 4 : variational calculus for data assimilation by integrated model

$$\forall \eta \sum_k < \partial_y \varepsilon_k \, \eta_k, \Lambda_k^{-1} \varepsilon_k > = 0 \Leftrightarrow \forall \eta \sum_k < \eta_k, \partial_y \varepsilon_k * \Lambda_k^{-1} \varepsilon_k > = 0 \Leftrightarrow \forall k \;\; \partial_y \varepsilon_k * \Lambda_k^{-1} \varepsilon_k = 0$$

EM Algorithm

Given the data a and the space M of stochastic models

Step E : $m_i = \mathrm{argmin}\ \Delta(\varepsilon(y_{i-1}), M)$

Step M : $y_i = \mathrm{argmax}_y\ P(\varepsilon(y) | m_i, a)$

Cf: Information Geometry (Amari)

Upward and Downward Causality

Everything being helped and helping, caused and causing, I consider as impossible to know the whole without knowing the parts and to know the parts without knowing the whole.

– Pascal, ***Pensées***

Complex systems: think differently

Theoretical Reconstruction Projection Operator

Paul Bourgine – Juan Simoes

Grabert – Zwanzig – Mori - Zuba

Microscopic Dynamics

- Dynamical stage
  - N-particles distribution function: $N(p,q)=\Sigma\ \delta(q-q_k)\ \delta(p-p_k)$
  - Hamiltonian: $H(p,q)=\Sigma$ ..
- Kinetic stage
  - Single particle distribution function: $\rho(p,q)=\langle n(q,p)\rangle$
  - Hamiltonian density: $h(p,q)$
  - Liouvillian operator: $Lf = -i\ \{h,f\}$

Macroscopic Dynamics

- Macroscopic Observables: $A=(A_i)$ and $A(t) = e^{iLt}A(0)$
  - Heisenberg picture: $a_i(t) = \langle A_i(t) \rangle = Tr[A_i(t)\rho(0)]$
  - Schrödinger picture: $a_i(t) = Tr[A_i(0)\rho(t)]$
- Relevant Probability Density: $\bar{\rho}$ such that
  - Probability: $Tr[\bar{\rho}(t)] = 1$
  - Same initial value: $\bar{\rho}(0) = \rho(0)$
  - Macro-equivalent: $a(t) = Tr[A(0)\bar{\rho}(t)] = Tr[A(0)\rho(t)]$
  - Macroscopically specified: $\bar{\rho}(t) = \bar{\rho}(a(t))$

Projection Operator

- Definition:

  Given the relevant probability distribution $\bar{\rho}$, the projection operator P is:

$$\bar{F}(a_t) = P(a_t)F = Tr(\bar{\rho}(a_t)F) + \sum_i (A_i - a_{it})Tr(\frac{\partial \bar{\rho}(a_t)}{\partial a_{it}} F)$$

- Characterization: Given $\bar{\rho}$, P is uniquely defined by:

$$a. linear \mid P^2 = P$$

$$b. \mathrm{Im}(P) = \{F \mid F = c_0 + \sum c_i \mathrm{A}_i\}$$

$$c. Tr[\rho \bar{F}] = Tr[\bar{\rho} F]$$

$$d. Tr[\rho \frac{\partial \bar{F}}{\partial \mathrm{a}_i}] = 0$$

Two Parts of Time Evolution Operator

- Macro/Microscopic parts:

$$e^{iLt} = e^{iLt}P(a_t) + e^{iLt}(1 - P(a_t))$$

- Microscopic part:

$$e^{iLt}(1 - P(a_t)) = \int_s^t K(a_u^t)\,du + B(a_s^t)$$

$$With$$

$$G(a_s^t) = \int_s^t iL(1 - P(a_u))\,du$$

$$B(a_s^t) = e^{iLs}(1 - P(a_s))G(a_s^t)$$

$$K(a_u^t) = e^{iLu}P(a_u)(iL - \dot{P}(a_u))(1 - P(a_u))G(a_u^t)$$

Generalized Transport Equations

$$\dot{a}_t = v(a_t) + \gamma(a_0^t)$$

with

$$v_i(a_t) = Tr[\bar{\rho}_t \dot{A}_i]$$

$$\gamma_i(a_0^t) = \int_0^t C_i(a_u^t)\, du$$

$$C_i(a_u^t) = Tr[\bar{\rho}_u iL(1 - P_u) G(a_u^t) \dot{A}_i]$$

Generalized Langevin Equation

$$\delta \dot{A}_t = \Omega(a_t)\delta A_t + \int_0^t \Phi(a_0^u)\delta A_u \, du + \delta F_0^t$$

$with:$

$$\delta A_t = A_t - a_t$$

$$\Omega(a_t) = \frac{\partial v_t(a_t)}{\partial a_t}$$

$$\Phi(a_0^u) = \frac{\partial \gamma(a_0^u)}{\partial a_t}$$

$$\delta F_0^t = F_0^t - Tr(\rho_0 F_0^t) \; where \; F_0^t = B(a_0^t)\dot{A}$$

$$Verifying: <\delta F_0^t> = 0 \; and \; < Tr[\frac{\partial \overline{\rho}_0}{\partial a_{0j}} \delta F_{0i}^t] > = 0$$

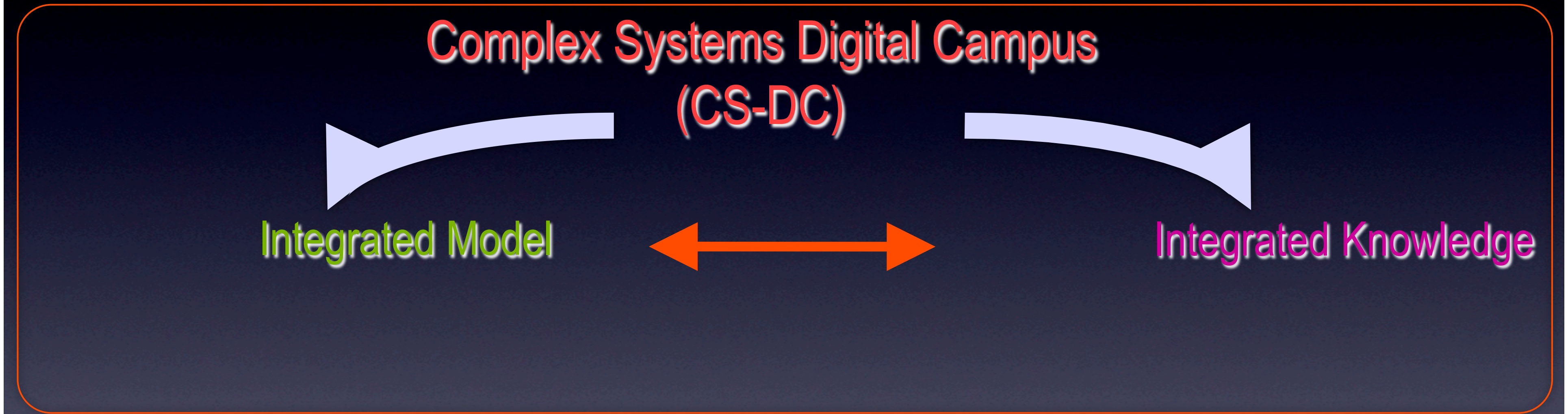
CS-Digital Campus
as
UniTwin UNESCO

CS-DC UNESCO UniTwin

Complex Systems Digital Campus (CS-DC)

Aim: Sharing all resources for facing the challenges of our ROADMAP for research and education on complex systems

70 Universities - 22 Countries - 4 Continents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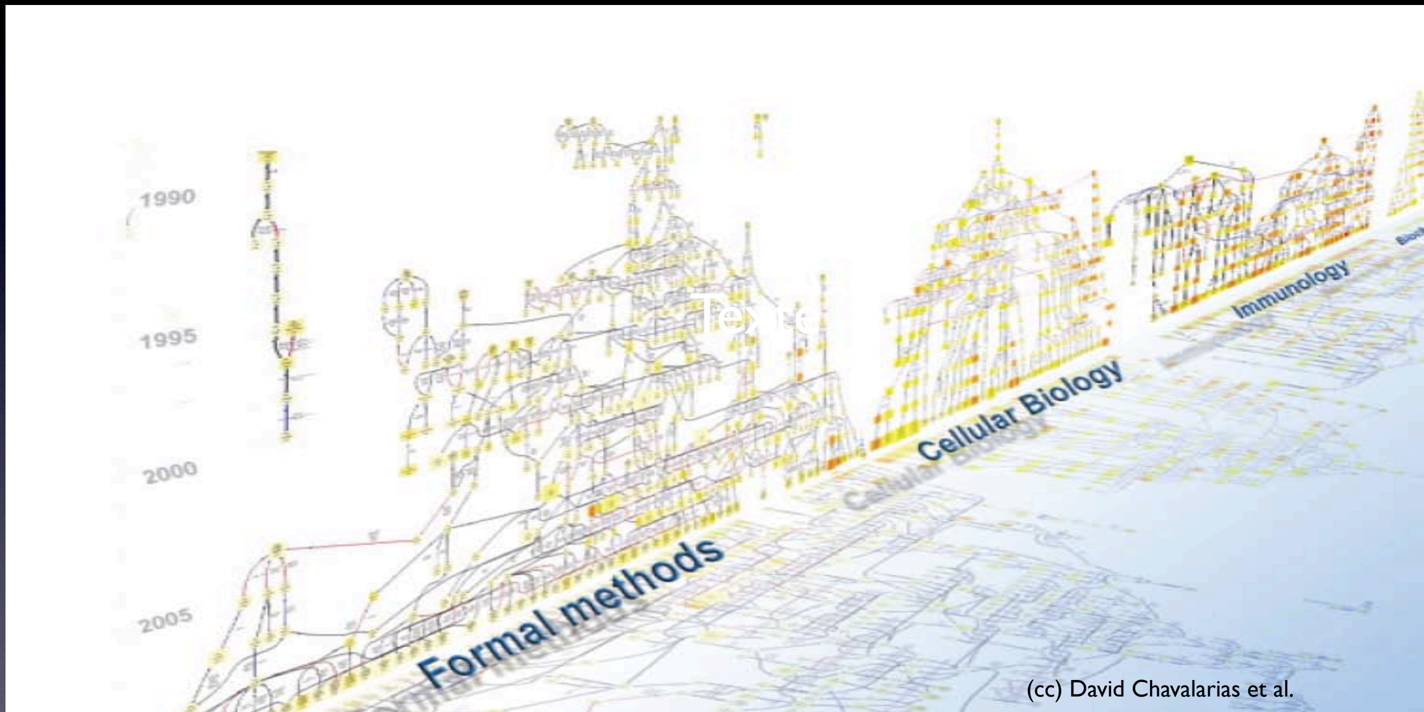
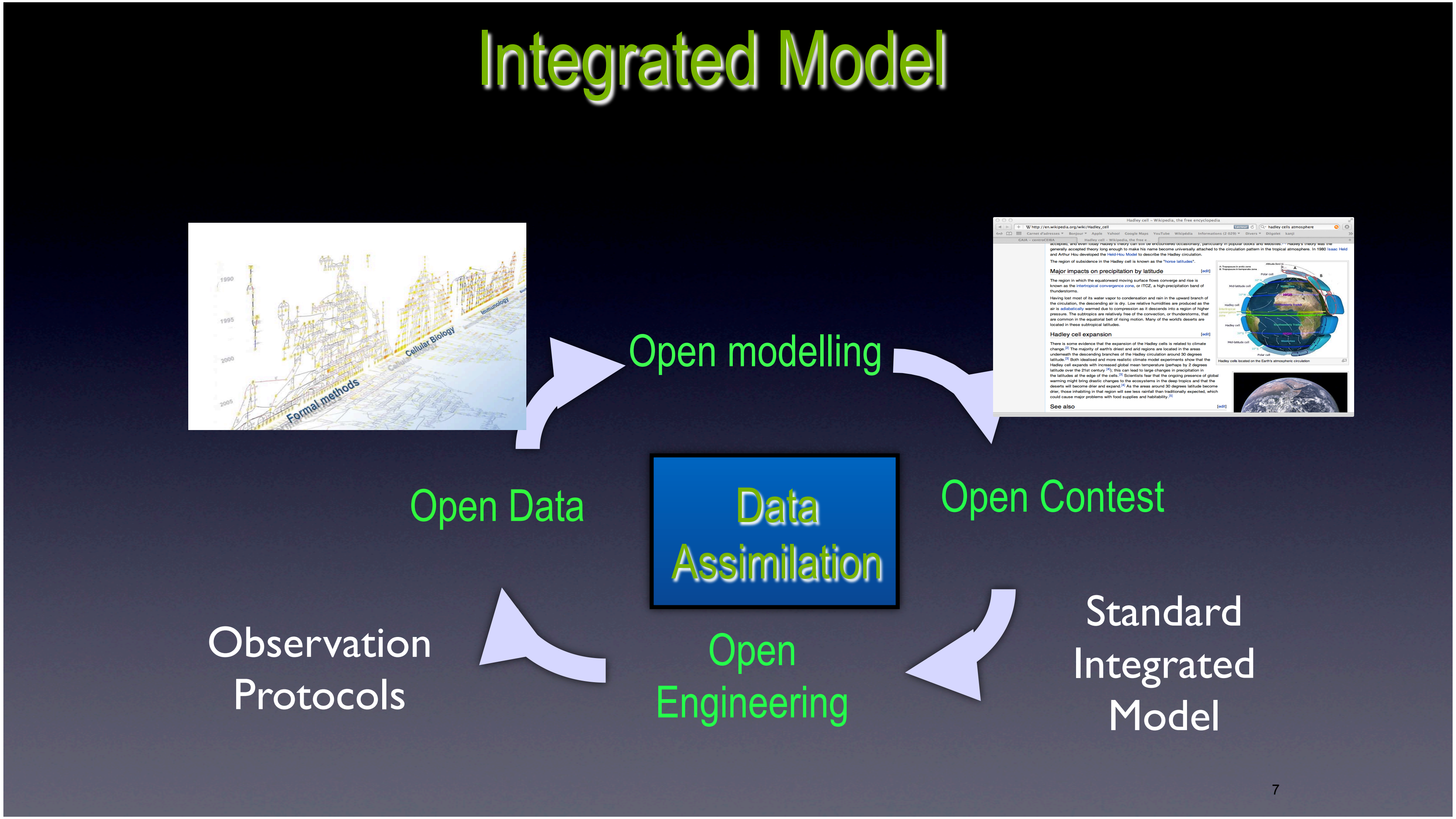
(CS-DC)
Integrated Model
Integrated Knowledge

Integrated Knowledge Map




Integrated Model
Formal methods
Cellular Biology
Open modelling
Open Data
Data Assimilation
Open Contest
Observation Protocols
Open Engineering
Standard Integrated Model
7

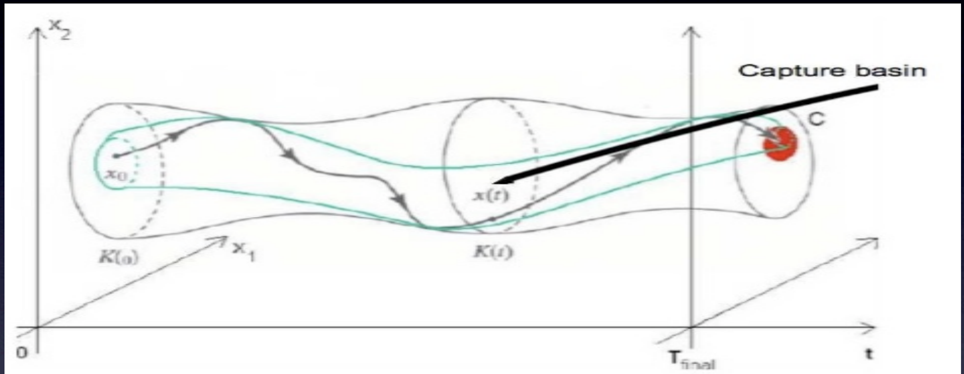
The aim is not to predict what will happen, but what can happen.

Ilya Prigogine

Complex Systems are Predictable in Probability
(if open big data)

Complex systems: think differently

Viability Tube - Viability Theory



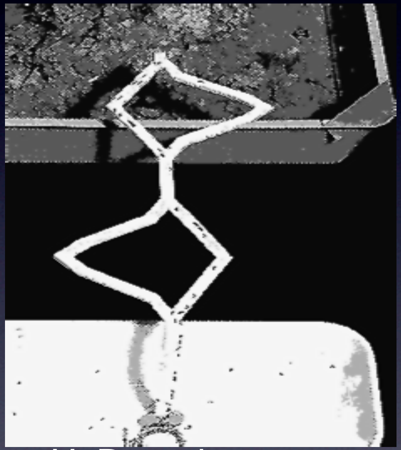
Robusteness - Prevention - Resilience: Personalized Health

Complex systems: think differently

Tell me and I forget,
Teach me and I remember
Involve me and I learn

Benjamin Franklin

Personalized Education for All



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MOOC (Massive Open Online Courses)

+

Participative: Inter-tutorship

+

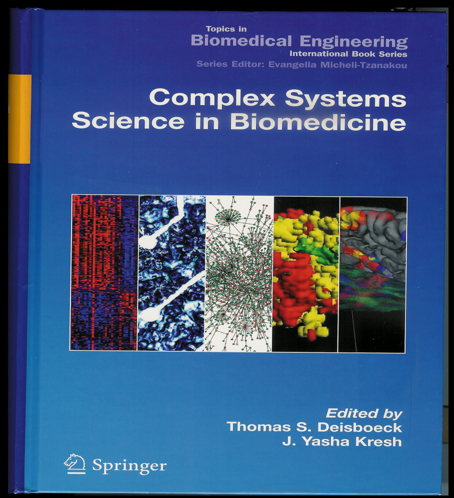
Predictive: Man-Hill Algorithm (if large open data)

Complex systems: think differently

Roadmap of Complex Systems Science

- Workshop : Paris 2005, Cargèse 2006 & 2007, Dakar 2011, Pampelona 2013

Great questions / Geat domains	Nano/Complex Matter	Living / Ecosphère	Cognition / Web	Environment / Energy	Human / Society / Internet	……
Observation in vivo, in toto / Reconstruction & prediction of multiscale dynamics	Morpho-scale	E2C2, Embryomics Mechanical Induction, MORPHEX	E2C2	E2C2	E2C2, EVERGROW, DELIS, ERG 4, TiGrESS	
Large interactive networks / collective behaviour	STARFLAG	Plurigenes, BioEmergences, Mechanical Induction		STARFLAG	STARFLAG, ISCOM	
Governance, prevention, resilience distributed vs centralized		PATRES, BioEmergences	PATRES	PATRES	PATRES, EVERGROW DELIS, TiGrESS, ISCOM, EVOTEST	
Design of Complex Adaptive Systems		MesoBionics, SynBioTIC	MesoBionics, DEVOBOTS, CogniMorph	MesoBionics, EnergyWeb,	MesoBionics	
. . . . . .						



« The task is not so much to see
what no one yet has seen,

But to think what

nobody yet has thought about that
which everybody sees »

Schopenhauer