Sustainable Autonomy and Designing Mind Time

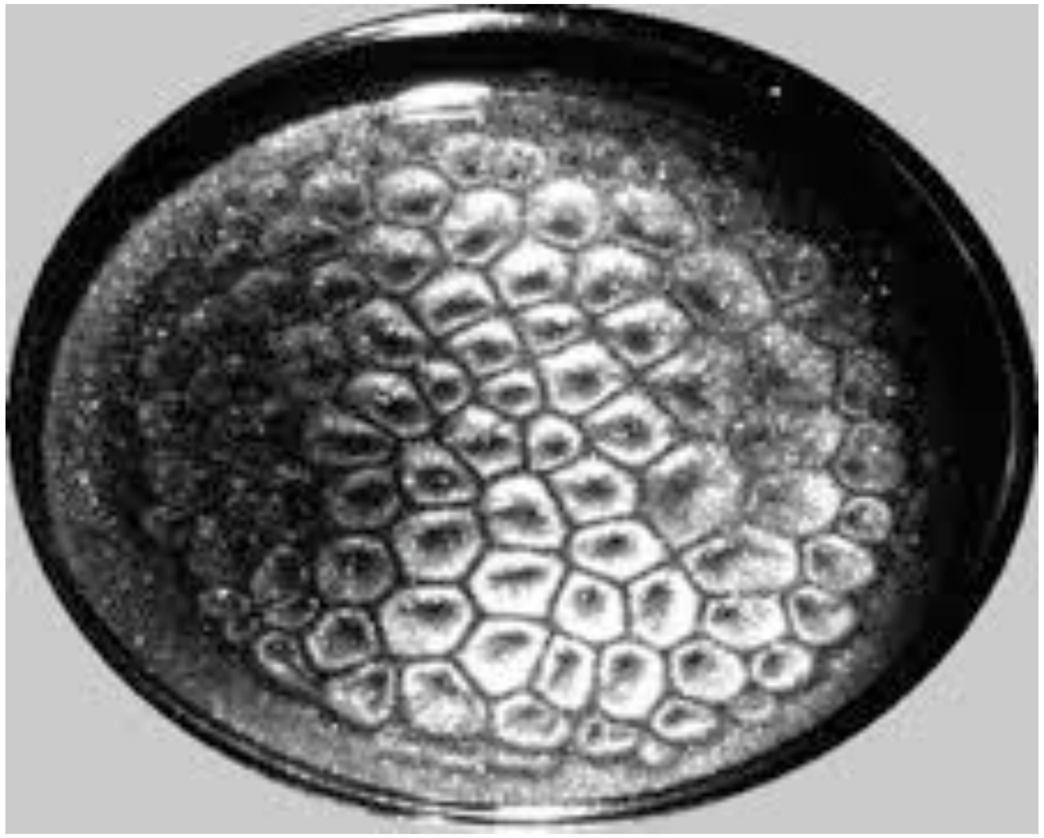
Takashi Ikegami (Universityof Tokyo)

What is life?

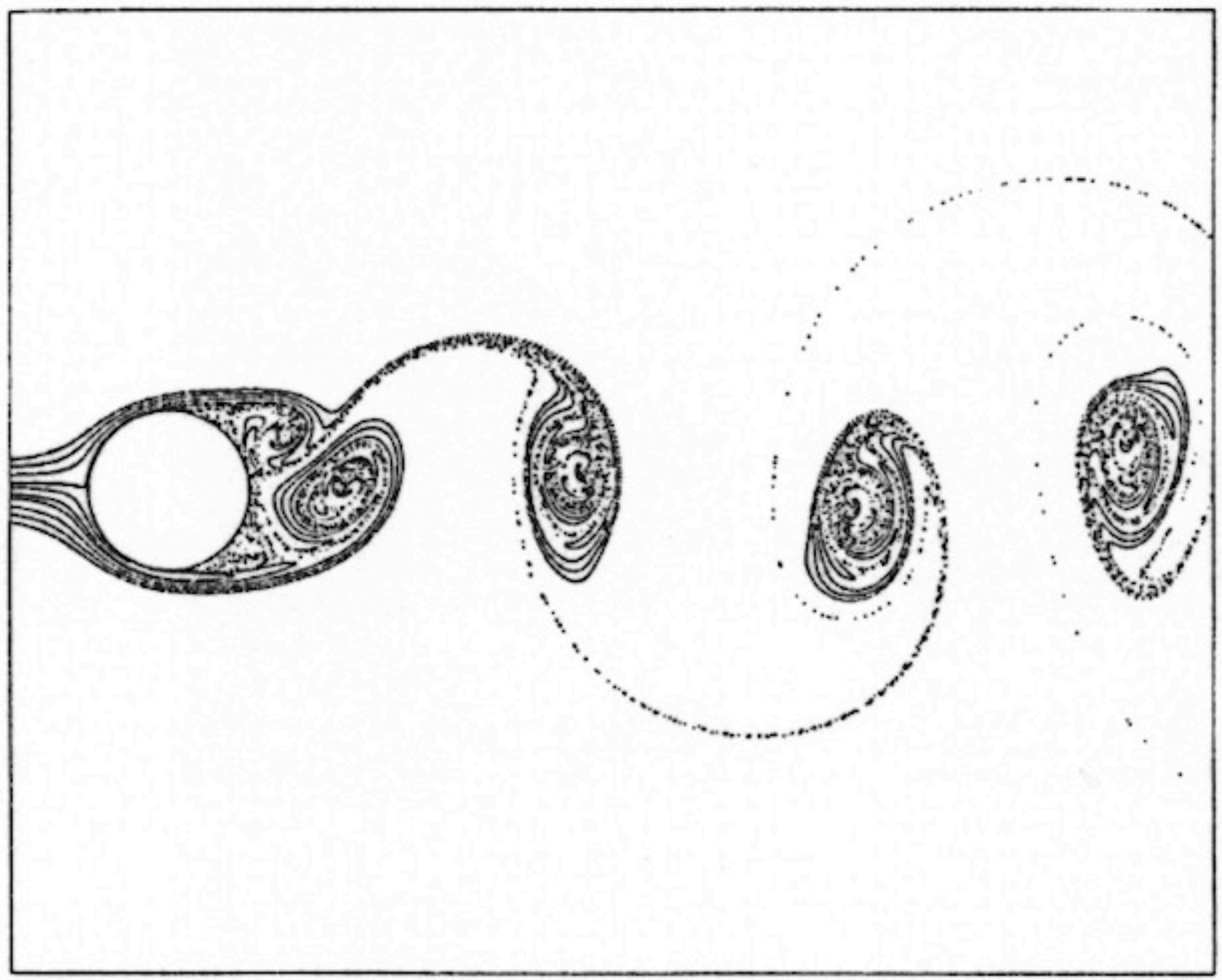
physicists' answer:

A dissipative structure in a non-equilibrium state.

Prigogine's hexagon.



Karman's vortexes



But they are not living...
Life systems must sustain their structures/non-equilibrium states by themselves.

Sustai-

nability

Rem:

Since every living systems die eventually, the sustainability is not perfect.

How to slow down the relaxation time towards the thermal equilibrium state?

Self-sustainability

system	self-sustained mechanism	sustained functional
life	autopoiesis Uribe et al. (1973)	life itself
brain	?	self identity
cell	homeodynamics Ikegami and Suzuki (2008)	autonomy
evolution	?	heritability
evolution	?	evolvability
brain	?	neural activity/consciousness
ecosystem	homeochaos Kaneko and Ikegami (1990)	species diversity
ecosystem	rein control Inman(2006)	temperature
cell	special spatial configuration	self-reproduction
life	?	adaptability

Sustainability of memory (Higher-level Inheritance)

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- Test-tube replicators

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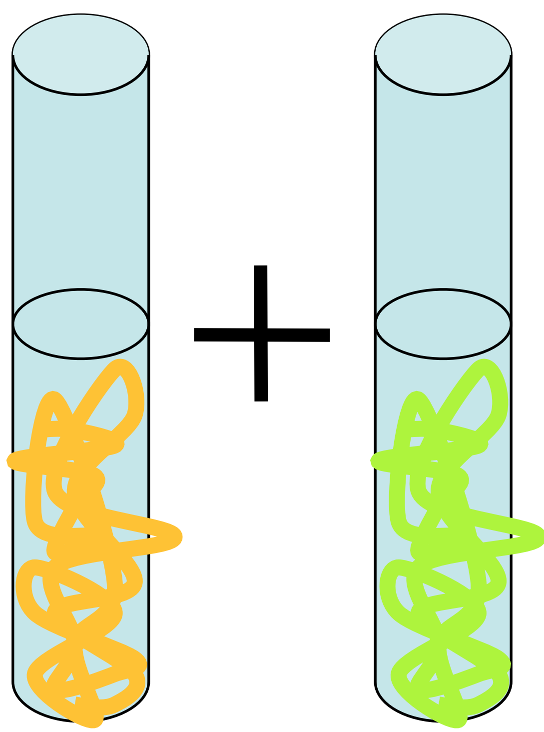

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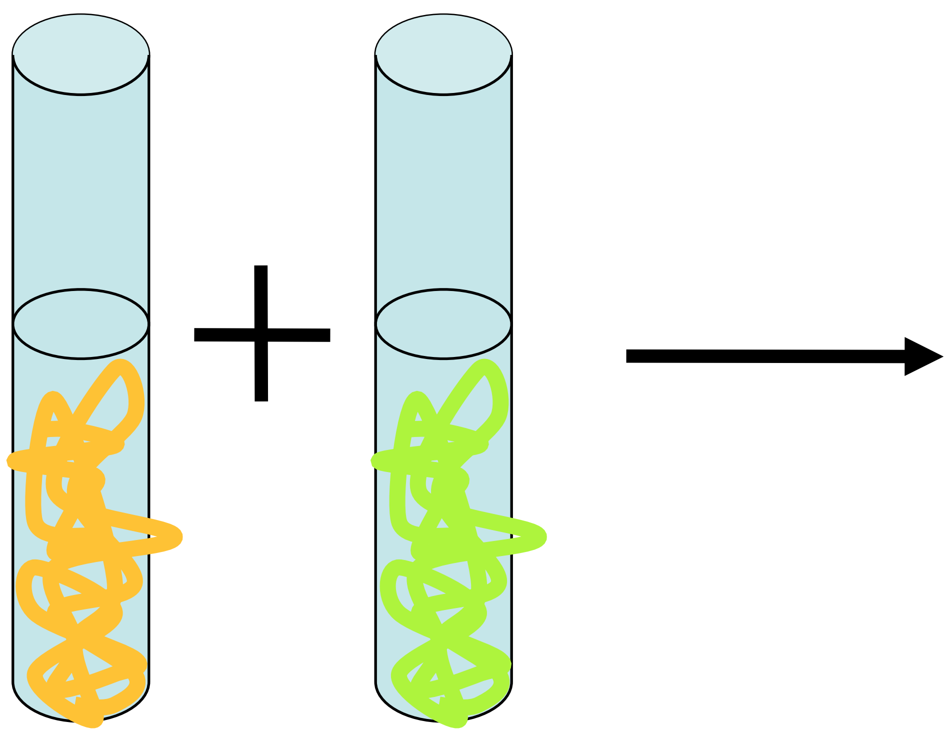

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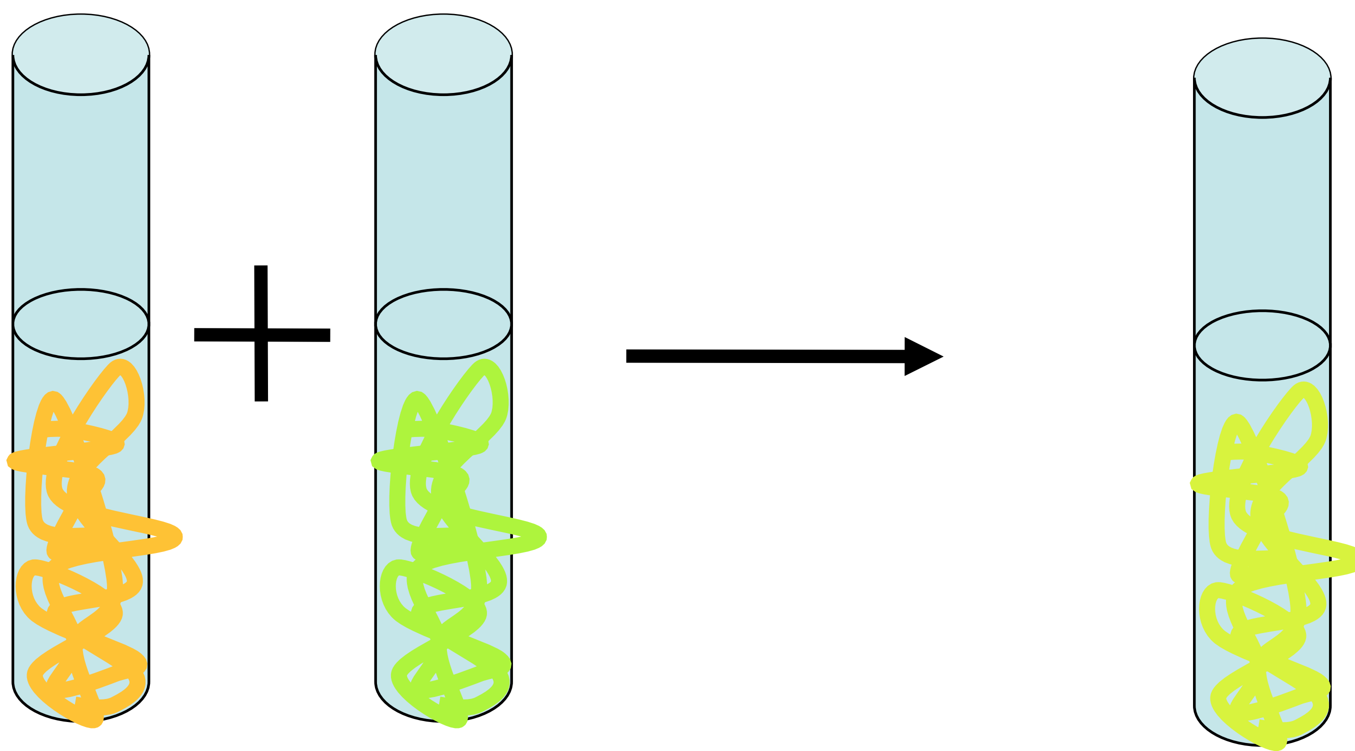

Sustainability of memory (Higher-level Inheritance)

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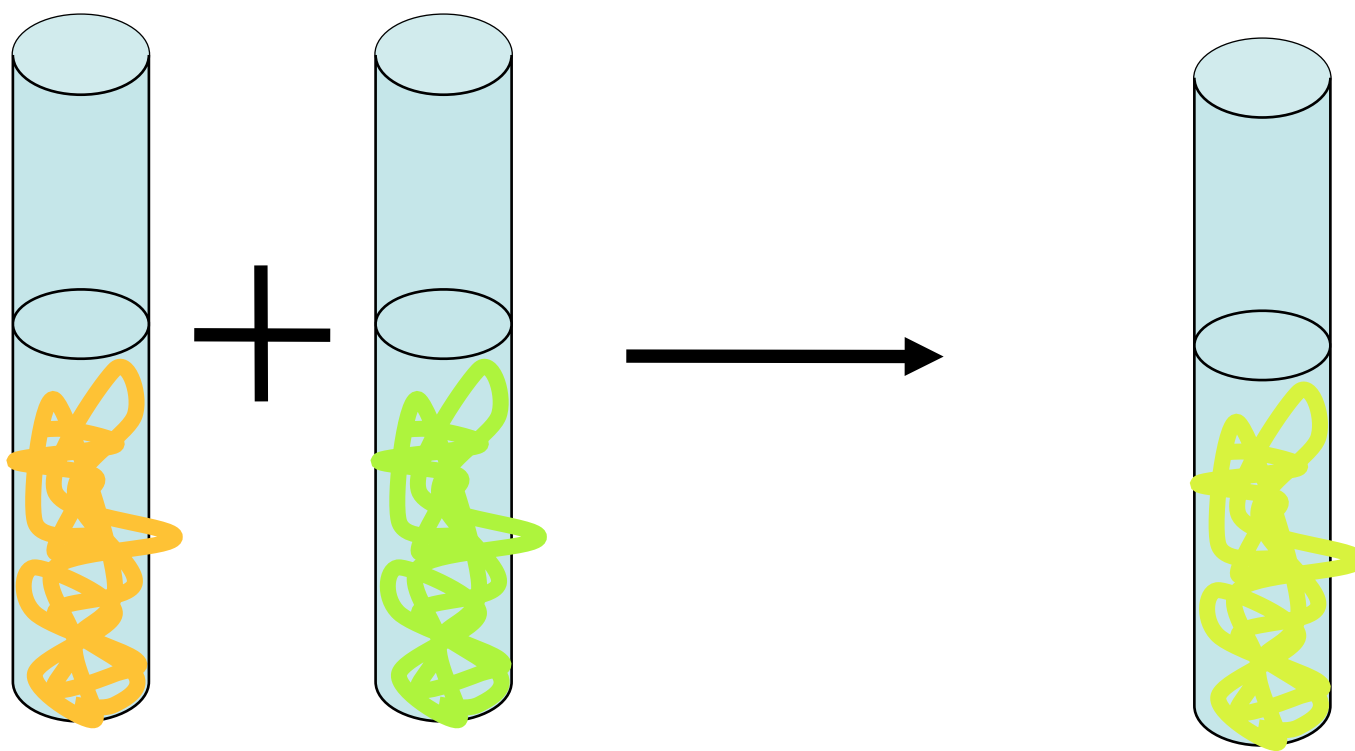

Cf. Swenson and Wilson's experiments (PNAS2000) on soil and aqua systems.

Artificial Selection on Microbe networks in the test tubes

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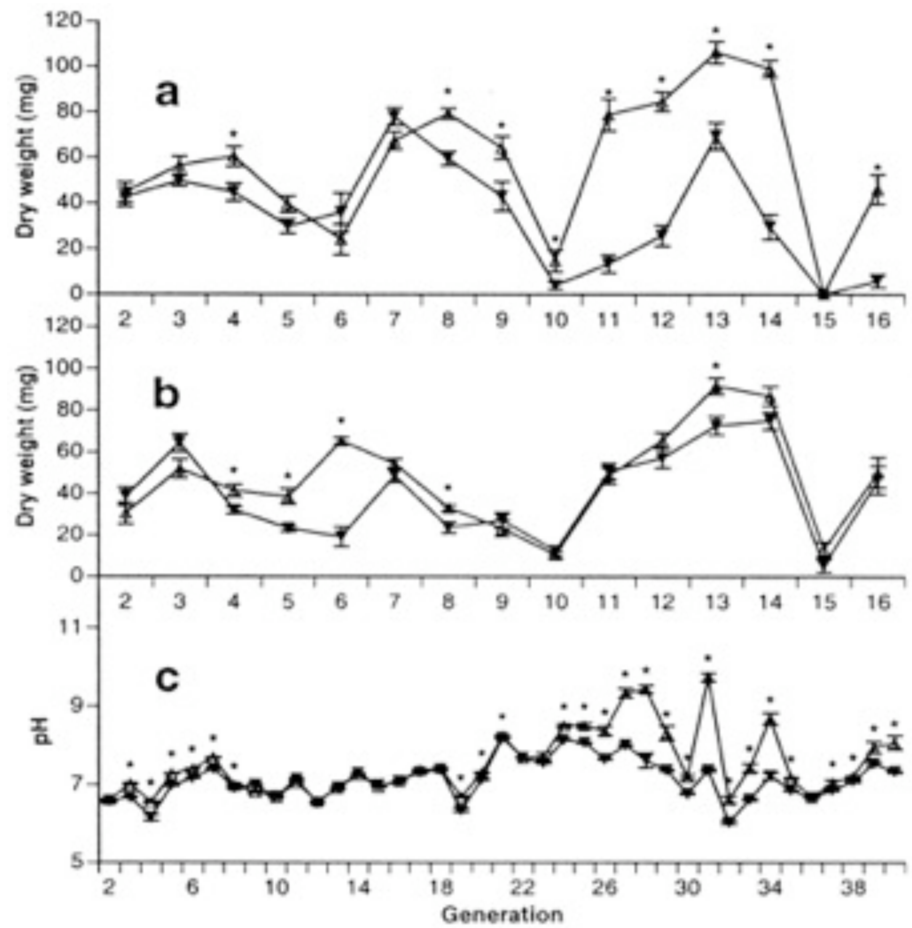
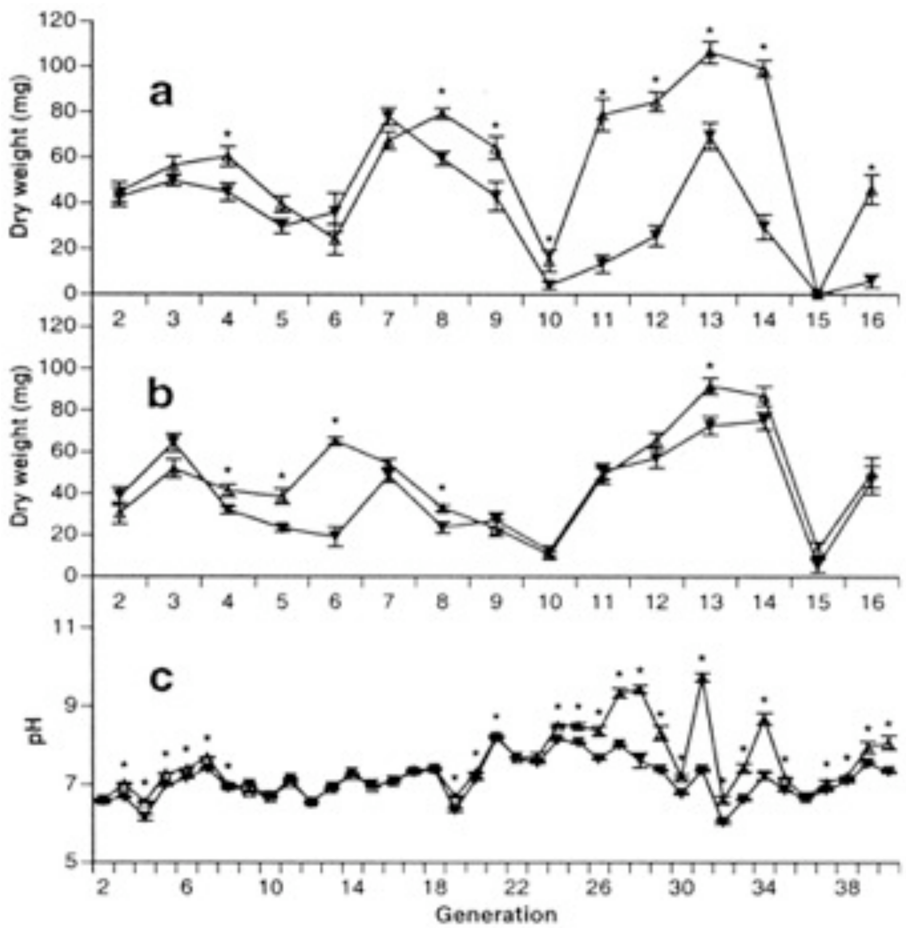
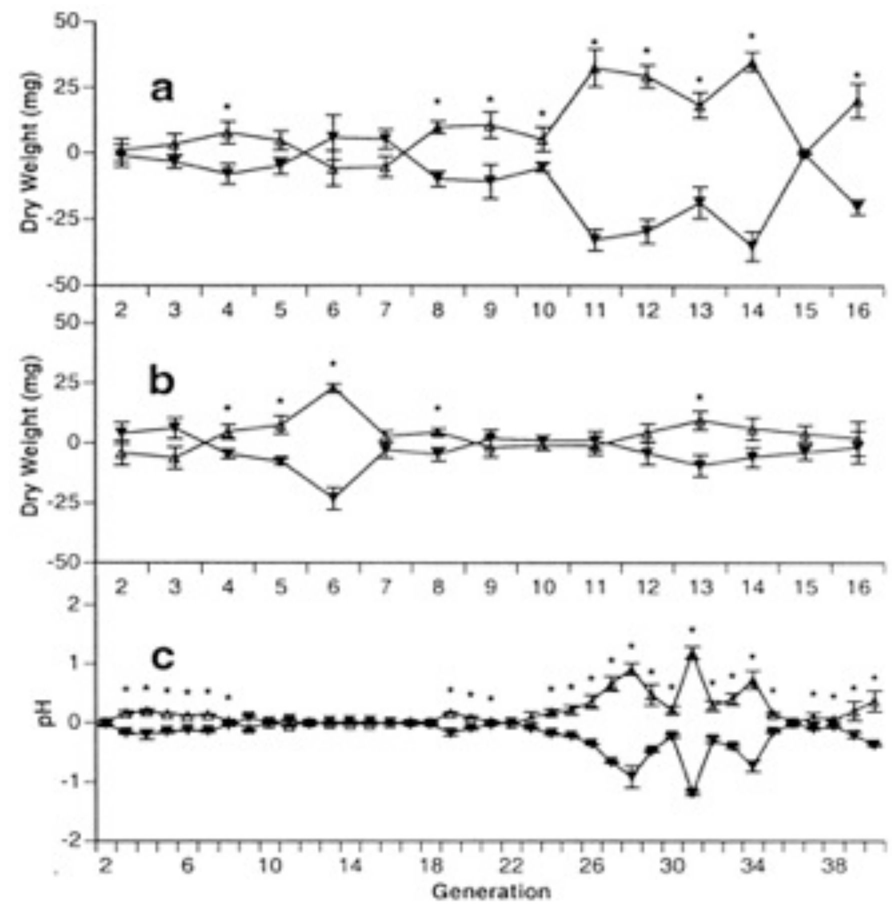


Soil system

Artificial Selection on Microbe networks in the test tubes

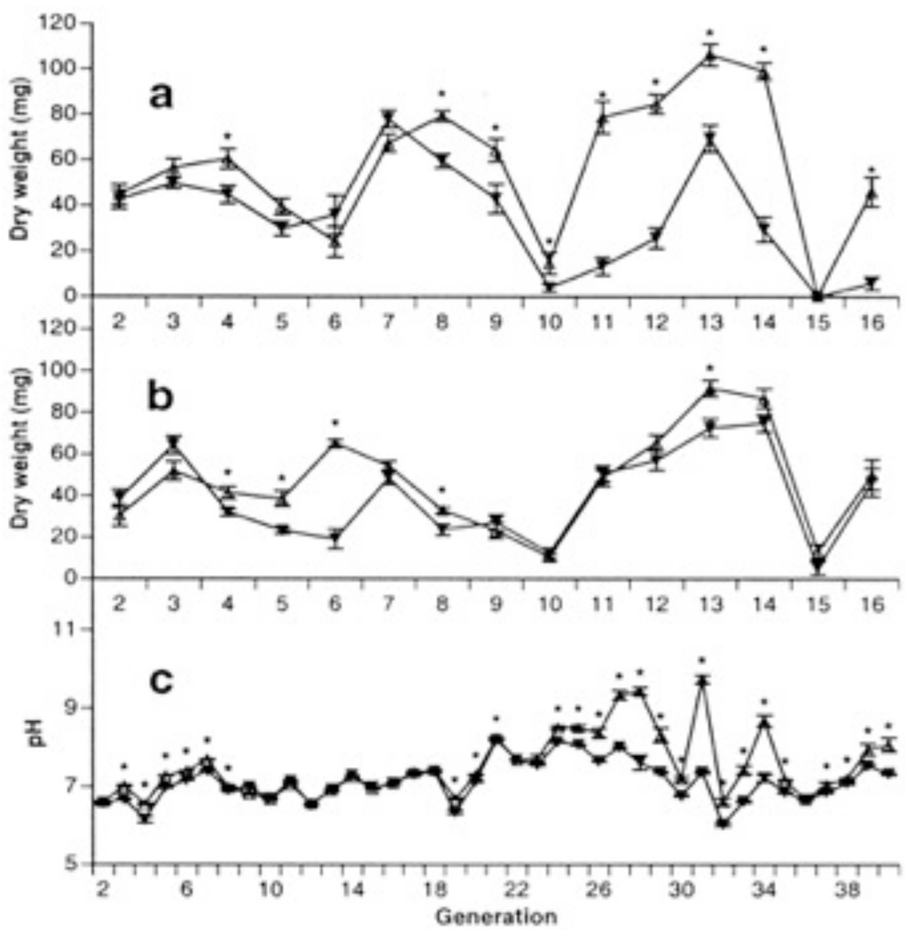


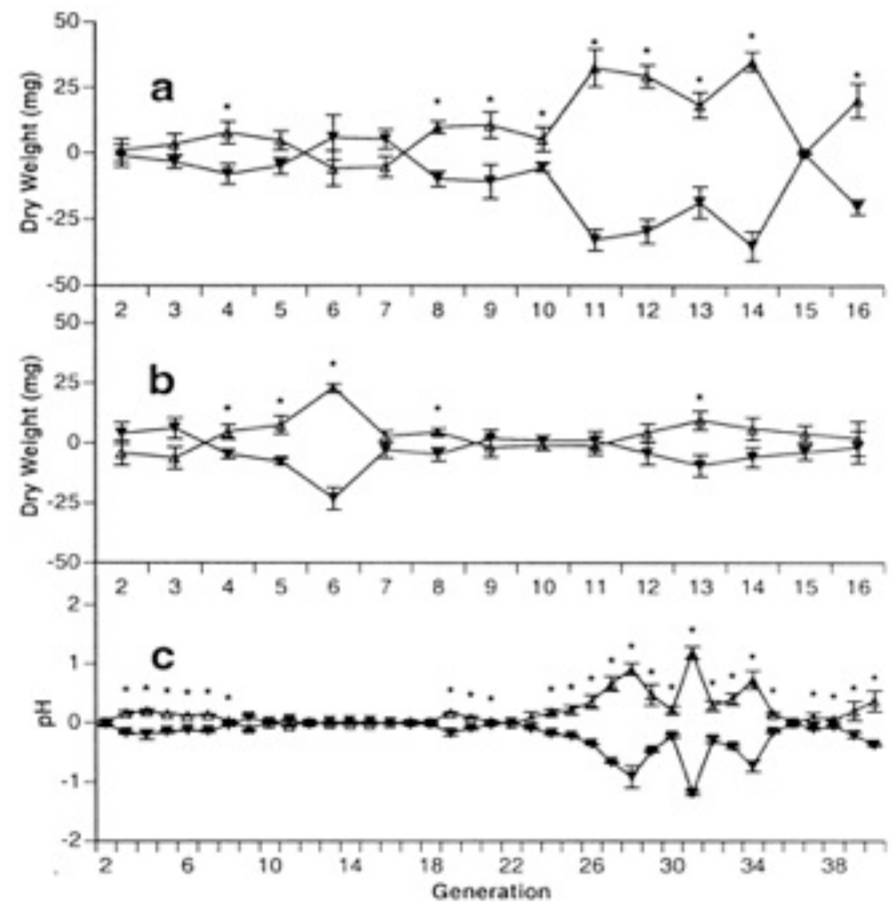
Soil system



Aqua system

Artificial Selection on Microbe networks in the test tubes



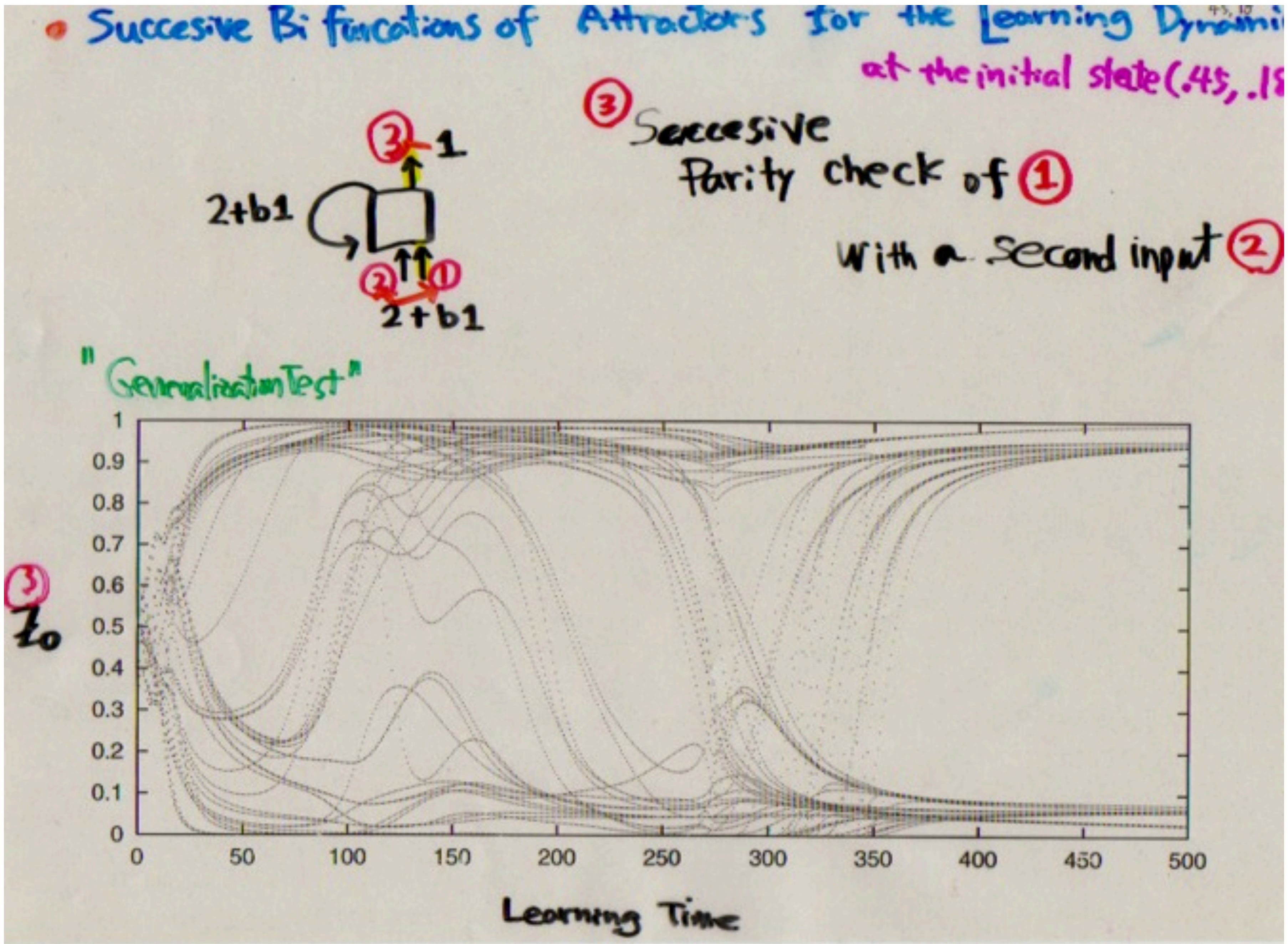


Soil system

Aqua system

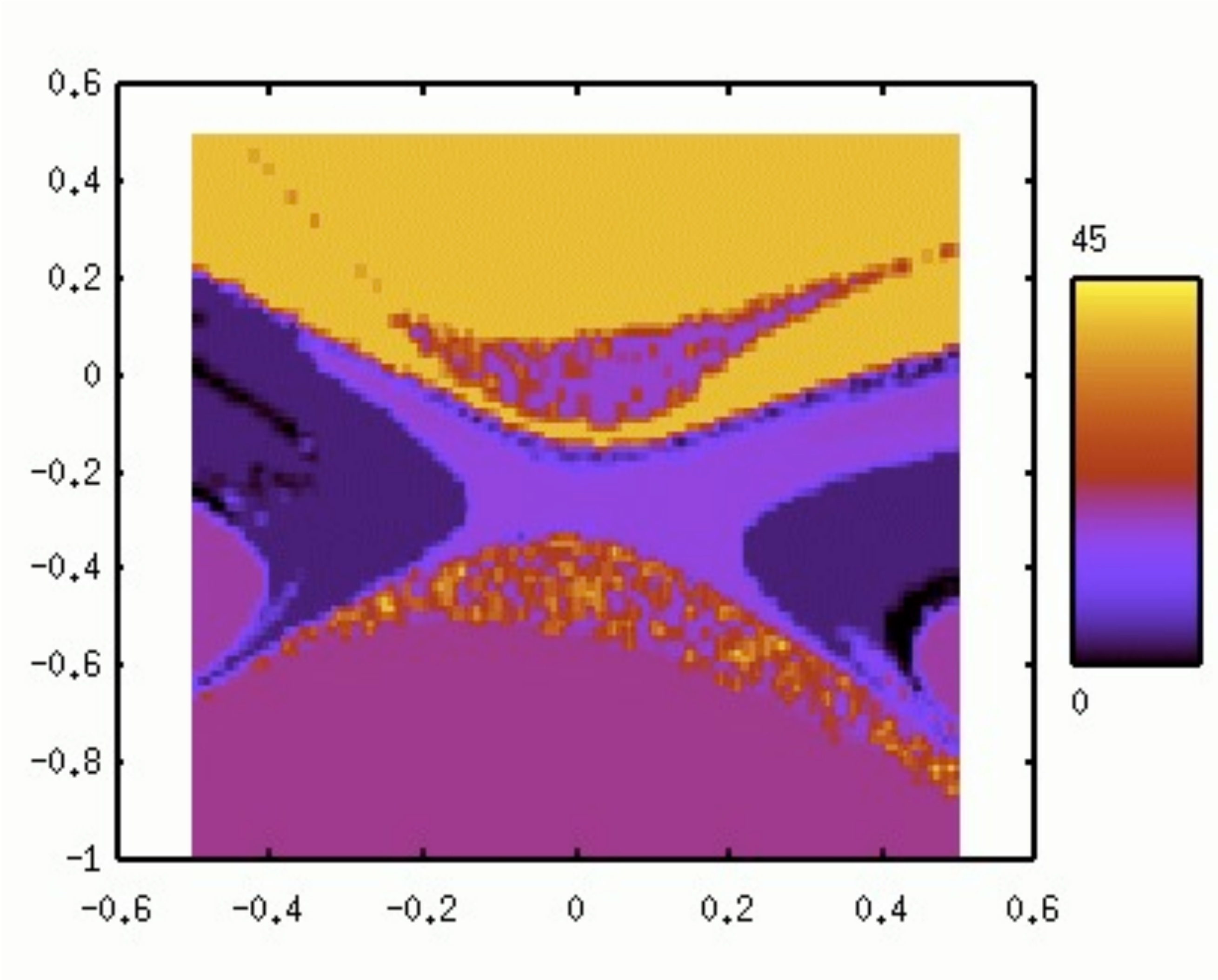
Cf. Good/bad soil. Soil-bone disease...

Sustainability of learning



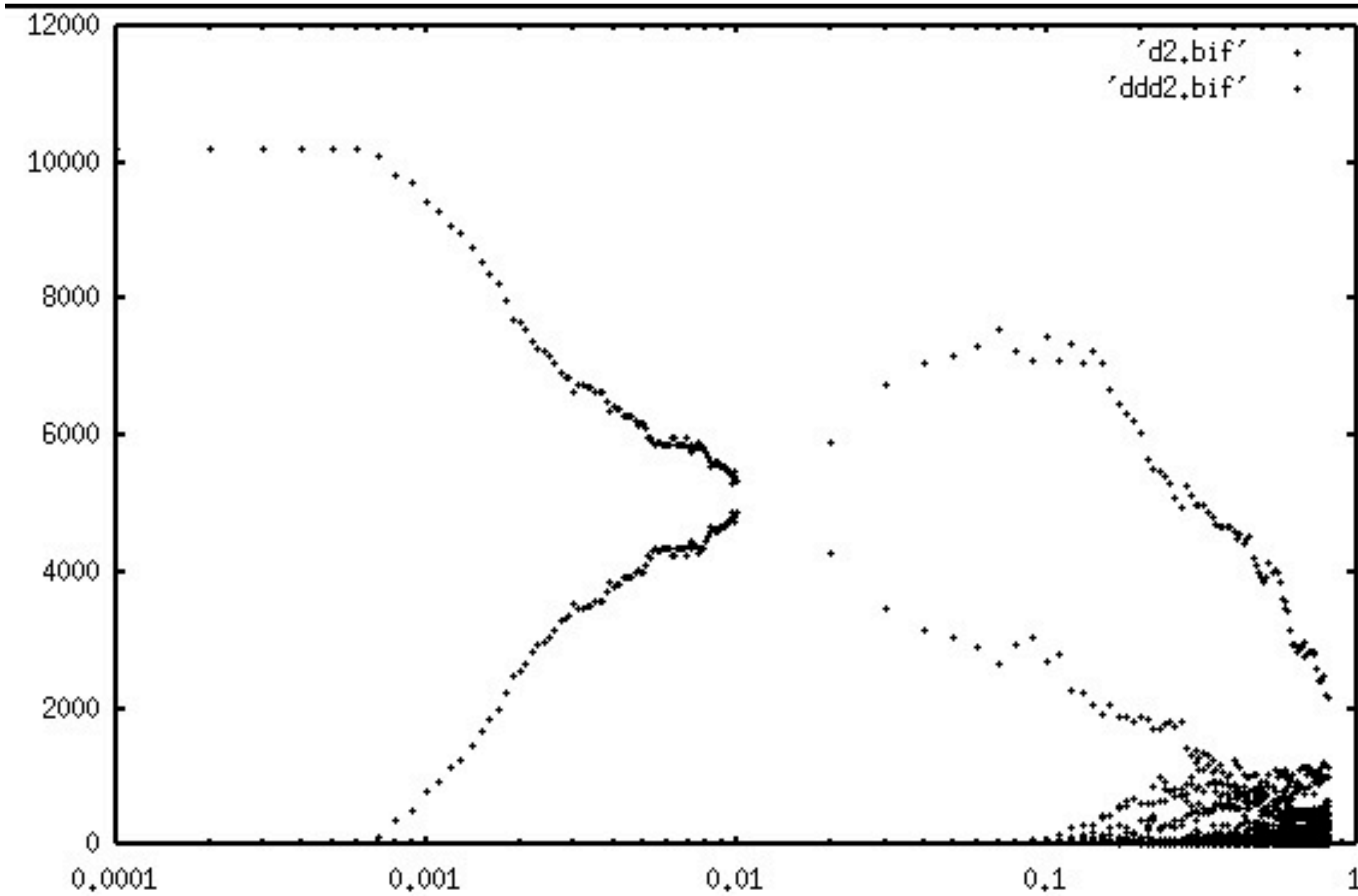
Basin Structure of Memory attractors

Different colors correspond to different error values

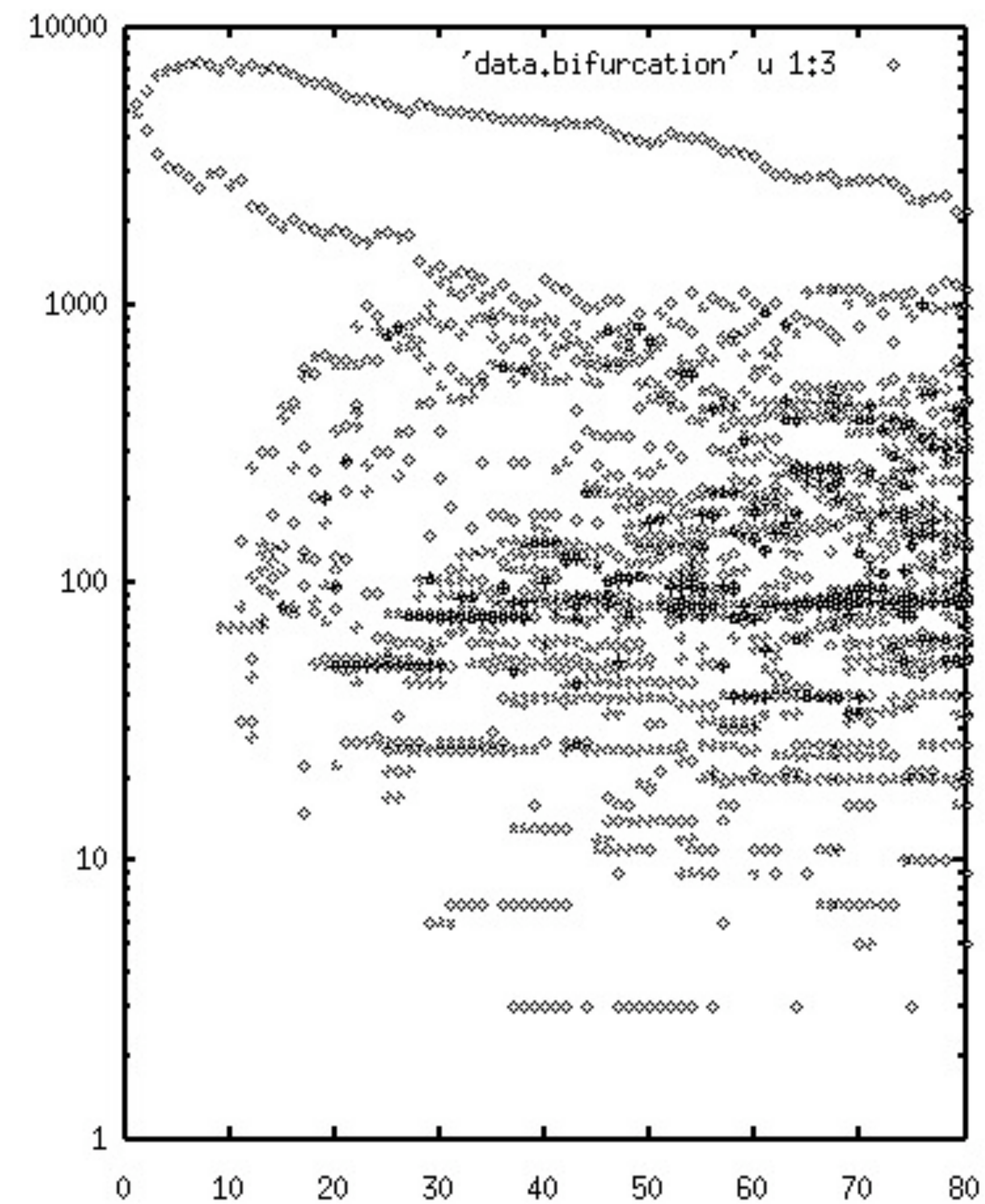


Stability of Attractors

Rates of having different attractors



Noise level



You make a model of me and I make a model of you to Anticipate future moves.

The Iterated Prisoner's Dilemma Game

- Two actions are possible; cooperate(C) or defect (D). Scores are assigned for each pair of actions.

Player A's action	C D D C D D…
Player B's action	D D C C D C…
A's score	0 q p 1 q p…
B's score	p q 0 1 q 0…

where $1<p<2$ and $0<q<1$.

-Taiji, M. and Ikegami, T. Dynamics of internal models in game players Physica D, 134, 253–266. 1999.
-Ikegami, T. and Taiji, M. Structures of Possible Worlds in a Game of Players with Internal Models Acta Polytechnica Scandinavica No. 91(1998) pp.283-292.
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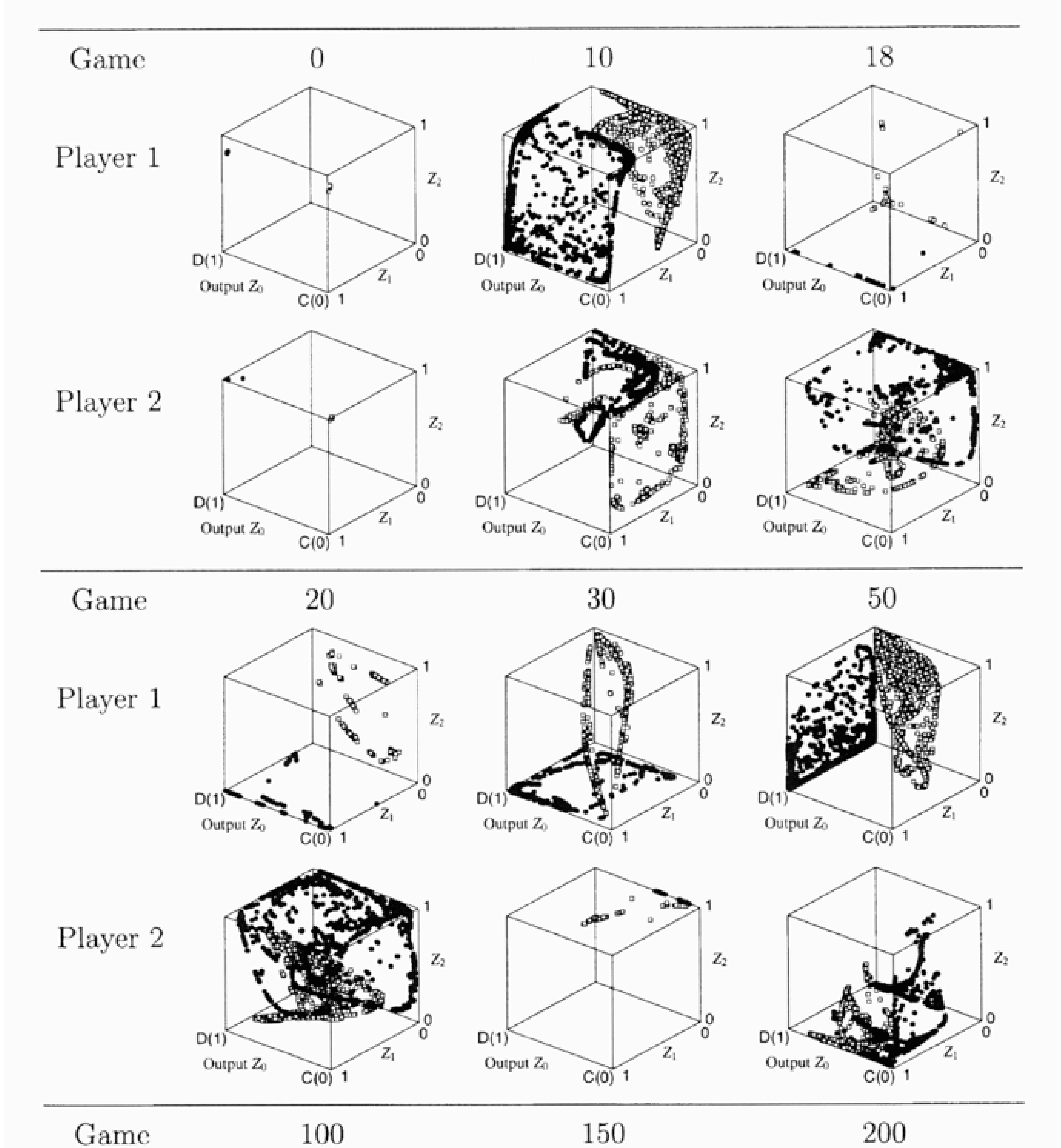
Time evolution of model patterns.



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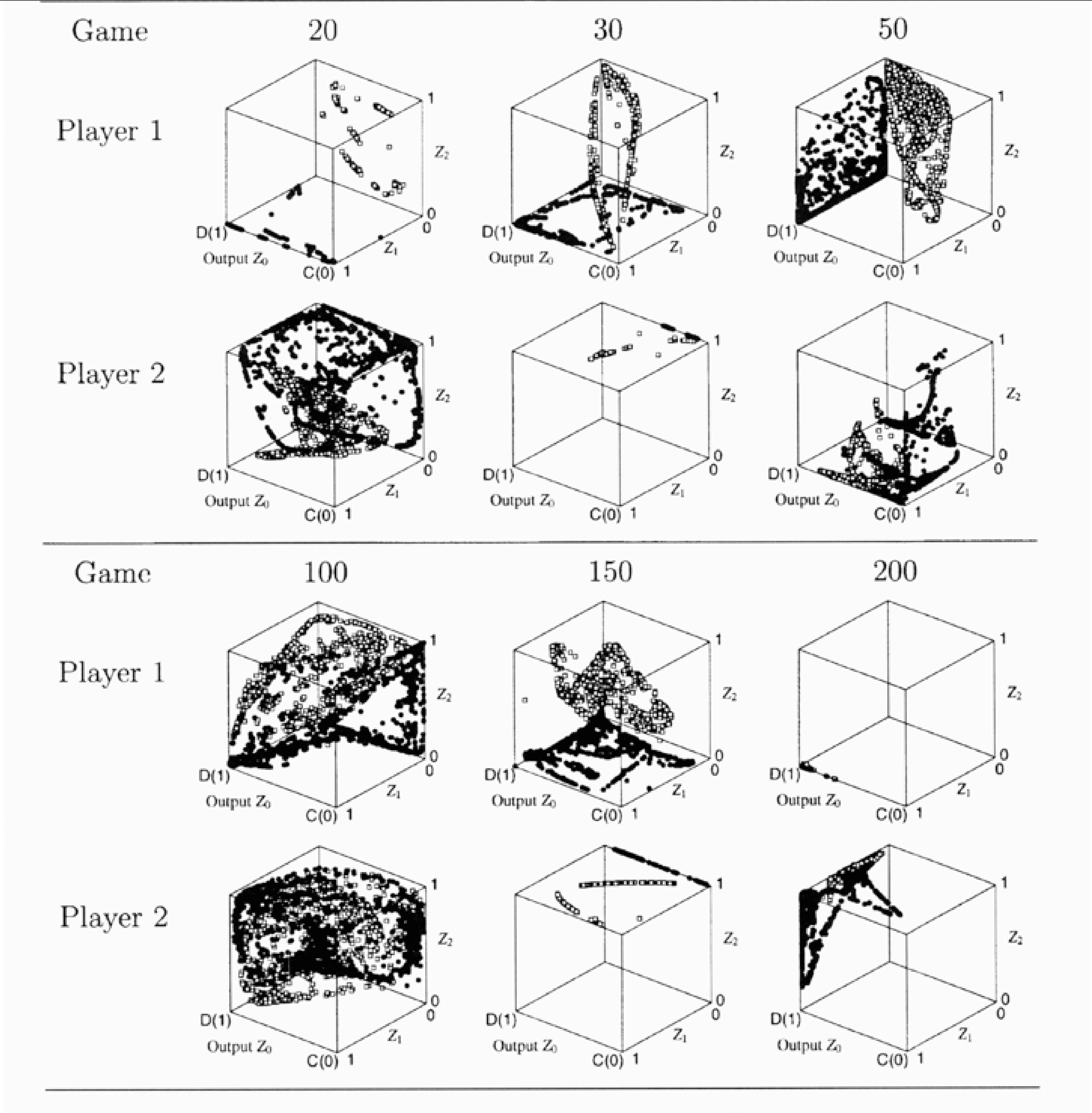
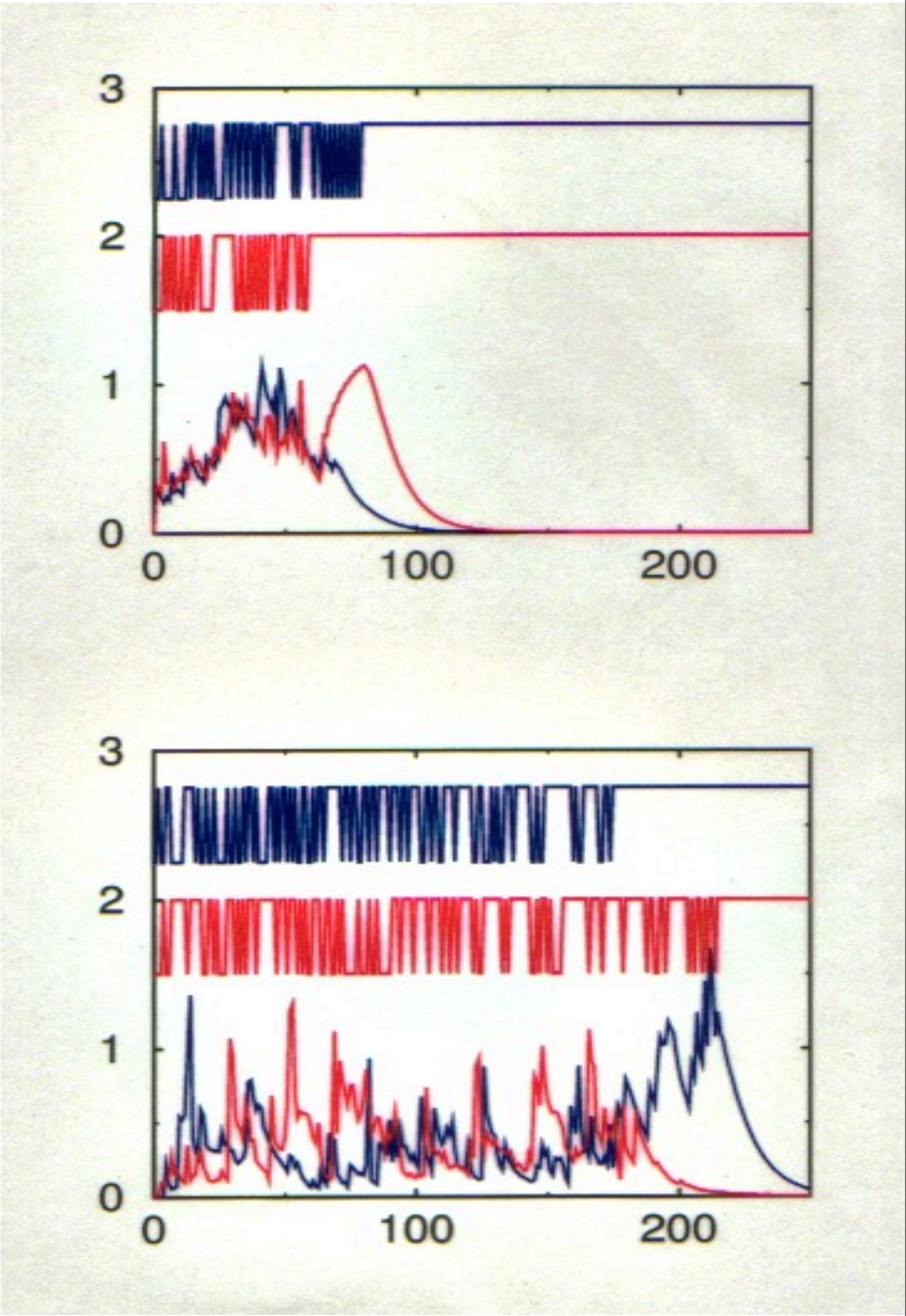
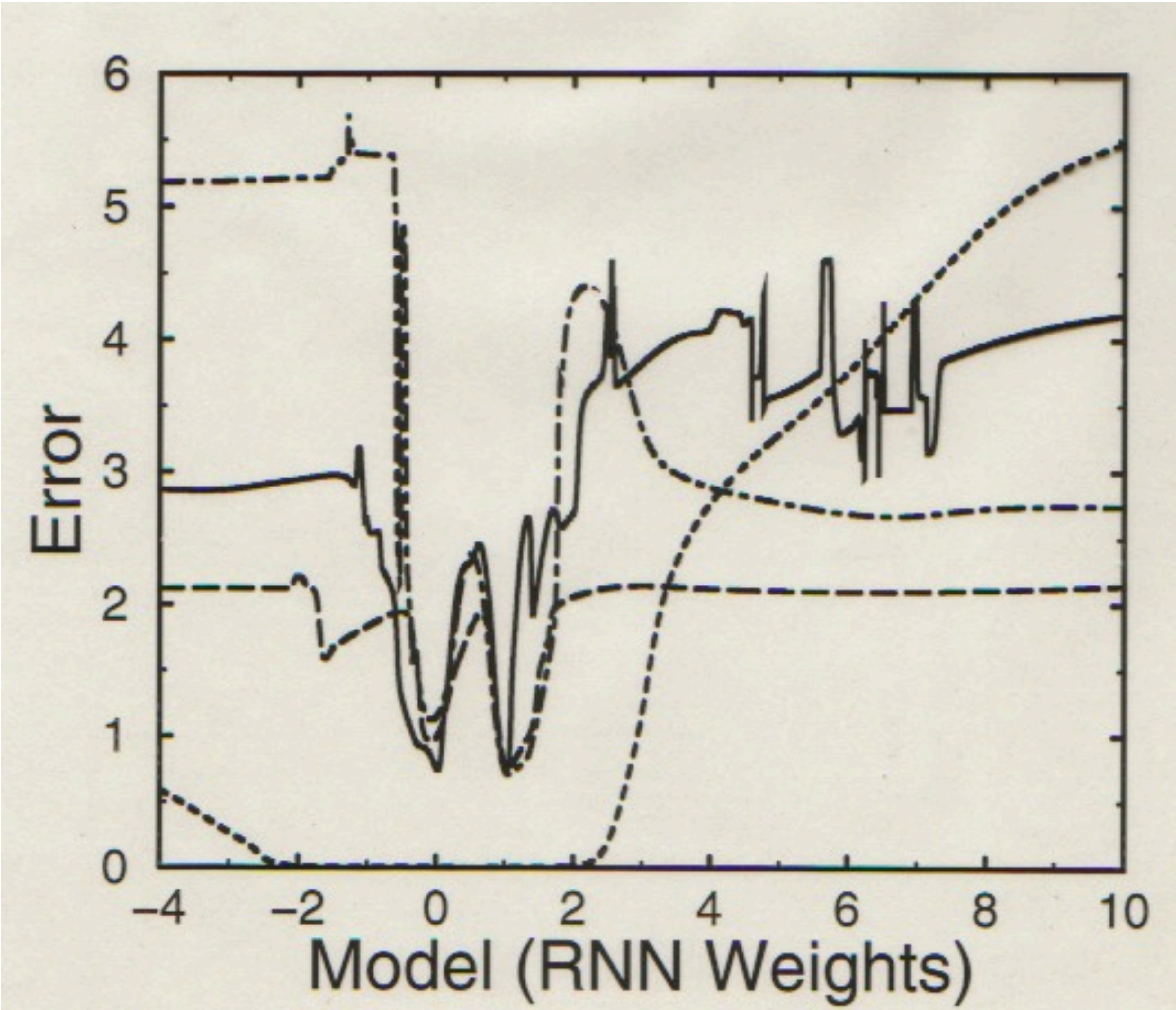


Learning error

- Time evolution of action sequences and the learning error.

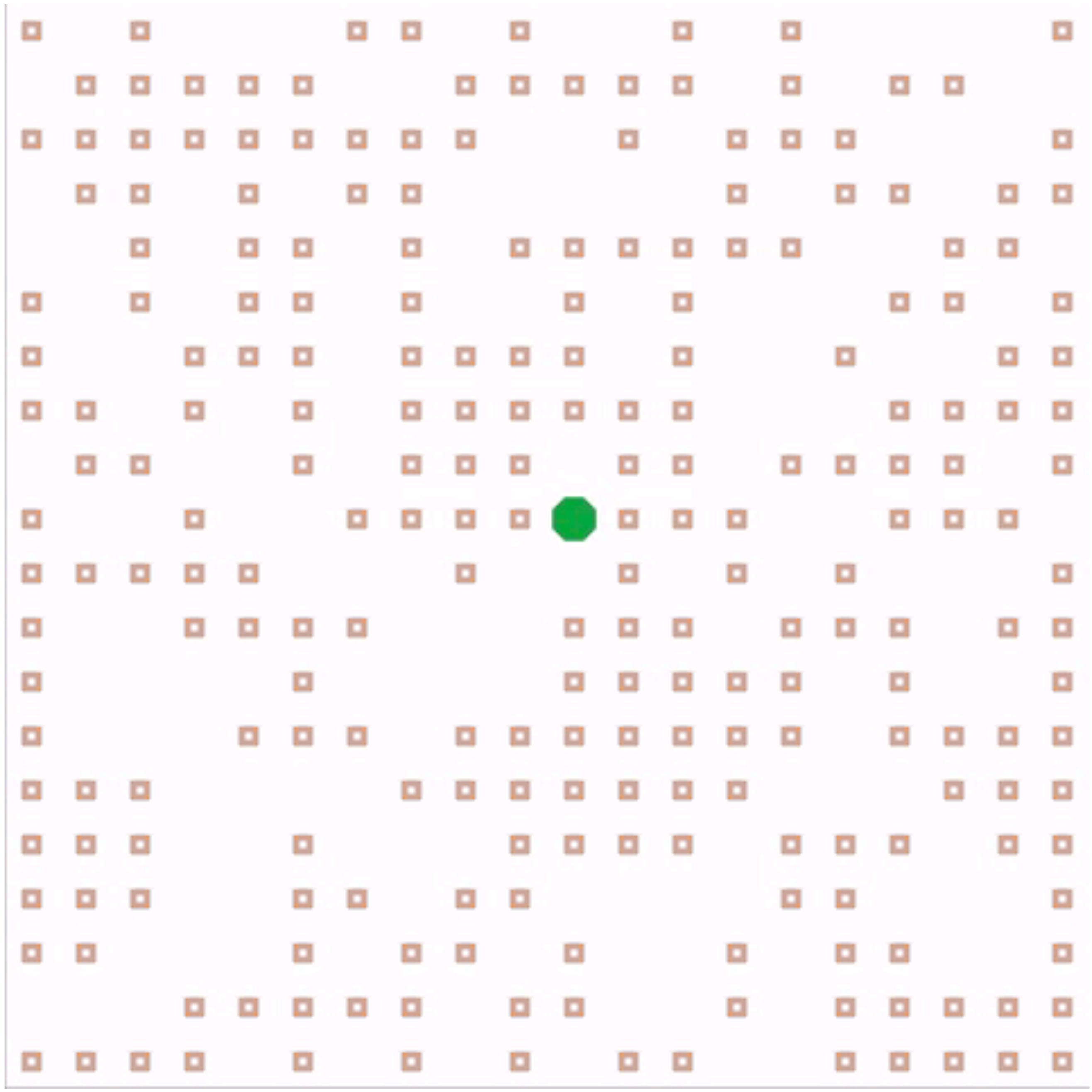


Weight Landscape



I. Here is the Varela's oriiginal abstract model of autopoiesis

Production: 2S+C→L
Bonding: L+L →L=L
Disintegration: L→ S+S



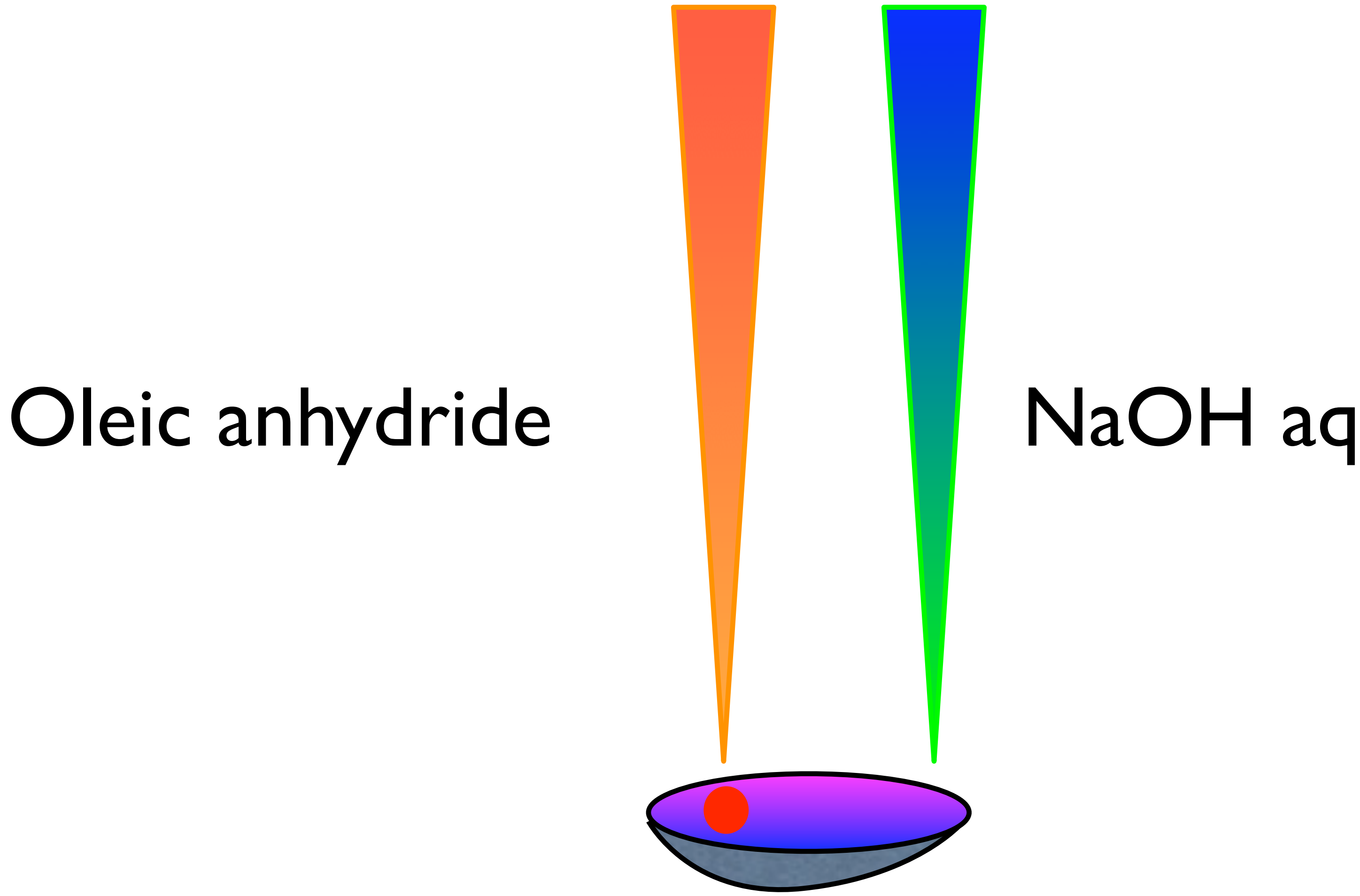
surfactant structures → membrane system → selecting chemical system

This circular relationship is called AUTOPOIESIS

Varela, F. J., Maturana, H. R. & Uribe, R. (1974), `Autopoiesis: The Organization of Living Systems, its Characterization and a Model', BioSystems 5, 187-196. This simulation program is by Keisuke Suzuki.

Chemical Experiments

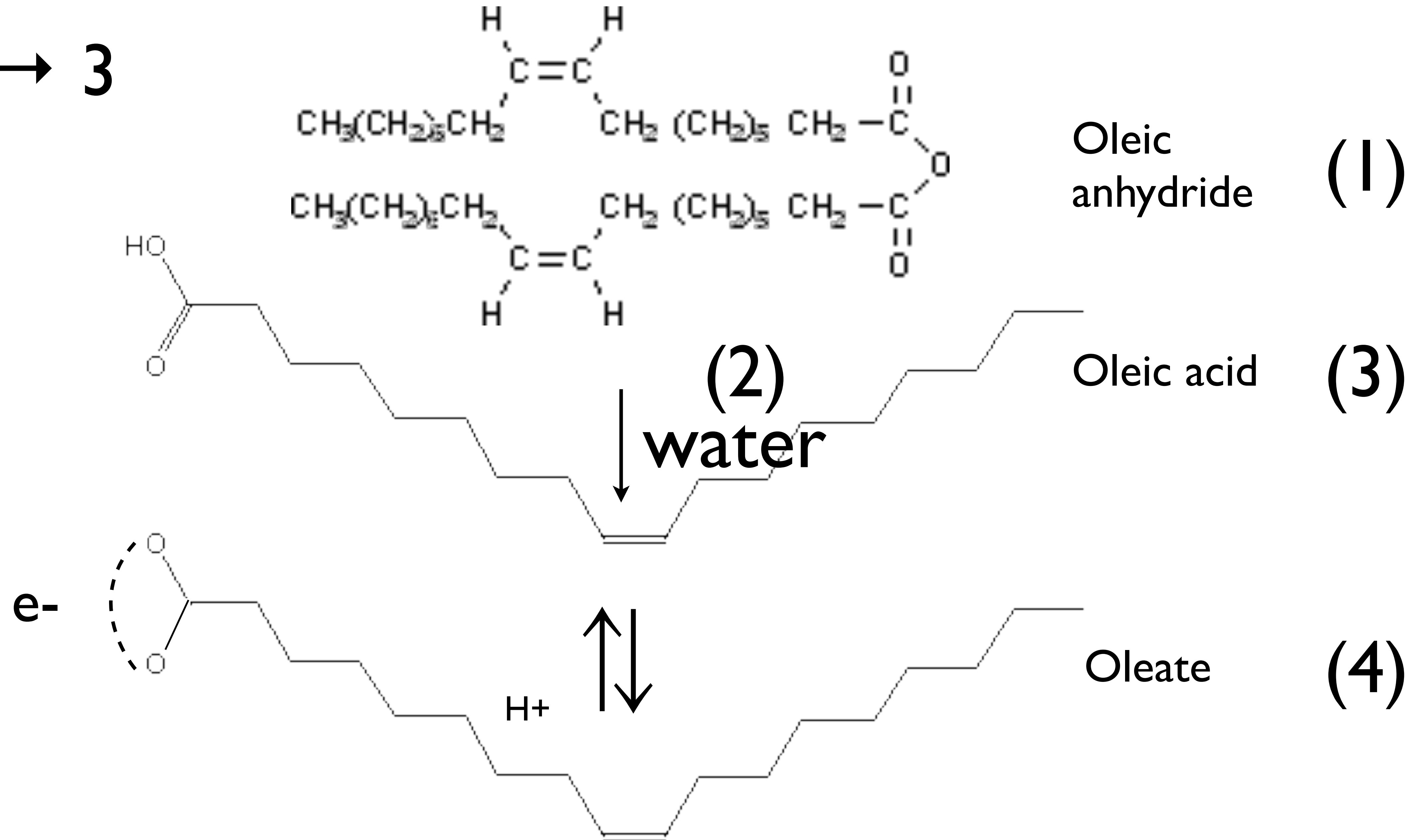
Basically we have used Luisi's oleic-acid system.
i) A certain pH range ($11<pH<12$)
ii) An oil droplet consists of oleic anhydride.
iii) An oil droplet should be a certain size (a few hundred micro meter)

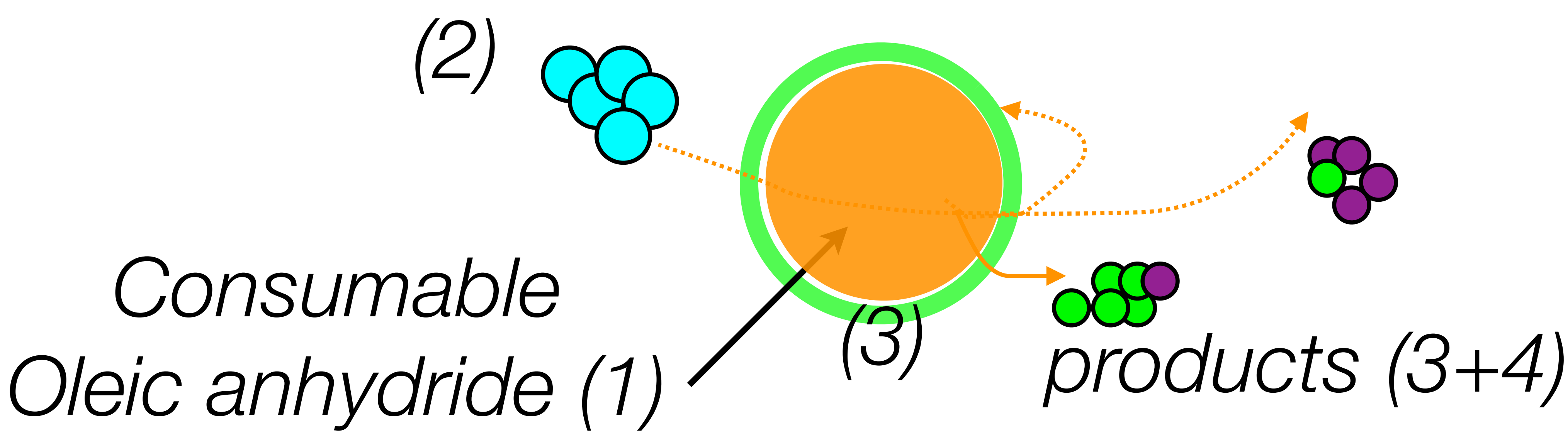


Basic reaction schema

$1+2 \rightarrow 3$

$3 \rightleftarrows 4$





NUMERICAL COMPUTATION

The surface tension as a function of the chemical mass

$$\nabla \cdot \mathbf{u}(\mathbf{x},t) = 0$$

$$(\frac{\partial}{\partial t} + \mathbf{u}(\mathbf{x},t)\cdot\nabla)\mathbf{u}(\mathbf{x},t) = -\frac{1}{\rho}\nabla P(\mathbf{x},t) + \nu\nabla^2\mathbf{u}(\mathbf{x},t) + aF_s\delta$$

$$F_s(\mathbf{x},t) = \gamma(v(\mathbf{x},t))\kappa\mathbf{n} + \nabla\gamma(v(\mathbf{x},t))$$

$$\gamma(v(\mathbf{x},t)) = v(\mathbf{x},t) + b$$

$$(\frac{\partial}{\partial t} + \mathbf{u}(\mathbf{x},t)\cdot\nabla)v(\mathbf{x},t) = G(v(\mathbf{x},t))\delta + D_v\nabla^2 v(\mathbf{x},t)$$

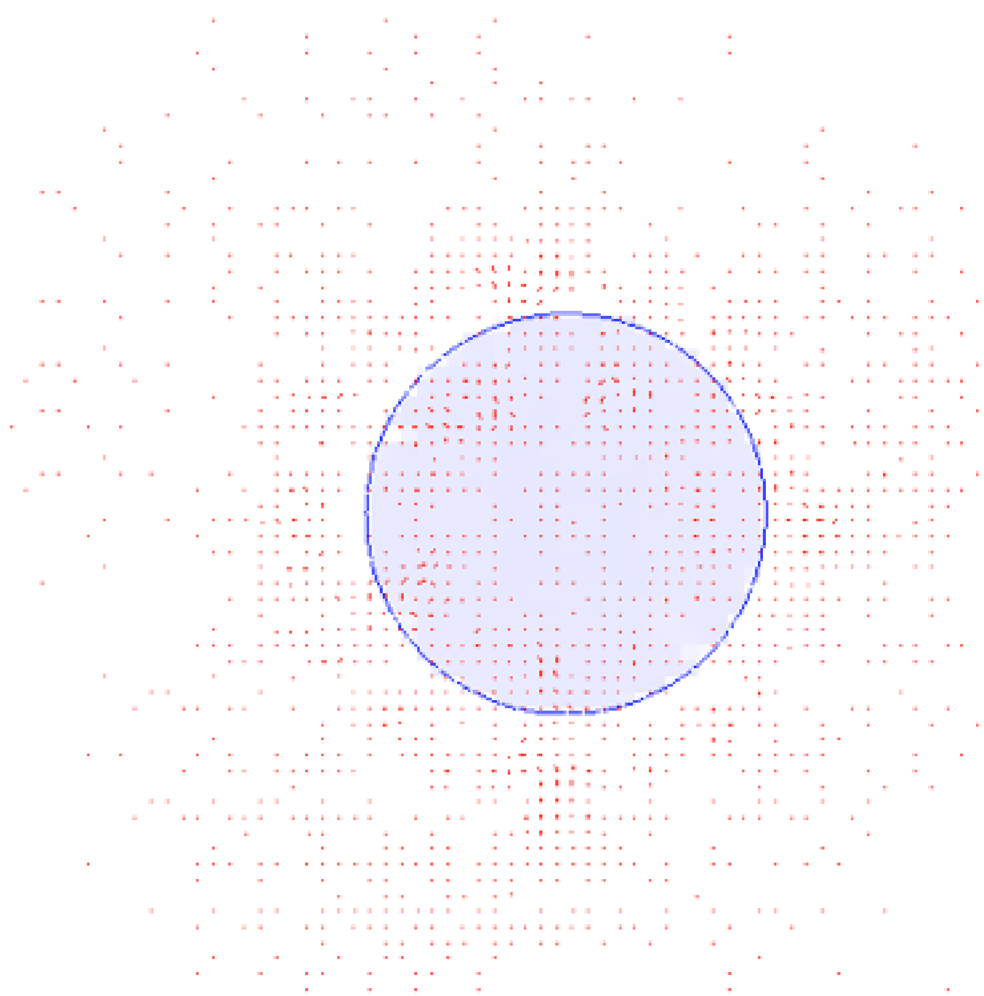
$$G(v(\mathbf{x},t)) = \begin{cases} c, & \text{if } 0 \leq x < 0.8 \\ 0.1c, & \text{else if } 0.8 \leq x < 1 \\ 0, & \text{otherwise} \end{cases}$$

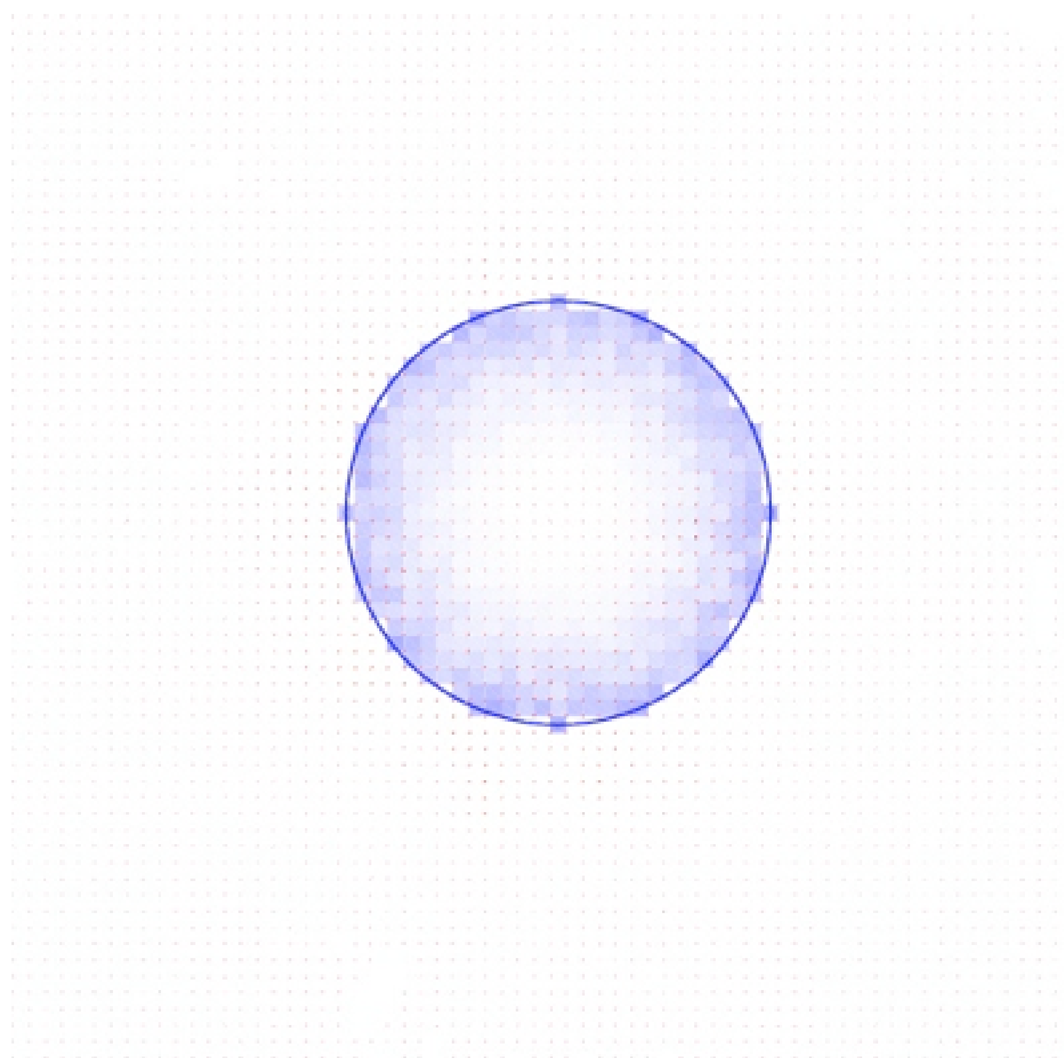
$$\left(\frac{\partial}{\partial t} + \mathbf{u}\cdot\nabla\right)\phi \;=\; 0$$

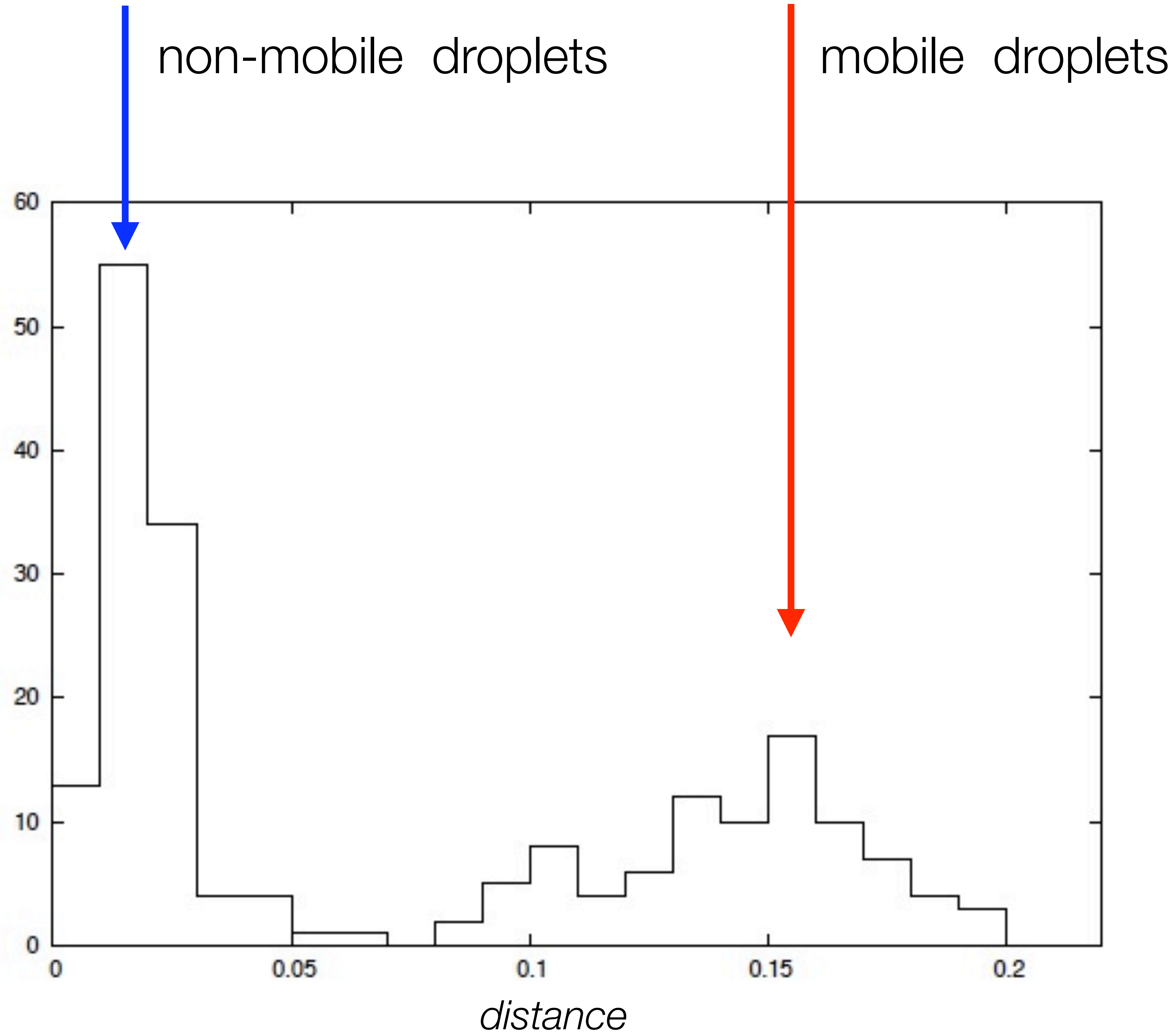
Reaction at the boundary. The reaction rate decreases when the chemical mass increases due to the surfactant.

Hiroki Matsuno, Martin M. Hanczyc, Takashi Ikegami: Self-maintained Movements of Droplets with Convection Flow. ACAL 2007: 179-188.

Spontaneous Symmetry Breaking by Selection of a pair of convection flow

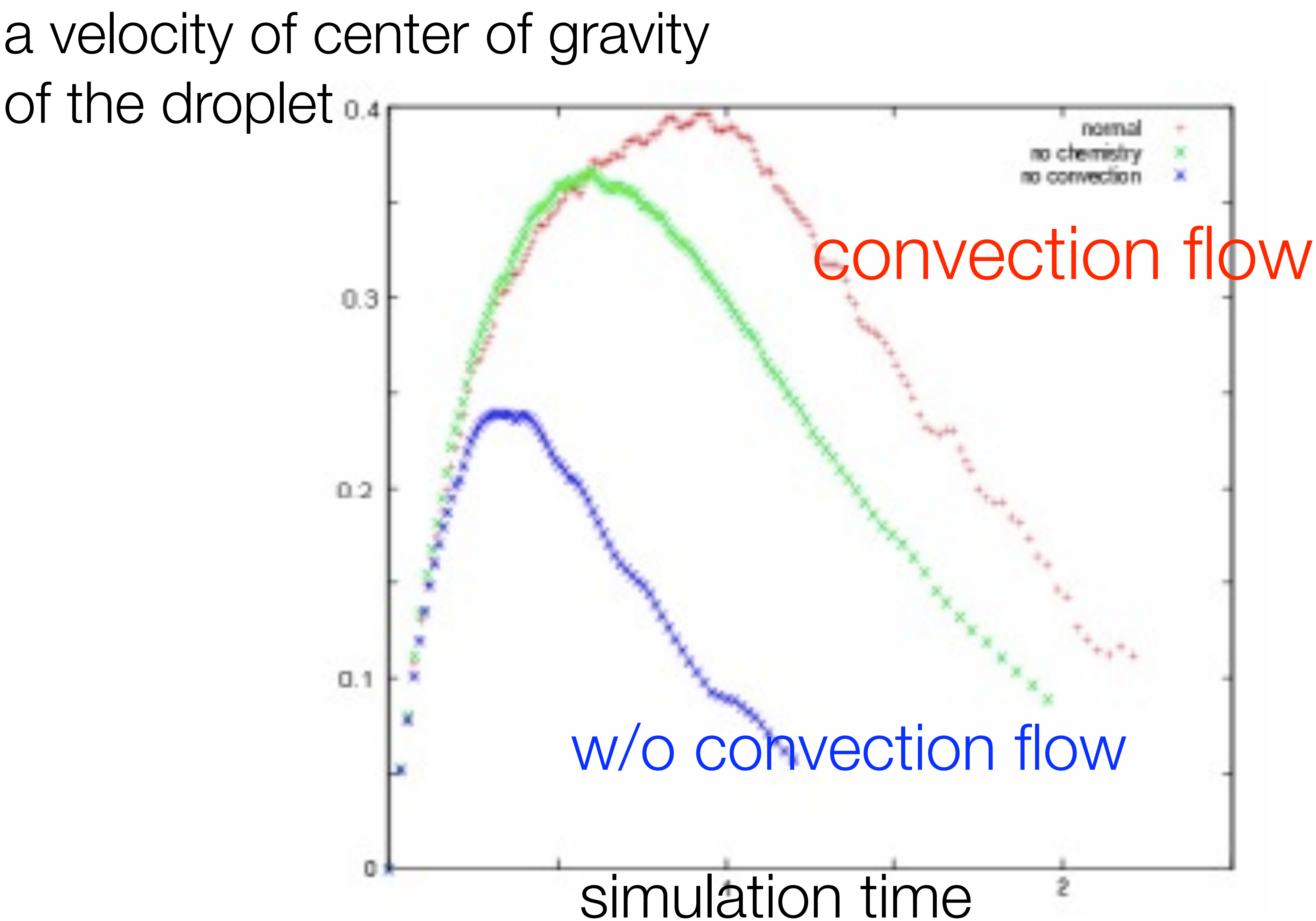






The histogram of moved distance for the initial droplets

There is a positive feedback between Chemical Reaction and Convection Flow: Without the convection flow, the droplet moves slowly and stops earlier.



Self-Organization of Subjective Time and Sustainable Autonomy in Mind Time Machine (MTM)

Life/consciousness
emerges
in a distributed
sensory network

As for the first trial, I constructed a machine called MTM (Mind Time Machine) that lived in in the real world.
MTM doesn't do anything. It only senses the environment and memorizes it, temporally changing very slowly its behavior.

I say MTM is living since it can die and since I feel a certain sense of attachment and also detachment while playing with MTM, which you would expect playing with your pets.

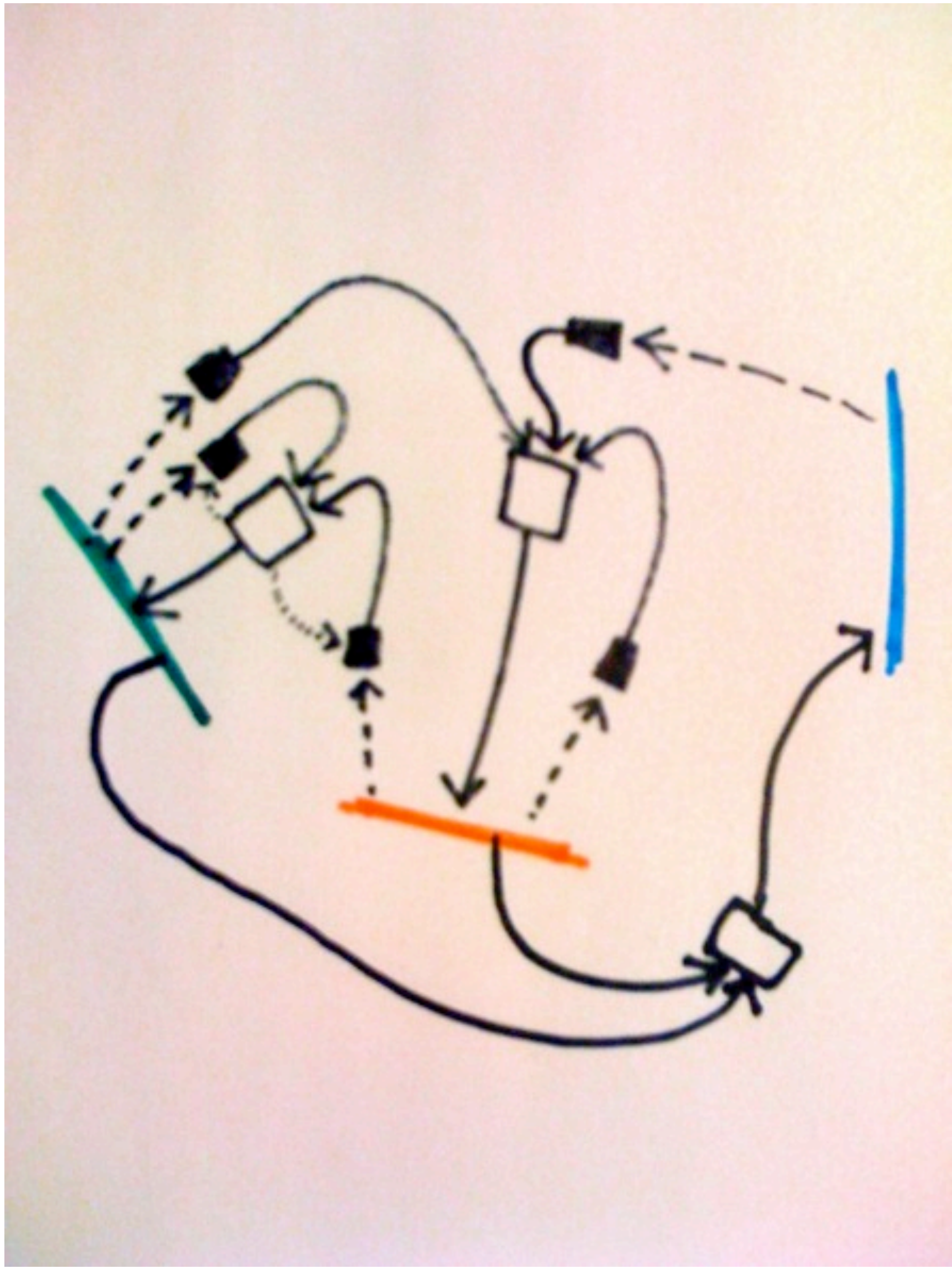
Maximalism Design Principle

Ikegami, T. and Hanczyc, M.M, "*The search for a first cell under the maximalism design principle*" Technoetic Arts 7 (2009) pp.153-164.

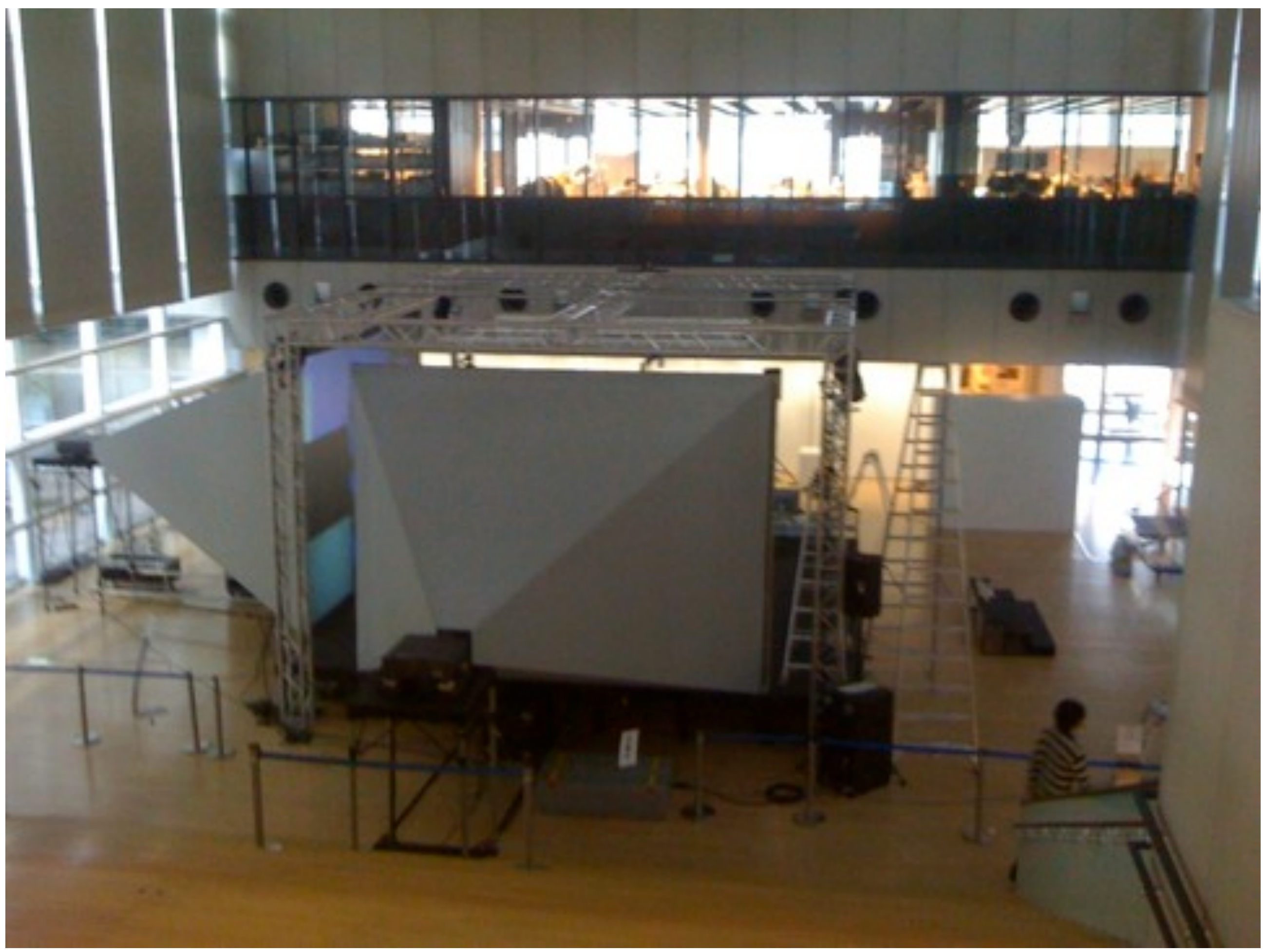
When designing MTM, I put many of my algorithm and knowledge (Hopfield type network, the Hebbian learning, chaos dynamics, vido feedback etc.) all together, which makes it difficult to analyze, but instead of that we can test and observe things.

But what I am aiming for is NOT a simple self-organization phenomena, but we need careful design of a sensory network and environment.

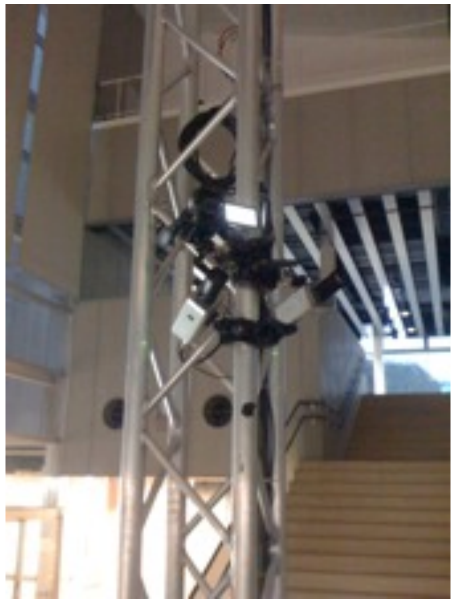
MTM consists of two parts; i) macro visual processing and ii)micro neural networks. The operating principle is to process timeframes of the visual inputs by combining chaotic instabilities from neural dynamics and optical feedback, in order to make autonomous "time-organizing" phenomena.

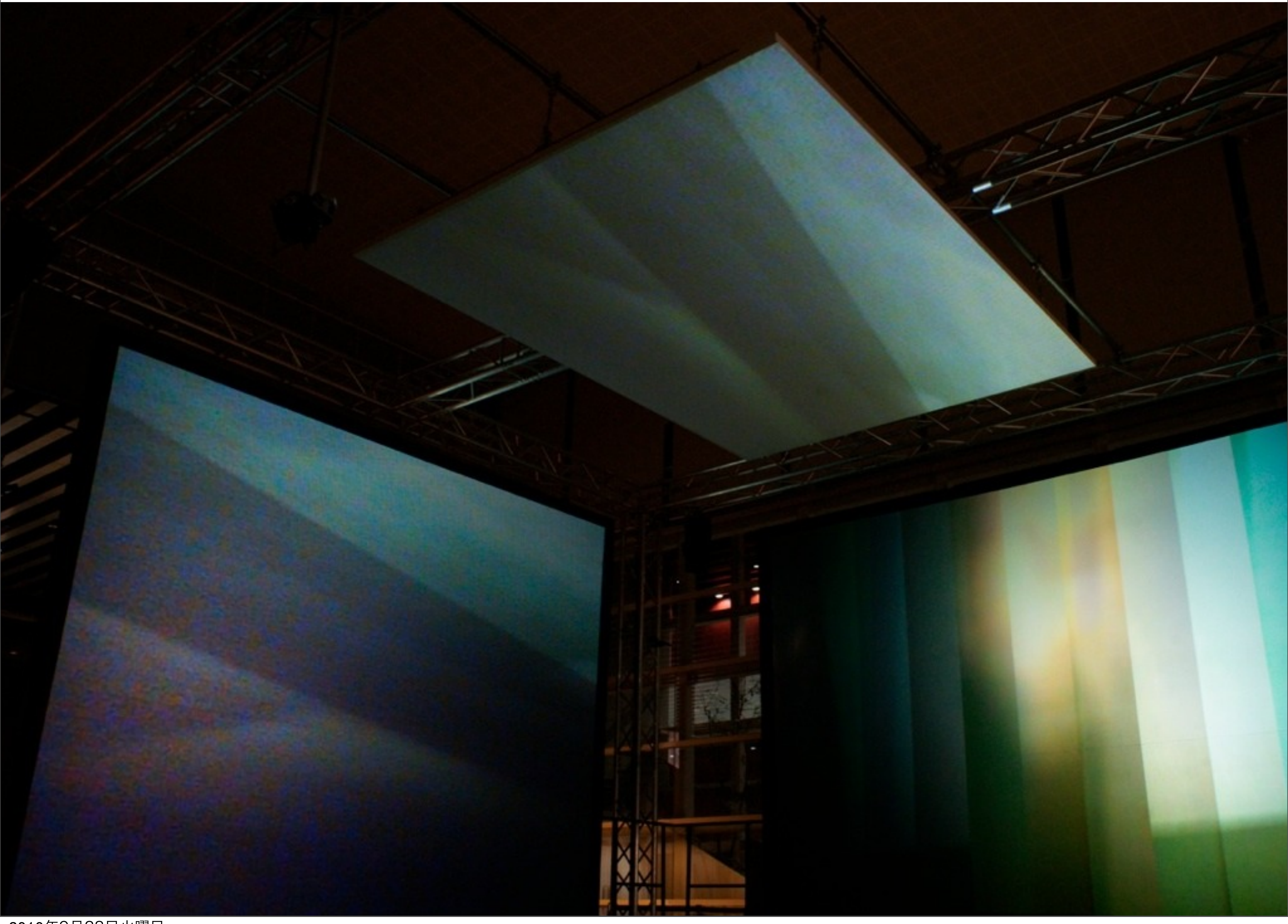


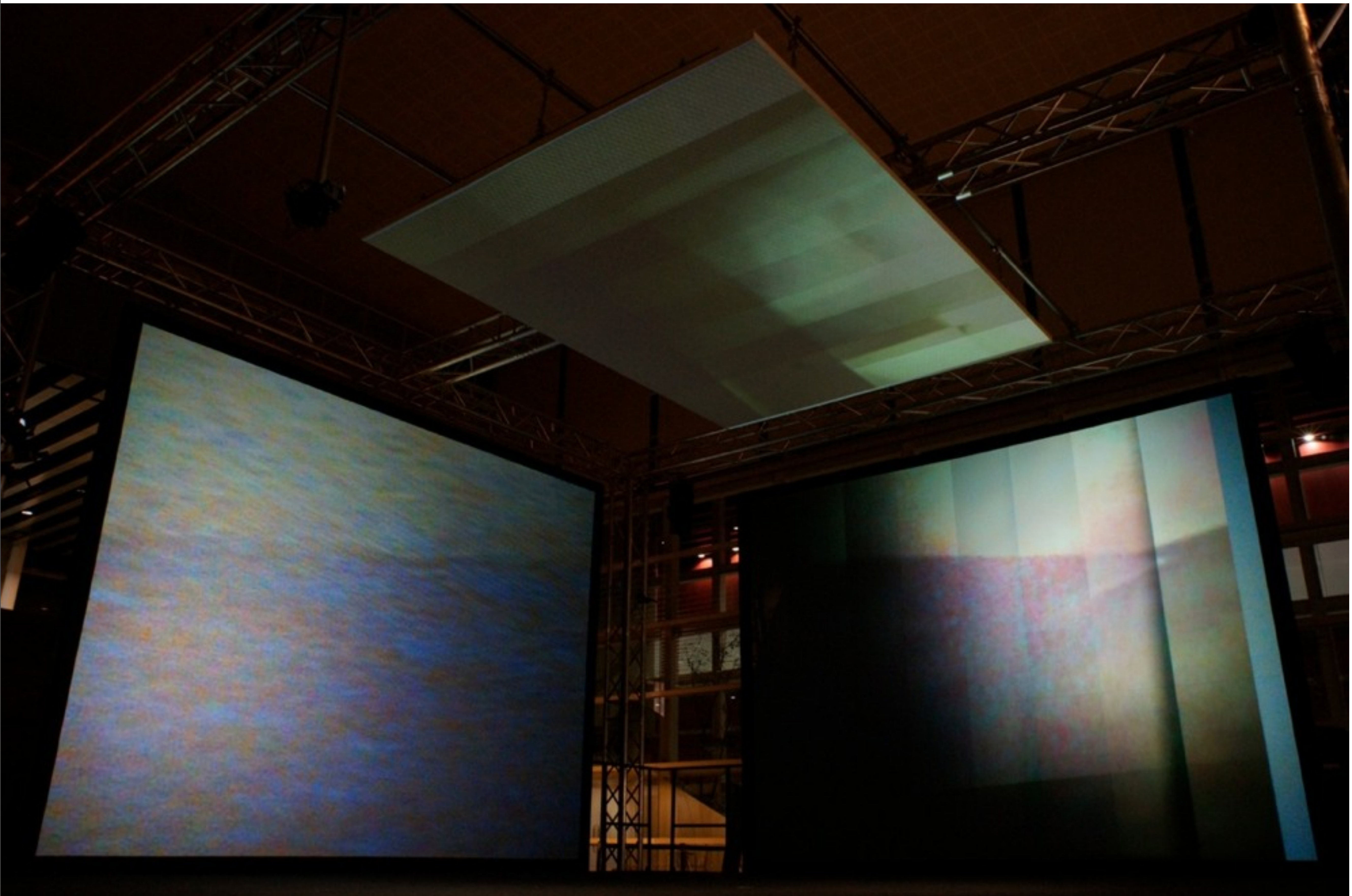
We presented this MTM for the first time at the Yamaguchi Center for Arts and Media in March, 2010. The machine consists of three screens: right, left and above, displayed at the corner of a cubic skeleton 5.400 meters per side. Fifteen cameras attached to each pole of the skeleton photograph things that happen in the venue. These images are decomposed into frames and chaotic neural dynamics control other macro processes that combine, reverse and superpose them to make new frames.



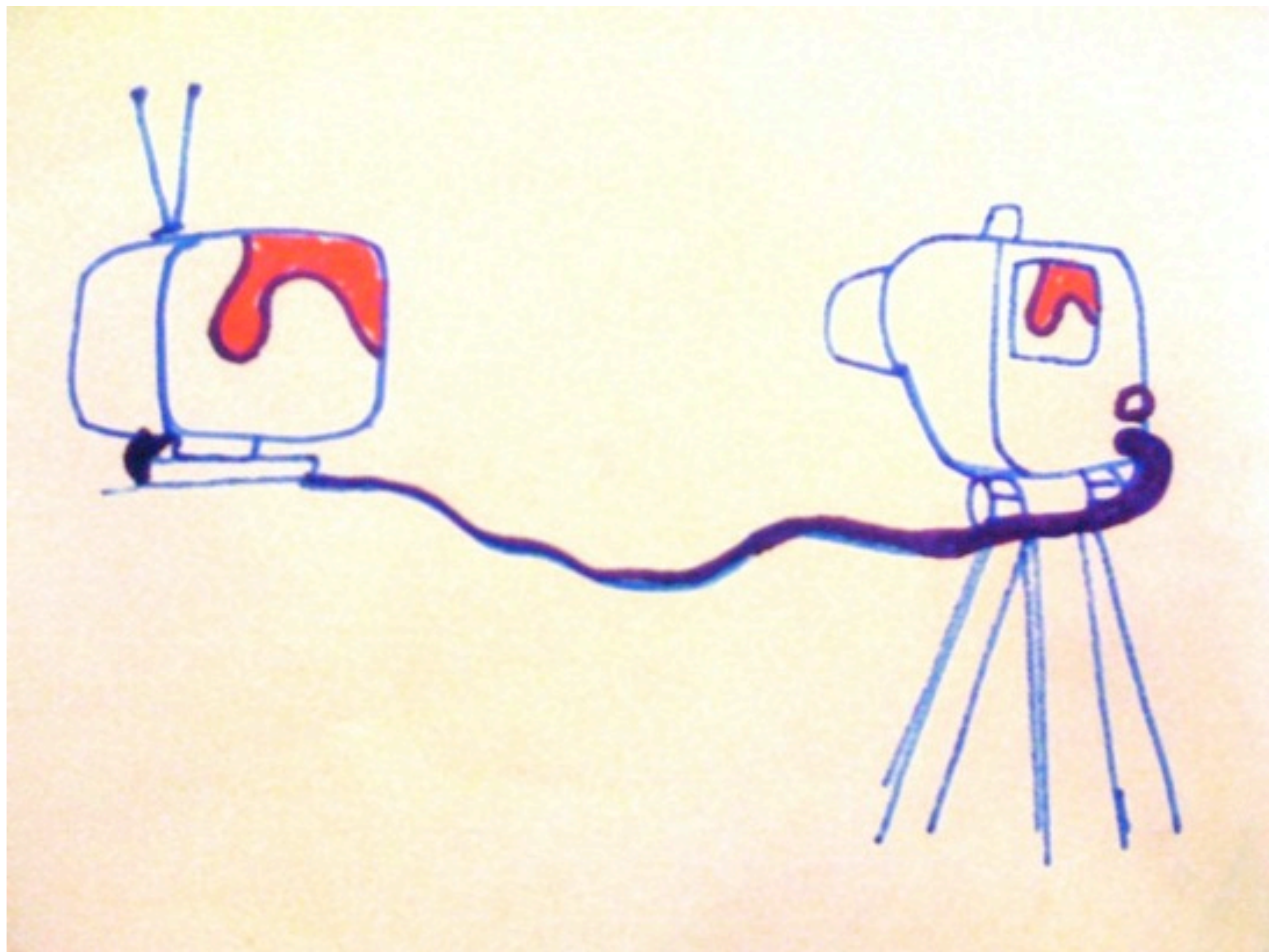
Intake images from cameras were progressively embedded into the network's connections as a memory of the patterns. Visual images are taken in and re-played again and again with recursive modifications. The system itself is completely deterministic and uses no random numbers, but it shows different images depending on its inherent instabilities, environmental lighting conditions, movement of people coming into the venue and the system's stored memory.



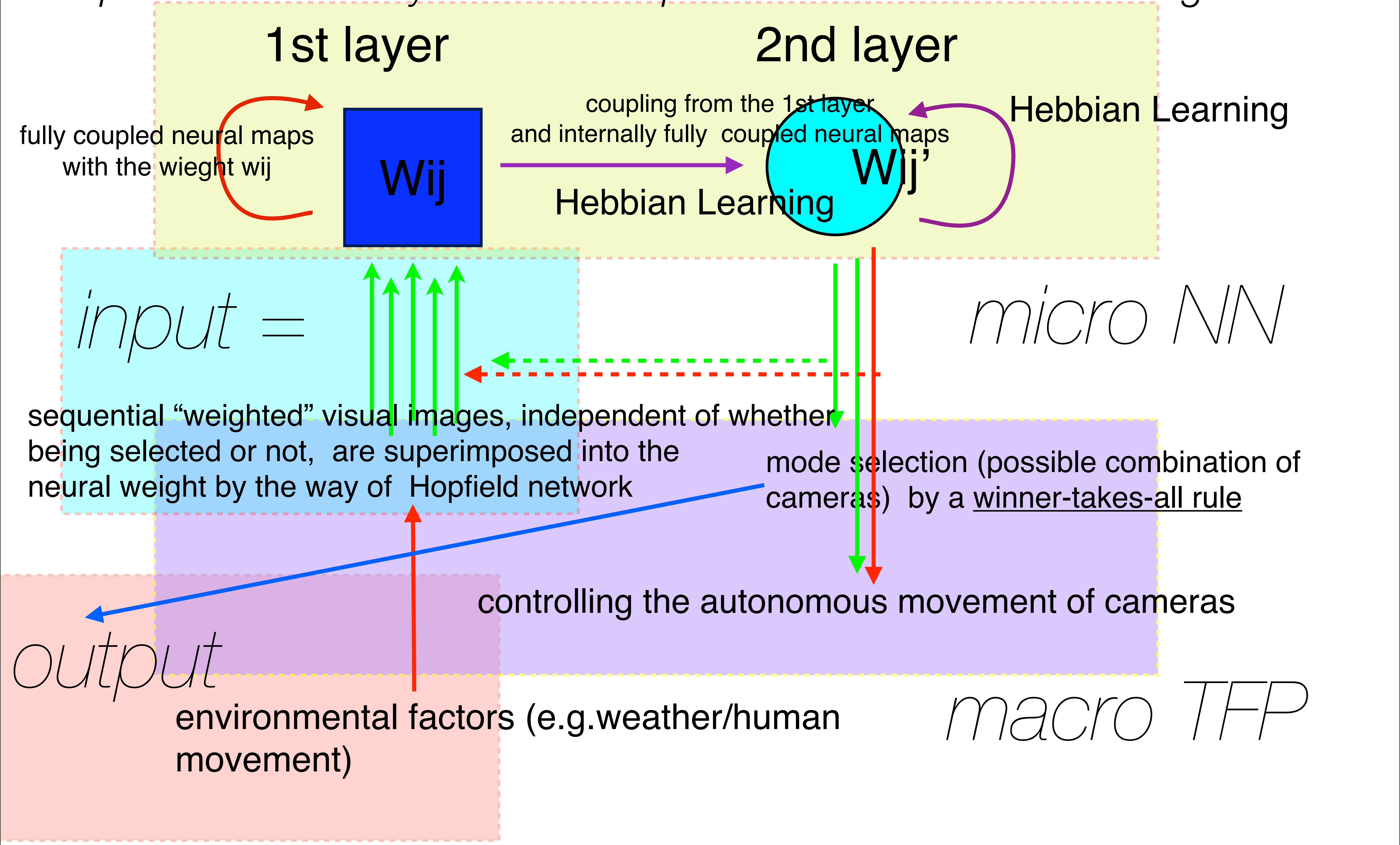




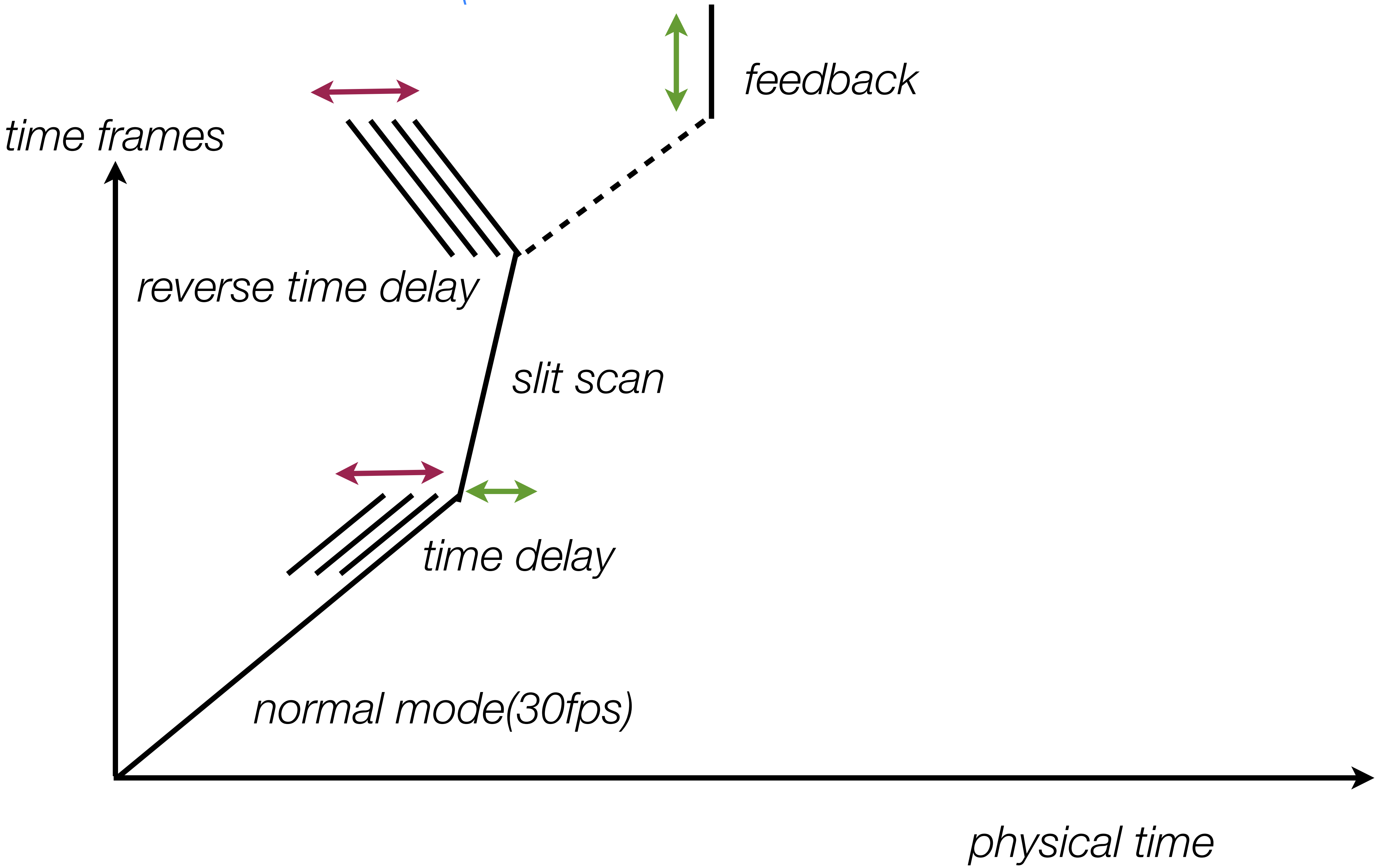
Video Feed Back



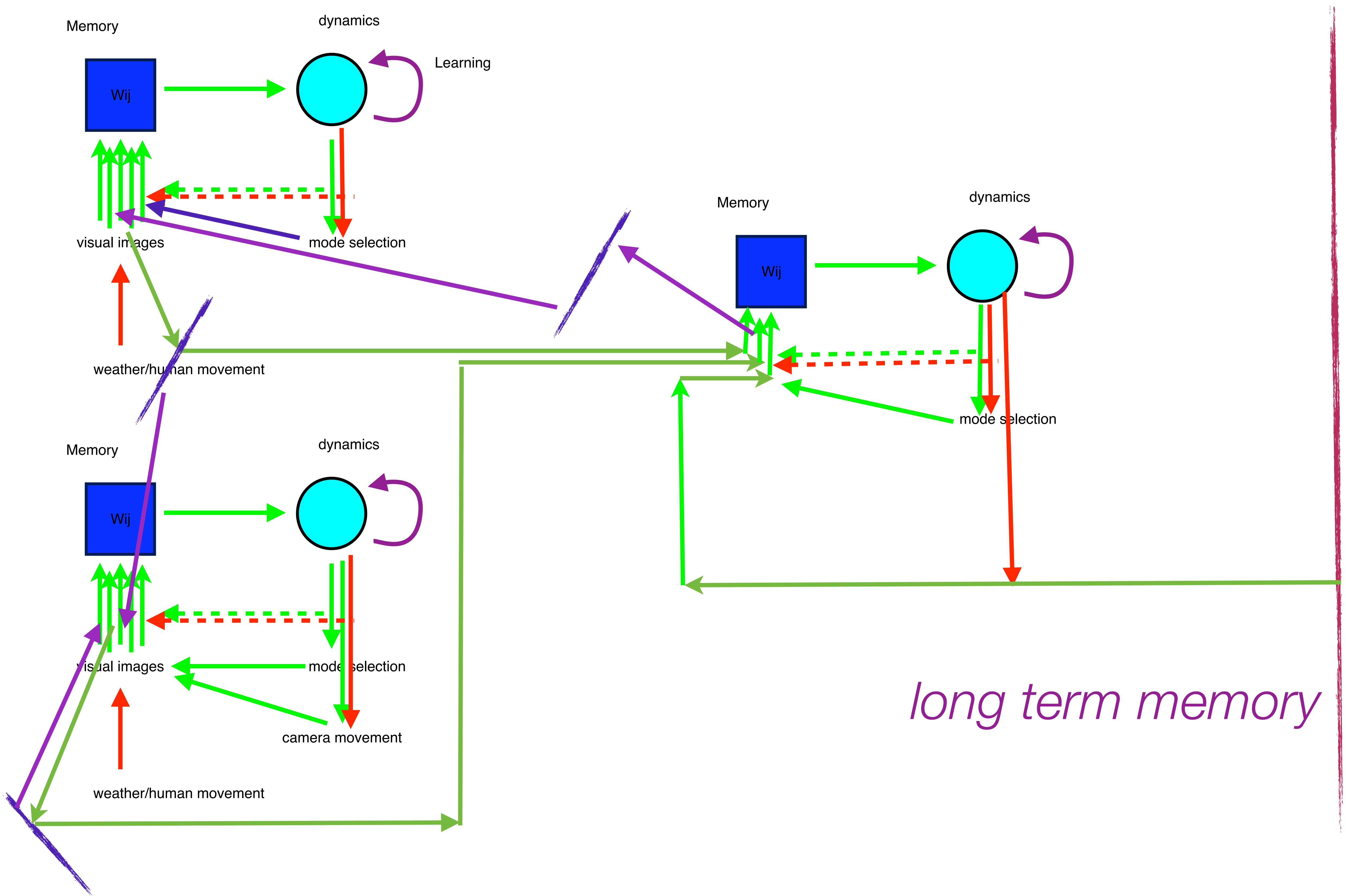
A basic architecture: 2 layered neural networks.Visual inputs are to change the parameters of a system and outputs are a selected visual image.



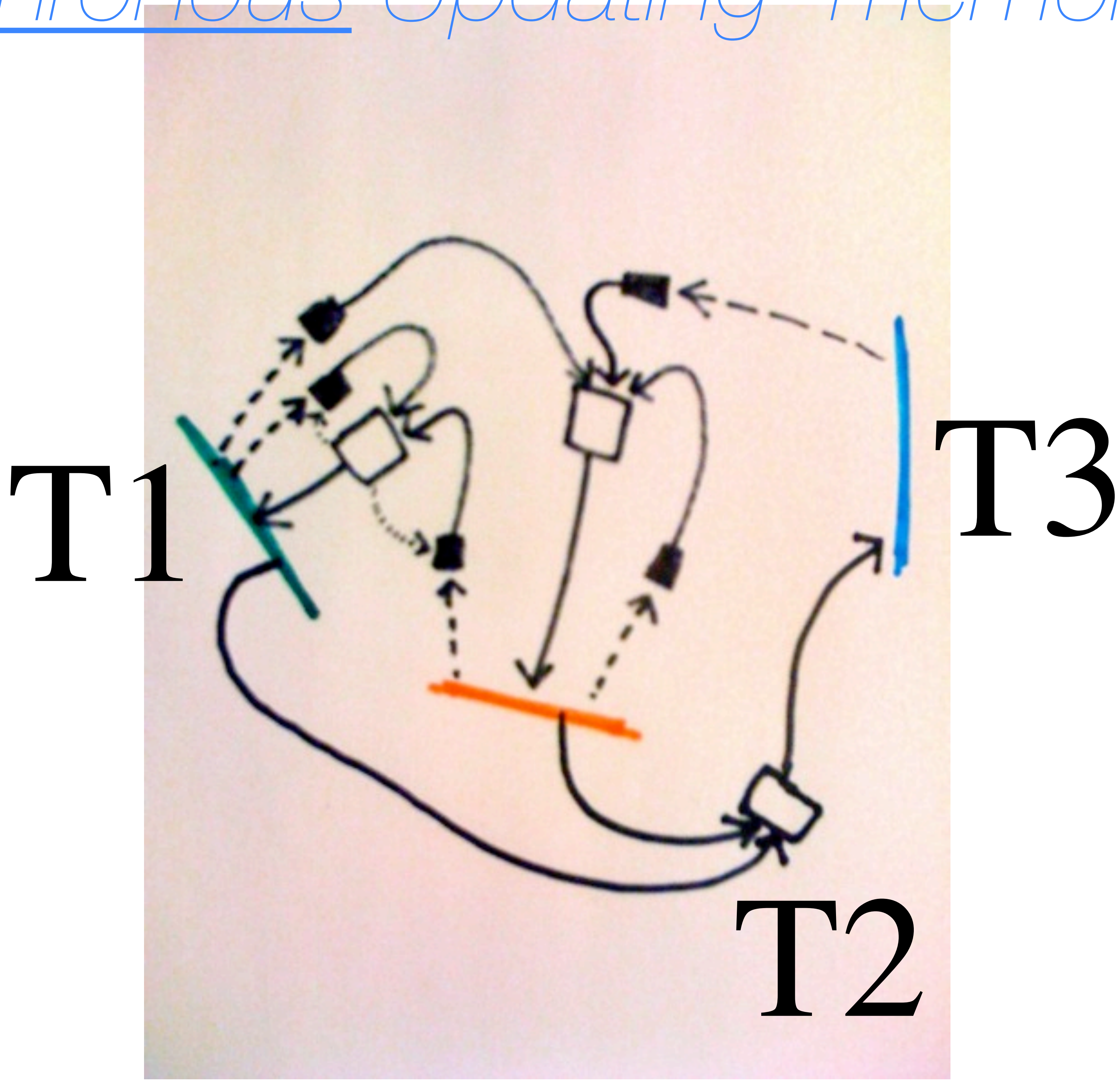
macro TFP(Time Frame Processing)



Three module networks are coupled asynchronously.



Asynchronous Updating memory

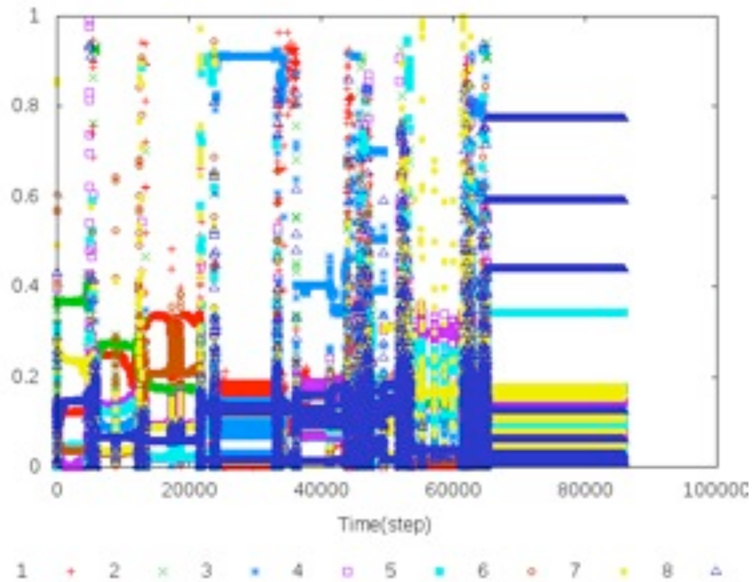


Remark!

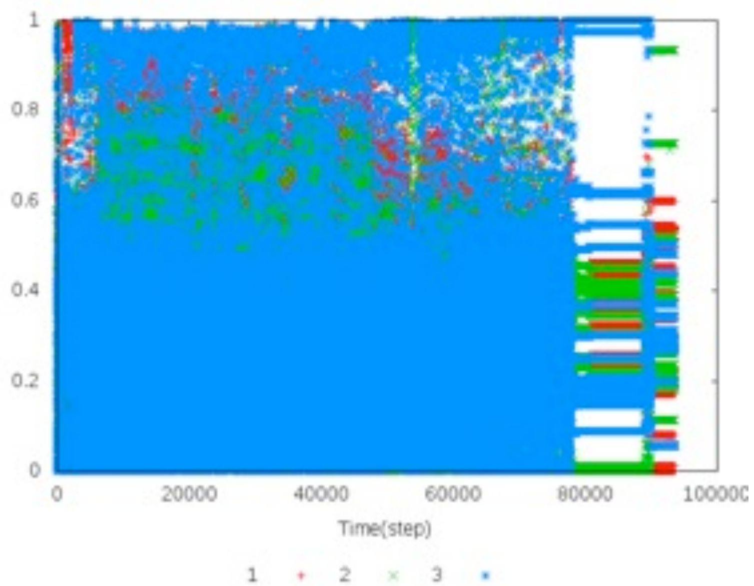
This is not a large chaotic dynamical system that updates the visual inputs randomly. Different from the mere chaotic system, MTM is designed as life-like system since its autonomy (autonomous dynamics) is only sustained by coupling with the environment. Namely, we claim that MTM is ”artificial life”, since we design it to

i) retrieve information from its environment,
ii) memorize it in the form of the Hopfield type learning which tunes the parameters of the overall dynamics,
iii) generate ”episodic memory” ,
vi) change the network structure by the way of the Hebbian dynamics continuously
v) organize its overall dynamics as adaptation to the environmental changes.

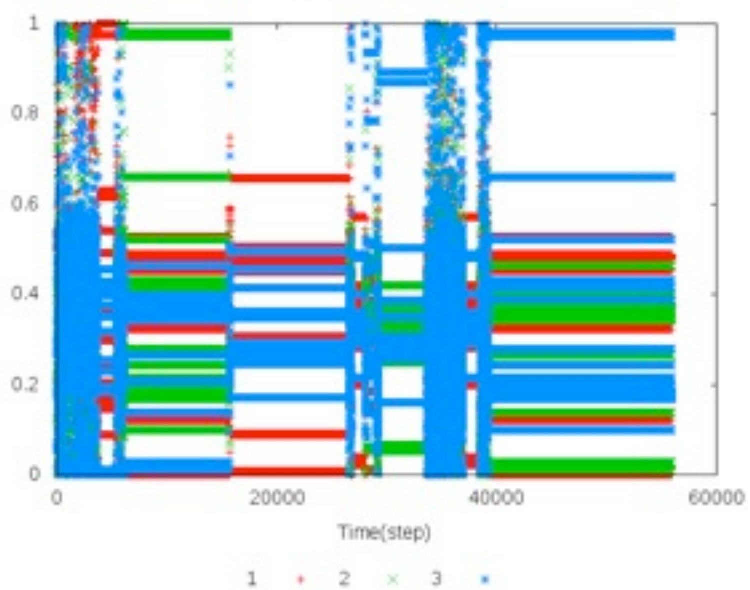
1. Temporal evolution



Time steps



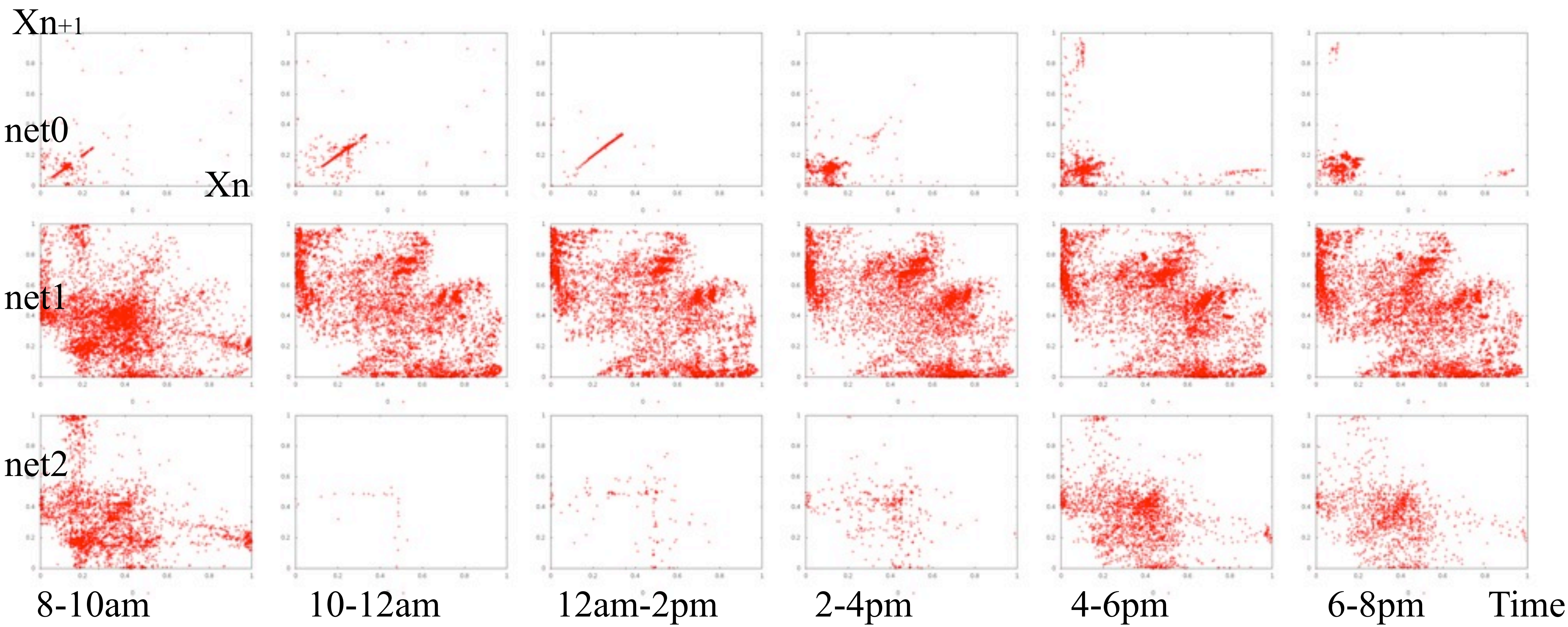
Time steps



Time steps

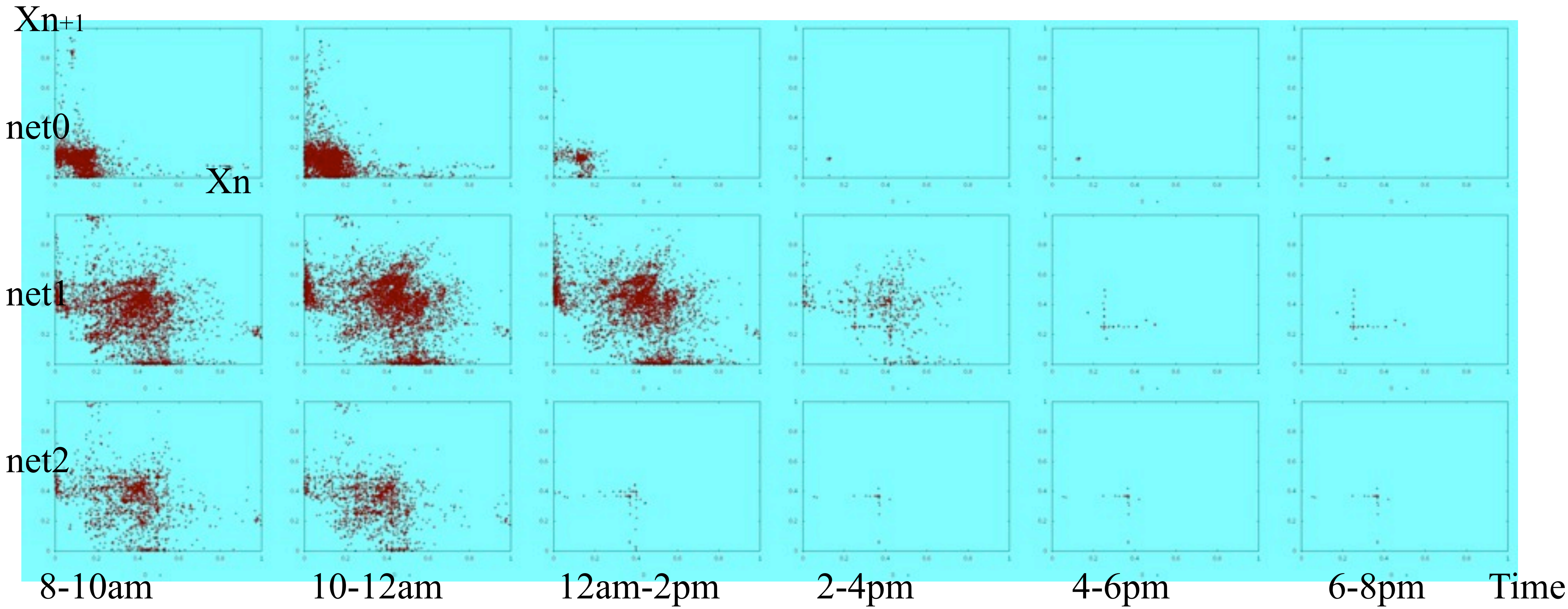
Time evolution of neural outputs for each modular network on the 7th of April 2010.
A neural state from the 2nd layer are superposed on the same figure.

2. Changes of return maps



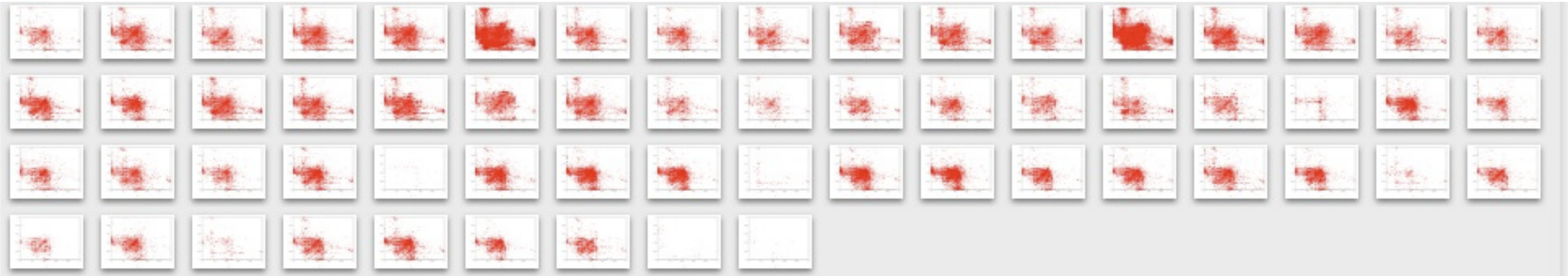
Time evolution of return maps (of a neural output) of each module network on the 7th of April 2010.

but sometimes MTM became quiet at the end.



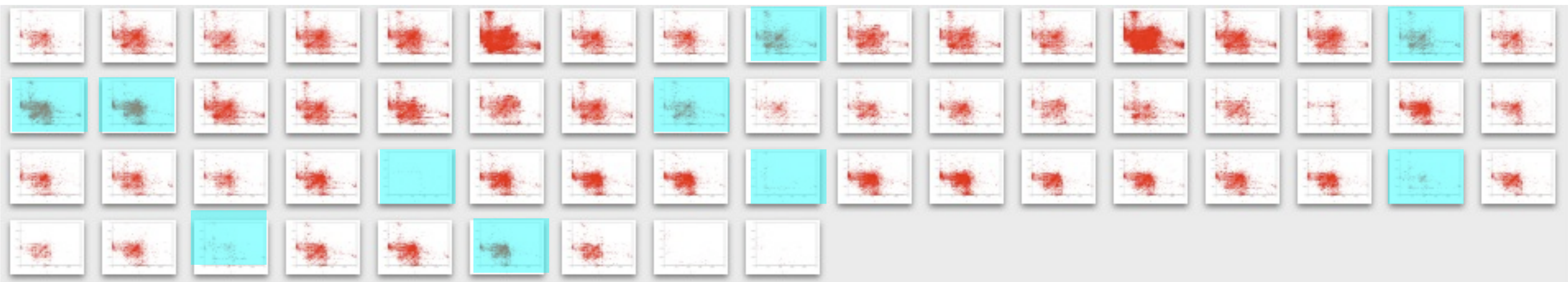
Time evolution of return maps (of a neural output) for each module network on the 1st of April 2010.

diary (3.25-6.02)



net0

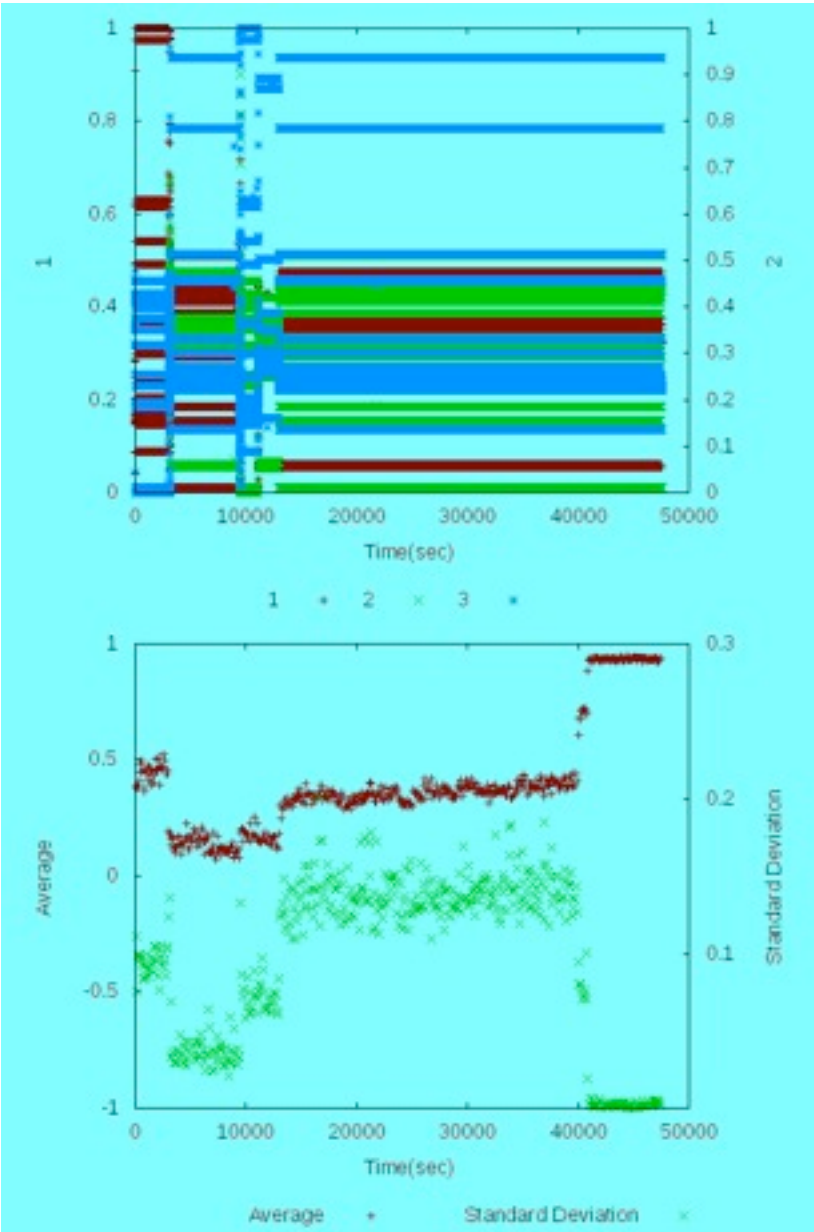
diary (3.25-6.02)



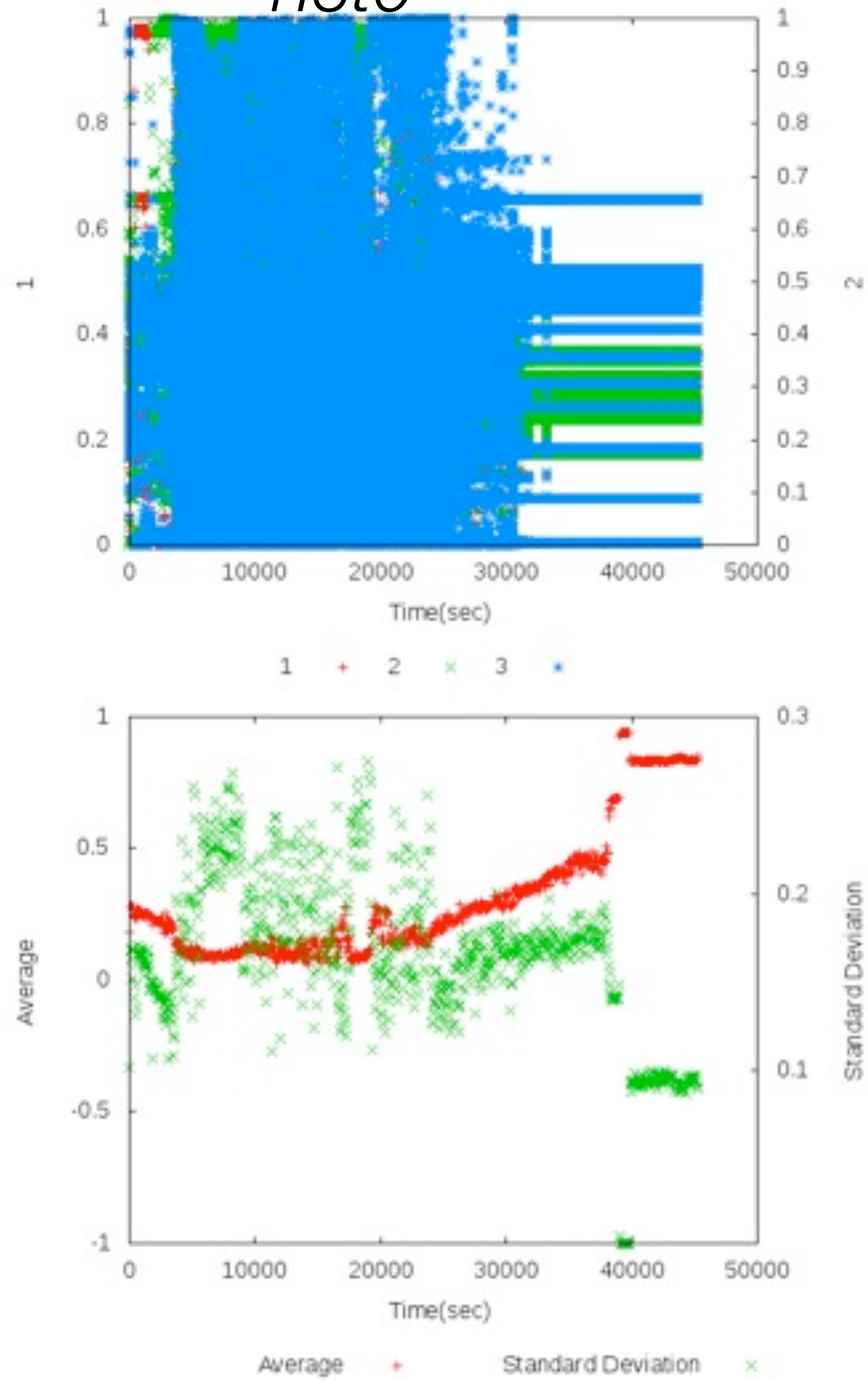
net0

3. Temporal evolution of weight average and the variance

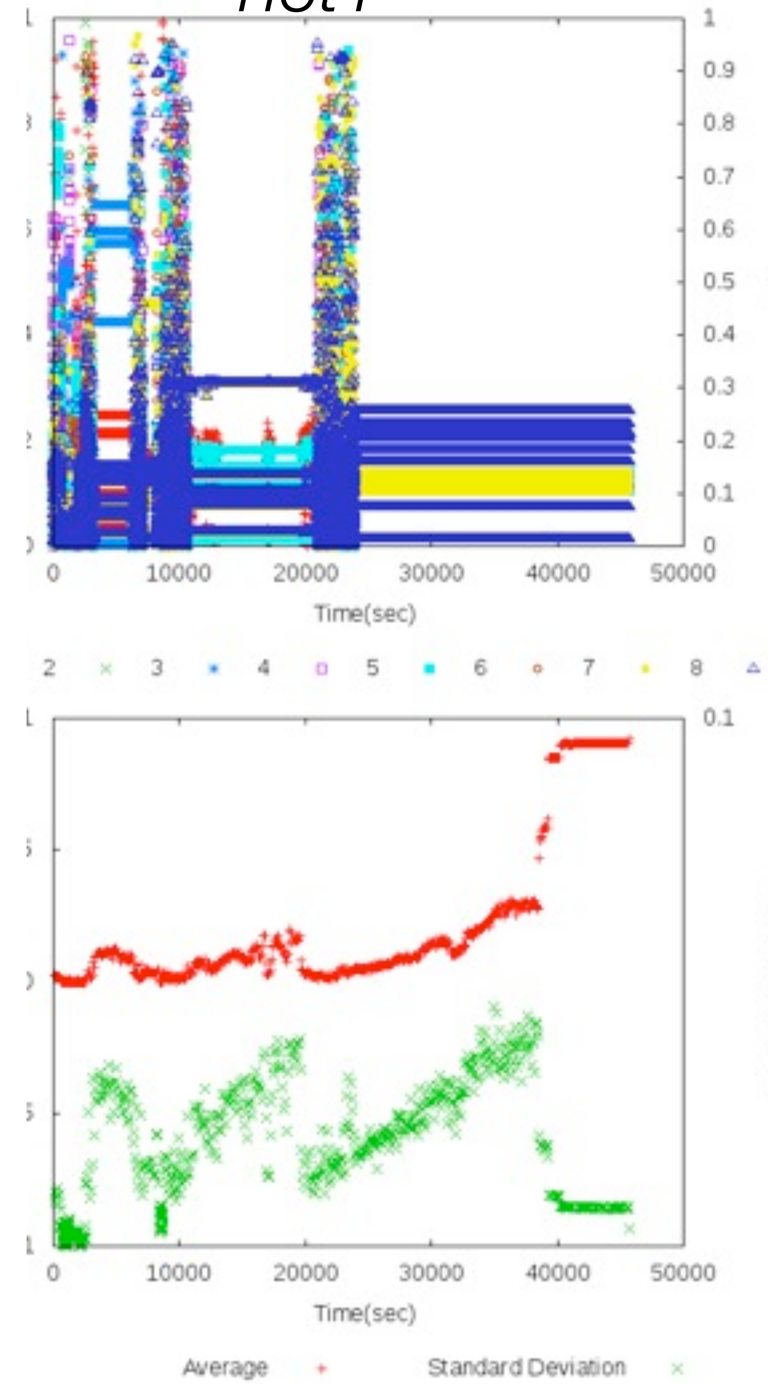
net0



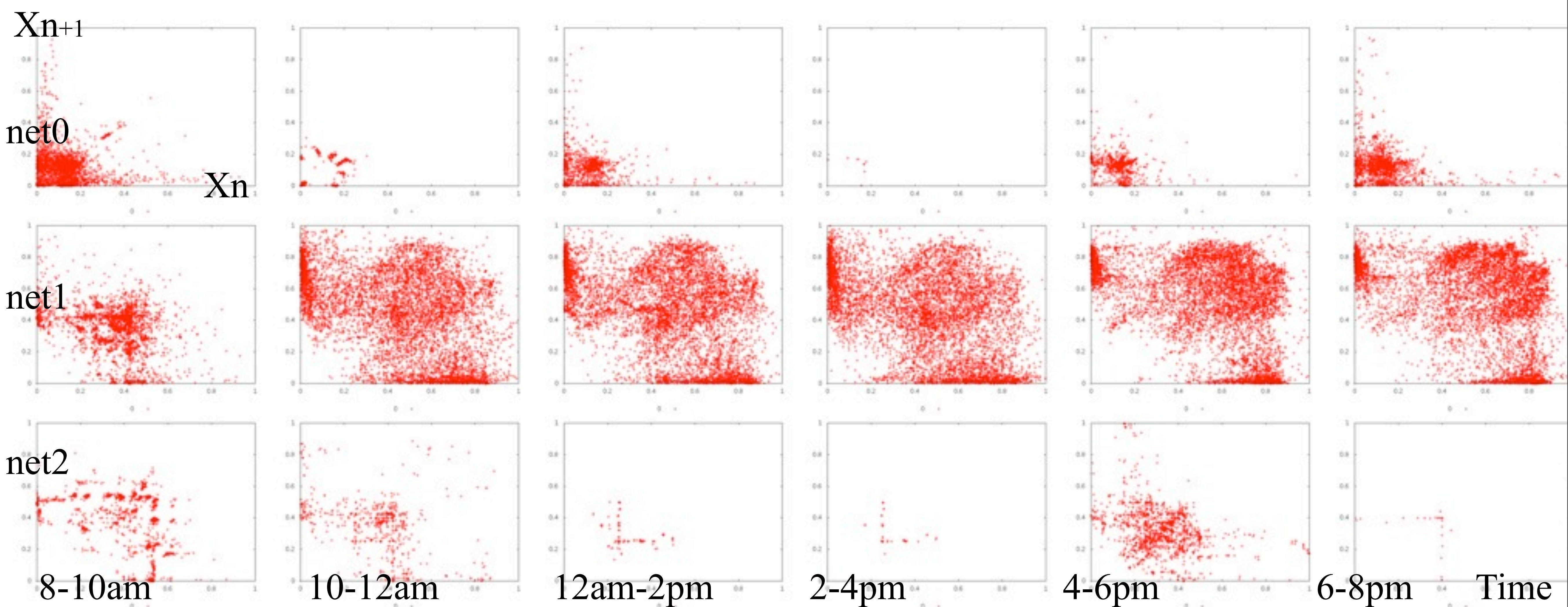
net0



net1

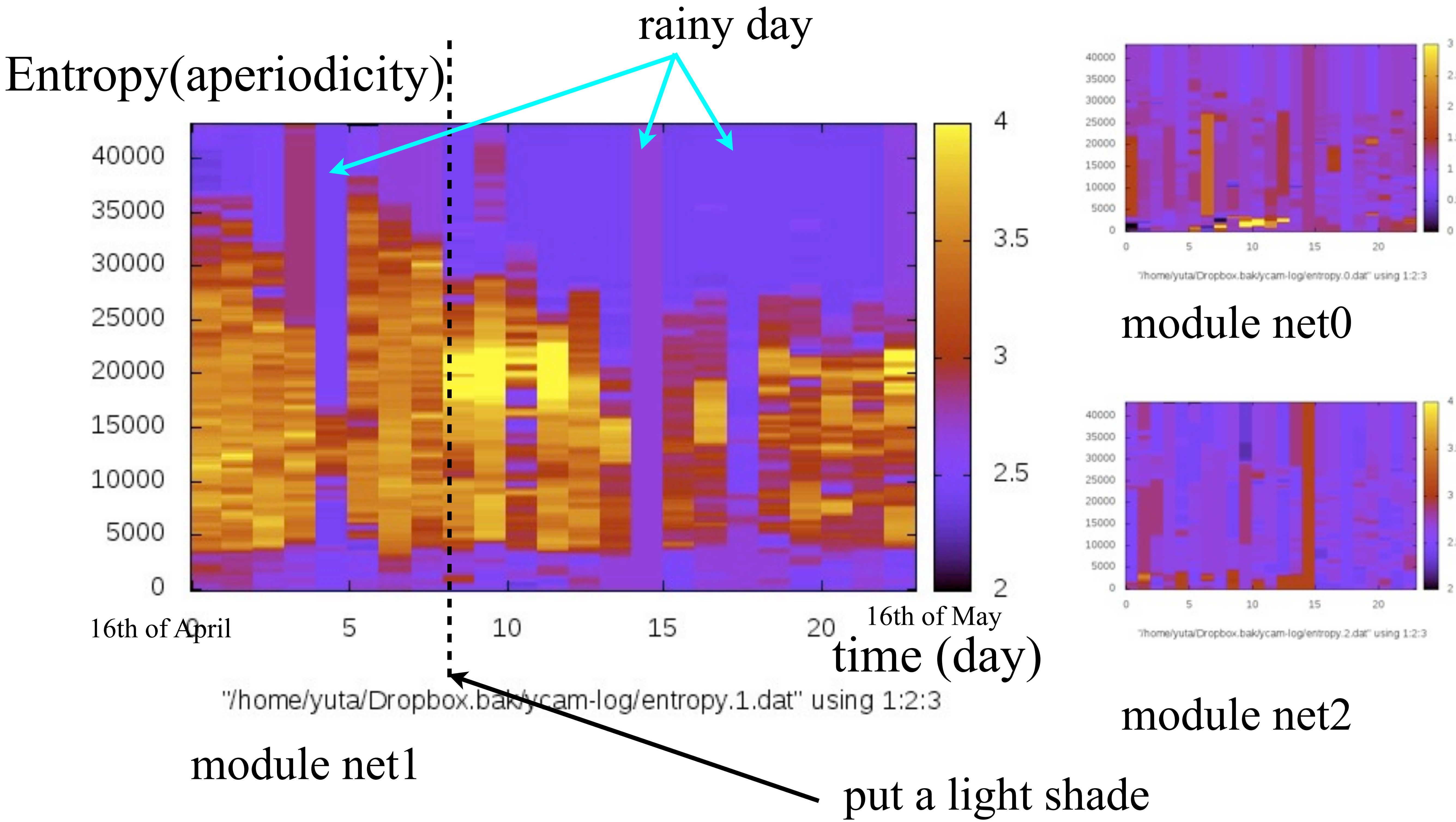


Mutual completion of modular networks



Time evolution of return maps (of a neural output) for each module network on the 1st of April 2010.

4. Characterizing dynamics



Summary and discussions

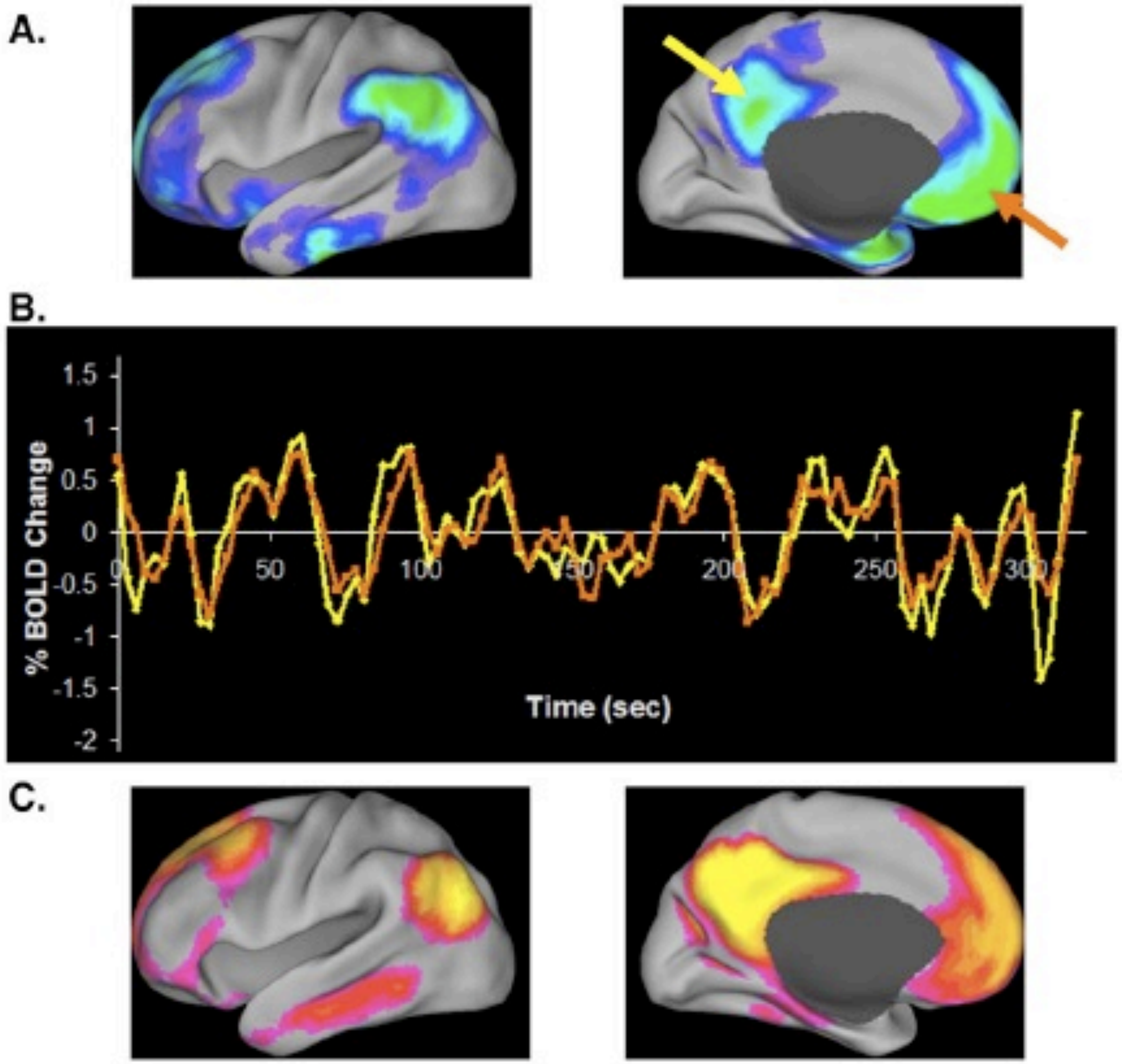
We here designed MTM in the sense of out-and-out constructing artificial life in the real world. The main mission is to make MTM not to die but sustains its adaptive behaviors. MTM sometimes it eventually loses the reversibility to come back to the "alive state" , but sometimes not. Where the sustainable and robust dynamics comes from?

1) We should carefully prepare a sensory network of that site (this time they are intake cameras), where we need to design the interface/environment .
2) Experience (slow time dynamics) and Learning (fast time dynamics) time scales should be carefully designed.
3) A system must consist of asynchronous modules in real time scales.

This sustainability is what I think as mind. We have done/ and planning to make different versions of MTM with sound sensory arrays.


MTM died on the 30th of May (born in the 20th of March).

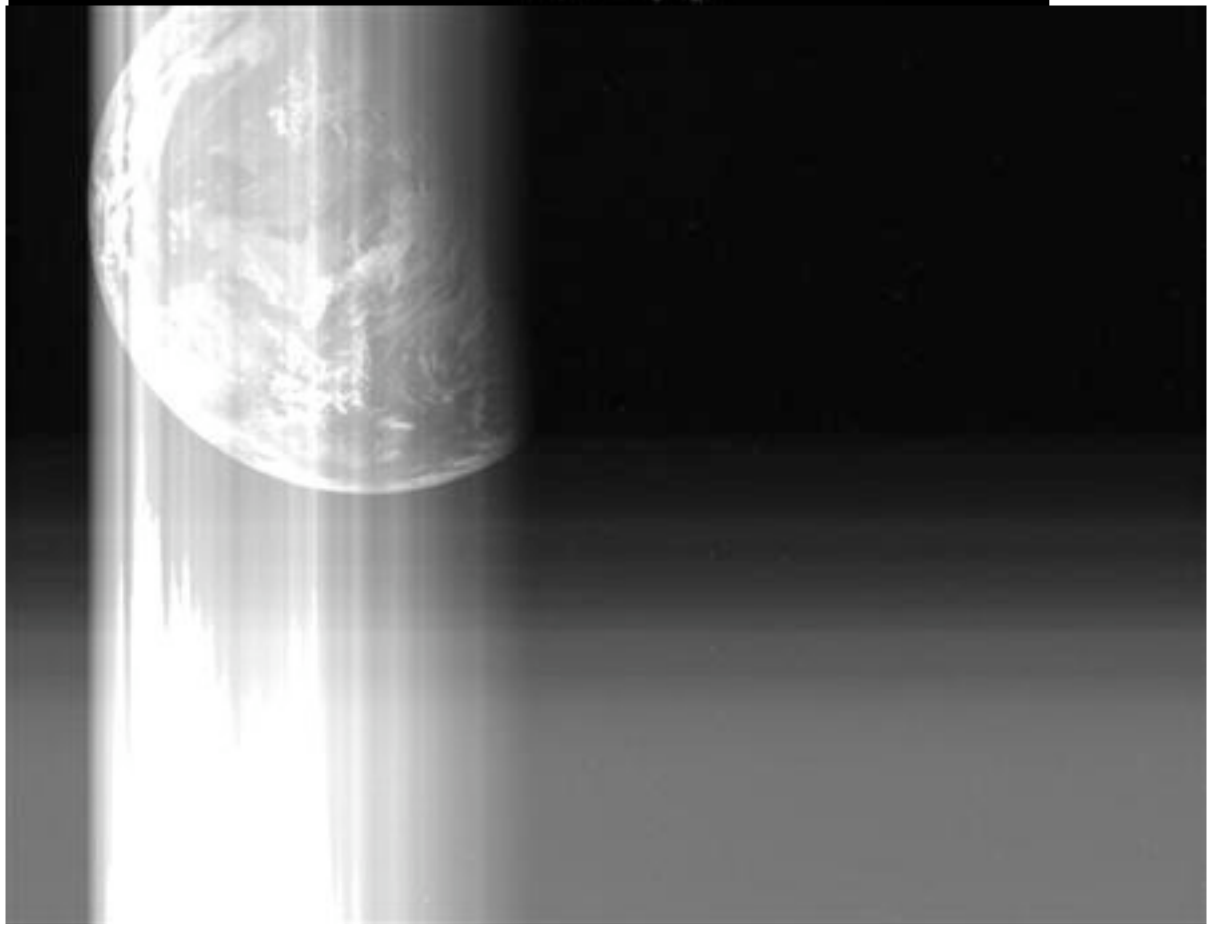
Stretching and Folding in the brain



Raichel's default network in the brain system.

Marcus E. Raichle[a,b,c,*] and Abraham Z. Snyder, "A default mode of brain function: A brief history of an evolving idea", NeuroImage 37 (2007) 1083–1090.

A story of the surveillance satellite Hayabusa



Life/consciousness emerges in a distributed sensory network

Different more complex sensory network do organize its own conscious states, which I am working on now.

cf. pingpong project with Mizuki Oka

collaborating with

** Yuta Ogai (univ. Tokyo)*
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micro NN(1st layer)

Coupled Chaos Neural state equation (of the map version) by Nozawa,H. (chaos 2(3) 1992 pp.377-386) This network can search the global minimum of the energy landscape which is given by

$$E = -\frac{1}{2}\sum_{i=1}^{N}\sum_{i=1}^{N} w_{ij}v_i v_j - \sum_{i=1}^{N} I_i$$

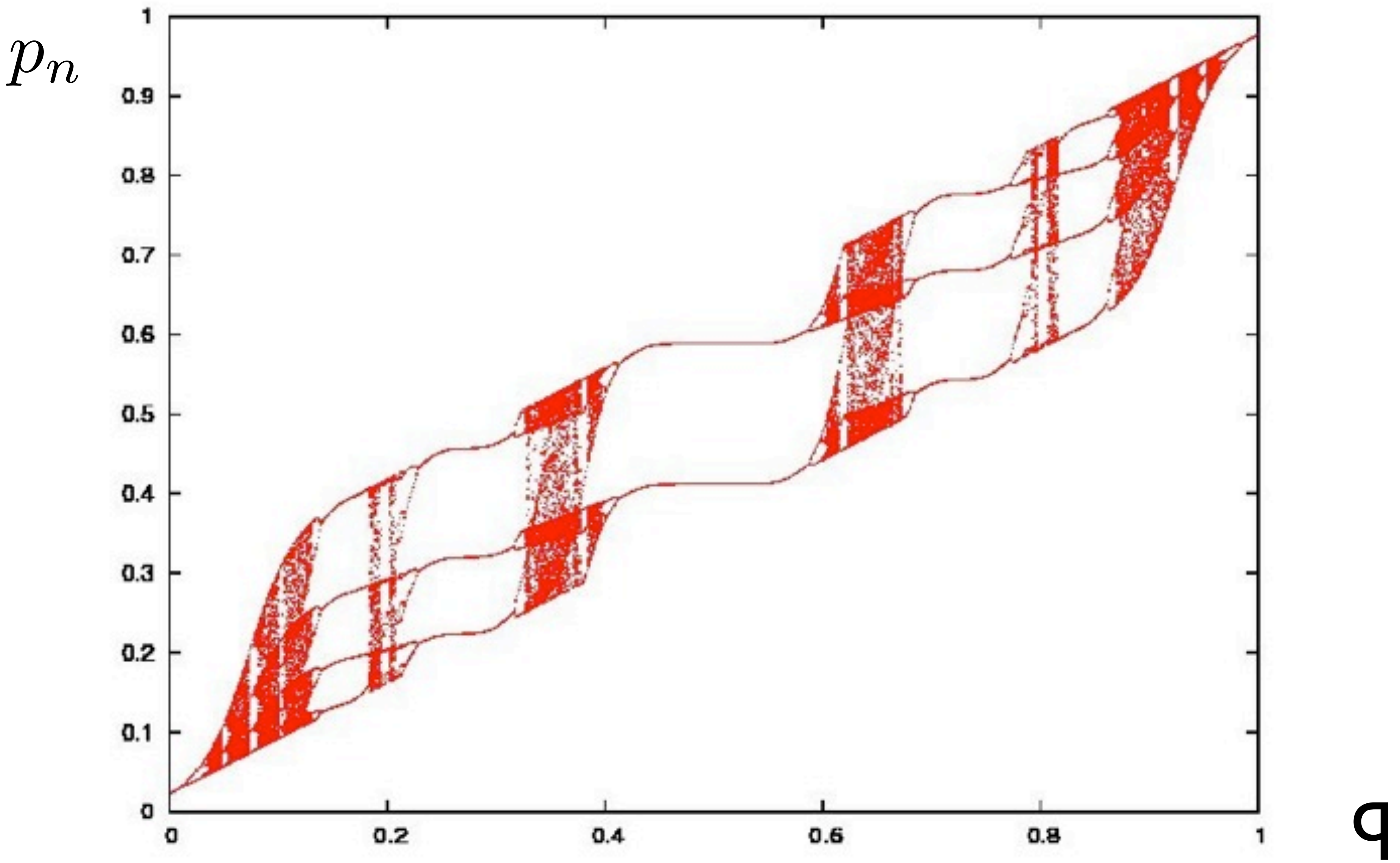
$$w_{ij} = \sum_{s=1}^{M}(2V_i^s - 1)(2V_j^s - 1)$$

where these v is the neural state filtered by the Sigmoid function g(u) and the capital V with the subscript s is the state of the embedded pattern. The way the system embeds the memory is called " Content Addressable memory (CAM)".

Chaos Neural state equation (of the map version) by Nozawa,H. (chaos 1992)
the attractor sets are bounded between p' = rp and p'= rp + 1-r

$$p_{n+1} = rp_n + (1-r)(1 - \frac{1}{1 + e^{(q-p)/\beta}})$$

with r=0.7 and $\beta = 0.006$



Coupled Chaos NN

$$p_{n+1}^k = rp_n^k + (1-r)(1-\frac{1}{1+e^{(q_n^k-p_n^k)/\beta}})$$

$$q_n^k = \frac{1}{w_{kk}}(\sum_{j\neq k} w_{kj}p_j + I_n^k)$$

Therefore, memory is accumulated to change the bifurcation parameter of this coupled network.

micro NN(2nd layer)

Modified Hebbian Dynamics

$$\frac{dw_{kj}}{dt} = \gamma(\frac{dp_k}{dt}p_j - \alpha w_{kj}p_jp_j)$$