Predictive and Sparse Neural Fields
in high dimensional dynamic environments

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and colleagues!

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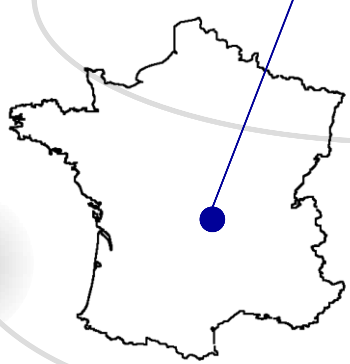

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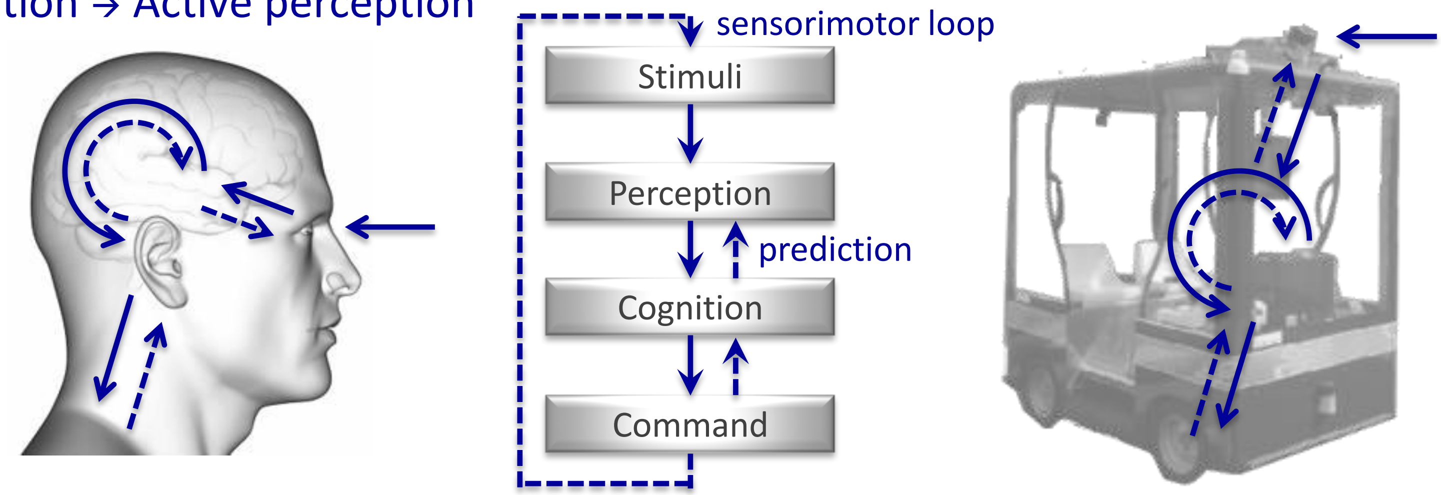
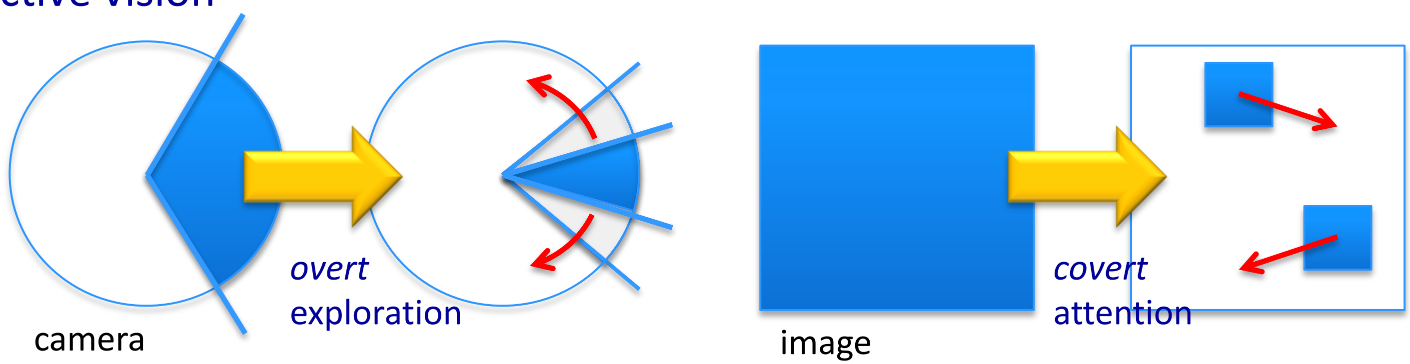
Active perception in humans and robots

Perception → Active perception



e.g. Active vision

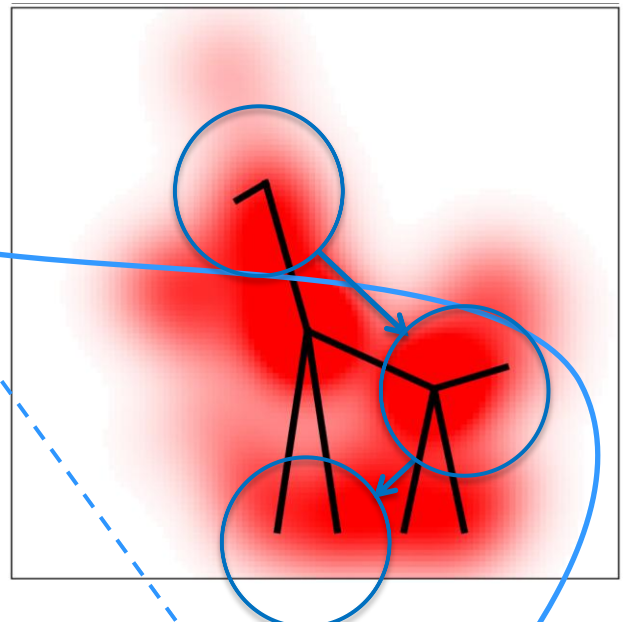


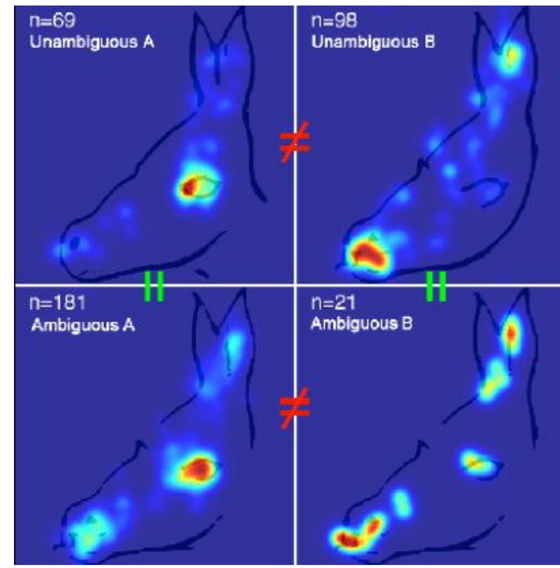
Giraffe

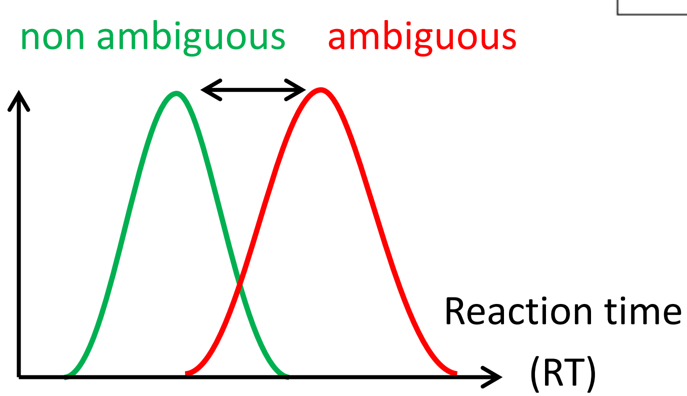
Dog

Stick figures (stimuli) from

[Olman & Kersten, *Cognitive Science*, 2004]







START

EyeTracker (saccade ≈ information)

[Kietzmann et al., *PLOS One*, 2012]

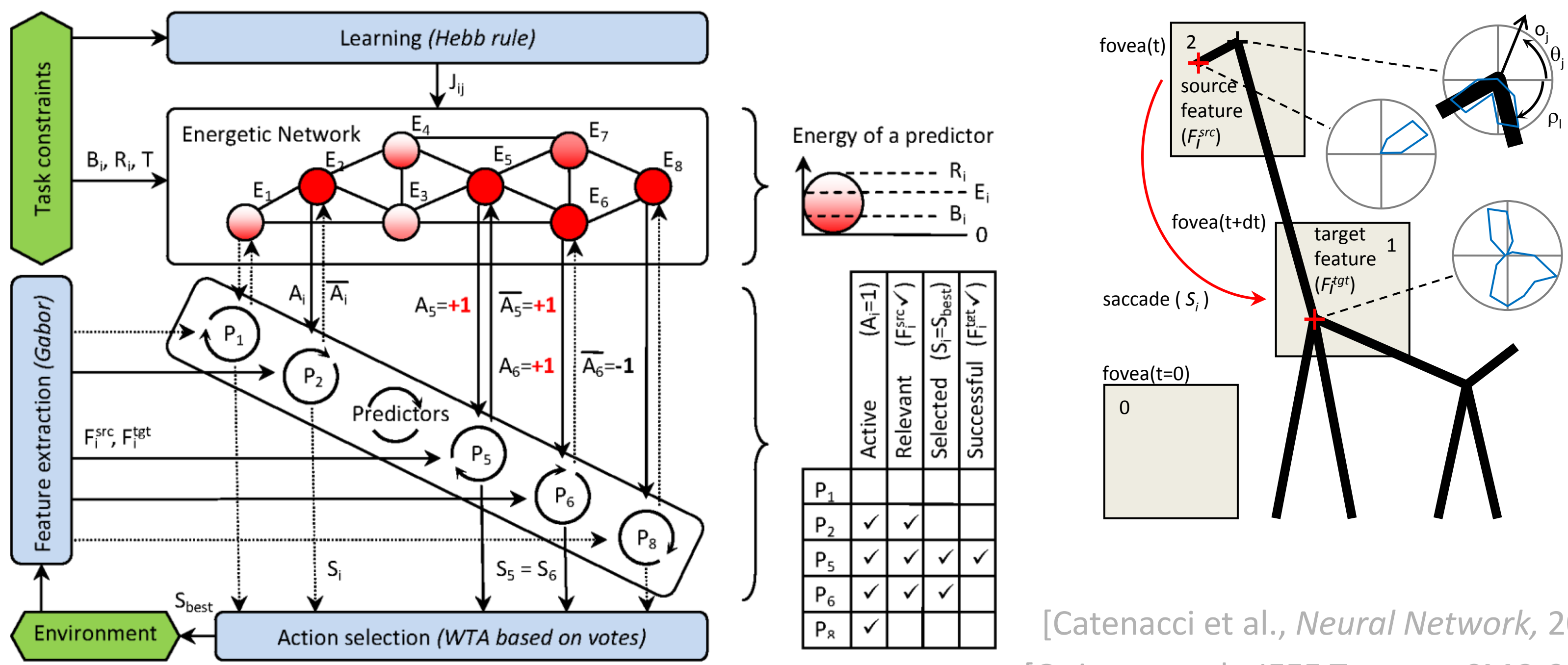
+

MouseTracker (movement ≈ decision)

[Freeman et al., *Front Psychol*, 2011]

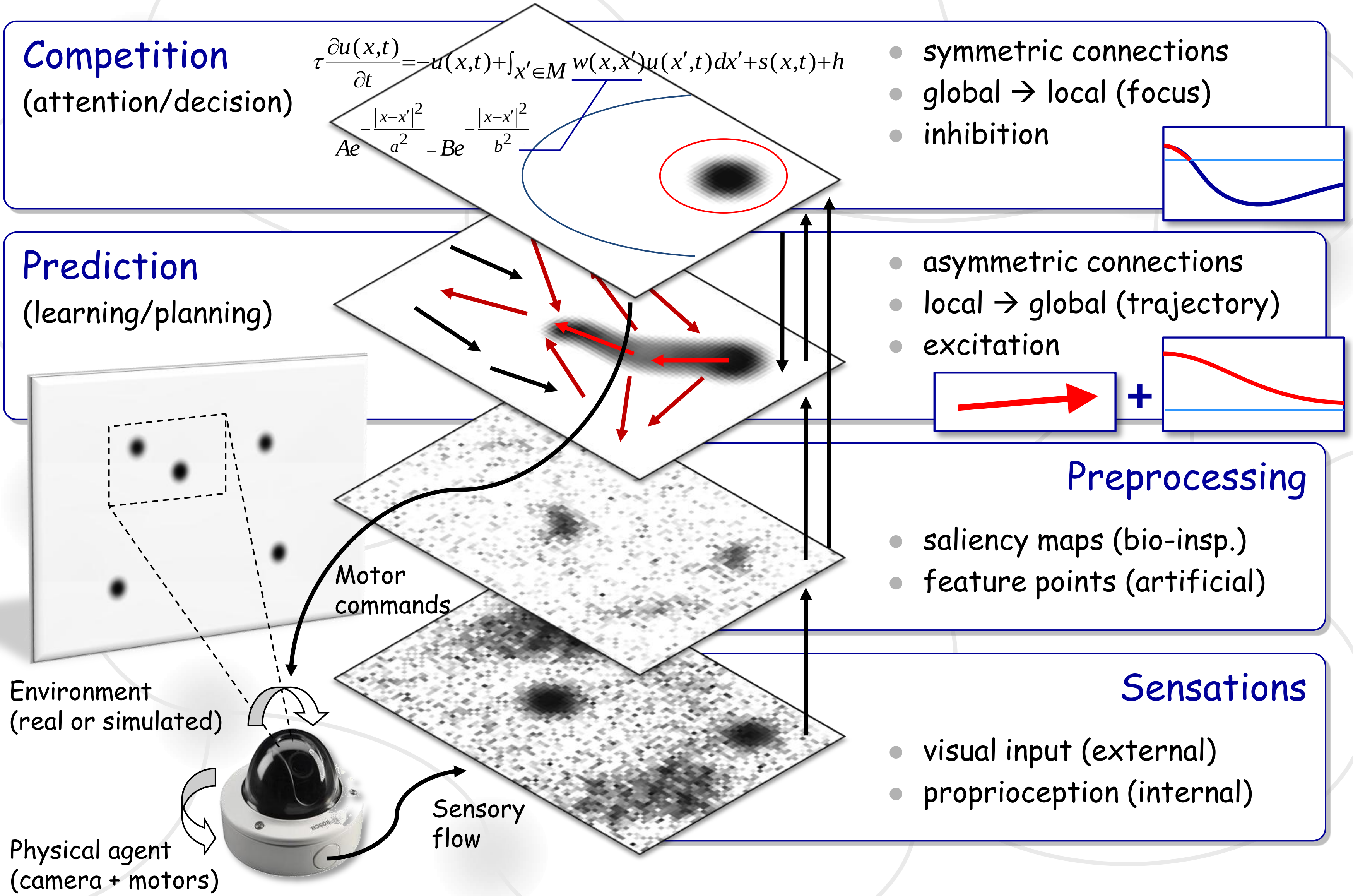
Dynamical decision-making involving prediction

- **Various domains** (motor control, categorization, stereotypes…)
- **Various models** (neural networks, classifiers, Bayesian, DNF)



[Catenacci et al., *Neural Network*, 2014]

[Quinton et al., *IEEE Trans.on SMC*, 2013]


Competition
(attention/decision)
$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x') u(x',t) dx' + s(x,t) + h$
$Ae^{-\frac{|x-x'|^2}{a^2}} - Be^{-\frac{|x-x'|^2}{b^2}}$
symmetric connections
global → local (focus)
inhibition
Prediction
(learning/planning)
asymmetric connections
local → global (trajectory)
excitation
+
Preprocessing
saliency maps (bio-insp.)
feature points (artificial)
Sensations
visual input (external)
proprioception (internal)
Motor commands
Environment (real or simulated)
Physical agent (camera + motors)
Sensory flow

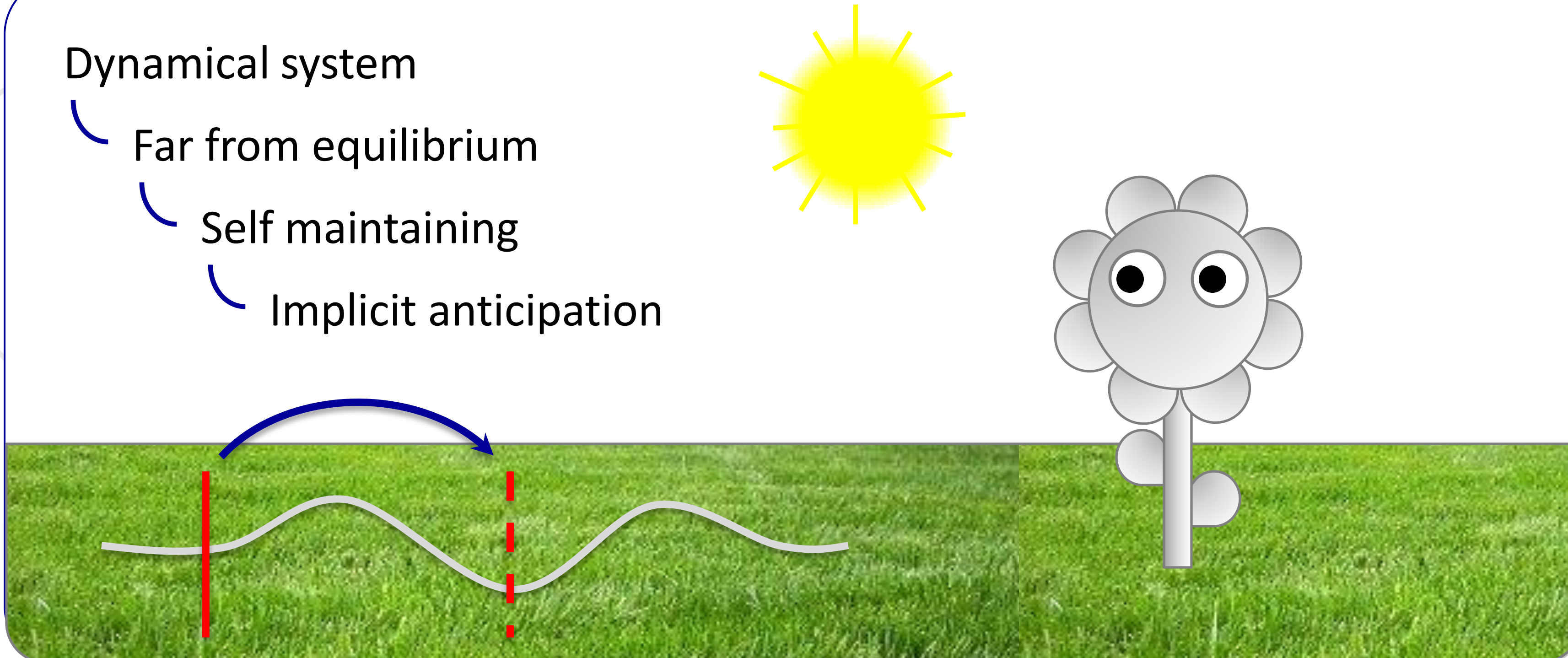
1. Introduction — One of many examples ? — Psycho/robotics section

2. Focus on anticipation — Why bothering so much ? — Philo/genetic section

3. Predictive Neural Field (PNF) — How to integrate it in DNF ? — Neural dynamics section

4. Sparse Neural Field (SNF) — With many dimensions ? — Mathematics section

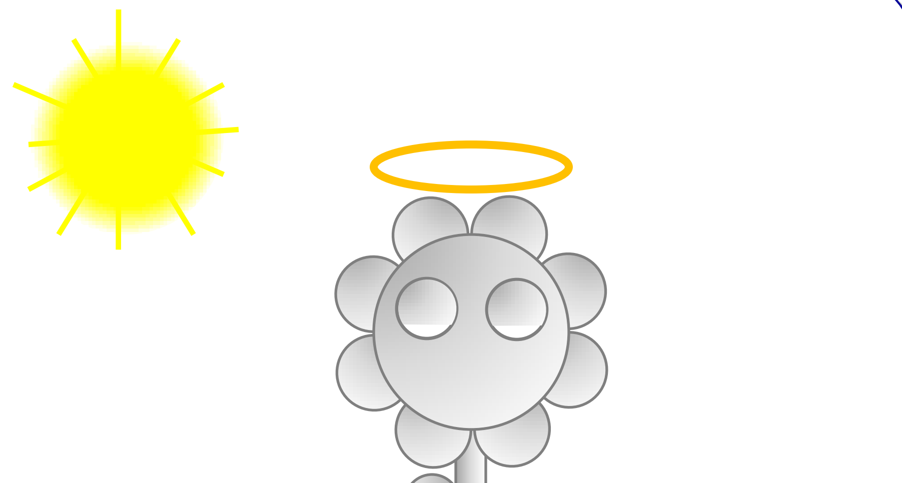
- Dynamical system
  - Far from equilibrium
    - Self maintaining
      - Implicit anticipation



- Continuously adapt to the environment
  - Chaotic changes → react to adverse conditions
  - Rhythm/structure → synchronize by predicting changes

Dynamical system

- Far from equilibrium
  - Self maintaining
    - Implicit anticipation



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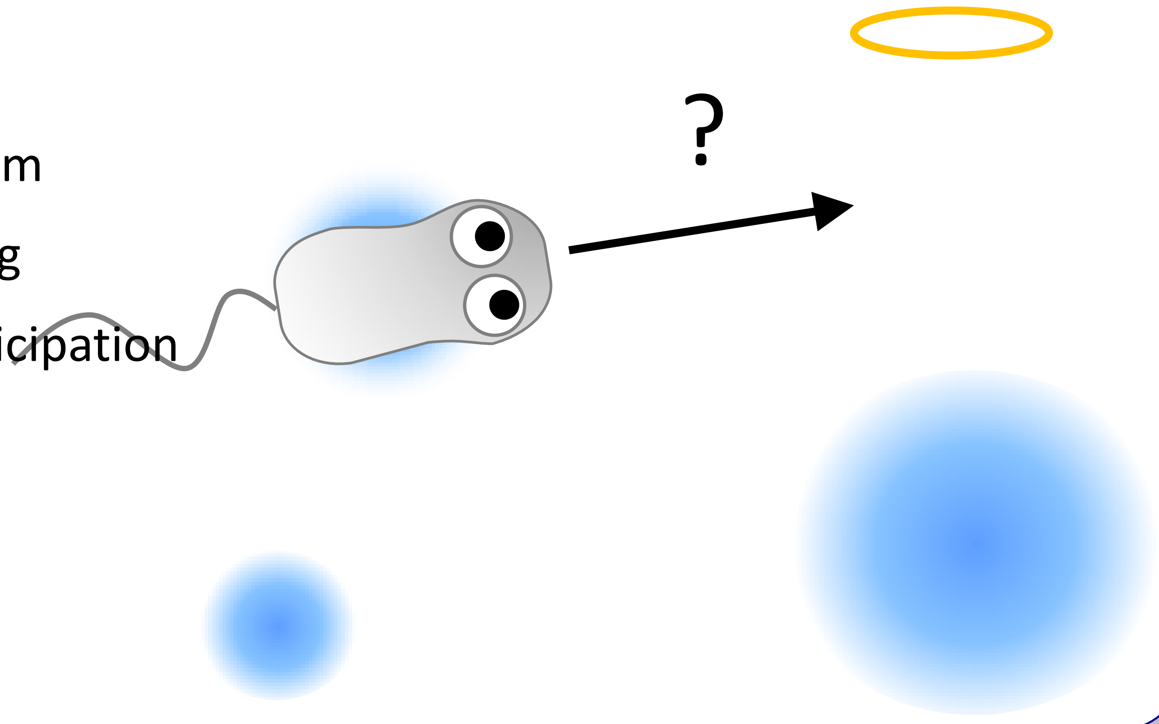
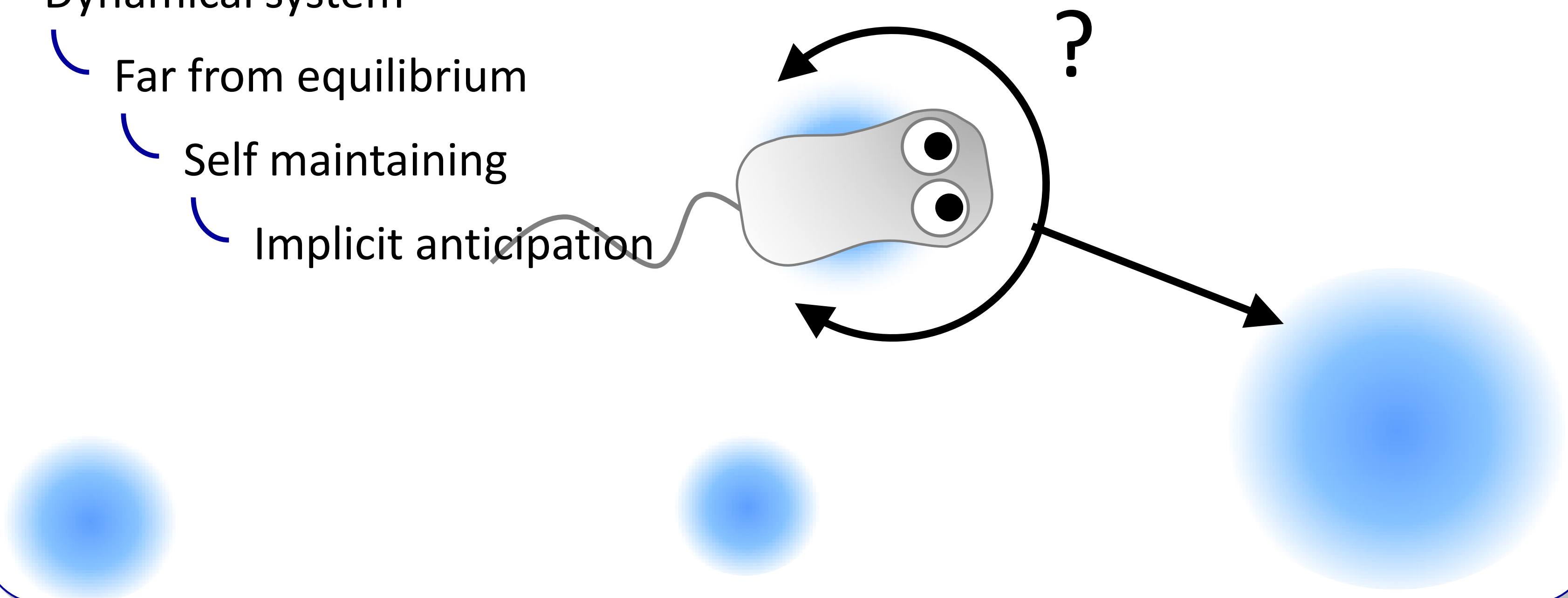


- Acting in a dynamical environment
  - Perception complexity increases with possible actions
  - Need to take genetically unpredictable choices anytime

Dynamical system
- Far from equilibrium
  - Self maintaining
    - Implicit anticipation



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Dynamical system
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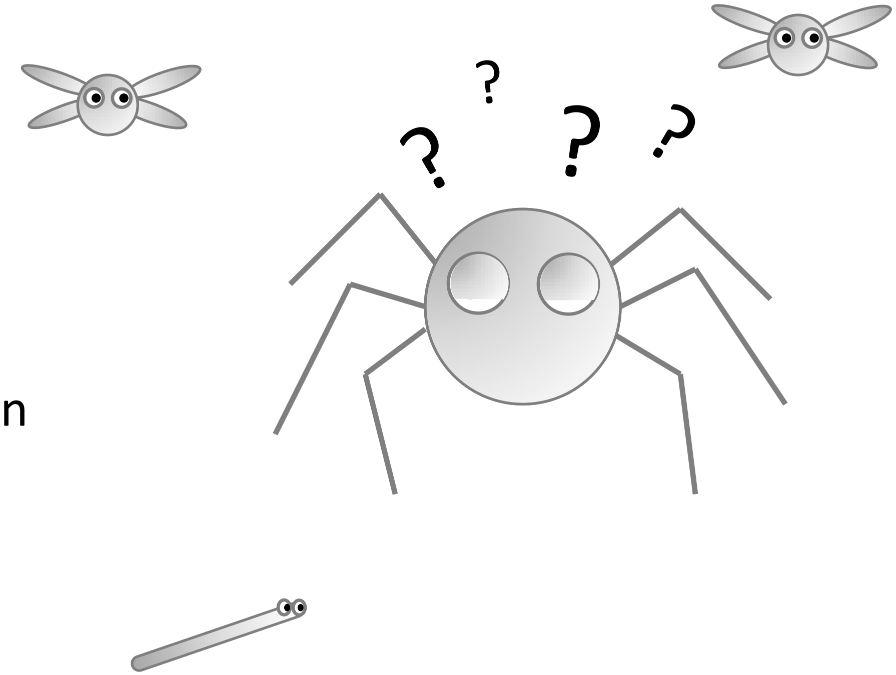
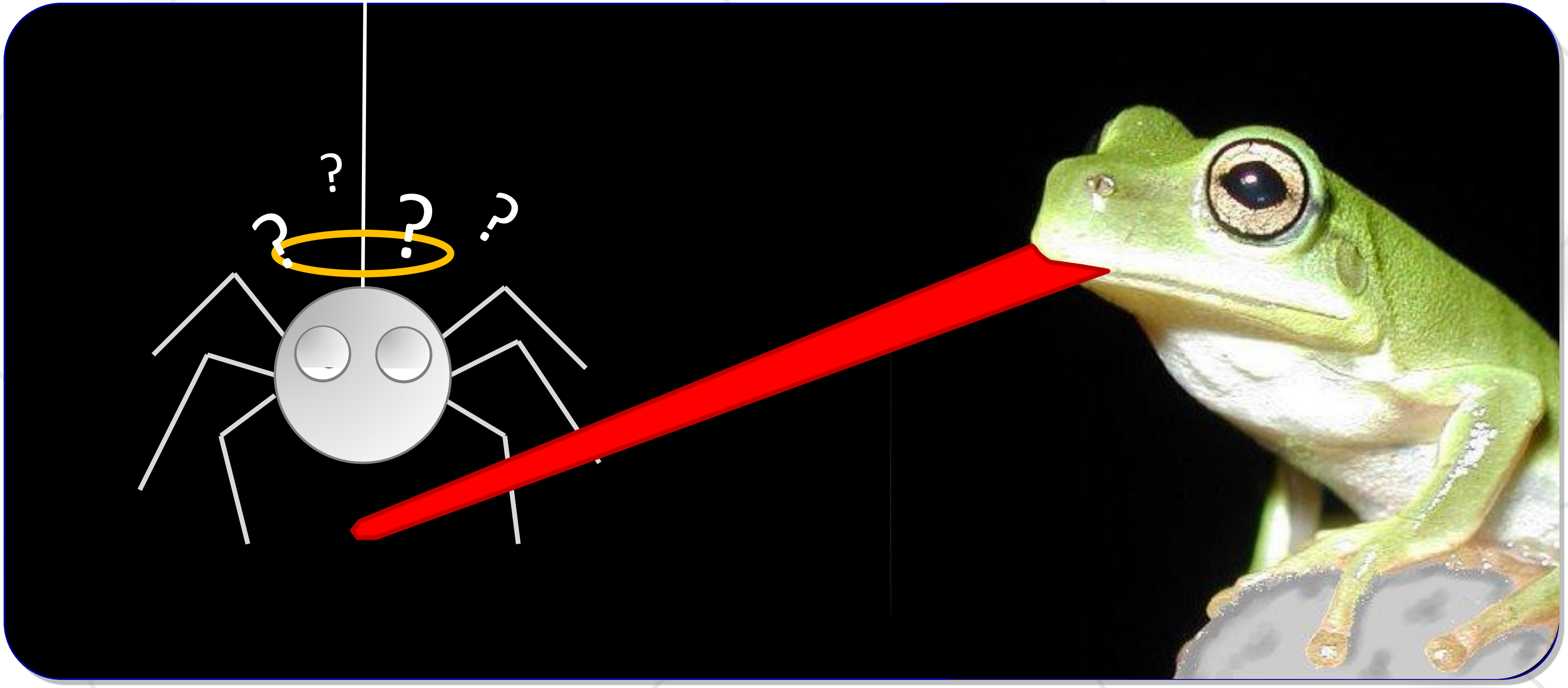


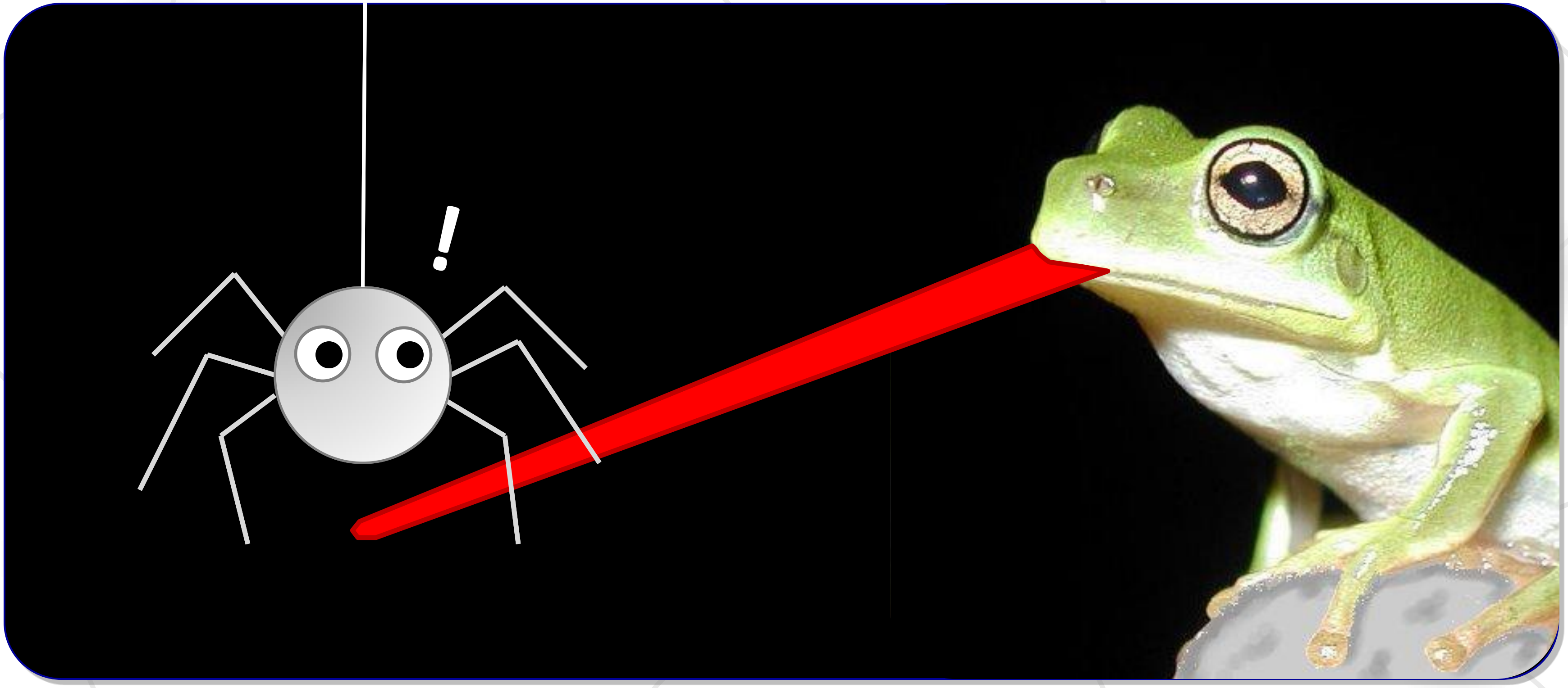
Immersed in a complex environment (because of one's actions)

- Full of other complex dynamical systems striving for survival
- The environment itself becomes genetically unpredictable



Adapting during life rather than evolution

- Basic set of reflexes to survive with immediate actions



Adapting during life rather than evolution

- Basic set of reflexes to survive with immediate actions
- Learning to better anticipate and act accordingly

Why bothering with anticipation?

[Pezzulo, *Minds and Machine*, 2008]
[Hawkins, *On Intelligence*, 2005]
[Bickhard, *JETAI*, 1998]

- eliminate lag from purely reactive behavior
- can be added up on top of reflexive behavior
- normative value of the prediction (epistemic contact)
- filter out noise and distractors from complex signals
- coordination/planning capabilities (in space and time)
- allows abstracting from sensorymotor signals
- concepts defined as networks of potential interactions
- easy to distribute and neurally plausible (population coding)

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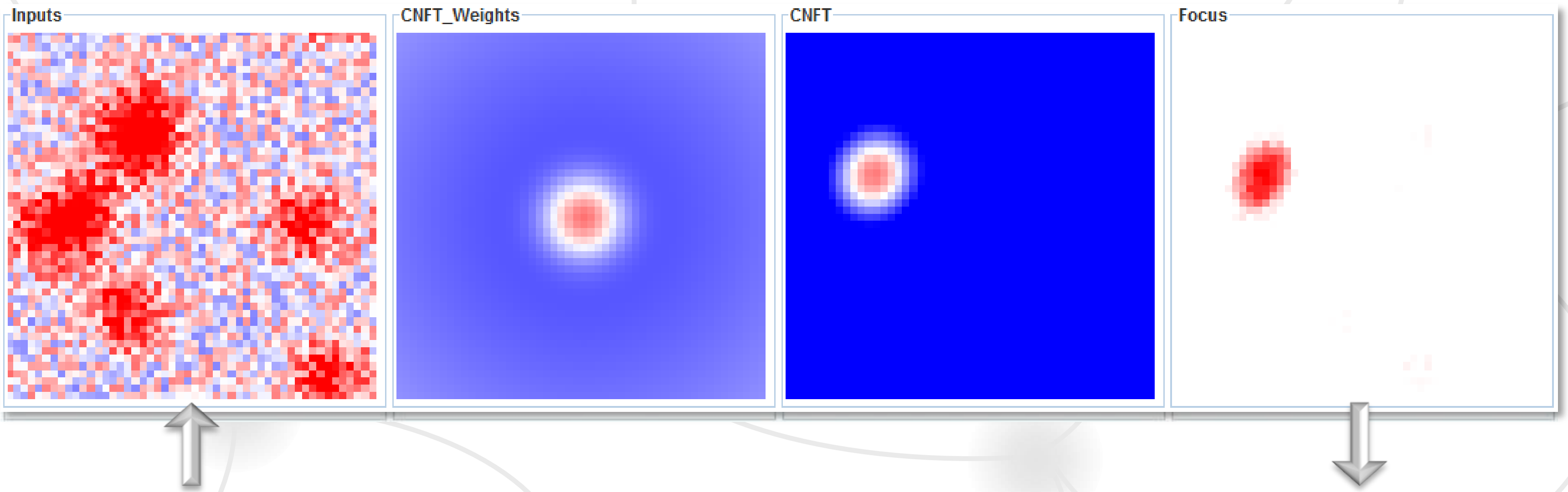
Dynamical Neural Field (DNF) + dynamic stimuli

- competition (between distant stimuli)
- non-linear convergence toward a stimulus
- noise/distracters robustness
- → good selection/tracking capabilities



Complex/noisy input

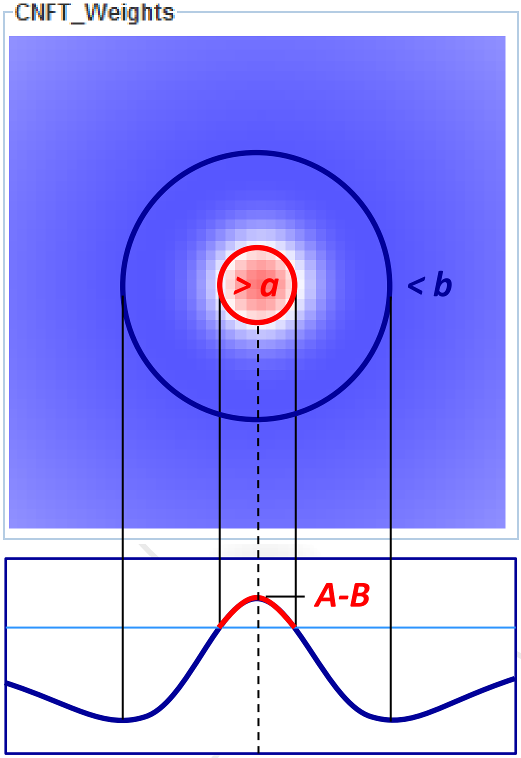
[Rougier & Vitay, *Neur. Net.*, 2006]

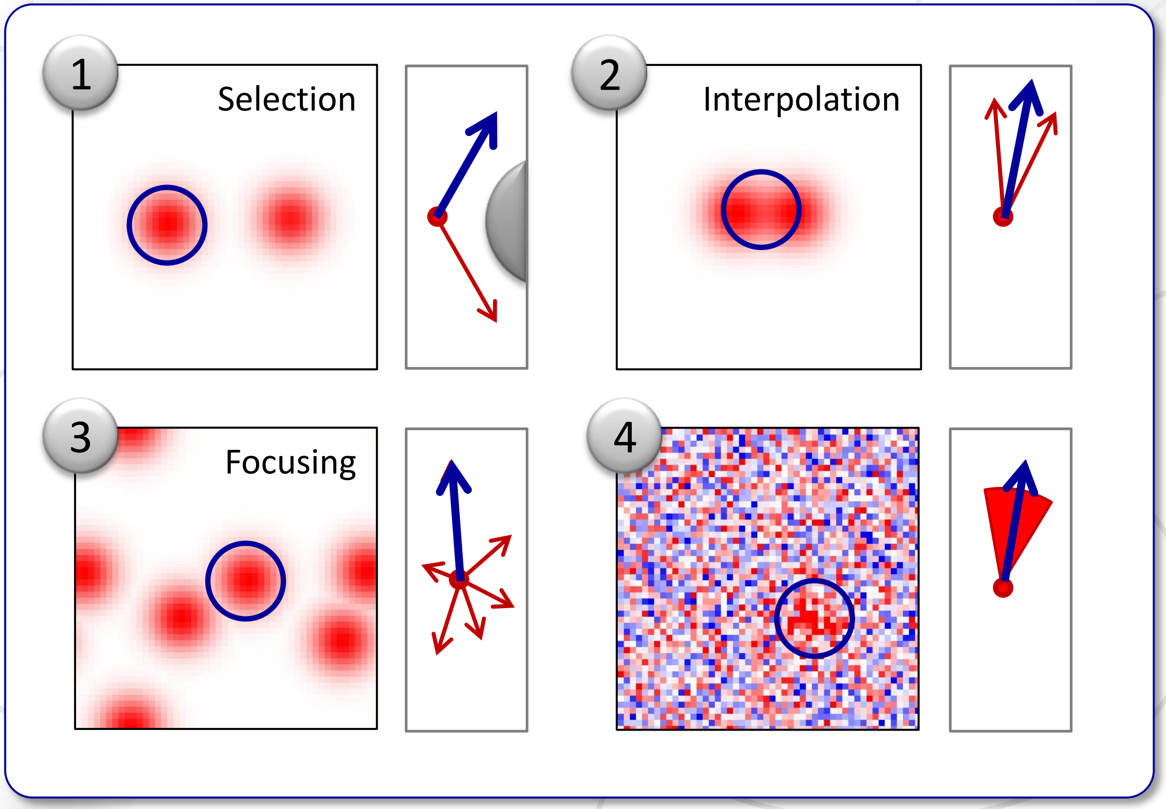
Focus on a stimulus

Standard equation and emergent properties

DNF equation: $$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x')\sigma(u(x',t))dx' + s(x,t) + h$$

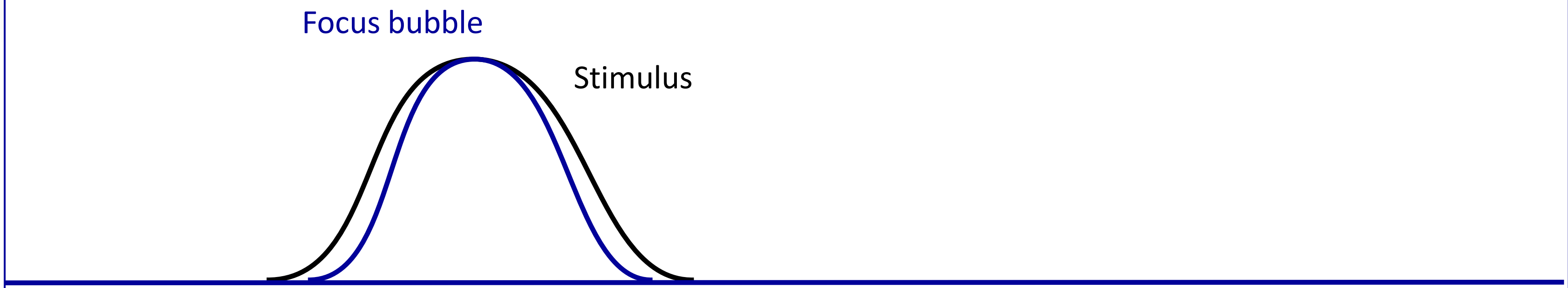
$$\hookrightarrow Ae^{-\frac{|x-x'|^2}{a^2}} - Be^{-\frac{|x-x'|^2}{b^2}}$$





Oscillations when tracking a moving input

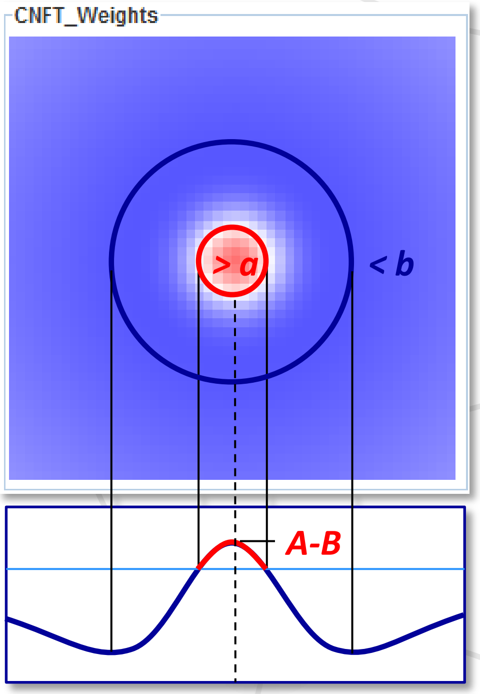
focus, assume the stimulus does not move, relax, focus… repeat

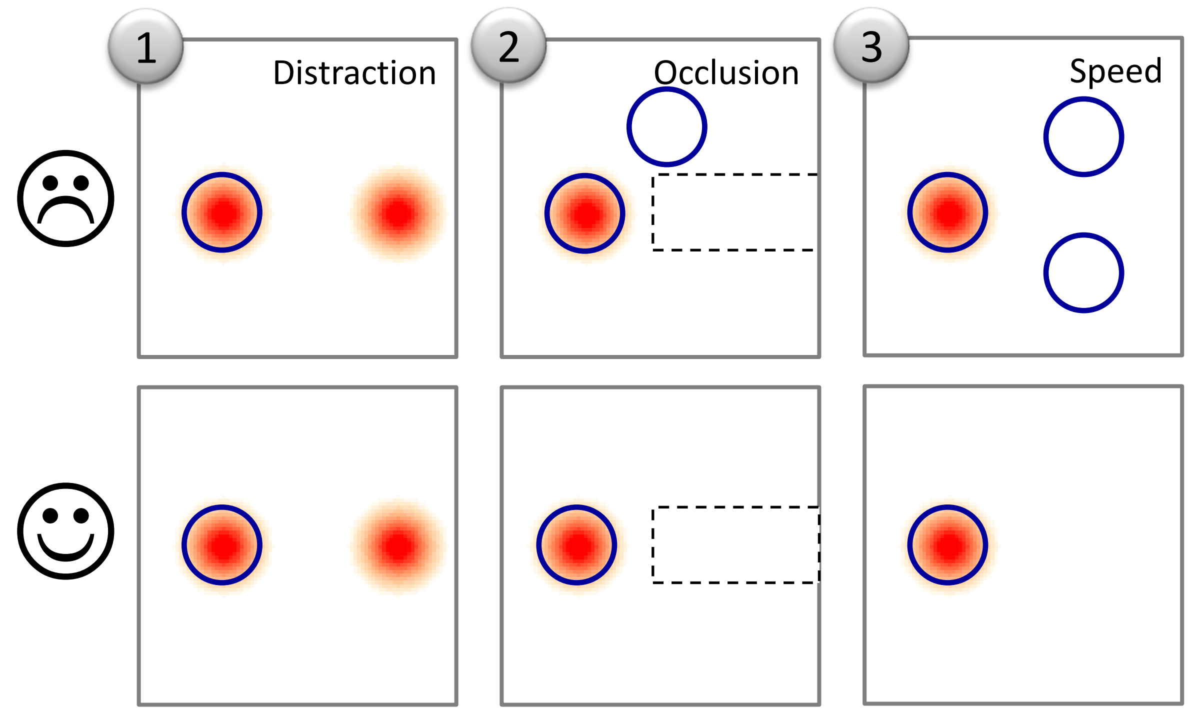


DNF extension:

$$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x')\sigma(u(x',t))dx' + i(x,t) + h$$

$$w(x,x') = Ae^{-\frac{|x-x'|^2}{a^2}} - Be^{-\frac{|x-x'|^2}{b^2}}$$





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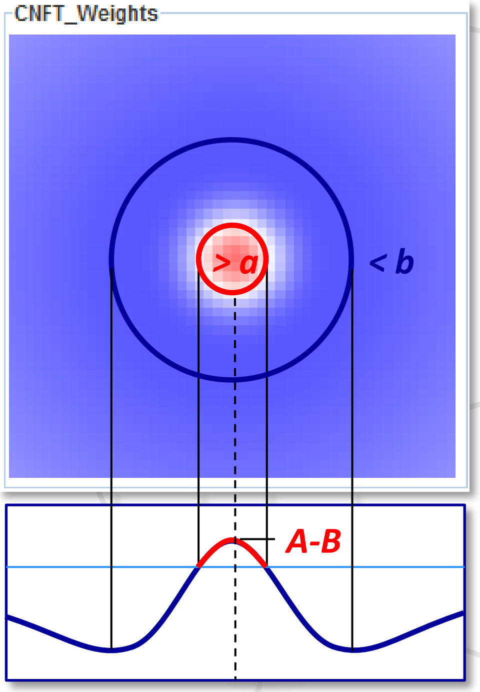
$$w(x,x') \rightarrow Ae^{-\frac{|x-x'|^2}{a^2}} - Be^{-\frac{|x-x'|^2}{b^2}}$$

$$i(x,t) \rightarrow \alpha p(x,t) + (1-\alpha)s(x,t)$$

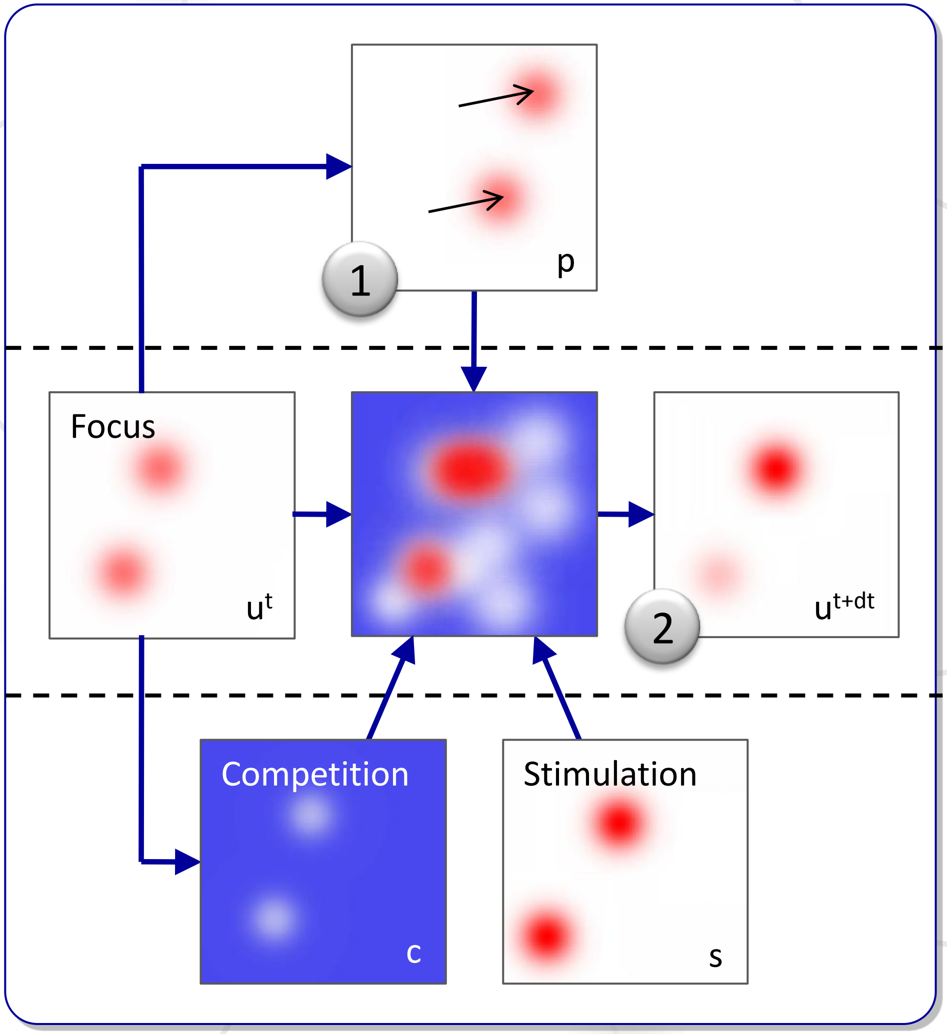
[Quinton & Girau, *IEEE IJCNN*, 2011]



Possible ways of introducing predictions

- Asymmetric kernels (e.g. ACNFT [Cerda, 2010])
  - merge kernels for different predictions?
  - different kernel at each point?
  - keep DNF properties?
- Bias the field activity
  - (similar problems)
- Bias the stimulation
  - bottom-up + top-down projections

Computation steps



1) Compute prediction (p)
- transform of u^t
- → expected activity u^{t+dt}

2) Update the CNFT (u^{t+dt})
- competition term
- integration scheme
- → biased convergence

How to evaluate performance ?

Environment…

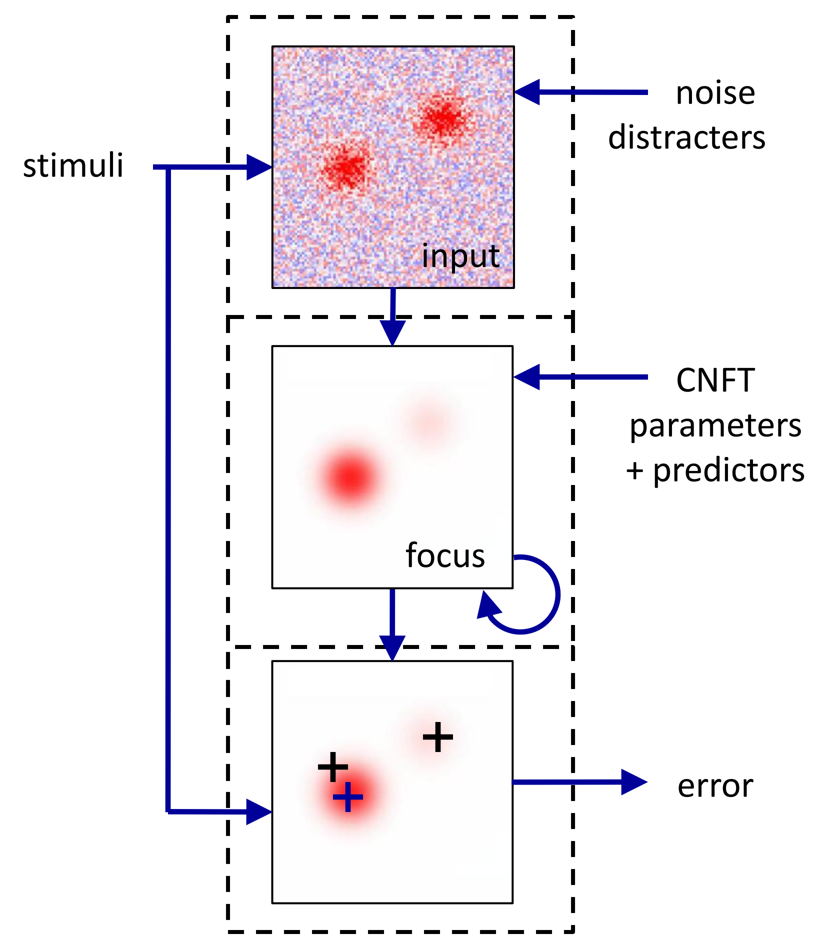
- inputs to the model
- representative dynamics
- → input scenario(s)

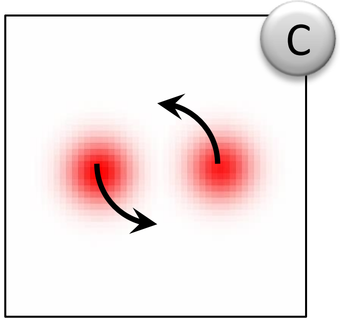
Tracking performance…

- hypothesis : 1 bubble
- compute center of mass
- compute error / inputs
- → expected properties

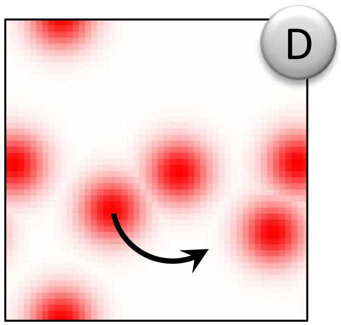
CNFT model

- → only access raw data

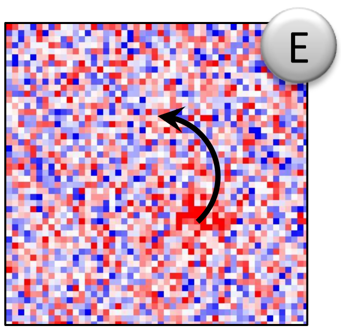




- 2 moving stimuli
- slight dissymmetry
- slow alternation

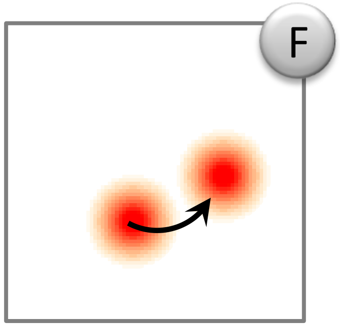


- 1 moving stimulus
- distracters at t=1

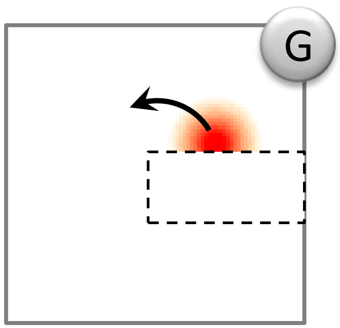


- 1 moving stimulus
- noise at t=0

Specific scenarios to test the predictive capabilities

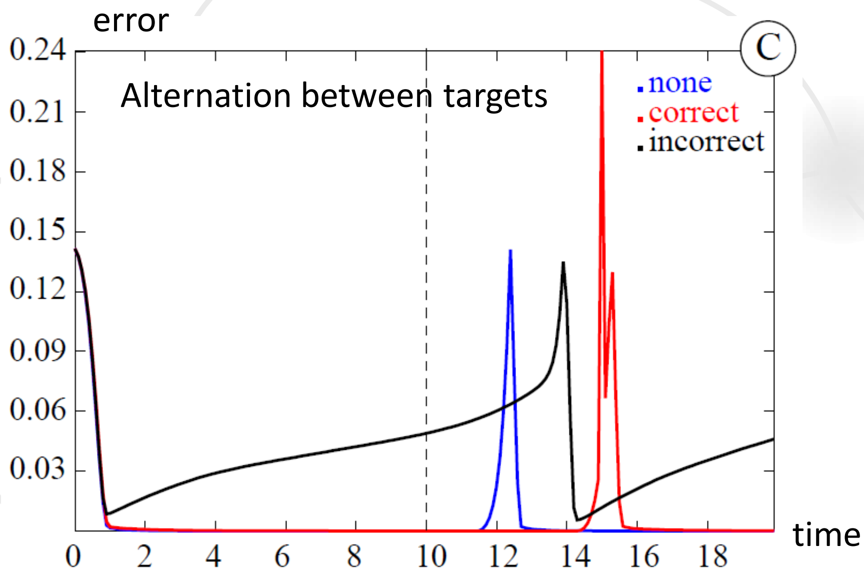


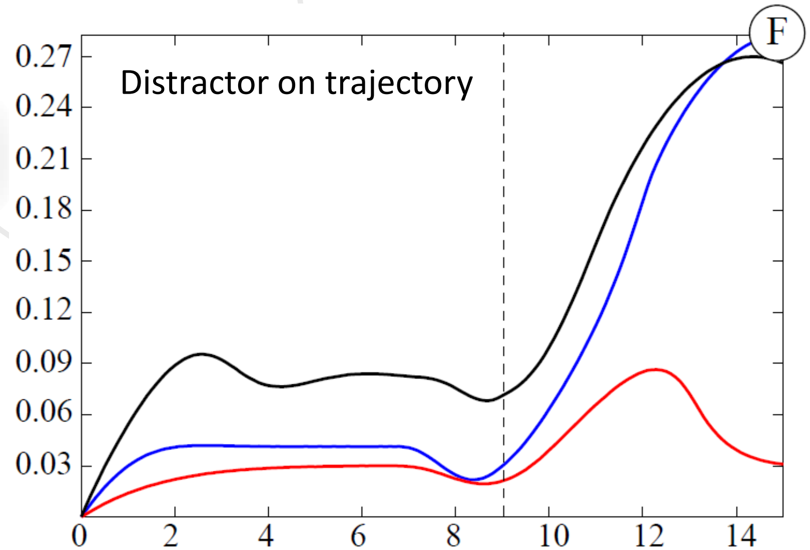
- 1 moving stimulus
- distracter on trajectory

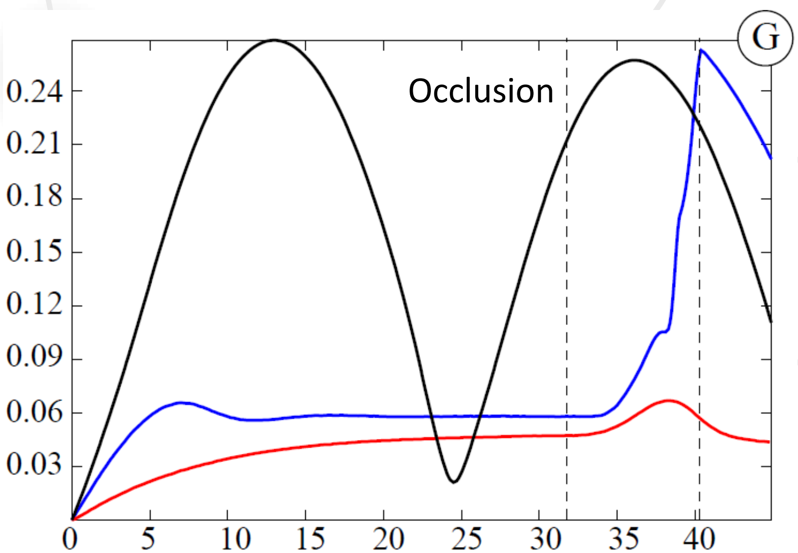


- 1 moving stimulus
- full occlusion

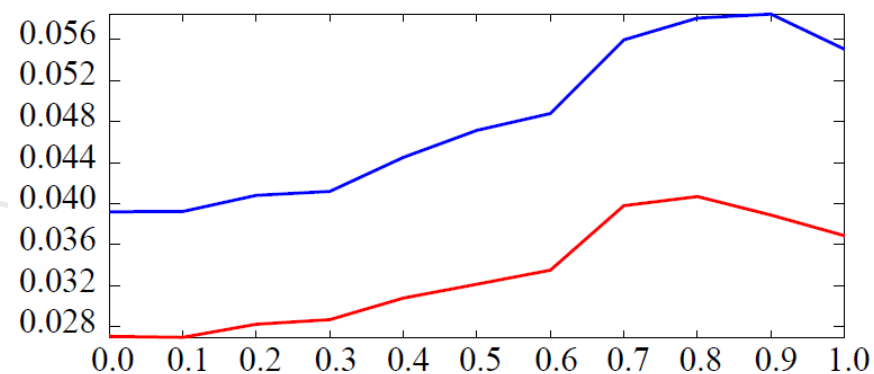
Results





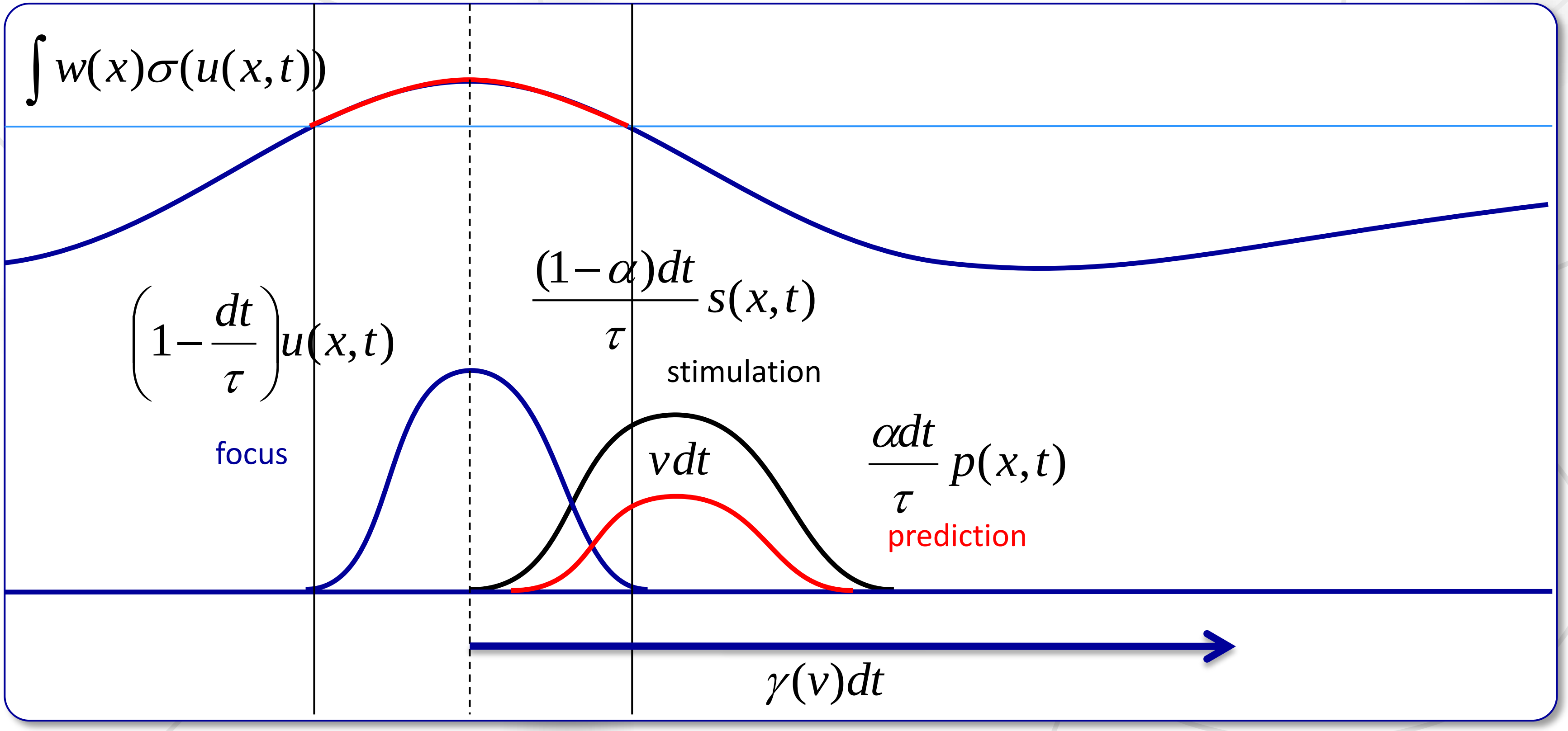


Mean tracking error as a function of the Gaussian noise standard deviation



Linear predictor: $\bar{p}(x,t) = u(x - vdt, t)$ ← Sensation from the CNFT

$p(x,t) = u(x - \gamma(v)dt, t)$ → Action on the CNFT



Tracking error for various scenarios and predictors (mean distance for a field of 1x1 unit)

Scenario	No prediction	Correct prediction	Incorrect prediction
C (alternation)	0.0066	0.0079	0.0407
D (distracters)	0.0179	0.0095	0.0156
E (noise)	0.0047	0.0032	0.0081
F (fixed distracter)	0.0090	0.0036	0.0123
G (occlusion)	0.0082	0.0041	0.0174

Qualitative results

- reproduces the DNF properties and add new properties
- lower error with correct predictor (hopefully)
- fallback on the standard version with bad predictor

→ how to deal with an arbitrary trajectory ?

DNF extension:

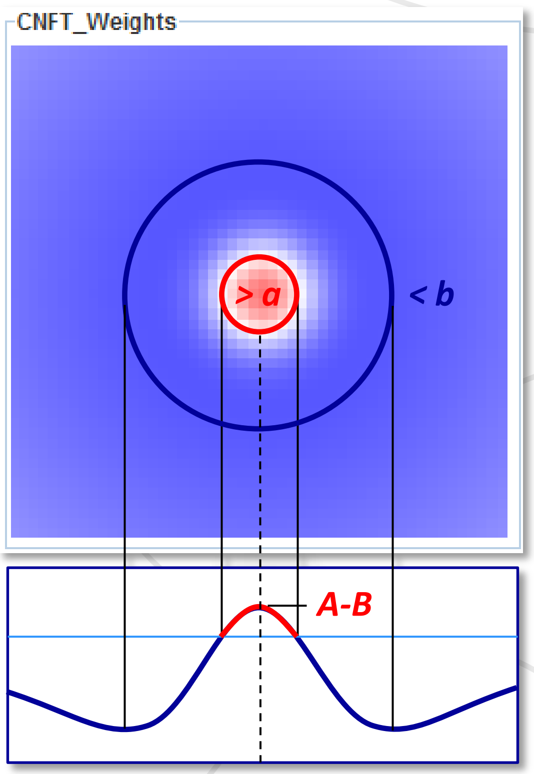
$$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x')\sigma(u(x',t))dx' + i(x,t) + h$$

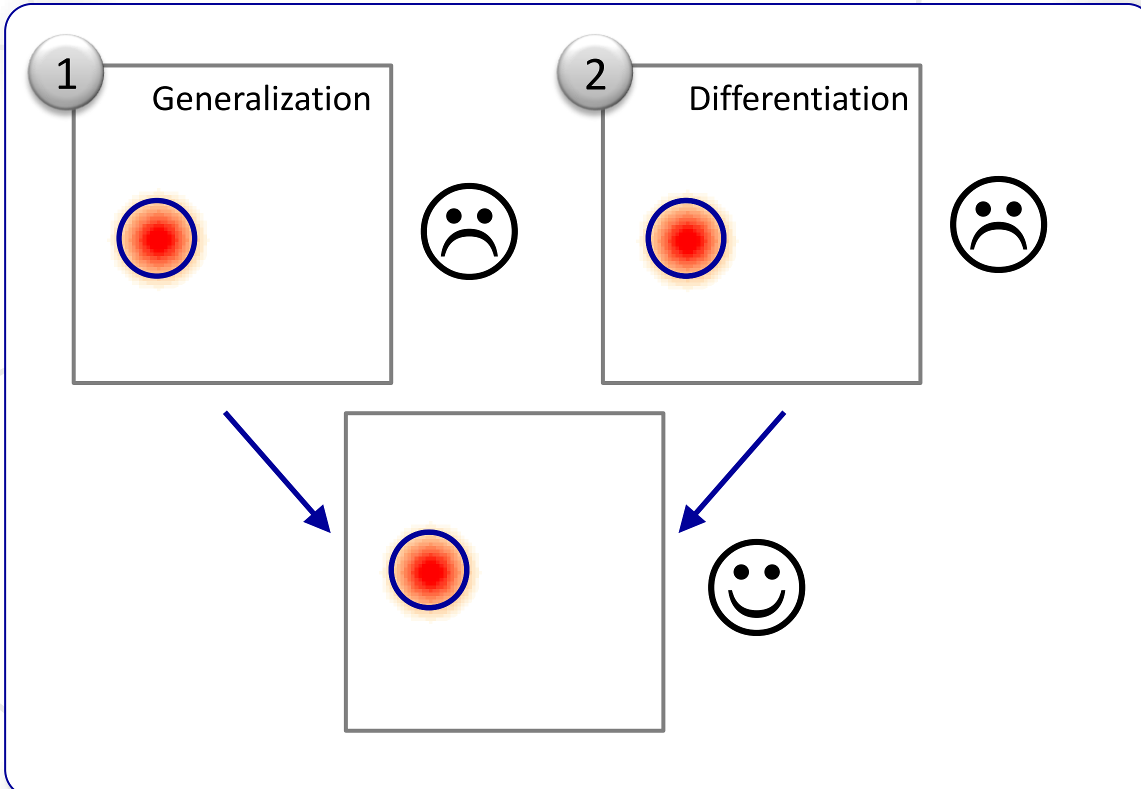
$$w(x,x') \rightarrow Ae^{-\frac{|x-x'|^2}{a^2}} - Be^{-\frac{|x-x'|^2}{b^2}}$$

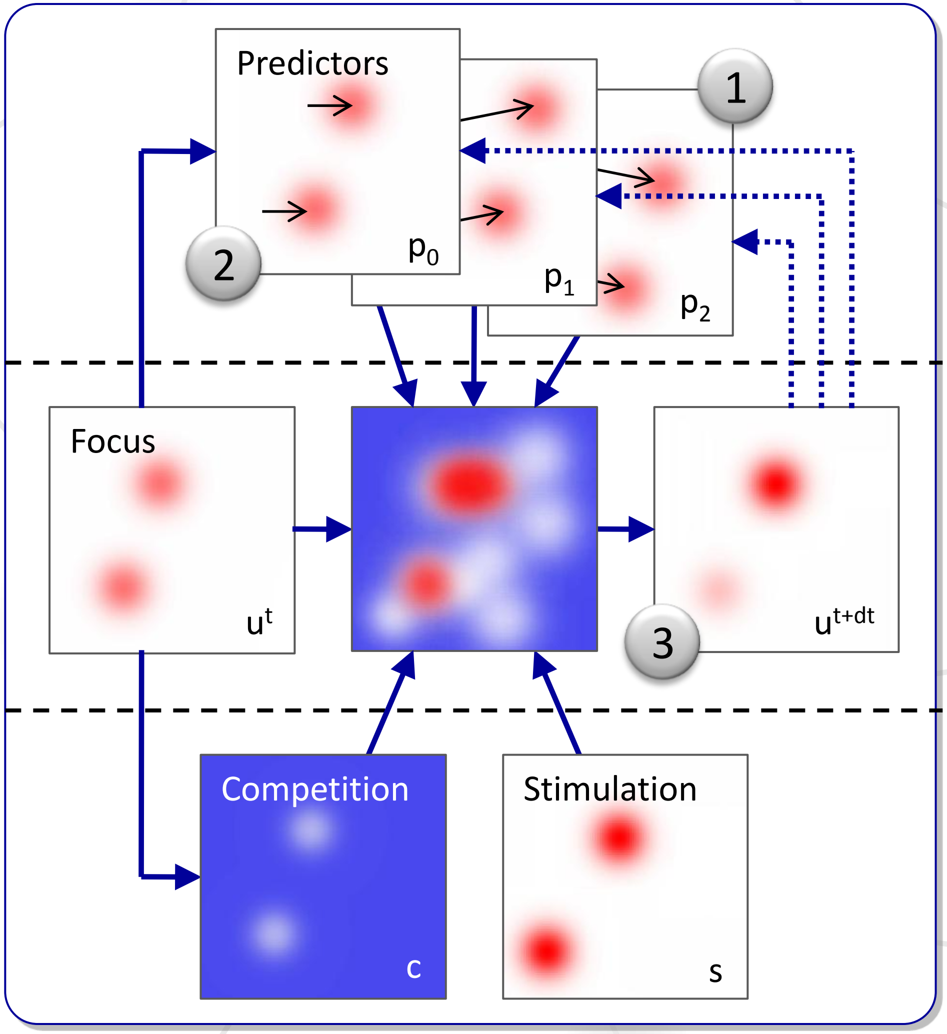
$$i(x,t) \rightarrow \alpha p(x,t) + (1-\alpha)s(x,t)$$

$$p(x,t) \rightarrow \frac{\sum w_k(t) p_k(x,t)}{\sum w_k(t)}$$

[Quinton & Girau, *CNS*, 2012]



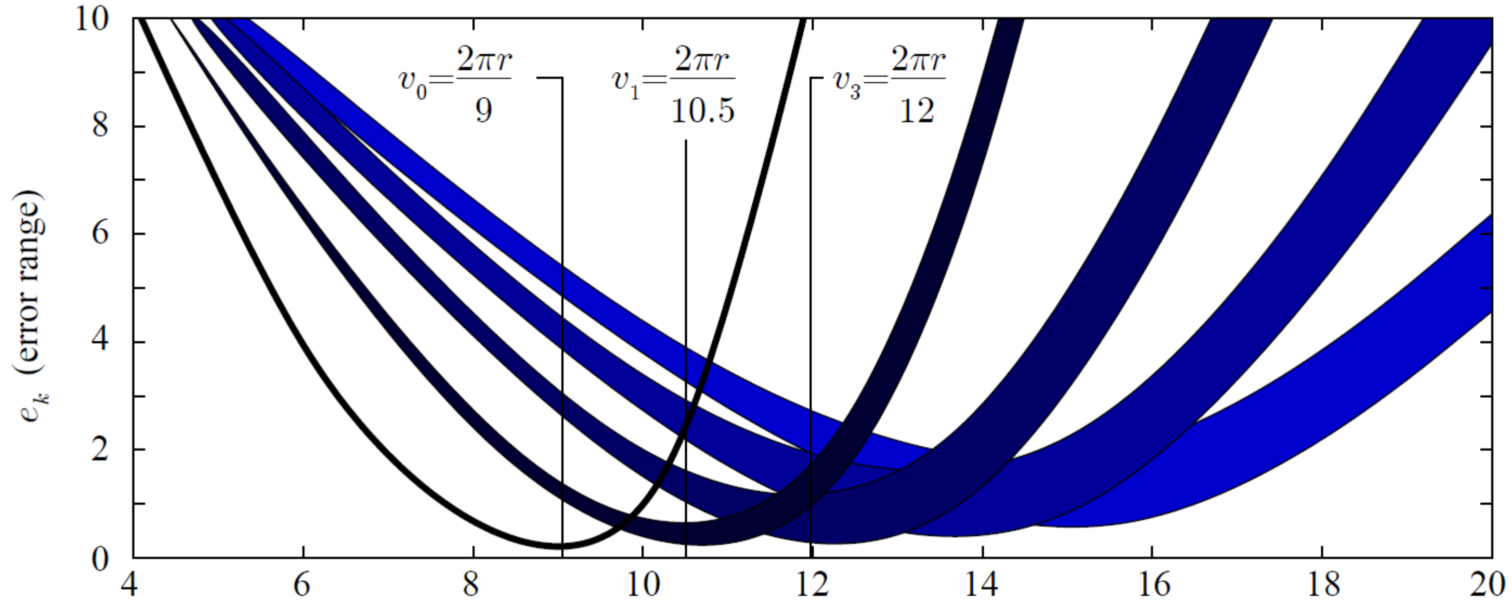




1) Confidence update (w_k)
- match prediction
- to stimulation
- → error committed

2) Compute predictions (p_k)
- transform of u^t
- merge in a single field
- → expected activity u^{t+dt}

3) Update the CNFT (u^{t+dt})
- competition term
- integration scheme
- → biased convergence

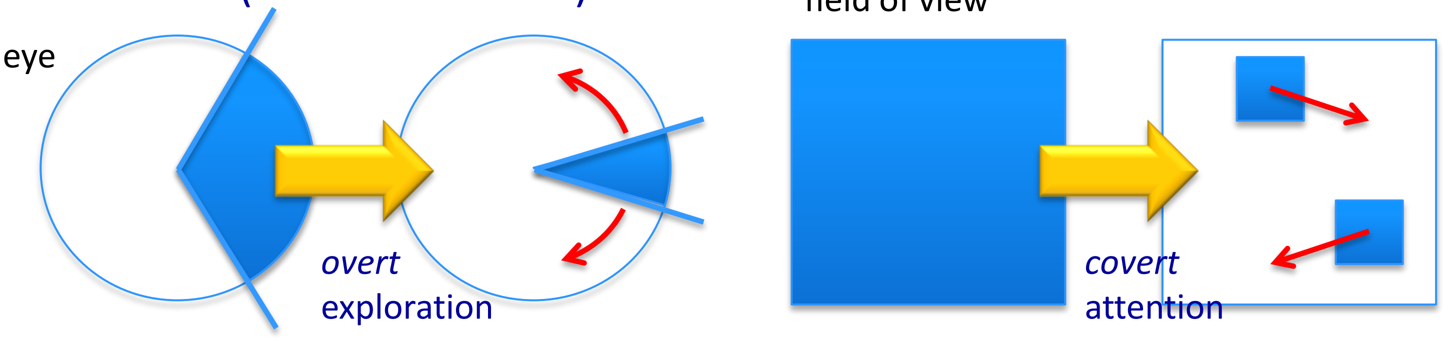


Qualitative results

- reproduces the results obtained with a single predictor
- fast selection of adequate predictors
- interpolation in time and space + multi-scale support (hyperacuity)

Combining overt and covert predictions

Visual attention (overt and covert)

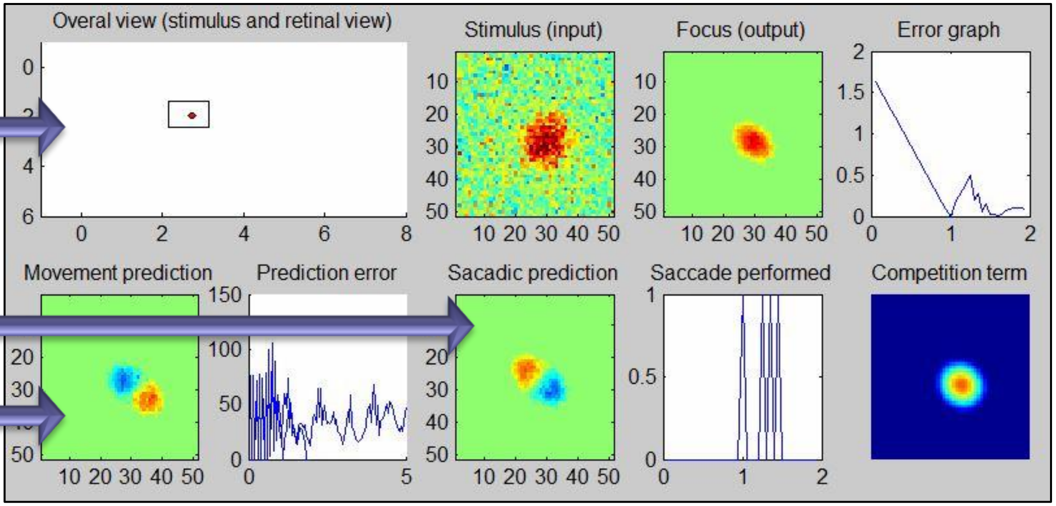


Implementation for tracking

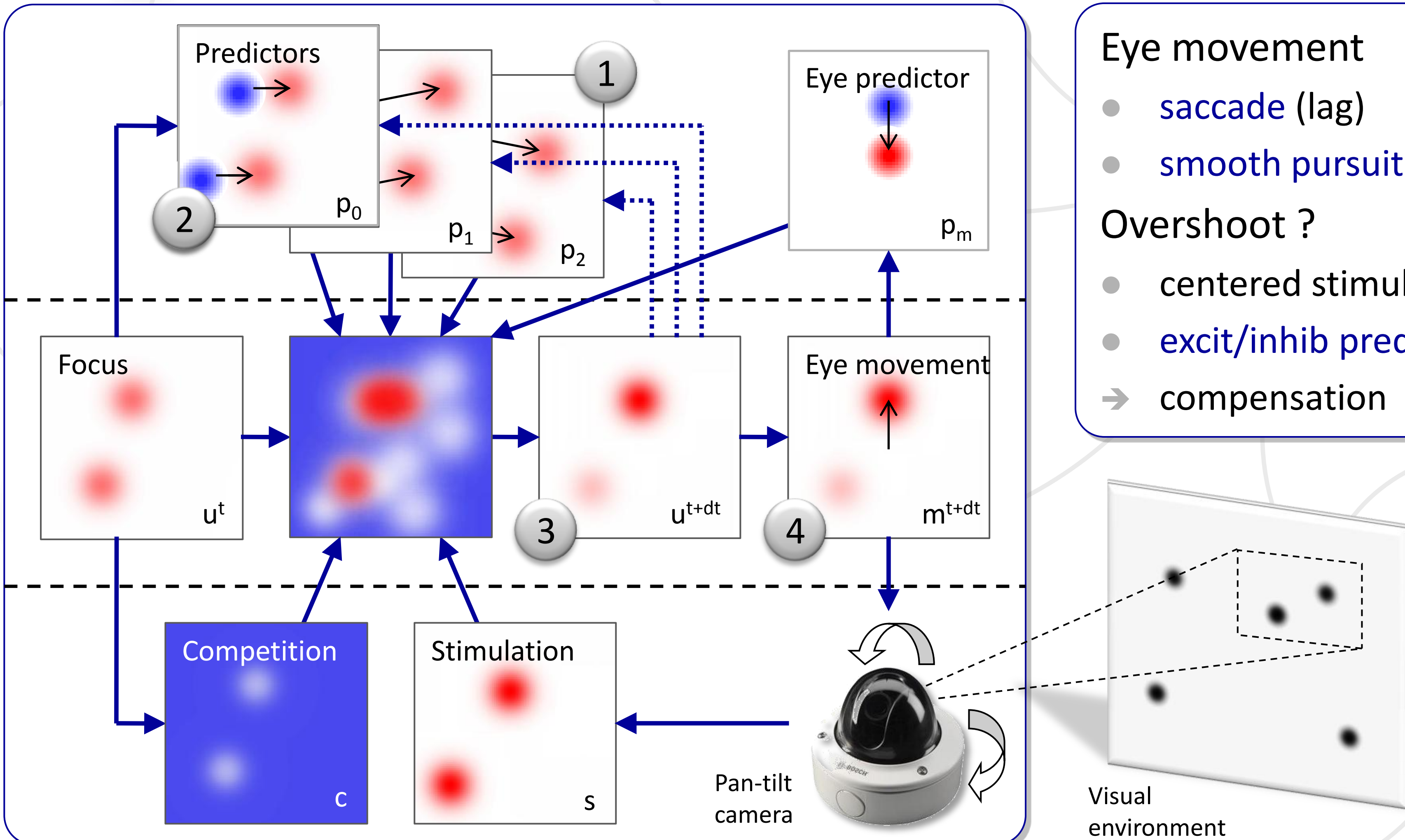
Stimuli rapidly
crossing the field of view

Eye movement prediction

Stimulus movement prediction



Computation steps



Eye movement

- saccade (lag)
- smooth pursuit

Overshoot ?

- centered stimuli
- excit/inhib pred.

→ compensation

Conclusion

- DNF as robust competition mechanism (to noise, distracters, occlusions)
- PNF reproduces the original behavior, but also allows active perception
- simple extension of the original DNF (inner/outer interactions)
- compatible with learning methods (e.g. sensorimotor contingencies)

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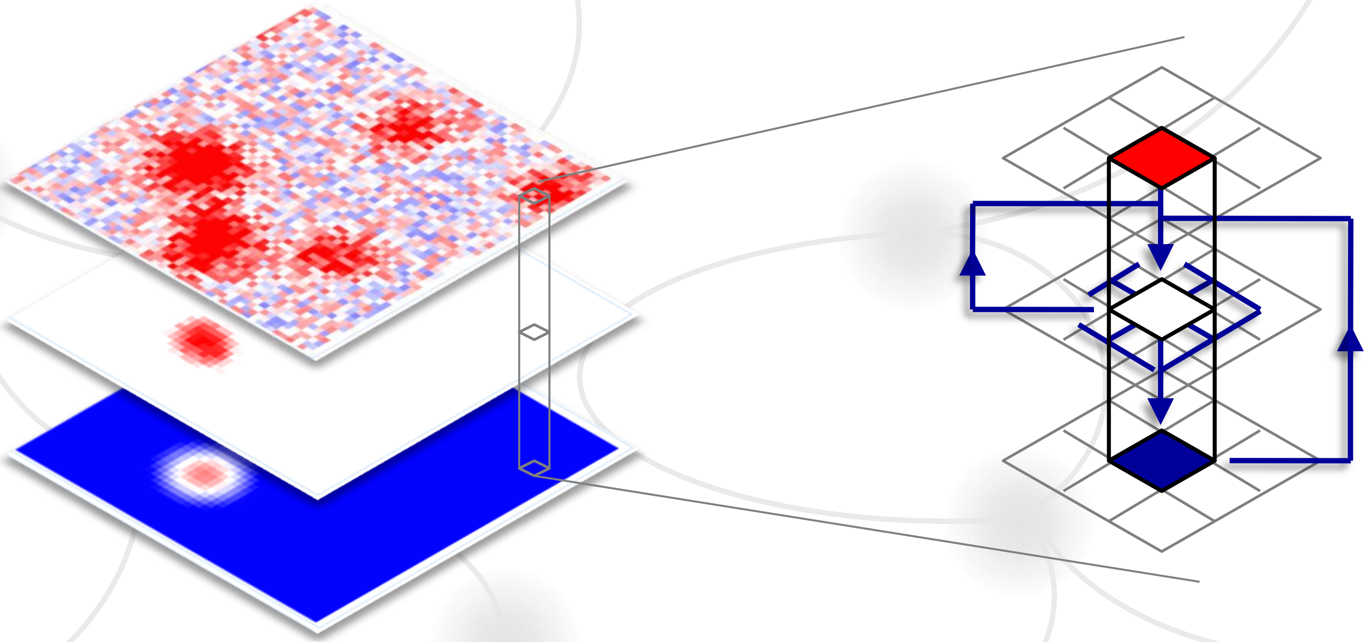
Dynamic Neural Fields (DNF)

- mesoscopic distributed model (tissue level, cortical sheet)
- over a topological manifold (1D / 2D continuous space)
- spatiotemporal evolution of variables (e.g. mean-field potential)
- described by (local) equations (same at all points)



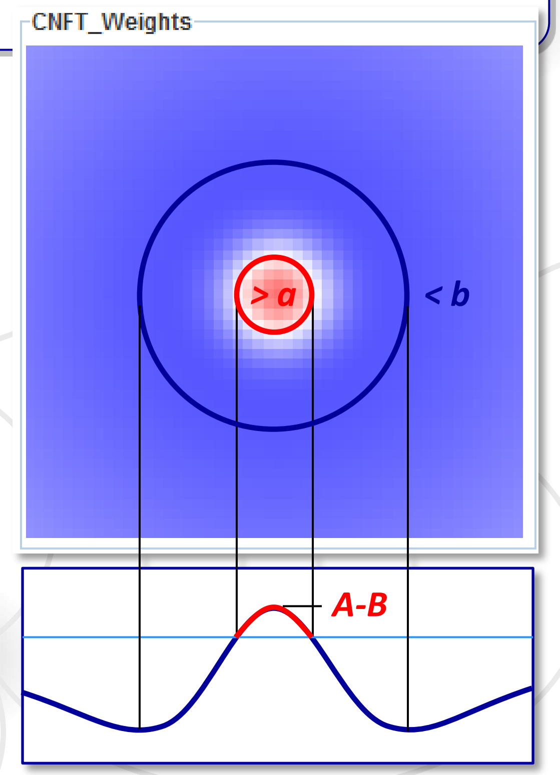
Parameters and equation for the potential…

$$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x')\sigma(u(x',t))dx' + s(x,t) + h$$

$$Ae^{-\frac{|x-x'|^2}{a^2}} - Be^{-\frac{|x-x'|^2}{b^2}}$$

Many implementations…

- rate coding [Rougier & Vitay, *Neur. Net.*, 2006]
- spikes [Chevallier & Tarroux, ESANN, 2008]
  [Vasquez, Quinton & Girau, IJCNN, 2011]



Similar constraints…

- 1D-3D manifold → fixed dimensionality
- matrix computations → fixed resolution
- convolution → polynomial complexity

Dealing with high dimensional data (and the curse of dimensionality!)

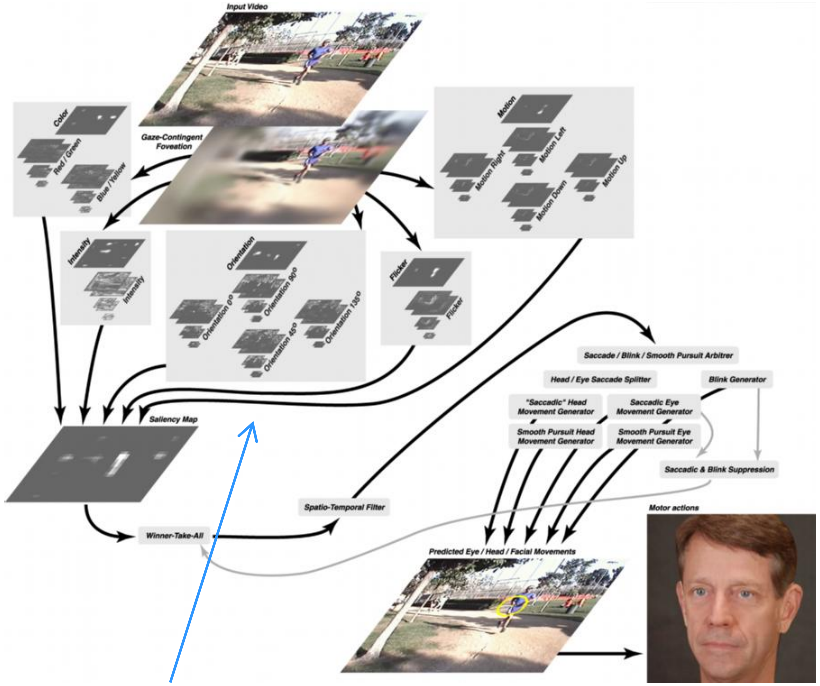
- Brute force
  - Higher order matrix convolution — complexity $O(n^{2d})$
  - Numerical linear algebra (SVD, FFT…) — SVD → $O(nd+1)$
  - Fast hardware implementation (GPU, FPGA) — connectivity pb
- Reduce dimensionality
  - Machine learning techniques (SVD, PCA…) — meaningfulness ?
  - Self-organizing maps (e.g. projection in 2D) — shearing, distortions
  - Combination (e.g. detectors/descriptors) — hard tuning

Visual saliency

designed to be salient

[Itti & Koch, *PAMI*, 1998]

Architectures and improvements



adaptive weights

[Frintrop & Jensfelt, *Trans.Rob.*, 2008]

[Fix et al., *Cognitive Computation*, 2010]

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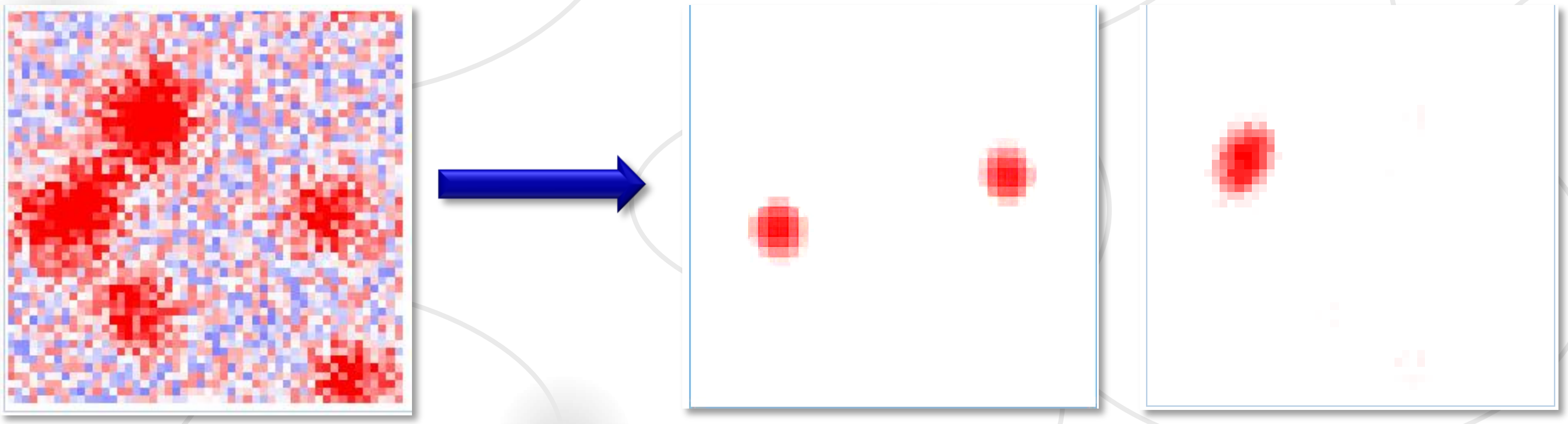
  - Combination (e.g. detectors/descriptors) — hard tuning
- Couple low dimensional maps
  - Sharing dimensions (i.e. linear projections) — binding pb
  - Other projections — lattice + constraints ?
- Other approximations of the continuum
  - Spiking neurons — update potential
  - Mixtures (GMM, RBF…) — robustness ?

From simple observations

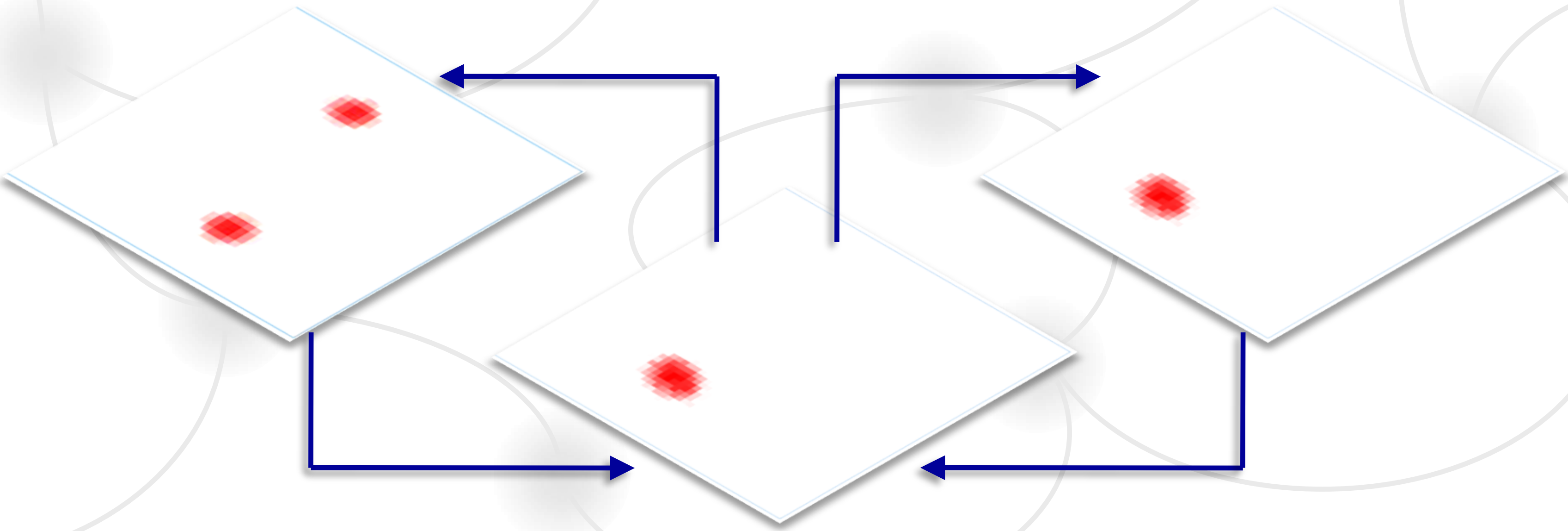
- dynamics converges toward a set of peaks
- peaks often have spatial and temporal continuity
- peaks are stereotyped (shape depending on the kernel)



From simple observations

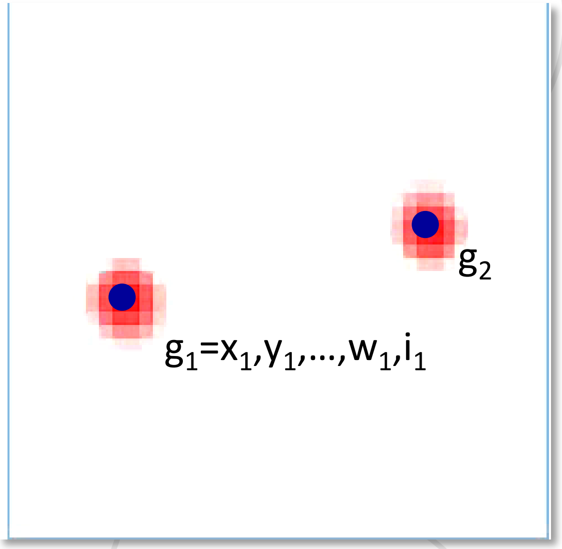
- dynamics converges toward a set of peaks
- peaks often have spatial and temporal continuity
- peaks are stereotyped (shape depending on the kernel)
- architectures with might be many interconnected maps
- learning method that requires dense mapping (no regression)

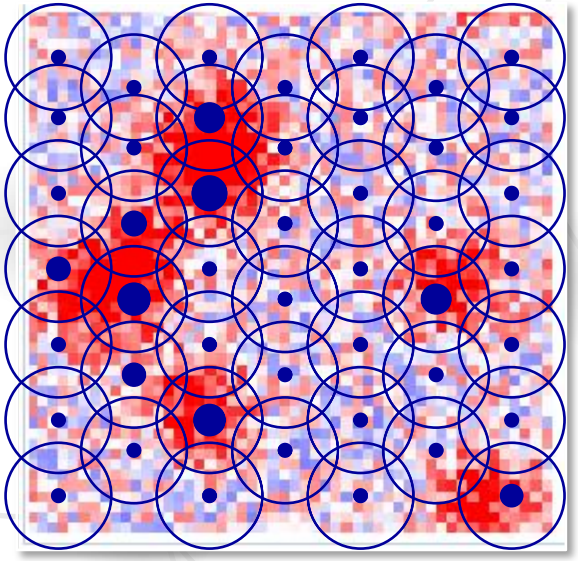
← (only true when the goal is to select/track)

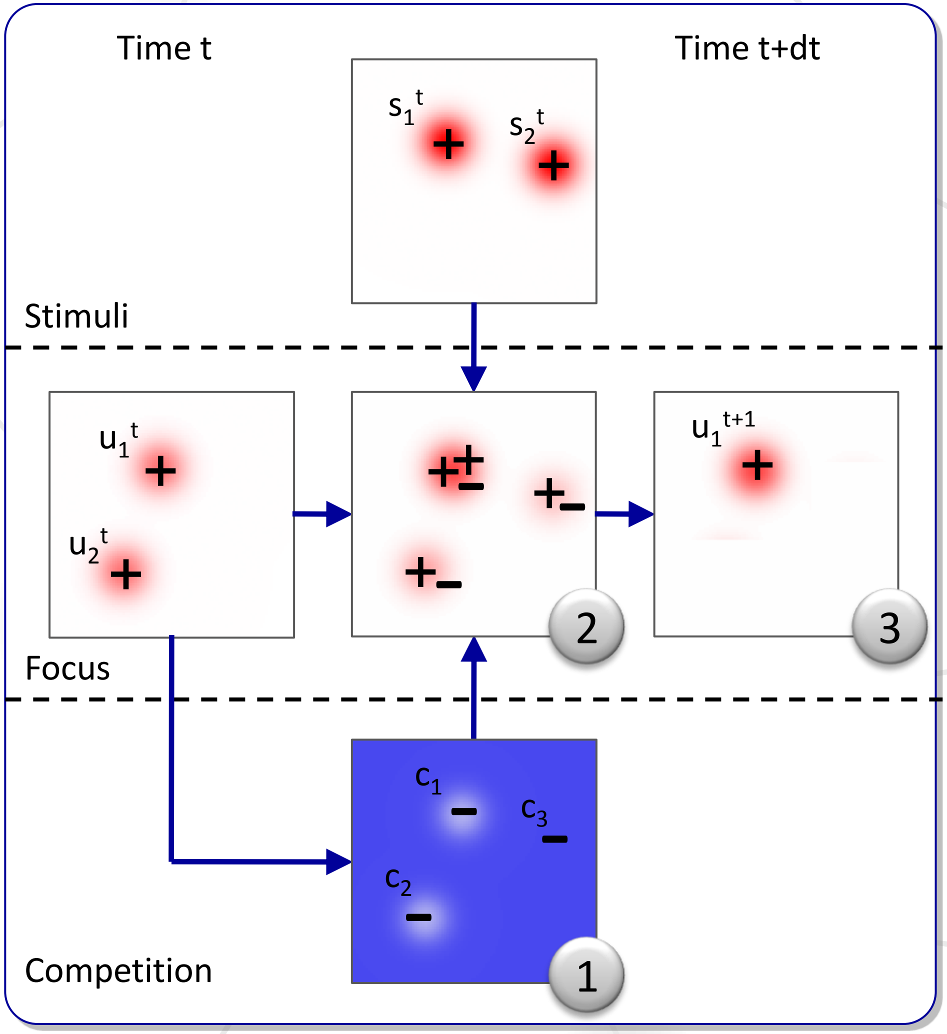


Model peaks of activity as point-like elements

- center coordinates (2D+), (width) and intensity (arbitrary distribution)
- input as a set of points (use receptive fields and filters)
- → exclusively manipulate point-like elements







1) Competition step

- between centers only
- mainly inhibition (-)
- → need to account for s_i^t

2) Integration step

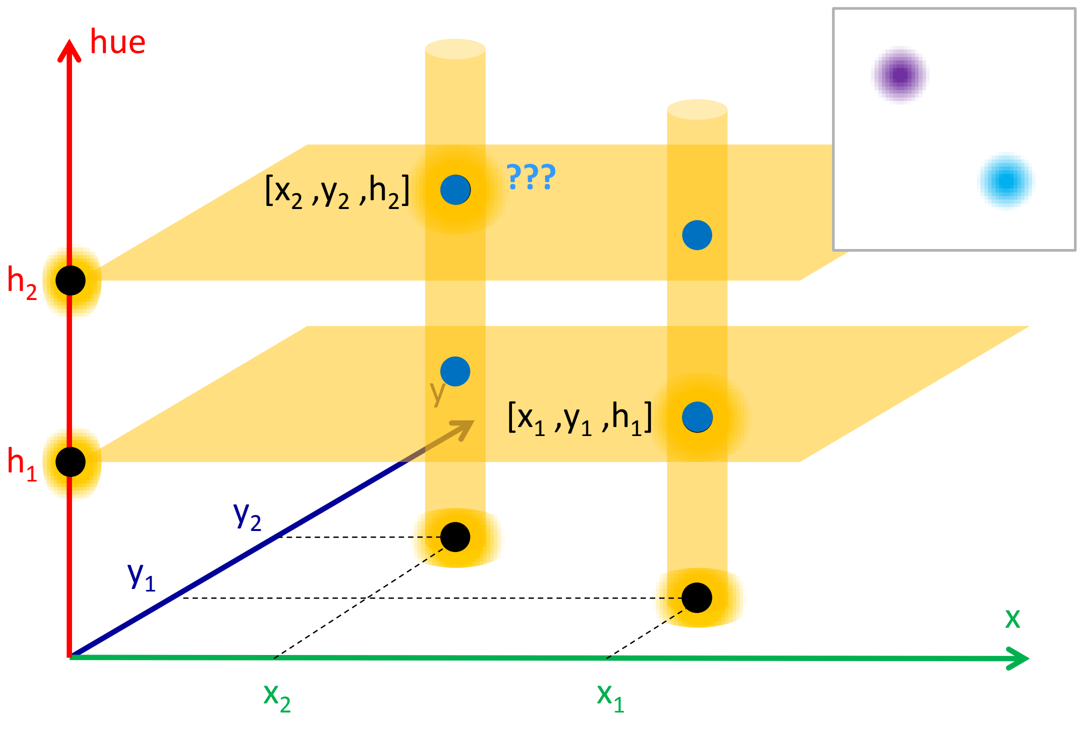
- all in one sparse map
- excitatory & inhibitory
- → growing number of elts

3) Merging step

- merge close elements
- eliminate weak ones
- → convergence

Activity in hyperspaces (i.e. lower dimensional fields)

- binding through attention → prediction / planning or multiple hypotheses?
- ridges with matrix (DNF) → sparse vectors with arbitrary distributions (SNF²)



Sparse vectors

- $[h_1]$ $[h_2]$ $[x_1,y_1]$ $[x_2,y_2]$
- $[x_1,y_1,h_1]$ $[x_2,y_2,h_2]$

Similarity measure

- $[x_1,y_1,h_1] \rightarrow [x_2,y_2,h_2]$
  $\approx \| [x_1-x_2,y_1-y_2,h_1h_1] \|$
- $[x_1,y_1,h_1] \rightarrow [x_2,y_2]$
  $\approx \| [x_1-x_2,y_1-y_2] \|$
- [h1] → [x1,x2]
  ≈ 0

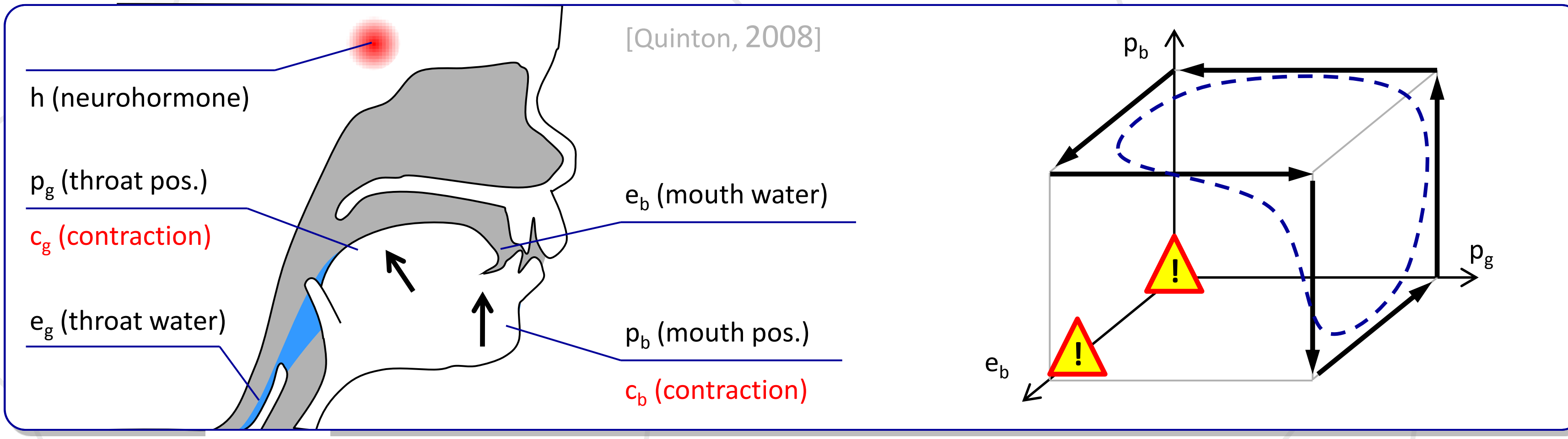
Iteration time (in µs) for the various versions implemented and tested

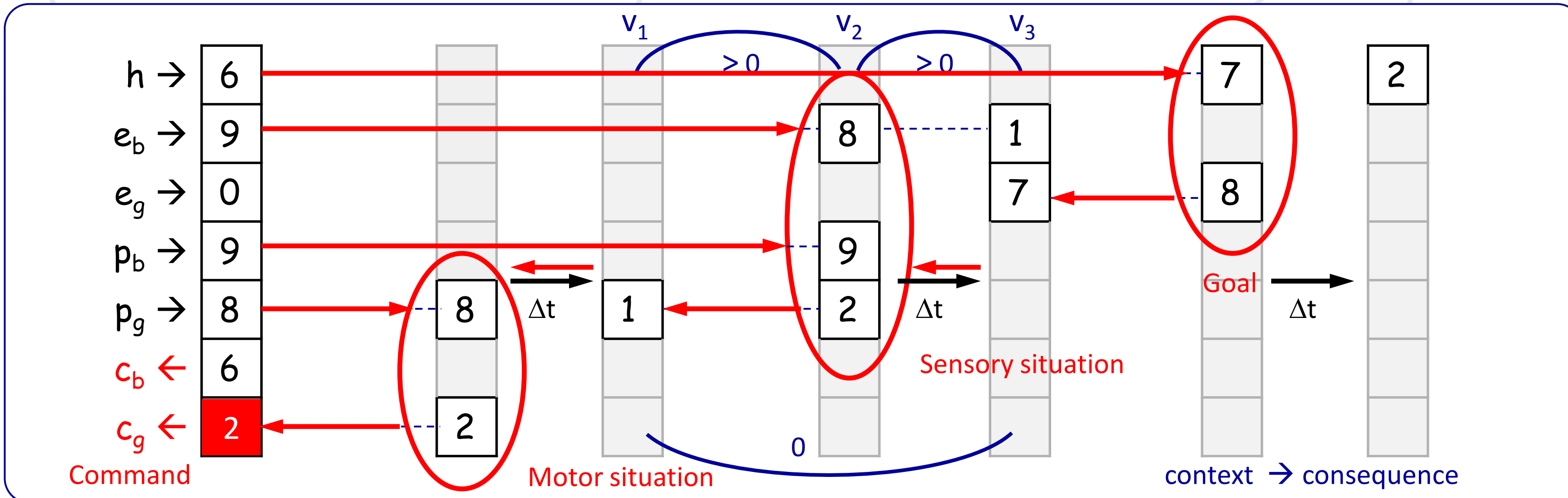
Scenario	Discrete version	Discrete (SVD)	Sparse version
A (alternation	321131	37537	596
B (distracters)	321084	37724	953
C (noise)	321003	37491	632

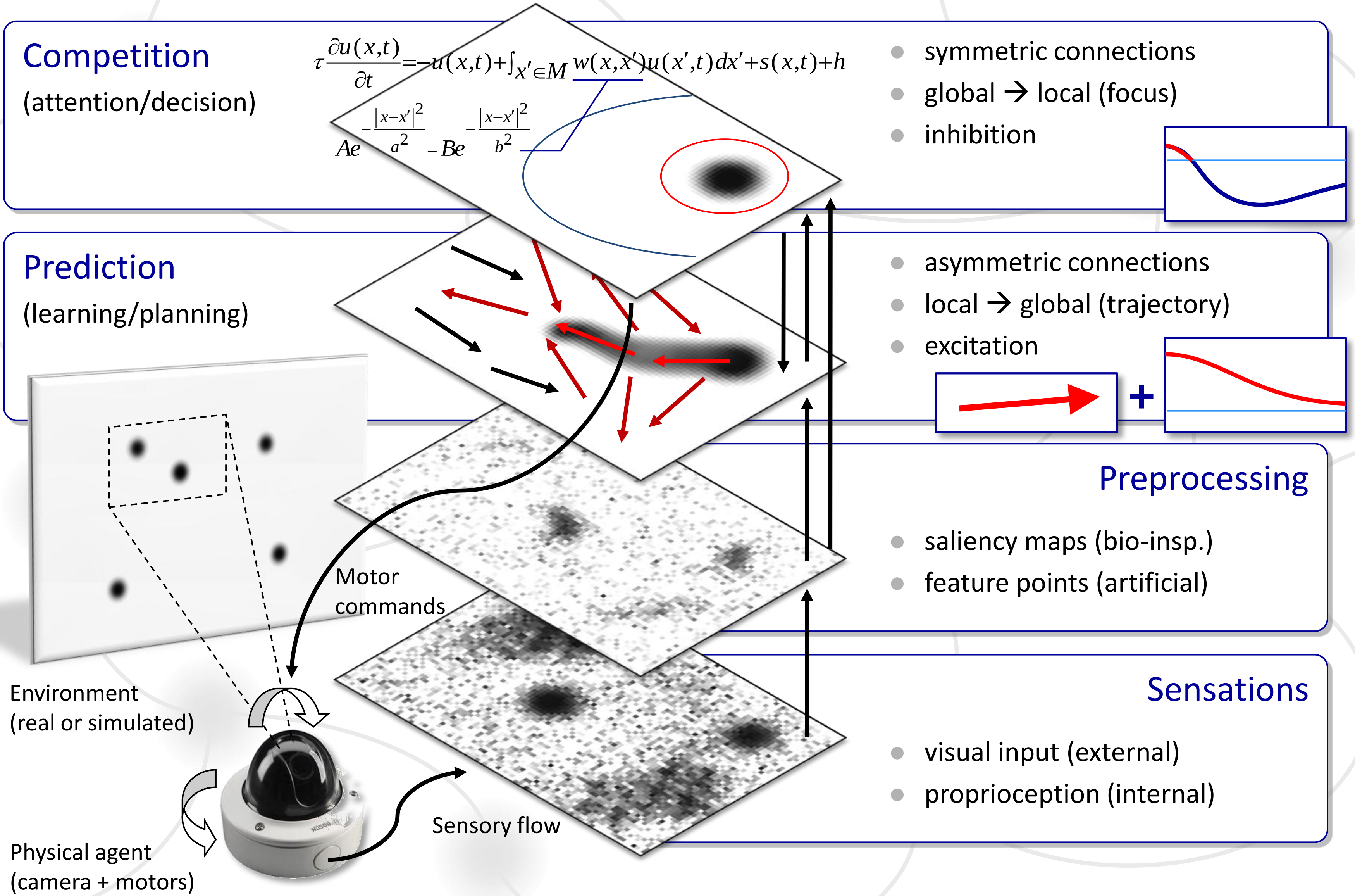
Qualitative results

- low computational cost (even with non parallel hardware)
- update time depending on the number of elements (quadratic)
- another approximation of the continuous neural dynamics
- reproduces the properties of the standard version
- produces synthetic values for easy interfacing with artificial systems
- able to simulate multi-dimensional DNF in a single field
- sparsity in space and in dimensions (abstract adaptive topology)
- yet, if too few components → reduced robustness
- except for performance, functionally/theoretically useful?

Swallowing (autonomy, goal constraints)






Competition
(attention/decision)
$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{x' \in M} w(x,x') u(x',t) dx' + s(x,t) + h$
$Ae^{-\frac{|x-x'|^2}{a^2}} - Be^{-\frac{|x-x'|^2}{b^2}}$
symmetric connections
global → local (focus)
inhibition
Prediction
(learning/planning)
asymmetric connections
local → global (trajectory)
excitation
+
Preprocessing
saliency maps (bio-insp.)
feature points (artificial)
Sensations
visual input (external)
proprioception (internal)
Motor commands
Sensory flow
Environment
(real or simulated)
Physical agent
(camera + motors)